

A Simple Poverty Scorecard for Mozambique

Mark Schreiner and Hélia Nsthandoca Dezimahata Lory

12 July 2013

This document and related tools are at microfinance.com/#Mozambique.

Uma versão em Português está disponível em microfinance.com/Portugues.

Abstract

This study uses Mozambique's 2008/9 Household Budget Survey to construct an easy-to-use scorecard that estimates the likelihood that a household has consumption below a given poverty line. The scorecard uses ten simple indicators that field workers can quickly collect and verify. Poverty scores can be computed on paper in the field in five to ten minutes. The scorecard's bias and precision are reported for a range of poverty lines. The simple poverty scorecard is a practical way for pro-poor programs in Mozambique to measure poverty rates, to track changes in poverty rates over time, and to target services.

Acknowledgements

This work was funded by the Swiss Development Corporation (SDC) through its INOVAGRO project. Data are from Mozambique's *Instituto Nacional de Estatística*, with thanks to Antonio Adriano, Arão Balate, João Dias Loureiro, and Clara Dias Panguana. Special thanks go to Channing Arndt, M. Azhar Hussain, and Rose Mungai.

Authors

Mark Schreiner is the Director of Microfinance Risk Management, L.L.C., microfinance.com. He is also Senior Scholar at the Center for Social Development in Washington University in Saint Louis. Hélia Nsthandoca Dezimahata Lory may be contacted at heliadlory@yahoo.es.

Simple Poverty Scorecard for Mozambique

<u>Entity</u>	<u>Name</u>	<u>ID</u>	<u>Date (DD/MM/YY)</u>
Member:	_____	_____	Date joined: _____
Field agent:	_____	_____	Date scored: _____
Service point:	_____	_____	# household members: _____

Indicator	Response	Points	Score
1. How many members does the household have?	A. Eight or more	0	
	B. Seven	2	
	C. Six	7	
	D. Five	9	
	E. Four	15	
	F. Three	23	
	G. Two	30	
	H. One	34	
2. What is the main material of the floor of the residence (excluding kitchen and bathrooms)?	A. Uncovered, or other	0	
	B. Packed earth, wood/parquet, marble/granite, cement, or mosaic/tile	6	
3. What is the main material of the walls of the residence?	A. Reeds/sticks/bamboo/palm, wood or metal sheets, tin/cardboard/paper/sacks, or other	0	
	B. Adobe blocks, wattle and daub, cement blocks, or bricks	7	
4. What toilet arrangement does the household use in its residence?	A. None, or other	0	
	B. Latrine of any kind	6	
	C. Toilet connected to a septic tank	14	
5. What is the main source of energy for lighting in the residence?	A. Firewood, or batteries	0	
	B. LPG, oil/paraffin/kerosene, or candles	1	
	C. Other	3	
	D. Electricity, generator, or solar panel	5	
6. Does the household have a non-electric or electric clothes iron?	A. No	0	
	B. Yes	3	
7. Does the household have a clock (wall, wrist, or pocket)?	A. No	0	
	B. Yes	4	
8. Does the household have a radio, stereo system, or cassette player?	A. No	0	
	B. Radio only	5	
	C. Stereo system or cassette player (regardless of radio)	7	
9. Does the household have a bicycle, motorcycle, or car?	A. No	0	
	B. Bicycle only	5	
	C. Motorcycle or car (regardless of bicycle)	15	
10. How many beds does the household have (single, double, bunk beds, or for children)?	A. None	0	
	B. One	2	
	C. Two or more	5	

Look-up table to convert scores to poverty likelihoods

Score	Poverty likelihood (%) by poverty line					
	National			USAID	Intl. 2005 PPP	
	100%	150%	200%	'Extreme'	\$1.25/day	\$2.50/day
0-4	97.1	100.0	100.0	77.7	100.0	100.0
5-9	93.0	98.6	100.0	65.6	96.9	100.0
10-14	89.9	97.5	99.6	62.9	92.6	100.0
15-19	79.4	93.4	97.7	52.3	84.1	98.5
20-24	76.1	91.8	97.3	42.9	81.6	98.1
25-29	72.0	91.1	97.3	35.0	78.3	98.1
30-34	60.8	88.2	96.9	27.0	68.5	97.8
35-39	50.8	78.4	89.2	19.9	59.3	91.8
40-44	31.7	67.1	84.3	12.9	41.5	88.0
45-49	28.8	52.1	73.8	9.7	33.0	78.2
50-54	21.4	45.1	67.8	5.7	26.3	73.4
55-59	8.5	30.6	50.7	3.2	11.9	58.6
60-64	7.2	24.9	43.5	0.0	10.1	51.6
65-69	3.2	15.6	27.1	0.0	5.0	31.7
70-74	0.6	4.8	15.6	0.0	1.4	21.0
75-79	0.0	1.3	9.9	0.0	0.0	13.5
80-84	0.0	0.0	0.0	0.0	0.0	0.0
85-89	0.0	0.0	0.0	0.0	0.0	0.0
90-94	0.0	0.0	0.0	0.0	0.0	0.0
95-100	0.0	0.0	0.0	0.0	0.0	0.0

A Simple Poverty Scorecard for Mozambique

1. Introduction

This paper presents an easy-to-use poverty scorecard that pro-poor programs in Mozambique can use to estimate the likelihood that a household has consumption below a given poverty line, to measure groups' poverty rates at a point in time, to track changes in groups' poverty rates between two points in time, and to target services to households.

The direct approach to poverty measurement via surveys is difficult and costly, asking households about a lengthy list of consumption items. As a case in point, Mozambique's 2008/9 Household Budget Survey (*Inquérito sobre Orçamento Familiar*, IOF) runs 49 pages. Enumerators visit households three times over a two-week period. The first visit covers more than 180 characteristics of the household and its members and asks about the consumption of 48 food items from the previous day. The second and third visits also collect data on the previous day's consumption. Over the course of the second and third visits, enumerators also ask about the consumption of more than 300 non-food items in the past month. All in all, Mozambique's 2008/9 IOF usually requires 4 to 9 hours per household.

In contrast, the indirect approach via poverty scoring is simple, quick, and inexpensive. It uses ten verifiable indicators (such as “What is the main material of the walls of the residence?” or “Does the household have a non-electric or electric clothes iron?”) to get a score that is highly correlated with poverty status as measured by the exhaustive survey.

Poverty scoring differs from “proxy means tests” (Coady, Grosh, and Hoddinott, 2004) in that it is tailored to the capabilities and purposes not of national governments but rather of local, pro-poor organizations. The feasible poverty-measurement options for these organizations are typically subjective and relative (such as participatory wealth ranking by skilled field workers) or blunt (such as rules based on land-ownership or housing quality). Measurements from these approaches are not comparable across organizations, they may be costly, and their bias and precision are unknown.

Poverty scoring can be used to measure the share of a pro-poor organization’s participants who are below a given poverty line, such as the Millennium Development Goals’ \$1.25/day poverty line at 2005 purchase-power parity. It can be used by USAID microenterprise partners to report how many of its participants are among the poorest half of people below the national poverty line. It can also be used to measure movement across a poverty line over time. In all these cases, the poverty scorecard provides a consumption-based, objective tool with known accuracy. While consumption surveys are costly even for governments, some small, local organizations may be able to implement an inexpensive scorecard to help with poverty monitoring and targeting.

The statistical approach here aims to be understood by non-specialists. After all, if managers are to adopt poverty scoring on their own and apply it to inform their decisions, they must first trust that it works. Transparency and simplicity build trust. Getting “buy-in” matters; proxy means tests and regressions on the “determinants of poverty” have been around for three decades, but they are rarely used to inform decisions at the local level. This is not because they do not work, but because they are presented (when they are presented at all) as tables of regression coefficients incomprehensible to non-specialists (with cryptic indicator names such as “LGHHSZ_2”, negative values, and many decimal places). Thanks to the predictive-modeling phenomenon known as the “flat maximum”, simple scorecards can be about as accurate as complex ones (Schreiner, 2013).

The technical approach here is innovative in how it associates scores with poverty likelihoods, in the extent of its accuracy tests, and in how it derives formulas for standard errors. Although these accuracy tests are simple and commonplace in statistical practice and in the for-profit field of credit-risk scoring, they have rarely been applied to poverty scorecards.

The scorecard is based on the 2008/9 IOF conducted by Mozambique’s *Instituto Nacional de Estatística*. Indicators are 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 points in the scorecard are non-negative integers, and total scores range from 0 (most likely below a poverty line) to 100 (least likely below a poverty line). Non-specialists can collect data and tally scores on paper in the field in five to ten minutes.

Poverty scoring can be used to estimate three basic quantities. First, it can estimate a particular household's "poverty likelihood", that is, the probability that the household has per-capita consumption below a given poverty line.

Second, poverty scoring can estimate the poverty rate of a group of households at a point in time. This estimate is the average poverty likelihood among the households in the group.

Third, poverty scoring can estimate changes in the poverty rate for a group of households (or for two independent samples of households that are representative of the same population) between two points in time. This estimate is the change in the average poverty likelihood of the group(s) of households over time.

Poverty scoring can also be used for targeting. To help managers choose the most appropriate targeting cut-off for their purposes, this paper reports several measures of targeting accuracy for a range of possible cut-offs.

This paper presents a single scorecard whose indicators and points are derived from household consumption data and Mozambique's national poverty line. Scores from this one scorecard are calibrated to poverty likelihoods for six poverty lines.

The scorecard is constructed and calibrated using half of the data from the 2008/9 IOF, and its accuracy is validated on the other half of the data.

All three scoring estimators are *unbiased*. That is, they match the true value on average in repeated samples when constructed from (and applied to) the same population from which the scorecard was built. Like all predictive models, the specific scorecard here is biased to some extent when constructed from a single sample (such as the 2008/9 IOF) and when applied to a different population.¹

Thus, while the indirect scoring approach is less costly than the direct survey approach, it is also biased. (The survey approach is unbiased by definition.) There is bias because scoring must assume that the future relationships between indicators and poverty will be the same as in the data used to build the scorecard. Of course, this assumption—ubiquitous and inevitable in predictive modeling—holds only partly.

When applied to the validation sample with bootstraps of $n = 16,384$, the difference between scorecard estimates of groups' poverty rates and the true rates at a point in time is -3.1 percentage points for the national line, and the average absolute difference across all six lines is 1.7 percentage points. These differences are due to sampling variation and not biased estimators; the average difference would be zero if the whole 2008/9 IOF were to be repeatedly redrawn and divided into sub-samples before repeating the entire process of building and validating scorecards.

¹ Important examples include nationally representative samples at a different point in time or non-nationally representative sub-groups (Tarozzi and Deaton, 2007).

The 90-percent confidence intervals for these estimates are ± 1.0 percentage points or less. For $n = 1,024$, the 90-percent intervals are ± 3.9 percentage points or less.

Section 2 below describes data and poverty lines. Sections 3 and 4 describe scorecard construction and offer guidelines for use in practice. Sections 5 and 6 detail the estimation of households' poverty likelihoods and of groups' poverty rates at a point in time. Section 7 discusses estimating changes in poverty rates through time, and Section 8 covers targeting. Section 9 places the new scorecard here in the context of past exercises for Mozambique, and Section 10 is a summary.

2. Data and poverty lines

This section discusses the data used to construct and validate the poverty scorecard. It also presents the poverty lines to which scores are calibrated.

2.1 Data

The scorecard is based on data from the 10,832 households in the 2008/9 IOF conducted from September 2008 to August 2009. This is Mozambique's most recent available national consumption survey.

For the purposes of poverty scoring, the households in the 2008/9 IOF are randomly divided into two sub-samples:

- *Construction and calibration* for selecting indicators and points and for associating scores with poverty likelihoods
- *Validation* for measuring accuracy with data not used in construction or calibration

2.2 Poverty rates and poverty lines

2.2.1 Rates

As a general definition, the *poverty rate* is the share of people in a group who live in households whose total household consumption (divided by the number of household members) is below a given poverty line.

Beyond this general definition, the two most-common cases are *household-level poverty rates* and *person-level poverty rates*. With household-level rates, each household is counted as if it had only one person, regardless of true household size, so all households are counted equally. With person-level rates (the “head-count index”), each household is weighted by the number of people in it, so larger households count more.

For example, consider a group of two households, the first with one member and the second with two members. Suppose further that the first household has per-capita consumption above a poverty line (it is “non-poor”) and that the second household has per-capita consumption below a poverty line (it is “poor”). The household-level rate counts both households as if they had only one person and so gives a poverty rate of $1 \div (1 + 1) = 50$ percent. In contrast, the person-level rate weighs each household by the number of people in it and so gives a poverty rate of $2 \div (1 + 2) = 67$ percent.

Whether the household-level rate or the person-level rate is relevant depends on the situation. If an organization’s “participants” include all the people in a household, then the person-level rate is relevant. Governments, for example, are concerned with the well-being of people, regardless of how those people are arranged in households, so governments typically report person-level poverty rates.

If an organization has only one “participant” per household, however, then the household-level rate may be relevant. For example, if a microlender has only one borrower in a household, then it might prefer to report household-level poverty rates.

Figure 1 reports poverty rates and poverty lines for Mozambique at both the household-level and the person-level.² The poverty scorecard is constructed using the 2008/9 IOF and household-level lines. Scores are calibrated to household-level poverty likelihoods, and accuracy is measured for household-level rates. This use of household-level rates reflects the belief that they are relevant for most pro-poor organizations.

Organizations can estimate person-level poverty rates by taking a household-size-weighted average of the household-level poverty likelihoods. It is also possible to construct a scorecard based on person-level lines, to calibrate scores to person-level likelihoods, and to measure accuracy for person-level rates, but it is not done here.

2.2.2 Poverty lines

Mozambique’s national poverty line (sometimes called here “100% of the national poverty line) is defined for each of 13 poverty-line regions (Figure 2) using a refined version of the cost-of-basic-needs approach (Ravallion, 1998). For a given region, the steps are (Ministry of Planning and Development, 2010):

- Measure each household’s nominal food and non-food per-capita consumption
- Find individuals’ average age- and sex-adjusted daily caloric requirement (World Health Organization, 1985). For Mozambique overall, this is 2,144 Calories
- Using the 2008/9 IOF, find the average food basket consumed by “poor” households³ in a region that supplies the caloric requirement
- Adjust food prices across the four quarters when the 2008/9 IOF was in the field to prices as of June to August 2009. (Non-food prices are not temporally adjusted.)

² Figure 2 reports poverty rates and poverty lines (for households and people) for Mozambique’s 13 poverty-line regions (Ministry of Planning and Development, 2010).

³ This group is found iteratively (Pradhan *et al.*, 2001), starting with the assumption that 60 percent of people in each region are poor.

- Adjust the food basket to satisfy revealed-preference conditions (Arndt and Simler, 2010; Varian, 1982)
- Define the food poverty line as the cost of this food basket

The national line is then defined as the food line plus necessary non-food consumption, which is taken as average non-food consumption in the 2008/9 IOF for households whose total consumption is within 80 to 120 percent of the food line (with greater weights for households closer to the food line).

For Mozambique overall, the average national line is MZN18.41 per person per day (Figure 1). This gives a household-level poverty rate of 47.3 percent and a person-level poverty rate of 54.7 percent. The national line is used to construct the scorecard.

Because local pro-poor organizations may want to use different or various poverty lines, this paper calibrates scores from its single scorecard to poverty likelihoods for six lines:

- National
- 150% of national
- 200% of national
- USAID “extreme”
- \$1.25/day 2005 PPP
- \$2.50/day 2005 PPP

The USAID “extreme” line is defined as the median consumption of people (not households) below the national line (United States Congress, 2004).

The \$1.25/day 2005 PPP line is derived from:

- 2005 PPP exchange rate for “individual consumption expenditure by households” (World Bank, 2008): MZN11.62569 per \$1.00
- Average Consumer Price Index⁴ from June to August 2009 of 77.7000
- 2005 monthly average CPI of 56.2967

Given this, the \$1.25/day 2005 PPP line for Mozambique for the period of June through August 2009 is (Sillers, 2006):

$$\begin{aligned} & (\text{2005 PPP exchange rate}) \cdot \$1.25 \cdot \left(\frac{\text{CPI}_{\text{June-Sept. 2009}}}{\text{CPI}_{\text{2005 average}}} \right) = \\ & \left(\frac{\text{MZN11.62569}}{\$1.00} \right) \cdot \$1.25 \cdot \left(\frac{77.7000}{56.296} \right) = \text{MZN20.05}. \end{aligned}$$

The \$2.50/day 2005 PPP line is twice the \$1.25/day line.

These 2005 PPP lines apply to Mozambique as a whole. They are adjusted for cost-of-living differences across poverty-line regions using:

- L , the all-Mozambique \$1.25/day 2005 PPP poverty line (MZN20.06)
- i , an index to a poverty-line region
- N , the number of poverty-line regions in Mozambique (13)
- π_i , the national poverty line for area i (Table 2)
- w_i , the share of Mozambique’s people who live in poverty-line region i

The cost-of-living-adjusted 2005 PPP poverty line L_i for poverty-line region i is:

$$L_i = \frac{L \cdot \pi_i}{\left(\sum_{i=1}^N \pi_i \cdot w_i \right) / \sum_{i=1}^N w_i}.$$

⁴ This CPI covers only the cities of Maputo, Beira, and Nampula. It is assumed here that it can be extrapolated to all of Mozambique.

3. Scorecard construction

For Mozambique, about 90 potential indicators are initially prepared in the areas of:

- Family composition (such as household size)
- Education (such as school attendance by children)
- Housing (such as wall material)
- Ownership of durable goods (such as bicycles, motorcycles, or cars)
- Employment (such as number of household members working in agriculture)

Figure 3 lists the candidate indicators, ordered by the entropy-based “uncertainty coefficient” that measures how well a given indicator predicts poverty on its own (Goodman and Kruskal, 1979).

The scorecard also aims to measure *changes* in poverty through time. This means that, when selecting indicators and holding other considerations constant, preference is given to more sensitive indicators. For example, the ownership of a clothes iron is probably more likely to change in response to changes in poverty than is the age of the male head/spouse.

The scorecard itself is built using the national poverty line and Logit regression on the construction sub-sample. Indicator selection uses both judgment and statistics. The first step is to use Logit to build one scorecard for each candidate indicator. Each scorecard’s statistical power is taken as “c”, a measure of its ability to rank by poverty status (SAS Institute Inc., 2004).

One of these one-indicator scorecards is then selected based on several factors (Schreiner *et al.*, 2004; Zeller, 2004). These include improvement in accuracy, likelihood

of acceptance by users (determined by simplicity, cost of collection, and “face validity” in terms of experience, theory, and common sense), sensitivity to changes in poverty status, variety among indicators, and verifiability.

A series of two-indicator scorecards are then built, each based on the one-indicator scorecard selected from the first round, with a second candidate indicator added. The best two-indicator scorecard is then selected, again based on “c” and judgment. These steps are repeated until the scorecard has 10 indicators.

The final step is to transform the Logit coefficients into non-negative integers such that total scores range from 0 (most likely below a poverty line) to 100 (least likely below a poverty line).

This algorithm is the Logit analogue to the common R^2 -based stepwise least-squares regression. It differs from naïve stepwise in that the criteria for selecting indicators include not only statistical accuracy but also judgment and non-statistical factors. The use of non-statistical criteria can improve robustness through time and helps ensure that indicators are simple, sensible, and acceptable to users.

The single poverty scorecard here applies to all of Mozambique. Evidence from India and Mexico (Schreiner, 2006 and 2005a), Sri Lanka (Narayan and Yoshida, 2005), and Jamaica (Grosh and Baker, 1995) suggests that segmenting scorecards by urban/rural does not improve targeting accuracy much, although it may improve the bias and precision of estimates of poverty rates (Tarozzi and Deaton, 2007).

4. Practical guidelines for scorecard use

The main challenge of scorecard design is not to maximize statistical accuracy but rather to improve the chances that scoring is actually used in practice (Schreiner, 2005b). When scoring projects fail, the reason is not usually statistical inaccuracy but rather the failure of an organization to decide to do what is needed to integrate scoring in its processes and to learn to use it properly (Schreiner, 2002). After all, most reasonable scorecards have similar targeting accuracy, thanks to the empirical phenomenon known as the “flat maximum” (Hand, 2006; Baesens *et al.*, 2003; Lovie and Lovie, 1986; Kolesar and Showers, 1985; Stillwell, Barron, and Edwards, 1983; Dawes, 1979; Wainer, 1976; Myers and Forgy, 1963). The bottleneck is less technical and more human, not statistics but organizational-change management. Accuracy is easier to achieve than adoption.

The scorecard here is designed to encourage understanding and trust so that users will adopt it and use it properly. Of course, accuracy matters, but it is balanced against simplicity, ease-of-use, and “face validity”. Programs are more likely to collect data, compute scores, and pay attention to the results if, in their view, scoring does not imply a lot of additional work and if the whole process generally seems to make sense.

To this end, the scorecard here fits on one page. The construction process, indicators, and points are simple and transparent. Additional work is minimized; non-specialists can compute scores by hand in the field because the scorecard has:

- Only 10 indicators
- Only categorical indicators
- Only simple weights (non-negative integers, no arithmetic beyond addition)

The scorecard is ready to be photocopied. It can be used with a simple spreadsheet database (Microfinance Risk Management, L.L.C., 2013) that records identifying information, dates, indicator values, scores, and poverty likelihoods.

A field worker using the paper scorecard would:

- Record participant and field-worker identifiers, dates, and household size
- Read each question from the scorecard
- Circle the response and its points
- Write the points in the far-right column
- Add up the points to get the total score
- Implement targeting policy (if any)
- Deliver the paper scorecard to a central office for data entry and filing

Of course, field workers must be trained. The quality of outputs depends on the quality of inputs. If organizations or field workers gather their own data and believe that they have an incentive to exaggerate poverty rates (for example, if funders reward them for higher poverty rates), then it is wise to do on-going quality control via data review and random audits (Matul and Kline, 2003).⁵ IRIS Center (2007a) and Toohig

⁵ If an organization does not want field workers to know the points associated with indicators, then it can use a version of the scorecard without points and apply the points later at the central office. Schreiner (2011a) argues that experience in Colombia (Camacho and Conover, 2011) suggests that hiding points does little to deter cheating

(2008) are useful nuts-and-bolts guides for budgeting, training field workers and supervisors, logistics, sampling, interviewing, piloting, recording data, and controlling quality.

In particular, while collecting scorecard indicators is relatively easier than alternatives, it is still absolutely difficult. Training and explicit definitions of terms and concepts in the scorecard is essential, and field workers should scrupulously follow the “Guidelines for the Interpretation of Indicators” in the Appendix to this paper, as they are an integral element of the poverty scorecard.

For the example of Nigeria, Onwujekwe, Hanson, and Fox-Rushby (2006) found distressingly low inter-rater and test-retest correlations for indicators as seemingly simple and obvious as whether the household owns an automobile. At the same time, Grosh and Baker (1995) find that gross underreporting of assets does not affect targeting. For the first stage of targeting in a conditional cash-transfer program in Mexico, Martinelli and Parker (2007) find that “underreporting [of asset ownership] is widespread but not overwhelming, except for a few goods . . . [and] overreporting is common for a few goods, which implies that self-reporting may lead to the exclusion of deserving households” (pp. 24–25). Still, as is done in Mexico in the second stage of its targeting process, most false self-reports can be corrected by field agents who verify

and that cheating in an organization’s central office may be more likely and more damaging than cheating by field agents and respondents.

responses with a home visit, and this is the suggested procedure for poverty scoring in Mozambique.

In terms of sampling design, an organization must make choices about:

- Who will do the scoring
- How scores will be recorded
- What participants will be scored
- How many participants will be scored
- How frequently participants will be scored
- Whether scoring will be applied at more than one point in time
- Whether the same participants will be scored at more than one point in time

In general, the sampling design should follow from the organization's goals for the exercise.

The non-specialists who apply the scorecard with participants in the field can be:

- Employees of the organization
- Third-party contractors

Responses, scores, and poverty likelihoods can be recorded:

- On paper in the field and then filed at a central office
- On paper in the field and then keyed into a database or spreadsheet at an office
- On portable electronic devices in the field and uploaded to a database

Given a population relevant for a particular business question, the participants to be scored can be:

- All participants
- A representative sample of all participants
- All participants in a representative sample of field offices
- A representative sample of all participants in a representative sample of offices

If not determined by other factors, the number of participants to be scored can be derived from sample-size formulas (presented later) for a desired level of confidence and a desired confidence interval.

Frequency of application can be:

- As a once-off project (precluding measuring change)
- Once a year (or at some other time interval, allowing measuring change)
- Each time a field worker visits a participant at home (allowing measuring change)

When the scorecard is applied more than once in order to measure change in poverty rates, it can be applied:

- With a different set of participants
- With the same set of participants

An example set of choices are illustrated by BRAC and ASA, two microlenders in Bangladesh who each have more than 7 million participants and who are applying a poverty scorecard similar to the one here (Chen and Schreiner, 2009). Their design is that loan officers in a random sample of branches score all participants each time they visit a homestead (about once a year) as part of their standard due diligence prior to loan disbursement. They record responses on paper in the field before sending the forms to a central office to be entered into a database. ASA's and BRAC's sampling plans cover 50,000–100,000 participants each.

5. Estimates of household poverty likelihoods

The sum of scorecard points for a household is called the *score*. For Mozambique, scores range from 0 (most likely below a poverty line) to 100 (least likely below a poverty line). While higher scores indicate less likelihood of being below a line, the scores themselves have only relative units. For example, doubling the score increases the likelihood of being above a given poverty line, but it does not double the likelihood.

To get absolute units, scores must be converted to *poverty likelihoods*, that is, probabilities of being below a poverty line. This is done via simple look-up tables. For the example of the national line, scores of 35–39 have a poverty likelihood of 50.8 percent, and scores of 40–44 have a poverty likelihood of 31.7 percent (Figure 4).

The poverty likelihood associated with a score varies by poverty line. For example, scores of 35–39 are associated with a poverty likelihood of 50.8 percent for the national line but 89.2 percent for 200% of the national line.⁶

⁶ Starting with Figure 4, many figures have six versions, one for each of the six poverty lines. To keep them straight, they are grouped by poverty line. Single tables pertaining to all poverty lines are placed with the tables for the national line.

5.1 Calibrating scores with poverty likelihoods

A given score is non-parametrically associated (“calibrated”) with a poverty likelihood by defining the poverty likelihood as the share of households in the calibration sub-sample who have the score and who are below a given poverty line.

For the example of the national line (Figure 5), there are 13,914 (normalized) households in the calibration sub-sample with a score of 35–39, of whom 7,074 (normalized) are below the poverty line. The estimated poverty likelihood associated with a score of 35–39 is then 50.8 percent, because $7,074 \div 13,914 = 50.8$ percent.

To illustrate with the national line and a score of 40–44, there are 13,576 (normalized) households in the calibration sample, of whom 4,297 (normalized) are below the line (Figure 5). Thus, the poverty likelihood for this score is $4,297 \div 13,576 = 31.7$ percent.

The same method is used to calibrate scores with estimated poverty likelihoods for the other five poverty lines.⁷

⁷ To ensure that poverty likelihoods always decrease as scores increase, it is sometimes necessary to iteratively combine likelihoods across series of adjacent scores before grouping scores into ranges. This preserves unbiasedness, and it keeps users from balking when sampling variation in score ranges with few households leads to higher scores being linked with higher poverty likelihoods.

Figure 6 shows, for all scores, the likelihood that consumption falls in a range demarcated by two adjacent poverty lines. For example, the daily consumption of a person in a household with a score of 35–39 falls in the following ranges with probability:

- 19.9 percent below the USAID “extreme” line
- 30.9 percent between the USAID “extreme” line and 100% of the national line
- 8.4 percent between 100% of the national line and \$1.25/day
- 19.1 percent between \$1.25/day and 150% of the national line
- 10.7 percent between 150% and 200% of the national line
- 2.6 percent between 200% of the national line and \$2.50/day
- 8.2 percent above \$2.50/day

Even though the scorecard is constructed partly based on judgment, the calibration process produces poverty likelihoods that are objective, that is, derived from survey data on consumption and quantitative poverty lines. The poverty likelihoods would be objective even if indicators and/or points were selected without any data at all. In fact, objective scorecards of proven accuracy are often constructed using only expert judgment (Fuller, 2006; Caire, 2004; Schreiner *et al.*, 2004). Of course, the scorecard here is constructed with both data and judgment. The fact that this paper acknowledges that some choices in scorecard construction—as in any statistical analysis—are informed by judgment in no way impugns the objectivity of the poverty likelihoods, as this depends on using data in score calibration, not on using data (and nothing else) in scorecard construction.

Although the points in the Mozambique poverty scorecard are transformed coefficients from a Logit regression, (untransformed) scores are not converted to poverty

likelihoods via the Logit formula of $2.718281828^{\text{score}} \times (1 + 2.718281828^{\text{score}})^{-1}$. This is because the Logit formula is esoteric and difficult to compute by hand. Non-specialists find it more intuitive to define the poverty likelihood as the share of households with a given score in the calibration sample who are below a poverty line. In the field, going from scores to poverty likelihoods in this way requires no arithmetic at all, just a look-up table. This non-parametric calibration can also improve accuracy, especially with large samples.

5.2 Accuracy of estimates of households' poverty likelihoods

As long as the relationships between indicators and poverty do not change over time, and as long as the scorecard is applied to households that are representative of the same population from which the scorecard was constructed, then this calibration process produces unbiased estimates of poverty likelihoods. *Unbiased* means that in repeated samples from the same population, the average estimate matches the true poverty likelihood. The scorecard also produces unbiased estimates of poverty rates at a point in time and of changes in poverty rates between two points in time.⁸

Of course, the relationships between indicators and poverty do change to some unknown extent over time and also across sub-groups in Mozambique's population, so the scorecard will generally be biased when applied after August 2009 (the last month

⁸ This follows because these estimates of groups' poverty rates are linear functions of the unbiased estimates of households' poverty likelihoods.

of fieldwork for the 2008/9 IOF) or when applied with non-nationally representative sub-groups.

How accurate are estimates of households' poverty likelihoods, given the assumption of constant relationships between indicators and poverty over time and the assumption of a sample that is representative of Mozambique overall? To measure, the scorecard is applied to 1,000 bootstrap samples of size $n = 16,384$ from the validation sub-sample. Bootstrapping entails (Efron and Tibshirani, 1993):

- Score each household in the validation sample
- Draw a new bootstrap sample *with replacement* from the validation sample
- For each score, compute the true poverty likelihood in the bootstrap sample, that is, the share of households with the score and consumption below a poverty line
- For each score, record the difference between the estimated poverty likelihood (Figure 4) and the true poverty likelihood in the bootstrap sample
- Repeat the previous three steps 1,000 times
- For each score, report the average difference between estimated and true poverty likelihoods across the 1,000 bootstrap samples
- For each score, report the two-sided interval containing the central 900, 950, or 990 differences between estimated and true poverty likelihoods

For each score range and for $n = 16,384$, Figure 7 shows the average difference between estimated and true poverty likelihoods as well as confidence intervals for the differences.

For the national line, the average poverty likelihood across bootstrap samples for scores of 35–39 in the validation sample is too high by 4.1 percentage points. For scores of 40–44, the estimate is too high by 1.8 percentage points.⁹

⁹ These differences are not zero, in spite of the estimator's unbiasedness, because the scorecard comes from a single sample. The average difference by score range would be

The 90-percent confidence interval for the differences for scores of 35–39 is ± 2.0 percentage points (Figure 7). This means that in 900 of 1,000 bootstraps, the difference between the estimate and the true value is between +2.1 and +6.1 percentage points (because $+4.1 - 2.0 = +2.1$, and $+4.1 + 2.0 = +6.1$). In 950 of 1,000 bootstraps (95 percent), the difference is $+4.1 \pm 2.5$ percentage points, and in 990 of 1,000 bootstraps (99 percent), the difference is $+4.1 \pm 3.5$ percentage points.

For some scores, Figure 7 shows differences—sometimes large ones—between estimated poverty likelihoods and true values. This is because the validation sub-sample is a single sample that—thanks to sampling variation—differs in distribution from the construction/calibration sub-samples and from Mozambique’s population. For targeting, however, what matters is less the difference in all score ranges and more the difference in score ranges just above and below the targeting cut-off. This mitigates the effects of bias and sampling variation on targeting (Friedman, 1997). Section 8 below looks at targeting accuracy in detail.

In addition, if estimates of groups’ poverty rates are to be usefully accurate, then errors for individual households must largely balance out. This is generally the case, as discussed in the next section.

zero if samples were repeatedly drawn from the population and split into sub-samples before repeating the entire process of scorecard construction/calibration and validation.

Another possible source of differences between estimates and true values is overfitting. The scorecard here is unbiased, but it may still be *overfit* when applied after the end of the IOF fieldwork in August 2009. That is, it may fit the data from the 2008/9 IOF so closely that it captures not only some timeless patterns but also some random patterns that, due to sampling variation, show up only in the 2008/9 IOF. Or the scorecard may be overfit in the sense that it is not robust when relationships between indicators and poverty change over time or when it is applied to non-nationally representative samples.

Overfitting can be mitigated by simplifying the scorecard and by not relying only on data but rather also considering experience, judgment, and theory. Of course, the scorecard here does this. Combining scorecards can also reduce overfitting, at the cost of greater complexity.

Most errors in individual households' likelihoods do cancel out in the estimates of groups' poverty rates (see later sections). Furthermore, at least some of the differences will come from non-scorecard sources such as changes in the relationships between indicators and poverty, sampling variation, changes in poverty lines, inconsistencies in data quality across time, and imperfections in cost-of-living adjustments across time and geography. These factors can be addressed only by improving data quantity and quality (which is beyond the scope of the scorecard) or by reducing overfitting (which likely has limited returns, given the scorecard's parsimony).

6. Estimates of a group's poverty rate at a point in time

A group's estimated poverty rate at a point in time is the average of the estimated poverty likelihoods of the individual households in the group.

To illustrate, suppose a program samples three households on Jan. 1, 2013 and that they have scores of 20, 30, and 40, corresponding to poverty likelihoods of 76.1, 60.8, and 31.7 percent (national line, Figure 4). The group's estimated poverty rate is the households' average poverty likelihood of $(76.1 + 60.8 + 31.7) \div 3 = 56.2$ percent.

Be careful; the group's poverty rate is *not* the poverty likelihood associated with the average score. Here, the average score is 30, which corresponds to a poverty likelihood of 60.8 percent. This differs from the 56.2 percent found as the average of the three individual poverty likelihoods associated with each of the three scores. Unlike poverty likelihoods, scores are ordinal symbols, like letters in the alphabet or colors in a spectrum. Scores are not cardinal numbers, and so scores cannot be added up or averaged across households. Only three operations are valid for scores: conversion to poverty likelihoods, distributional analysis (Schreiner, 2013), or comparison—if desired—with a cut-off for targeting. The best rule to follow is: Always analyze poverty likelihoods, never scores.

6.1 Accuracy of estimated poverty rates at a point in time

For the Mozambique scorecard applied to the validation sample with $n = 16,384$, the absolute differences between the estimated poverty rate at a point in time and the

true rate are 3.1 percentage points or less (Figure 9, summarizing Figure 8 across poverty lines). The average absolute difference across the six poverty lines is 1.7 percentage points. At least part of these differences is due to sampling variation in the division of the 2008/9 IOF into two sub-samples.

When estimating poverty rates at a point in time, the bias reported in Figure 9 should be subtracted from the average poverty likelihood to make the estimate unbiased. For Mozambique's scorecard and the national line, bias is -3.1 percentage points, so the unbiased estimate in the three-household example above is $56.2 - (-3.1) = 59.3$ percent.

In terms of precision, the 90-percent confidence interval for a group's estimated poverty rate at a point in time with $n = 16,384$ is ± 1.0 percentage points or less (Figure 9). This means that in 900 of 1,000 bootstraps of this size, the estimate (after subtracting off bias) is within 1.0 percentage points or less of the true value.

For example, suppose that the average poverty likelihood in a sample of $n = 16,384$ with the Mozambique scorecard and the national line is 56.2 percent. Then estimates in 90 percent of samples of $n = 16,384$ would be expected to fall in the range of $56.2 - (-3.1) - 1.0 = 58.3$ percent to $56.2 - (-3.1) + 1.0 = 60.3$ percent, with the most likely true value being the unbiased estimate in the middle of this range ($56.2 - (-3.1) = 59.3$ percent). This is because the original (biased) estimate is 56.2 percent, bias is -3.1 percentage points, and the 90-percent confidence interval for the national line is ± 1.0 percentage points.

6.2 Formula for standard errors for estimates of poverty rates

How precise are the point-in-time estimates? Because they are averages of binary (0/1, or poor/non-poor) variables, the estimates (in “large” samples) have a Normal distribution and can be characterized by their average difference vis-à-vis true values together with the standard error of the average difference.

To derive a formula for the standard errors of estimated poverty rates at a point in time from indirect measurement via poverty scorecards (Schreiner, 2008a), first note that the textbook formula (Cochran, 1977) that relates confidence intervals with standard errors in the case of direct measurement of rates is $\pm c = \pm z \cdot \sigma$, where:

$\pm c$ is a confidence interval as a proportion (*e.g.*, 0.02 for ± 2 percentage points),

z is from the Normal distribution and is $\begin{cases} 1.28 \text{ for confidence levels of 80 percent} \\ 1.64 \text{ for confidence levels of 90 percent,} \\ 1.96 \text{ for confidence levels of 95 percent} \end{cases}$

σ is the standard error of the estimated poverty rate, that is, $\sqrt{\frac{\hat{p} \cdot (1 - \hat{p})}{n}} \cdot \phi$,

\hat{p} is the estimated proportion of households below the poverty line in the sample,

ϕ is the finite population correction factor of $\sqrt{\frac{N - n}{N - 1}}$,

N is the population size, and

n is the sample size.

For example, Mozambique’s 2008/9 IOF estimates a household-level poverty rate for the national line of $\hat{p} = 47.3$ percent (Figure 1) by direct measurement. If this estimate came from a sample of $n = 16,384$ households from a population N of 4,611,545 (the number of households in Mozambique), then the finite population

correction ϕ is $\sqrt{\frac{4,611,545 - 16,384}{4,611,545 - 1}} = 0.9982$, which can be taken as one (1). If the

desired confidence level is 90-percent ($z = 1.64$), then the confidence interval $\pm c$ is

$$\pm z \cdot \sqrt{\frac{\hat{p} \cdot (1 - \hat{p})}{n}} \cdot \sqrt{\frac{N - n}{N - 1}} = \pm 1.64 \cdot \sqrt{\frac{0.473 \cdot (1 - 0.473)}{16,384}} \cdot 1 = \pm 0.640 \text{ percentage points.}$$

Poverty scorecards, however, do not measure poverty directly, so this formula is not applicable. To derive a formula for the Mozambique scorecard, consider Figure 8, which reports empirical confidence intervals c for the differences for the scorecard applied to 1,000 bootstrap samples of various sizes from the validation sample. For example, with $n = 16,384$ and the national line, the 90-percent confidence interval is 1.000 percentage points.¹⁰

Thus, the 90-percent confidence interval with $n = 16,384$ is ± 1.000 percentage points for the Mozambique poverty scorecard and ± 0.640 percentage points for direct measurement. The ratio of the two intervals is $1.000 \div 0.640 = 1.56$.

¹⁰ Due to rounding, Figure 8 displays 1.0, not 1.000.

Now consider the same case, but with $n = 8,192$. The confidence interval under direct measurement is $\pm 1.64 \cdot \sqrt{\frac{0.473 \cdot (1 - 0.473)}{8,192}} \cdot 1 = \pm 0.905$ percentage points. The empirical confidence interval with the Mozambique poverty scorecard (Figure 8) is 1.435 percentage points. Thus for $n = 8,192$, the ratio of the two intervals is $1.435 \div 0.905 = 1.59$.

This ratio of 1.59 for $n = 8,192$ is close to the ratio of 1.56 for $n = 16,384$. Across all sample sizes of 256 or more in Figure 8, the average ratio turns out to be 1.54, implying that confidence intervals for indirect estimates of poverty rates via the Mozambique scorecard and this poverty line are 54 percent wider than confidence intervals for direct estimates via the 2008/9 IOF. This 1.54 appears in Figure 9 as the “ α factor” because if $\alpha = 1.54$, then the formula for confidence intervals c for the Mozambique poverty scorecard is $\pm c = \pm z \cdot \alpha \cdot \sigma$. That is, the formula for the standard error σ for point-in-time estimates of poverty rates via scoring is

$$\alpha \cdot \sqrt{\frac{\hat{p} \cdot (1 - \hat{p})}{n}} \cdot \sqrt{\frac{N - n}{N - 1}}.$$

In general, α can be more or less than 1.00. When α is less than 1.00, it means that the scorecard is more precise than direct measurement. This occurs for none of the six poverty lines in Figure 9.

The formula relating confidence intervals with standard errors for poverty scoring can be rearranged to give a formula for determining sample size before

measurement.¹¹ If \tilde{p} is the expected poverty rate before measurement, then the formula for sample size n from a population of size N that is based on the desired confidence level that corresponds to z and the desired confidence interval $\pm c$ is

$$n = N \cdot \left(\frac{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1 - \tilde{p})}{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1 - \tilde{p}) + c^2 \cdot (N - 1)} \right).$$

If the population N is “large” relative to the sample size n , then the finite population correction factor ϕ can be taken as one, and

$$n = \left(\frac{\alpha \cdot z}{c} \right)^2 \cdot \tilde{p} \cdot (1 - \tilde{p}).$$

To illustrate how to use this, suppose the population N is 4,611,545 (the number of households in Mozambique overall while the 2008/9 IOF was in the field), suppose $c = 0.07900$, $z = 1.64$ (90-percent confidence), and the relevant poverty line is the national line so that the most sensible expected poverty rate \tilde{p} is Mozambique’s overall poverty rate for the national line (47.3 percent, Figure 1) and the α factor is 1.54 (Figure 9). Then the sample-size formula gives

$$n = 4,611,545 \cdot \left(\frac{1.64^2 \cdot 1.54^2 \cdot 0.473 \cdot (1 - 0.473)}{1.64^2 \cdot 1.54^2 \cdot 0.473 \cdot (1 - 0.473) + 0.07900^2 \cdot (4,611,545 - 1)} \right) = 254,$$

almost exactly the sample size of 256 observed for these parameters in Figure 8 for the

¹¹ IRIS Center (2007a and 2007b) says that a sample size of $n = 300$ is sufficient for USAID reporting. If a scorecard is as precise as direct measurement, if the expected (before measurement) poverty rate is 50 percent, and if the confidence level is 90 percent, then $n = 300$ implies a confidence interval of ± 2.2 percentage points. In fact, USAID has not specified confidence levels or intervals. Furthermore, the expected poverty rate may not be 50 percent, and the scorecard could be more or less precise than direct measurement.

national line. Taking the finite population correction factor ϕ as one gives the almost

the same answer, as $n = \left(\frac{1.54 \cdot 1.64}{0.07900} \right)^2 \cdot 0.473 \cdot (1 - 0.473) = 255$.

Of course, the α factors in Figure 9 are specific to Mozambique, its poverty lines, its poverty rates, and this scorecard. The derivation of the formulas, however, is valid for any poverty scorecard following the approach in this paper.

In practice after the end of fieldwork for the IOF in August 2009, an organization would select a poverty line (say, the national line), note their participants' population size (say, $N = 10,000$ participants), select a desired confidence level (say, 90 percent, or $z = 1.64$), select a desired confidence interval (say, ± 2.0 percentage points, or $c = 0.02$), make an assumption about \tilde{p} (perhaps based on a previous measurement such as the 47.3 percent national average in the 2008/9 IOF in Figure 1), look up α (here, 1.54, Figure 9), assume that the scorecard will still work in the future and/or for non-nationally representative sub-groups,¹² and then compute the required sample size. In

this illustration, $n = 10,000 \cdot \left(\frac{1.64^2 \cdot 1.54^2 \cdot 0.473 \cdot (1 - 0.473)}{1.64^2 \cdot 1.54^2 \cdot 0.473 \cdot (1 - 0.473) + 0.02^2 \cdot (10,000 - 1)} \right) =$

2,845.

¹² This paper reports accuracy for the scorecard applied to the validation sample, but it cannot test accuracy for later years or for other groups. Performance after August 2009 will resemble that in the 2008/9 IOF with deterioration to the extent that the relationships between indicators and poverty status change over time.

7. Estimates of changes in group poverty rates over time

The change in a group's poverty rate between two points in time is estimated as the change in the average poverty likelihood of the households in the group. With data only from the 2008/9 IOF, this paper cannot test estimates of change over time for Mozambique, and it can only suggest approximate formulas for standard errors. Nevertheless, the relevant concepts are presented here because, in practice, pro-poor organizations can apply the scorecard to collect their own data and measure change through time.

7.1 Warning: Change is not impact

Scoring can estimate change. Of course, poverty could get better or worse, and scoring does not indicate what caused change. This point is often forgotten or confused, so it bears repeating: poverty scoring simply estimates change, and it does not, in and of itself, indicate the reason for the change. In particular, estimating the impact of program participation requires knowing what would have happened to participants if they had not been participants. Knowing this requires either strong assumptions or a control group that resembles participants in all ways except participation. To belabor the point, poverty scoring can help estimate program impact only if there is some way to know what would have happened in the absence of the program. And that information must come from somewhere beyond poverty scoring.

7.2 Calculating estimated changes in poverty rates over time

Consider the illustration begun in the previous section. On Jan. 1, 2013, a program samples three households who score 20, 30, and 40 and so have poverty likelihoods of 76.1, 60.8, and 31.7 percent (national line, Figure 4). Adjusting for the known bias of -3.1 percentage points, the group's baseline estimated poverty rate is the households' average poverty likelihood of $[(76.1 + 60.8 + 31.7) \div 3] - (-3.1) = 59.3$ percent.

After baseline, two sampling approaches are possible for the follow-up round:

- Score a new, independent sample, measuring change across samples
- Score the same sample at follow-up as at baseline

By way of illustration, suppose that a year later on Jan. 1, 2014, the program samples three additional households who are in the population as the three households originally sampled (or suppose that the program scores the same three original households a second time) and finds that their scores are 25, 35, and 45 (poverty likelihoods of 72.0, 50.8, and 28.8 percent, national line, Figure 4). Adjusting for bias, their average poverty likelihood at follow-up is now $[(72.0 + 50.8 + 28.8) \div 3] - (-3.1) = 53.6$ percent, an improvement of $59.3 - 53.6 = 5.7$ percentage points.¹³

¹³ Of course, such a huge reduction in poverty in one year is unlikely, but this is just an example to show how poverty scoring can be used to estimate change.

Thus, about one in 18 participants in this hypothetical example crossed the poverty line in 2013.¹⁴ Among those who started below the line, about one in ten ($5.7 \div 59.3 = 9.6$ percent) on net ended up above the line.¹⁵

7.3 Accuracy for estimated change in two independent samples

With only the 2008/9 IOF, it is not possible to measure the accuracy of scorecard estimates of changes in groups' poverty rates over time. In practice, of course, local pro-poor organizations can still use the Mozambique poverty scorecard to estimate change. The rest of this section suggests approximate formulas for standard errors that may be used until there is additional data.

For two equal-sized independent samples, the same logic as above can be used to derive a formula relating the confidence interval c with the standard error σ of a poverty scorecard's estimate of the change in poverty rates over time:

$$\pm c = \pm z \cdot \sigma = \pm z \cdot \alpha \cdot \sqrt{\frac{2 \cdot \hat{p} \cdot (1 - \hat{p})}{n}} \cdot \sqrt{\frac{N - n}{N - 1}}.$$

z , c , \hat{p} and N are defined as above, n is the sample size at both baseline and follow-up,¹⁶ and α is the average (across a range of bootstrapped sample sizes) of the

¹⁴ This is a net figure; some people start above the line and end below it, and vice versa.

¹⁵ Poverty scoring does not reveal the reasons for this change.

¹⁶ This means that, for a given precision and with direct measurement, estimating the change in a poverty rate between two points in time requires four times as many measurements (not twice as many) as does estimating a poverty rate at a point in time.

ratio of the observed confidence interval from a poverty scorecard and the theoretical confidence interval under direct measurement.

As before, the formula for standard errors can be rearranged to give a formula for sample sizes before indirect measurement via a poverty scorecard, where \tilde{p} is based on previous measurements and is assumed equal at both baseline and follow-up:

$$n = 2 \cdot N \cdot \left(\frac{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1 - \tilde{p})}{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1 - \tilde{p}) + c^2 \cdot (N - 1)} \right). \text{ If } \phi \text{ can be taken as one, then the}$$

formula becomes $n = 2 \cdot \left(\frac{\alpha \cdot z}{c} \right)^2 \cdot \tilde{p} \cdot (1 - \tilde{p})$.

For countries for which this α has been measured (Schreiner, 2013, 2010, 2009a, 2009b, 2009c, 2009d, 2009e, and 2008b; Chen and Schreiner, 2009; and Schreiner and Woller, 2010a and 2010b), the simple average of α across poverty lines and years for a given country and then across countries is 1.19. This is as reasonable a figure as any to use for Mozambique.

To illustrate the use of the formula above to determine sample size for estimating changes in poverty rates across two independent samples, suppose the desired confidence level is 90 percent ($z = 1.64$), the desired confidence interval is 2 percentage points ($c = \pm 0.02$), the poverty line is the national line, $\alpha = 1.19$, $\hat{p} = 0.473$ (from Figure 1), and the population N is large enough relative to the expected sample size n that the finite population correction factor ϕ can be taken as one. Then the baseline

sample size is $n = 2 \cdot \left(\frac{1.19 \cdot 1.64}{0.02} \right)^2 \cdot 0.473 \cdot (1 - 0.473) \cdot 1 = 4,748$, and the follow-up sample size is also 4,748.

7.4 Accuracy for estimated change for one sample, scored twice

Analogous to previous derivations, the general formula relating the confidence interval c to the standard error σ when using a poverty scorecard to estimate change for a single group of households, all of whom are scored at two points in time, is:¹⁷

$$\pm c = \pm z \cdot \sigma = \pm z \cdot \alpha \cdot \sqrt{\frac{\hat{p}_{12} \cdot (1 - \hat{p}_{12}) + \hat{p}_{21} \cdot (1 - \hat{p}_{21}) + 2 \cdot \hat{p}_{12} \cdot \hat{p}_{21}}{n}} \cdot \sqrt{\frac{N - n}{n - 1}},$$

where z , c , α , N , and n are defined as usual, \hat{p}_{12} is the share of all sampled households that move from below the poverty line to above it, and \hat{p}_{21} is the share of all sampled households that move from above the line to below it.

The formula for confidence intervals can be rearranged to give a formula for sample size before measurement. This requires an estimate (based on information available before measurement) of the expected shares of all households who cross the poverty line \tilde{p}_{12} and \tilde{p}_{21} . Before measurement, it is reasonable to assume that the change in the poverty rate will be zero, which implies $\tilde{p}_{12} = \tilde{p}_{21} = \tilde{p}_*$, giving:

$$n = 2 \cdot \left(\frac{\alpha \cdot z}{c} \right)^2 \cdot \tilde{p}_* \cdot \sqrt{\frac{N - n}{n - 1}}.$$

¹⁷ See McNemar (1947) and Johnson (2007). John Pezzullo helped find this formula.

Because \tilde{p}_* could be anything between 0–0.5, more information is needed to apply this formula. Suppose that the observed relationship between \tilde{p}_* , the number of years y between baseline and follow-up, and $p_{\text{pre-baseline}} \cdot (1 - p_{\text{pre-baseline}})$ is—as in Peru (Schreiner, 2009a)—close to:

$$\tilde{p}_* = -0.02 + 0.016 \cdot y + 0.47 \cdot [p_{\text{pre-baseline}} \cdot (1 - p_{\text{pre-baseline}})].$$

Given this, a sample-size formula for a group of households to whom the Mozambique scorecard is applied twice (once after August 2009 and then again later) is

$$n = 2 \cdot \left(\frac{\alpha \cdot z}{c} \right)^2 \cdot \left\{ -0.02 + 0.016 \cdot y + 0.47 \cdot [p_{\text{pre-baseline}} \cdot (1 - p_{\text{pre-baseline}})] \right\} \cdot \sqrt{\frac{N - n}{n - 1}}.$$

In Peru (the only other country for which there is an estimate, Schreiner 2009a), the average α across years and poverty lines is about 1.30.

To illustrate the use of this formula, suppose the desired confidence level is 90 percent ($z = 1.64$), the desired confidence interval is 2.0 percentage points ($c = \pm 0.02$), the poverty line is the national line, the sample will first be scored in 2013 and then again in 2016 ($y = 3$), and the population N is so large relative to the expected sample size n that the finite population correction factor ϕ can be taken as one. The pre-baseline poverty rate is 47.3 percent ($p_{2013} = 0.473$, Figure 1), and suppose $\alpha = 1.30$.

Then the baseline sample size is

$$n = 2 \cdot \left(\frac{1.30 \cdot 1.64}{0.02} \right)^2 \cdot \left\{ -0.02 + 0.016 \cdot 3 + 0.47 \cdot [0.473 \cdot (1 - 0.473)] \right\} \cdot 1 = 3,300. \text{ The}$$

same group of 3,300 households is scored at follow-up as well.

8. Targeting

When a program uses poverty scoring for targeting, households with scores at or below a cut-off are labeled *targeted* and treated—for program purposes—as if they are below a given poverty line. Households with scores above a cut-off are labeled *non-targeted* and treated—for program purposes—as if they are above a given poverty line.

There is a distinction between *targeting status* (scoring at or below a targeting cut-off) and *poverty status* (having consumption below a poverty line). Poverty status is a fact that depends on whether consumption is below a poverty line as directly measured by a survey. In contrast, targeting status is a program’s policy choice that depends on a cut-off and on an indirect estimate from a scorecard.

Targeting is successful when households truly below a poverty line are targeted (*inclusion*) and when households truly above a poverty line are not targeted (*exclusion*). Of course, no scorecard is perfect, and targeting is unsuccessful when households truly below a poverty line are not targeted (*undercoverage*) or when households truly above a poverty line are targeted (*leakage*). Figure 10 depicts these four possible targeting outcomes. Targeting accuracy varies by the cut-off score; a higher cut-off has better inclusion (but greater leakage), while a lower cut-off has better exclusion (but higher undercoverage).

Programs should weigh these trade-offs when setting a cut-off. A formal way to do this is to assign net benefits—based on a program’s values and mission—to each of the four possible targeting outcomes and then to choose the cut-off that maximizes total net benefits (Adams and Hand, 2000; Hoadley and Oliver, 1998).

Figure 11 shows the distribution of households by targeting outcome for Mozambique. For an example cut-off of 35–39, outcomes for the national line in the validation sample are:

- Inclusion: 36.3 percent are below the line and correctly targeted
- Undercoverage: 10.9 percent are below the line and mistakenly not targeted
- Leakage: 19.2 percent are above the line and mistakenly targeted
- Exclusion: 33.7 percent are above the line and correctly not targeted

Increasing the cut-off to 40–44 improves inclusion and undercoverage but worsens leakage and exclusion:

- Inclusion: 40.9 percent are below the line and correctly targeted
- Undercoverage: 6.2 percent are below the line and mistakenly not targeted
- Leakage: 28.1 percent are above the line and mistakenly targeted
- Exclusion: 24.8 percent are above the line and correctly not targeted

Which cut-off is preferred depends on total net benefit. If each targeting outcome has a per-household benefit or cost, then total net benefit for a given cut-off is:

Benefit per household correctly included	x	Households correctly included	–
Cost per household mistakenly not covered	x	Households mistakenly not covered	–
Cost per household mistakenly leaked	x	Households mistakenly leaked	+
Benefit per household correctly excluded	x	Households correctly excluded.	

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

- Assign benefits and costs to possible outcomes, based on its values and mission
- Tally total net benefits for each cut-off using Figure 11 for a given poverty line
- Select the cut-off with the highest total net benefit

The most difficult step is assigning benefits and costs to targeting outcomes. A program that uses targeting—with or without scoring—should thoughtfully consider how it values successful inclusion or exclusion versus errors of undercoverage and leakage. It is healthy to go through a process of thinking explicitly and intentionally about how possible targeting outcomes are valued.

A common choice of benefits and costs is “Total Accuracy” (IRIS Center, 2005; Grootaert and Braithwaite, 1998). With “Total Accuracy”, total net benefit is the number of households correctly included or correctly excluded:

$$\begin{array}{rclcl}
 \text{Total Accuracy} = & 1 & \times & \text{Households correctly included} & - \\
 & 0 & \times & \text{Households mistakenly undercovered} & - \\
 & 0 & \times & \text{Households mistakenly leaked} & + \\
 & 1 & \times & \text{Households correctly excluded.} &
 \end{array}$$

Figure 11 shows “Total Accuracy” for all cut-offs for the Mozambique scorecard. For the national line in the validation sample, total net benefit is greatest (70.1) for a cut-off of 30–34, with about seven in ten households in Mozambique correctly classified.

“Total Accuracy” weighs successful inclusion of households below the line the same as successful exclusion of households above the line. If a program valued inclusion more (say, twice as much) than exclusion, it could reflect this by setting the benefit for inclusion to 2 and the benefit for exclusion to 1. Then the chosen cut-off would maximize $(2 \times \text{Households correctly included}) + (1 \times \text{Households correctly excluded})$.¹⁸

¹⁸ Figure 11 also reports “BPAC”, the Balanced Poverty Accuracy Criteria adopted by USAID for certifying poverty scorecards. IRIS Center (2005) says that BPAC considers

As an alternative to assigning benefits and costs to targeting outcomes and then choosing a cut-off to maximize total net benefit, a program could set a cut-off to achieve a desired poverty rate among targeted households. The third column of Figure 12 (“% targeted who are poor”) shows, for the Mozambique scorecard applied to the validation sample, the expected poverty rate among households who score at or below a given cut-off. For the example of the national line, targeting households who score 39 or less would target 55.4 percent of all households (second column) and produce a poverty rate among those targeted of 65.4 percent (third column).

Figure 12 also reports two other measures of targeting accuracy. The first is a version of coverage (“% of poor who are targeted”). For the example of the national line with the validation sample and a cut-off of 39 or less, 76.9 percent of all poor households are covered.

The final targeting measure in Figure 12 is the number of successfully targeted poor households for each non-poor household mistakenly targeted (right-most column). For the national line with the validation sample and a cut-off of 39 or less, covering 1.9 poor households means leaking to 1 non-poor household.

accuracy in terms of estimated poverty rates and in terms of targeting inclusion. $BPAC = (\text{Inclusion} - |\text{Undercoverage} - \text{Leakage}|) \times [100 \div (\text{Inclusion} + \text{Undercoverage})]$.

9. The context of Mozambique poverty scorecards

This section discusses existing scorecards for Mozambique in terms of their goals, methods, indicators, cost, and accuracy. The advantages of the new scorecard here are its use of the latest available nationally representative data, its focus on feasibility for local, pro-poor organizations, its reporting of bias and precision, and its reporting of formulas for standard errors.

9.1 Gwatkin *et al.*

Gwatkin *et al.* (2007) construct a poverty scorecard for Mozambique with an approach that they apply in 56 countries with Demographic and Health Surveys (Rutstein and Johnson, 2004). They use Principal Components Analysis to make an asset index from simple, low-cost indicators available for the 12,315 households in Mozambique’s 2003 DHS. The PCA index is like the poverty scorecard here except that, because the DHS does not collect data on income or consumption, it is based on a different conception of poverty, its accuracy vis-à-vis consumption-based poverty is unknown, and it can only be assumed to be a proxy for long-term wealth/economic status.¹⁹ Well-known examples of the PCA asset-index approach include Sahn and Stifel (2000 and 2003), and Filmer and Pritchett (2001).

¹⁹ Nevertheless, the indicators are similar and the “flat maximum” is important, so carefully built asset indexes and consumption-based poverty scorecards may pick up the same underlying construct (perhaps “permanent income”, see Bollen, Glanville, and

The 14 indicators in Gwatkin *et al.* are similar to those in the new scorecard here

in terms of their simplicity, low cost, and verifiability:

- Characteristics of the residence:
 - Main type of floor
 - Source of drinking water
 - Type of toilet arrangement
 - Main type of cooking fuel
 - Presence of electricity
- Ownership of consumer durables:
 - Radio
 - Television set
 - Refrigerator
 - Bicycles
 - Motorcycle or scooter
 - Car or truck
 - Telephone
- Presence of a domestic worker not related to the head
- Whether members of the household work their own or family's agricultural land

Gwatkin *et al.* discuss three basic uses for their index:

- Segmenting households by quintiles to see how health, population, and nutrition vary with socio-economic status
- Monitoring (via exit surveys) how well local health-service posts reach the poor
- Measuring coverage of health services via local, small-scale surveys

The first goal is akin to targeting, and the last two goals resemble the monitoring goals here, so the uses of the PCA asset index are similar to those of the scorecard here.

Stecklov, 2007), and often they rank households much the same. Tests of how well rankings correspond between asset indexes and consumption-based scorecards include Lindelow (2006, for Mozambique), Wagstaff and Watanabe (2003), and Montgomery *et al.* (2000).

Still, the Gwatkin *et al.* index is more difficult and costly to use because it cannot be computed by hand in the field, as it has 84 point values (half of them negative, all with five decimal places) which must be added up to get a score.

Unlike the asset index, the scorecard here is linked directly to an absolute, consumption-based poverty line. Thus, while both approaches can rank households, only the poverty scorecard does so based on consumption-based poverty likelihood.

In essence, Gwatkin *et al.*—like all PCA asset indexes—define poverty in terms of the indicators in their index. Thus, the index is not a proxy standing in for something else (such as consumption) but rather a direct measure of a non-consumption-based definition of poverty. There is nothing wrong—and a lot right—about defining poverty in this way, but it is not as common as a consumption-based definition.

The asset-index approach defines people as *poor* if their assets (physical, human, financial, and social) falls below a threshold. Arguments for the asset-based view include Carter and Barrett (2006), Schreiner and Sherraden (2006), Sahn and Stifel (2003), and Sherraden (1991). The main points in its favor are that:

- Asset ownership is easier to measure accurately than consumption
- Access to resources in the long term—and thus capacity to produce income and to consume—depends on the control of assets
- Assets get at capability more directly, the difference between, say, “Does your income permit adequate sanitation?” versus “Do your toilet have a septic tank?”

While the asset view and the income/consumption view are distinct, they are also tightly linked. After all, income/consumption are flows of resources

received/consumed from the use of stocks of assets. Both views are low-dimensional simplifications—due to practical limits on definitions and measurement—of a higher-dimensional and more complete conception of the production of human well-being.

9.2 Lindelow

Lindelow (2006) compares the association between health outcomes and socioeconomic status as defined by consumption and as defined by a PCA-based asset index using Mozambique’s National Survey of Household Living Conditions (*Inquérito Nacional aos Agregados Familiares sobre as Condições de Vida*), fielded from February 1996 to April 1997. Like its grandchild the 2008/9 IOF, the 1996/7 IAF measures consumption and collects many items related to assets and to health.

Lindelow uses the same indicators as Gwatkin *et al.* (2007), except that he excludes the type of cooking fuel, excludes whether the household has a domestic worker, and includes an indicator for the number of people per sleeping room.

Lindelow concludes that measures of health inequality are materially different when using consumption-based poverty versus asset-based poverty. In particular, he finds that health outcomes vary more with asset-based ranks than with consumption-based ranks.

9.3 Simler and Nhate

Simler and Nhate (2005) apply to Mozambique the “poverty mapping” approach of Elbers, Lanjouw, and Lanjouw (2003) and Hentschel *et al.* (2000).²⁰ They seek to inform geographical targeting of poverty programs at sub-provincial levels.

To do this, Simler and Nhate use data on consumption and indicators for the 8,250 households in the 1996/7 IAF to build 11 poverty scorecards (one for each province, and Maputo City). Most indicators appear in both the 1996/7 IAF and in the Second General Population and Housing Census (*II Recenseamento Geral de População e Habitação*, fielded in August 1997) and that show similar distributions across sources. The rest of the indicators are administrative-post-level averages derived from the Census. The 11 scorecards are constructed using generalized least-squares regressions of the indicators on the natural logarithm of per-capita aggregate household consumption.

Simler and Nhate’s scorecards use 12 to 22 indicators chosen—using stepwise regression—from among 37 simple, inexpensive, and verifiable candidates:

- Demographics:
 - Proportion of household members ages 0 to 5
 - Proportion of household members who are males ages 10 to 16
 - Proportion of household members who are males ages 17 to 30
 - Proportion of household members who are females ages 10 to 16
 - Proportion of household members who are females ages 17 to 30
 - Proportion of household members who have disabilities

²⁰ See also Nhate and Simler (2002).

- Education:
 - Whether any household member can read and write
 - Number of male household members who can read and write
 - Proportion of male household members who can read and write
 - Number of female household members who can read and write
 - Whether any household members completed educational level EP1
 - Whether any household members completed educational level EP2
 - Whether the head of the household completed educational level EP1
 - Whether the head of the household completed educational level EP2
 - Number of male household members who completed educational level EP1
 - Number of male household members who completed educational level EP2
 - Highest education level completed by any household member
- Employment: Proportion of adult household members who are employed
- Characteristics of the residence:
 - Type of floor
 - Type of wall
 - Type of roof
 - Presence of a latrine or toilet
 - Presence of electricity
- Asset ownership: Radio
- Agriculture:
 - Head of large livestock
 - Head of small livestock
 - Ownership of land
- Indicators at the level of the administrative post:
 - Proportion of school-aged children who are enrolled in school
 - Proportion of household heads who are female
 - Proportion of household heads who are literate
 - Proportion of household heads who completed educational level EP1
 - Proportion of household heads who completed educational level EP2
 - Proportion of residences with good-quality walls
 - Proportion of residences with good-quality roofs
 - Proportion of residences with a latrine or toilet
 - Proportion of residences with electricity
 - Proportion of adults employed in the commerce or service sectors

The 11 scorecards are applied to household-level census data to get estimates of consumption for all households in Mozambique. Simler and Nhate can then estimate poverty rates (and other measures of consumption-based well-being) for small areas

(146 districts and 424 administrative posts) with less bias and greater precision than would be possible with the 1996/7 IAF alone. They report the results as poverty maps that quickly show—in a way that is clear for non-specialists—how poverty varies across Mozambique. Simler and Nhate’s work is unique in the poverty-mapping literature in that it looks not only at the geographical distribution of poverty rates but also of poor people, and in that they relate both of those to the distribution of roads.

Poverty mapping by Simler and Nhate (and poverty mapping in general) is similar to poverty scoring in this paper in that they both:

- Build scorecards with nationally representative survey data and then apply them to data on sub-groups that may not be nationally representative
- Use simple, verifiable indicators that are quick and inexpensive to collect
- Provide unbiased estimates when their assumptions hold
- Are used to estimate poverty rates for groups
- Seek to be useful in practice and so aim to be understood by non-specialists

Strengths of poverty mapping include that it:

- Has formally established theoretical properties
- Can be applied straightforwardly to measures of well-being (such as the poverty gap) that go beyond just head-count poverty rates
- Requires data on fewer households for scorecard construction and calibration
- Often includes community-level indicators, increasing accuracy and precision
- Uses only indicators that appear in a census
- Reports standard errors (albeit with complex formula)²¹

²¹ In their abstract and conclusion, Simler and Nhate say that they compute standard errors. But they are not in the paper. This irony—highlighting the ability to estimate standard errors, but not reporting them—is so common that it might be called (with apologies to McCloskey and Ziliak, 1996) the “standard error of poverty mapping”.

Strengths of poverty scoring include that it:

- Is simpler in terms of both construction and application
- Tests accuracy empirically
- Associates poverty likelihoods with scores non-parametrically
- Uses judgment and theory in scorecard construction to reduce overfitting²²
- Reports simple formulas for standard errors

The basic difference between the two approaches is that poverty mapping seeks to help governments design and target pro-poor policies, while poverty scoring seeks to help local pro-poor organizations to manage their social performance.²³ On a technical level, Simler and Nhate estimate consumption directly, whereas poverty scoring (as in this paper) estimates poverty likelihoods.

In practice, the most relevant advantages of the simple poverty scorecard for Mozambique presented here are that it:

- Uses the most recent available data
- Is simpler and easier to understand and so is more likely to be adopted and used
- Reports both bias and standard errors
- Can be used by non-specialists in local, pro-poor organizations

²² A scorecard is *overfit* if it is tailored too closely to the construction sample and any random patterns it may have, leading to inaccuracies when applied at later times or with different populations. Simler and Nhate's scorecards risk overfitting by using stepwise regression and by dividing the IAF 1996/7 data among 11 scorecards.

²³ Another apparent difference is that the developers of poverty mapping (Demombynes *et al.*, 2008; Elbers, Lanjouw, and Lanjouw, 2003) say that it is too inaccurate to be used for targeting individual households. In contrast, Schreiner (2008c) supports such targeting as a legitimate, potentially useful application of poverty scoring. The developers of poverty mapping, however, may have taken a small step away from their original position (Elbers *et al.*, 2007).

The poverty scorecard's main disadvantage is that it is not constructed in cooperation with the government, the largest and most important potential anti-poverty actor in Mozambique. Still, the government is free to use the poverty scorecard. For example, Simler and Nhate float the idea of using their poverty map to target small areas and another tool—perhaps the poverty scorecard here—to target particular households in the targeted area.

Simler and Nhate is unique in the poverty-mapping literature in their explicit discussion of the likely usefulness of the tool for targeting. In their abstract, they note that “unfortunately, the notion of [targeting] poor areas might not always be especially useful, and this appears to be the case in Mozambique. The poverty maps do not reveal a particularly strong spatial correlation of poverty” (p. ii). The poor in Mozambique are not much segregated from the non-poor, even in small areas, so geographic targeting will inevitably have high rates of undercoverage and leakage. The poor would be better served if all researchers were as forthright as Simler and Nhate, willing to report—when appropriate—that “it does not work as well as we had hoped.”

Low targeting power is also reflected in the analysis by Elbers *et al.* (2005) of what must be Simler and Nhate's poverty map for Mozambique. Elbers *et al.* find that “even at a very high level of spatial disaggregation, the contribution of within-community inequality to overall inequality remains very high” (p. ii).

As Simler and Nhate point out, this result reflects the nature of poverty in Mozambique (not the poverty-mapping approach) because the poor are less spatially segregated than they apparently are in Asia and Latin America.

9.4 Mathiassen and Roll-Hansen

Mathiassen and Roll-Hansen (2007)²⁴ apply poverty mapping with consumption data from Mozambique’s 2002/3 IAF ($n = 8,700$) and matched poverty indicators from two other surveys that do not collect consumption data:

- 2000/1 Core Welfare Indicators Questionnaire (*Questionário de Indicadores Básicos de Bem-Estar*, QUIBB, $n = 13,790$)
- 2004/5 Labor Force Survey (*Inquérito Integrado à Força de Trabalho*, IFTRAB, $n = 17,500$)

Mathiassen and Roll-Hansen seek to test how well the poverty-mapping approach can track changes in poverty in years between consumption surveys. Because the 8-page QUIBB and the IFTRAB (which is based on the QUIBB, with an added employment module) do not collect consumption data, they are less expensive and can be done more frequently. The use of such “light” surveys to monitor poverty is often the stated purpose of proposed poverty scorecards (for example, Mathiassen, 2006, and Fofack, 2000). The approach, however is rarely tested, and—as far as we know—not used regularly by any government.

²⁴ Simler (2005) and Simler, Harrower, and Massingarella (2003) also apply poverty mapping to the 1996/7 IAF and 2000/1 QUIBB, but their reports are preliminary.

Mathiassen and Roll-Hansen match indicators from the 2002/3 IAF separately:

- Back in time to the 2000/1 QUIBB
- Forward in time to the 2004/5 IFTRAB

They then construct several sets of scorecards:

- All-Mozambique (1 scorecard)
- All-urban, and all-rural (2 scorecards)
- North, Central, and South (each by urban and rural), and Maputo (7 scorecards)

Mathiassen and Roll-Hansen follow Hentschel *et al.* (2000), using stepwise regression of indicators against the logarithm of per-capita aggregate household consumption from the 2002/3 IAF.²⁵ They then apply the resulting scorecard(s) to indicators from the 2000/1 QUIBB and 2004/5 IFTRAB to get estimates of consumption. These are transformed into poverty likelihoods with a parametric method that differs from the non-parametric one used in this paper. They remove bias and find standard errors using closed-form solutions from Mathiassen (2007).

Looking back from the 2002/3 IAF to the 2000/1 QUIBB, Mathiassen and Roll-Hansen find changes in poverty rates that are almost exactly in line with the trend observed between the 1996/7 IAF and the 2002/3 IAF. Looking forward to the 2004/5 IFTRAB, they also find changes that conform closely to trend—if extrapolated—between the two earlier IAF surveys. With the all-Mozambique scorecard, the estimated poverty rate fell from 58.4 percent in the 2000/1 QUIBB to 55.5 percent in the 2002/3 IAF (with indicators matched to the QUIBB), and then from 54.7 percent in the 2002/3

²⁵ Indicators and point values are not reported, so a potential user would have to contact Mathiassen and Roll-Hansen.

IAF (with indicators matched to the IFTRAB) to 49.3 percent in the 2004/5 IFTRAB.

The results fit the IAF trend even better with the urban/rural scorecard, leading Mathiassen and Roll-Hansen to argue for that approach.

Unfortunately, poverty rates have turned out to be almost unchanged between the 2002/3 IAF and the 2008/9 IOF, moving from 54.1 to 54.7 percent.

10. Conclusion

This paper presents a simple poverty scorecard for Mozambique that can be used to estimate the likelihood that a household has consumption below a given poverty line, to estimate the poverty rate of a group of households at a point in time, and to estimate changes in the poverty rate of a group of households between two points in time. The scorecard can also be used for targeting.

The scorecard is inexpensive to use and can be understood by non-specialists. It is designed to be practical for local pro-poor organizations that want to improve how they monitor and manage their social performance.

The scorecard is built with half of the data from Mozambique's 2008/9 IOF, tested on the other half, and calibrated to six poverty lines.

Bias and precision are reported for estimates of households' poverty likelihoods, groups' poverty rates at a point in time, and changes in groups' poverty rates over time. Of course, the scorecard's estimates of changes are not the same as estimates of program impact. Targeting accuracy is also reported.

When the scorecard is applied to the validation sample with $n = 16,384$, the absolute difference between estimates versus true poverty rates for groups of households at a point in time is 3.1 percentage points or less and averages—across the six poverty lines—about 1.7 percentage points. Unbiased estimates may be had by subtracting this known bias from the original poverty-rate estimates. For $n = 16,384$ and 90-percent confidence, the precision of these differences is ± 1.0 percentage points or better.

If a program wants to use the scorecard for targeting, then the results here provide the information needed to select a cut-off that fits its values and mission.

Although the statistical technique is innovative, and although technical accuracy is important, the design of the scorecard here focuses on transparency and ease-of-use. After all, a perfectly accurate scorecard is worthless if programs feel so daunted by its complexity or its cost that they do not even try to use it. For this reason, the poverty scorecard is kept simple, using ten indicators that are inexpensive to collect and that are straightforward to verify. Points are all zeros or positive integers, and scores range from 0 (most likely below a poverty line) to 100 (least likely below a poverty line). Scores are related to poverty likelihoods via simple look-up tables, and targeting cut-offs are likewise simple to apply. The design attempts to facilitate adoption by helping managers understand and trust scoring and by allowing non-specialists to generate scores quickly in the field.

In summary, the poverty scorecard is a practical, objective way for pro-poor programs in Mozambique to estimate consumption-based poverty rates, track changes in poverty rates over time, and target services. The same approach can be applied to any country with similar data.

References

- Adams, Niall M.; and David J. Hand. (2000) “Improving the Practice of Classifier Performance Assessment”, *Neural Computation*, Vol. 12, pp. 305–311.
- Arndt, Channing; and Kenneth R. Simler. (2010) “Estimating Utility-Consistent Poverty Lines with Applications to Egypt and Mozambique”, *Economic Development and Cultural Change*, Vol. 58, pp. 449–474.
- Baesens, Bart; Van Gestel, Tony; Viaene, Stijn; Stepanova, Maria; Suykens, Johan A. K.; and Jan Vanthienen. (2003) “Benchmarking State-of-the-Art Classification Algorithms for Credit Scoring”, *Journal of the Operational Research Society*, Vol. 54, pp. 627–635.
- Bollen, Kenneth A.; Glanville, Jennifer L.; and Guy Stecklov. (2007) “Socio-Economic Status, Permanent Income, and Fertility: A Latent-Variable Approach”, *Population Studies*, Vol. 61, No. 1, pp. 15–34.
- Caire, Dean. (2004) “Building Credit Scorecards for Small-Business Lending in Developing Markets”, Bannock Consulting, microfinance.com/English/Papers/Scoring_SMEs_Hybrid.pdf, retrieved 16 June 2013.
- Camacho, Adriana; and Emily Conover. (2011) “Manipulation of Social-Program Eligibility”, *American Economic Journal: Economic Policy*, Vol. 3, No. 2, pp. 41–65.
- Carter, Michael R.; and Christopher B. Barrett. (2006) “The Economics of Poverty Traps and Persistent Poverty: An Asset-Based Approach”, *Journal of Development Studies*, Vol. 42, No. 2, pp. 178–199.
- Chen, Shiyuan; and Mark Schreiner. (2009) “A Simple Poverty Scorecard for Vietnam”, microfinance.com/English/Papers/Scoring_Poverty_Vietnam_EN_2006.pdf, retrieved 16 June 2013.
- Coady, David; Grosh, Margaret; and John Hoddinott. (2004) *Targeting of Transfers in Developing Countries*, Washington, D.C.: World Bank, ifpri.org/sites/default/files/pubs/pubs/cp/targettoc.pdf, retrieved 16 June 2013.
- Cochran, William G. (1977) *Sampling Techniques, Third Edition*, New York: Wiley.

- Dawes, Robyn M. (1979) “The Robust Beauty of Improper Linear Models in Decision Making”, *American Psychologist*, Vol. 34, No. 7, pp. 571–582.
- Demombynes, Gabriel; Elbers, Chris; and Peter Lanjouw. (2008) “How Good a Map? Putting Small-Area Estimation to the Test”, *Rivista Internazionale di Scienze Sociali*, Vol. 116, No. 4, pp. 465–494.
- Efron, Bradley; and Robert J. Tibshirani. (1993) *An Introduction to the Bootstrap*, New York: Chapman and Hall.
- Elbers, Chris; Fujii, Tomoki; Lanjouw, Peter; Özler, Berk; and Wesley Yin. (2007) “Poverty Alleviation through Geographic Targeting: How Much Does Disaggregation Help?”, *Journal of Development Economics*, Vol. 83, pp. 198–213.
- ; Lanjouw, Jean O.; and Peter Lanjouw. (2003) “Micro-Level Estimation of Poverty and Inequality”, *Econometrica*, Vol. 71, No. 1, pp. 355–364.
- ; Lanjouw, Peter; Mistiaen, Johan; Özler, Berk; and Kenneth Simler. (2005) “Are Neighbors Equal? Estimating Local Inequality in Three Developing Countries”, pp. 37–60 in Ravi Kanbur and Anthony J. Venables (eds.), *Spatial Inequality and Development*, Oxford: New York.
- Filmer, Deon; and Lant Pritchett. (2001) “Estimating Wealth Effects without Expenditure Data—or Tears: An Application to Educational Enrollments in States of India”, *Demography*, Vol. 38, No. 1, pp. 115–132.
- Fofak, Hippolyte. (2000) “Combining Light Monitoring Surveys with Integrated Surveys to Improve Targeting to Poverty Reduction: The Case of Ghana”, *World Bank Economic Review*, Vol. 14, No. 1, pp. 195–219.
- Friedman, Jerome H. (1997) “On Bias, Variance, 0–1 Loss, and the Curse-of-Dimensionality”, *Data Mining and Knowledge Discovery*, Vol. 1, pp. 55–77.
- Fuller, Rob. (2006) “Measuring the Poverty of Microfinance Clients in Haiti”, microfinance.com/English/Papers/Scoring_Poverty_Haiti_Fuller.pdf, retrieved 16 June 2013.
- Goodman, Leo A.; and Kruskal, William H. (1979) *Measures of Association for Cross Classification*, New York: Springer-Verlag.

- Grootaert, Christiaan; and Jeanine Braithwaite. (1998) “Poverty Correlates and Indicator-Based Targeting in Eastern Europe and the Former Soviet Union”, World Bank Policy Research Working Paper No. 1942, Washington, D.C., go.worldbank.org/VPMWVLU8E0, retrieved 16 June 2013.
- Grosh, Margaret; and Judy L. Baker. (1995) “Proxy Means Tests for Targeting Social Programs: Simulations and Speculation”, Living Standards Measurement Survey Working Paper No. 118, Washington, D.C.: World Bank, go.worldbank.org/W90WN57PD0, retrieved 16 June 2013.
- Gwatkin, Davidson R.; Rutstein, Shea; Johnson, Kiersten; Suliman, Eldaw; Wagstaff, Adam; and Agbessi Amouzou. (2007) “Socio-Economic Differences in Health, Nutrition, and Population: Mozambique”, Country Reports on HNP and Poverty, Washington, D.C.: World Bank, go.worldbank.org/T6LCN5A340, retrieved 16 June 2013.
- Hand, David J. (2006) “Classifier Technology and the Illusion of Progress”, *Statistical Science*, Vol. 22, No. 1, pp. 1–15.
- Hentschel, Jesko; Lanjouw, Jean Olson; Lanjouw, Peter; and Javier Poggi. (2000) “Combining Census and Survey Data to Trace the Spatial Dimensions of Poverty: A Case Study of Ecuador”, *World Bank Economic Review*, Vol. 14, No. 1, pp. 147–165.
- Hoadley, Bruce; and Robert M. Oliver. (1998) “Business Measures of Scorecard Benefit”, *IMA Journal of Mathematics Applied in Business and Industry*, Vol. 9, pp. 55–64.
- IRIS Center. (2007a) “Manual for the Implementation of USAID Poverty Assessment Tools”, povertytools.org/training_documents/Manuals/USAID_PAT_Manual_Eng.pdf, retrieved 16 June 2013.
- (2007b) “Introduction to Sampling for the Implementation of PATs”, povertytools.org/training_documents/Sampling/Introduction_Sampling.pdf, retrieved 16 June 2013.
- (2005) “Notes on Assessment and Improvement of Tool Accuracy”, povertytools.org/other_documents/AssessingImproving_Accuracy.pdf, retrieved 16 June 2013.

- Johnson, Glenn. (2007) “Lesson 3: Two-Way Tables—Dependent Samples”, <https://onlinecourses.science.psu.edu/stat504/node/96>, retrieved 16 June 2013.
- Kolesar, Peter; and Janet L. Showers. (1985) “A Robust Credit-Screening Model Using Categorical Data”, *Management Science*, Vol. 31, No. 2, pp. 124–133.
- Lindelow, Magnus. (2006) “Sometimes More Equal Than Others: How Health Inequalities Depend on the Choice of Welfare Indicator”, *Health Economics*, Vol. 15, pp. 263–279.
- Lovie, Alexander D.; and Patricia Lovie. (1986) “The Flat-Maximum Effect and Linear Scoring Models for Prediction”, *Journal of Forecasting*, Vol. 5, pp. 159–168.
- Martinelli, César; and Susan W. Parker. (2007) “Deception and Misreporting in a Social Program”, *Journal of the European Economic Association*, Vol. 4, No. 6, pp. 886–908.
- Mathiassen, Astrid. (2007) “A Model-Based Approach for Predicting Annual Poverty Rates without Expenditure Data”, *Journal of Economic Inequality*, DOI: 10.1007/s10888007-9059-7.
- (2006) “Predicting the Poverty Headcount Ratio Based on IHS2 and WMS Data”, pp. 106–108 in National Statistical Office, *Welfare Monitoring Survey 2005*, Lilongwe: Government of Malawi.
- ; and Dag Roll-Hansen. (2007) “Predicting Poverty for Mozambique 2000 to 2005: How Robust Are the Models?”, Statistics Norway Research Department, ssb.no/a/english/publikasjoner/pdf/doc_200704_en/doc_200704_en.pdf, retrieved 16 June 2013.
- Matul, Michal; and Sean Kline. (2003) “Scoring Change: Prizma’s Approach to Assessing Poverty”, Microfinance Centre for Central and Eastern Europe and the New Independent States Spotlight Note No. 4, Warsaw, impact.org/sites/default/files/mfc_sn4.pdf, retrieved 16 June 2013.
- McCloskey, Diedre; and Stephen T. Ziliak. (1996) “The Standard Error of Regressions”, *Journal of Economic Literature*, Vol. 34, pp. 97–114.
- McNemar, Quinn. (1947) “Note on the Sampling Error of the Difference between Correlated Proportions or Percentages”, *Psychometrika*, Vol. 17, pp. 153–157.

- Microfinance Risk Management, L.L.C. (2013) “Data-Entry Software for a Simple Poverty Scorecard for Mozambique”, microfinance.com/#Mozambique, retrieved 1 August 2013.
- Ministry of Planning and Development. (2010) “Poverty and Well-Being in Mozambique: Third National Poverty Assessment”, Maputo: National Directorate of Research and Policy Analysis, aec.msu.edu/%5C/fs2/mozambique/caadp/THIRD_NATIONAL_POVERTY_ASSESSMENT_october1.pdf, retrieved 16 June 2013.
- Montgomery, Mark; Gragnolati, Michele; Burke, Kathleen A.; and Edmundo Paredes. (2000) “Measuring Living Standards with Proxy Variables”, *Demography*, Vol. 37, No. 2, pp. 155–174.
- Myers, James H.; and Edward W. Forgy. (1963) “The Development of Numerical Credit-Evaluation Systems”, *Journal of the American Statistical Association*, Vol. 58, No. 303, pp. 779–806.
- Narayan, Ambar; and Nobuo Yoshida. (2005) “Proxy Means Tests for Targeting Welfare Benefits in Sri Lanka”, Report No. SASPR–7, Washington, D.C.: World Bank, documents.worldbank.org/curated/en/2005/07/6209268/proxy-means-test-targeting-welfare-benefits-sri-lanka, retrieved 16 June 2013.
- Nhate, Virgulino; and Kenneth R. Simler. (2002) “Mapeamento da Pobreza em Moçambique: Desagregação das Estimativas da Pobreza e Desigualdade aos Níveis de Distrito e Posto Administrativo”, Maputo: Ministério do Plano e Finanças, siteresources.worldbank.org/INTPGI/Resources/342674-1092157888460/Mozambique_MapeamentoPobreza.pdf, retrieved 16 June 2013.
- Onwujekwe, Obinna; Hanson, Kara; and Julia Fox-Rushby. (2006) “Some Indicators of Socio-Economic Status May Not Be Reliable and Use of Indexes with These Data Could Worsen Equity”, *Health Economics*, Vol. 15, pp. 639–644.
- Pradhan, Menno; Suryahadi, Asep; Sumarto, Sudarno; and Lant Pritchett. (2001) “Eating Like which ‘Joneses’? An Iterative Solution to the Choice of a Poverty Line ‘Reference Group’”, *Review of Income and Wealth*, Series 47, No. 4, pp. 473–487.
- Ravallion, Martin. (1998) “Poverty Lines in Theory and Practice”, Living Standards Measure Survey Working Paper No. 133, Washington, D.C.: World Bank, go.worldbank.org/8P3IBJPQS1, retrieved 16 June 2013.

- Rutstein, Shea Oscar; and Kiersten Johnson. (2004) “The DHS Wealth Index”, DHS Comparative Reports No. 6, Calverton, MD: ORC Macro, measuredhs.com/pubs/pdf/CR6/CR6.pdf, retrieved 16 June 2013.
- Sahn, David E.; and David C. Stifel. (2003) “Exploring Alternative Measures of Welfare in the Absence of Expenditure Data”, *Review of Income and Wealth*, Series 49, No. 4, pp. 463–489.
- (2000) “Poverty Comparisons over Time and across Countries in Africa”, *World Development*, Vol. 28, No. 12, pp. 2123–2155.
- SAS Institute Inc. (2004) “The LOGISTIC Procedure: Rank Correlation of Observed Responses and Predicted Probabilities”, in *SAS/STAT User’s Guide, Version 9*, Cary, NC., support.sas.com/documentation/cdl/en/statug/63033/HTML/default/statug_logistic_sect035.htm, retrieved 16 June 2013.
- Schreiner, Mark. (2013) “A Simple Poverty Scorecard for Bangladesh”, microfinance.com/English/Papers/Scoring_Poverty_Bangladesh_2010_EN.pdf, retrieved 9 July 2013.
- (2012) “An Expert-Based Poverty Scorecard for Rural China”, microfinance.com/English/Papers/Scoring_Poverty_China_EN.pdf, retrieved 9 July 2013.
- (2011a) “A Simple Poverty Scorecard for Colombia”, microfinance.com/English/Papers/Scoring_Poverty_Colombia_2009_EN.pdf, retrieved 16 June 2013.
- (2010) “A Simple Poverty Scorecard for Honduras”, microfinance.com/English/Papers/Scoring_Poverty_Honduras_EN_2007.pdf, retrieved 16 June 2013.
- (2009a) “A Simple Poverty Scorecard for Peru” (revised), microfinance.com/English/Papers/Scoring_Poverty_Peru.pdf, retrieved 16 June 2013.
- (2009b) “A Simple Poverty Scorecard for the Philippines”, microfinance.com/English/Papers/Scoring_Poverty_Philippines.pdf, retrieved 16 June 2013.
- (2009c) “A Simple Poverty Scorecard for Pakistan”, microfinance.com/English/Papers/Scoring_Poverty_Pakistan_2005.pdf, retrieved 16 June 2013.
- (2009d) “A Simple Poverty Scorecard for Bolivia”, microfinance.com/English/Papers/Scoring_Poverty_Bolivia_EN_2007.pdf, retrieved 16 June 2013.

- (2009e) “A Simple Poverty Scorecard for Mexico”, microfinance.com/English/Papers/Scoring_Poverty_Mexico_2008_EN.pdf, retrieved 16 June 2013.
- (2008a) “A Simple Poverty Scorecard for Peru”, microfinance.com/English/Papers/Scoring_Poverty_Peru_May_2008.pdf, retrieved 16 June 2013.
- (2008b) “A Simple Poverty Scorecard for India”, microfinance.com/English/Papers/Scoring_Poverty_India.pdf, retrieved 16 June 2013.
- (2008c) “A Simple Poverty Scorecard for Ecuador”, microfinance.com/English/Papers/Scoring_Poverty_Ecuador_EN_2005.pdf, retrieved 16 June 2013.
- (2006) “Is One Simple Poverty Scorecard Enough for India?”, microfinance.com/English/Papers/Scoring_Poverty_India_Segments.pdf, retrieved 16 June 2013.
- (2005a) “Un Índice de Pobreza para México”, microfinance.com/Castellano/Documentos/Scoring_Pobreza_Mexico_2002.pdf, retrieved 16 June 2013.
- (2005b) “IRIS Questions on Poverty Scorecards”, microfinance.com/English/Papers/Scoring_Poverty_Response_to_IRIS.pdf, retrieved 16 June 2013.
- (2002) *Scoring: The Next Breakthrough in Microfinance?* Occasional Paper No. 7, Consultative Group to Assist the Poor, Washington, D.C., <http://www.cgap.org/publications/scoring-next-breakthrough-microcredit>, retrieved 16 June 2013.
- ; Matul, Michal; Pawlak, Ewa; and Sean Kline. (2004) “Poverty Scorecards: Lessons from a Microlender in Bosnia-Herzegovina”, microfinance.com/English/Papers/Scoring_Poverty_in_BiH_Short.pdf, retrieved 16 June 2013.
- ; and Michael Sherraden. (2006) *Can the Poor Save? Saving and Asset Accumulation in Individual Development Accounts*, Piscataway, NJ: Transaction.
- ; and Gary Woller. (2010a) “A Simple Poverty Scorecard for Ghana”, microfinance.com/English/Papers/Scoring_Poverty_Ghana_EN_2005.pdf, retrieved 16 June 2013.
- ; and Gary Woller. (2010b) “A Simple Poverty Scorecard for Guatemala”, microfinance.com/English/Papers/Scoring_Poverty_Guatemala_EN_2006.pdf, retrieved 16 June 2013.

- Sherraden, Michael. (1991) *Assets and the Poor: A New American Welfare Policy*, Armonk: M.E. Sharpe.
- Sillers, Don. (2006) “National and International Poverty Lines: An Overview”, Washington, D.C.: United States Agency for International Development, pdf.usaid.gov/pdf_docs/Pnadh069.pdf, retrieved 16 June 2013.
- Simler, Kenneth R. (2005) “How Well Do Light Surveys Predict Poverty? Preliminary Results from a Validation Study”, ssb.no/a/english/publikasjoner/pdf/doc_200609_en/doc_200609_en.pdf, retrieved 16 June 2013.
- ; Harrower, Sarah; and Claudio Massingarella. (2003) “Estimating Poverty Indexes from Simple Indicator Surveys”, www.csae.ox.ac.uk/conferences/2004-GPRaHDiA/papers/3p-SimlerMassingerela-CSAE2004.pdf, retrieved 16 June 2013.
- ; and Virgulino Nhate. (2005) “Poverty, Inequality, and Geographic Targeting: Evidence from Small-Area Estimates in Mozambique”, Food and Consumption Division Discussion Paper No. 192, Washington, D.C.: International Food Policy Research Institute, ifpri.org/sites/default/files/publications/fcndp192.pdf, retrieved 16 June 2013.
- Stillwell, William G.; Barron, F. Hutton; and Ward Edwards. (1983) “Evaluating Credit Applications: A Validation of Multi-Attribute Utility-Weight Elicitation Techniques”, *Organizational Behavior and Human Performance*, Vol. 32, pp. 87–108.
- Tarozzi, Alessandro; and Angus Deaton. (2007) “Using Census and Survey Data to Estimate Poverty and Inequality for Small Areas”, *Review of Economics and Statistics*, Vol. 91, No. 4, pp. 773–792.
- Toohig, Jeff. (2008) “PPI Pilot Training Guide”, Grameen Foundation, microfinancegateway.org/gm/document-1.1.6364/PPITrainingGuide.pdf, retrieved 16 June 2013.
- United States Congress. (2004) “Microenterprise Results and Accountability Act of 2004 (HR 3818 RDS)”, November 20, gpo.gov/fdsys/pkg/PLAW-108publ484/pdf/PLAW-108publ484.pdf, retrieved 9 July 2013.
- Varian, Hal R. (1982) “The Non-Parametric Approach to Demand Analysis”, *Econometrica*, Vol. 9, No. 4, pp. 945–973.

- Wagstaff, Adam; and Naoko Watanabe. (2003) “What Difference Does the Choice of SES Make in Health-Inequality Measurement?”, *Health Economics*, Vol. 12, No. 10, pp. 885–890.
- Wainer, Howard. (1976) “Estimating Coefficients in Linear Models: It Don’t Make No Nevermind”, *Psychological Bulletin*, Vol. 83, pp. 223–227.
- World Bank. (2008) “International Comparison Project: Tables of Results”, Washington, D.C., siteresources.worldbank.org/ICPINT/Resources/icp-final-tables.pdf, retrieved 16 June 2013.
- World Health Organization. (1985) *Energy and Protein Requirements*, Technical Report Series No. 724, Geneva, fao.org/DOCREP/003/AA040E/AA040E00.HTM, retrieved 16 June 2013.
- Zeller, Manfred. (2004) “Review of Poverty Assessment Tools”, pdf.usaid.gov/pdf_docs/PNADH120.pdf, retrieved 16 June 2013.

Guidelines for the Interpretation of Scorecard Indicators

The following is taken from:

Instituto Nacional de Estatística. (2008) “Inquérito sobre Orçamento Familiar (IOF 2008/9): Manual do Inquiridor”, Maputo: Direcção de Censos e Inquéritos. (“the Manual”).

Interview guidelines

According to pp. 14–18 of the *Manual*, “An *interview* is a way to get information by way of questioning willing informants who answer directly and immediately. Effective interviewing is an art and should not be viewed as a mechanical process. It should flow like a normal conversation between two (or more) people. All this implies following some basic guidelines.

Access to the respondent

“Before the interview, you and the respondent are strangers to each other. Therefore, the first impressions that you make—based on your appearance, actions, and words—are crucial for convincing the respondent to cooperate. When you meet the respondent for the first time, introduce yourself in a friendly way, tell the respondent for whom you work, and explain the reason for the interview.

“Your basic introduction could go like this: ‘Good morning. I am an enumerator working with <*organization*>. We are conducting a survey in order to better understand our participants. I would appreciate it if—with your permission—I could ask you some questions, if you would be so kind.

“It is important to make a positive first impression. It is not a good idea to ask questions that may seem to invite rejection such as ‘Are you very busy?’, ‘Could you give me a few minutes of your time?’, nor ‘Could you answer a few questions for me?’. Instead, ask for cooperation in a way that invites the respondent to accept, such as ‘I would like to ask you some questions . . .’.

“You should explain clearly to the respondent the goals of the survey before diving in and asking any questions from the survey instrument.

“If anyone from your organization is accompanying you, be sure to introduce him or her to the respondent before starting the interview. Careful explanations play a key role in creating a positive atmosphere in which the respondent is willing to cooperate.

Keep the interview private

“It is of the utmost importance that the interview be kept private and that it be done with a member of the intended household. It is fine if the respondent asks other household members for help when answering questions for which he or she does not know the answer with certainty. If other people are present who are not members of the household, however, then it increases the risk that the respondent may give incorrect or dishonest answers. For this reason, do not conduct the interview—if at all possible—in the presence of friends, neighbors, or other people who are not part of the household.

“There are several ways to ensure that the interview is private. One of them is to request that the respondent tell non-household members to leave the interviewer and respondent alone. Another option is to explain to non-household members—as politely as possible—that the interview must be private and that they should go somewhere else until it is finished.

Confidentiality

“Before asking any questions, be sure to inform the respondent that all information collected will be treated as confidential. In particular, explain that the names of the respondent and other household members will never be divulged and that no information will be shared that could be linked to their particular household. Instead, the results of the survey will go into database. Statistical results from the database will be presented only in aggregate form, combining all households’ answers without linking any particular household to any particular response.

“In no case should you show allow anyone—including other enumerators—to see the completed questionnaires, even in the presence of the respondent.

Neutrality

The questionnaire was carefully designed to avoid any possibility of appearing to suggest answers to the respondent. For this reason, it is of the utmost importance that you maintain a completely neutral attitude and appearance in relation to the content and answers in the interview.

“If you do not carefully read each question exactly as it is written, then this neutrality could be destroyed.

“When the respondent gives a vague or imprecise answer, you should gently (and neutrally) probe for a clearer answer, saying, for example, ‘Could you explain a little more?’, ‘I am not sure that I heard what you said, could you please repeat it?’, or ‘Oh, there is no rush; please take as much time as you need to think.’ In no case should you interpret what the respondent said.

“You should never suggest to the respondent—be it through your facial expressions, body language, or tone of voice—that he or she has given an incorrect or unacceptable answer.

“Often the respondent will ask you about your opinion or point of view. You should tell the respondent that it is his or her opinion that matters for the purposes of the survey, but that you would be happy to talk about other things for a few minutes once the survey is complete, if the respondent so desires.

“If the respondent hesitates to answer a question—or if he or she outright refuses to answer—stay calm and politely try to break down the resistance. Explain again that all responses are confidential and that many other households are also being surveyed.

“If the respondent continues to refuse to answer, simply write a note (‘Refused’) next to the question and continue with the next question as you normally would. Once all the other items in the survey have been completed, go back to the missing item to try politely to get an answer for it.

Leading/managing the interview

“You are the one in charge of the interview and so you should be the one leading/managing it. If the respondent expresses doubts about your authority or right to ask certain questions, you should explain that you were trained for this task and that it is part of your job to ask these questions.

“If the respondent gives irrelevant answers to a question or digresses into topics that have nothing to do with the questionnaire, do not interrupt. Instead, wait for the first opportunity to present the question again, creatively and politely.

“During the interview, always maintain a positive and friendly atmosphere. Respondents are much more likely to make an effort to respond quickly and in good faith when they believe that you are a nice, friendly, accepting person.

Dealing with indecisive respondents

“Often, a respondent will say ‘I don’t know’, make an evasive comment in an attempt not to give a straight answer, just giggle or make some non-meaningful sounds, simply repeat the question in different words, or outright refuse to answer. When this happens (and before asking the next question or repeating the current question), try to find a way to restore confidence to help the respondent to feel comfortable in answering.

The art of asking questions

“Asking questions in the process of conducting an interview is both a science and an art, as such it requires practice. In addition, it helps to follow the practical guidelines that follow.

Ask the questions exactly as they are written in the survey instrument

“You must ask the questions by reading them off the questionnaire exactly as they are written, using the same words and in the same order as they appear there.

“If you change a question’s wording, then you may also inadvertently change its meaning. If the respondent does not understand the meaning of a question, then you should repeat it again, word-for-word, slowly, and clearly. If the respondent still does not seem to understand, you may then try to convey the meaning of the question in other words, but be sure to maintain its original sense. You should endeavor to do all this in a way that does not affect the neutrality of the interview.

Probe when answers are incomplete or inadequate

“Sometimes, respondents will give answers that are not satisfactory, whether because they are incomplete (intentionally or unintentionally) or because the respondent does not know how to answer a given question.

“When this happens, you should try to obtain an appropriate response by asking some additional questions. This process is called *probing*. Of course, you should continue to use neutral words and expressions to avoid suggesting that any particular answers are more appropriate or acceptable than others.

Do not assume that you know what an answer will be

“Regardless of the respondent’s social status, socio-economic level, location of residence, or quality of housing, you should never assume that you know what the answer to any question will be, nor should you expect to receive any particular answers.

“Do not assume what any answer will be based on a respondent’s culture, ethnic group, or appearance. In case of doubt—for example, when you are not sure whether you understand a response—you should probe until you are certain that you do understand. On the other hand, the respondent may have his or her own expectations about your behavior, and the respondent may fear that his or her point of view will not be understood or accepted. Just as you should work to avoid expressing (or acting on) any of your own preconceived notions about the respondent, you should also be sensitive to the possibility that the respondent may have preconceived notions about you and that these may affect their responses. You should always try to behave in such a way as to help the respondent feel at ease and without provoking discomfort.

Do not rush the interview

You should ask the questions slowly and deliberately to ensure that the respondent understands what is being asked. Once you have read the question, pause and allow the respondent the time that he or she needs to think of an answer. If you try to hurry the respondent, or if you do not give him or her enough time to come up with his or her own opinion, then it increases the risk of an evasive—and thus inadequate—response.

“If you suspect that the respondent is answering without thinking (perhaps to get the interview over with quickly), then it would be a good idea to explain to him or her that there is no rush and that the responses are very important to [your organization].

Language of the interview

“You can translate the items in the questionnaire to the local language as needed. Of course, you should take great care not to alter the meaning of the questions and to use the appropriate words when translating. If the respondent does not speak any language that you speak, then you should find a third party to serve as a translator.

End of the interview

“Once you have completed the interview, review the questionnaire again to make sure that no item has been omitted and that all responses are complete. If needed, ask any questions that are required to complete the interview.

“Before leaving the respondent’s residence, thank him or her profusely for his or her cooperation, and then say good-bye.

According to p. 22 of the *Manual*, “After completing each interview, you should carefully review the questionnaire, item by item. It is very important that there is one answer for each question and that each question has only one answer. If necessary, make any fixes or corrections. Of course, you should review the questionnaire before leaving the respondent’s residence, as that way he or she will still be available should you have to ask any follow-up questions of clarification. You should write notes about any important or unusual details of the interview on the back of the questionnaire. If you have any doubts about how to interpret a question or an answer, then you should speak with your manager. He or she is there to help you.

Guidelines for the interpretation of specific indicators

1. How many members does the household have?

According to p. 22 of the *Manual*, “The respondent should be the head of the household or another household member who can answer in the head’s stead and who can identify all people who normally live with the household as well as visitors who have been with the household for six months or more. . . . If the head is unavailable and if no one else is available to answer in his or her place, then do not interview children but rather arrange to return at another time.”

Note that the household head may or may not be the same person who participates with your organization. This is fine; the respondent does not need to be the same as the participant in your organization, although the respondent can be that person.

“The survey should count all people who normally reside with the household (including visitors who have been visiting for six months or more).

According to p. 25 of the *Manual*, the household is comprised of “all people who normally live with the household, including visitors who have been staying there for six months or more . . . Frequently, young children who have not yet been named or who are playing outside at the time of the interview are mistakenly omitted from the count of household members. Do not make this mistake. You should ask whether there are any children who have yet to be named or who are playing outside, and you should count them as household members if they meet the criteria. Likewise, be sure not to mistakenly omit elderly people or people who are hospitalized at the time of the interview (if they also meet the criteria to be counted as household members).”

According to p. 26 of the *Manual*, a “household is a group of people who normally reside together, who eat together, and who share most of their expenses. The household includes all people who live together in these conditions, regardless of whether they are blood relatives. For example, three unrelated men who live together in a residence and who share meals are to be considered as a household. Following these criteria, a maid is considered as a household member if she normally sleeps in the residence of the household. A household can also be comprised of only a single person living alone.

“*Normal residents* are those who are part of the household. They include those who, at the time of the interview, happen to be present at the residence or who those who (for a variety of possible reasons such as business trips, vacation, hospitalization, etc.) happen to be absent, whether inside or outside of Mozambique, but who do not have another residence. If their absence lasts for six months or more, however, then these people cannot be counted as household members.

“Visitors are to be counted as household members only if they have been there for six months or more.

“It is not always easy to determine who should be counted as a household member. Here are some examples to clarify some particular situations:

- A man has two wives who live in different residences. Ask where the husband spent the largest share of his time in the past six months, and then count him as a member of that household. If the respondent does not know where the husband spent most of his time in the past six months, then ask in which residence he slept the night before the interview, and count him as a member of that household
- A woman reports that her husband is the head of the household but that he lives in a different residence. The husband counts as a member of this household only if he spent the largest share of his time in the past six months with this household
- A person lives alone. He or she is the sole member of the household
- A domestic servant is counted as a household member if he or she normally resides with the household

2. What is the main material of the floor of the residence (excluding the kitchen and bathroom)?

According to p. 47 of the *Manual*, “In cases in which the floor is constructed of more than one type of material, count the one used for the largest share of floor space.”

3. What is the main material of the walls of the residence?

According to p. 47 of the *Manual*, “The walls of the residence may be constructed from various materials. In such cases, count the material that accounts for the largest share of wall space.”

4. What toilet arrangement does the household use in its residence?

According to p. 50 of the *Manual*, “The enumerator should read the response options one-by-one and then circle the one indicated by the respondent.”

5. What is the main source of energy for lighting in the residence?

According to p. 50 of the *Manual*, “If the household uses more than one source of energy for lighting, then record only the main one.”

6. Does the household have a non-electric or electric clothes iron?

According to p. 69 of the *Manual*, “Count only assets that the household possesses that are in working condition.”

7. Does the household have a clock (wall, wrist, or pocket)?

According to p. 69 of the *Manual*, “Count only assets that the household possesses that are in working condition.”

8. Does the household have a radio, stereo system, or cassette player?

According to p. 69 of the *Manual*, “Count only assets that the household possesses that are in working condition.”

9. Does the household have a bicycle, motorcycle, or car?

According to p. 69 of the *Manual*, “Count only assets that the household possesses that are in working condition.”

10. How many beds does the household have (single, double, bunk beds, or for children)?

According to p. 69 of the *Manual*, “Count only assets that the household possesses that are in working condition.”

Figure 1: Sample sizes, poverty lines, and poverty rates for all of Mozambique by sub-sample, poverty line, and household-level/person-level

Sample	Poverty line or rate	Households or people	Households surveyed	% with consumption below a poverty line					
				National			USAID	Intl. 2005 PPP	
				100%	150%	200%	'Extreme'	\$1.25/day	\$2.50/day
All Mozambique									
	Line			18.41	27.61	36.82	11.54	20.05	40.10
	Rate	Households	10,832	47.3	70.5	82.9	22.5	53.2	85.6
	Rate	People	10,832	54.7	77.3	88.0	27.3	60.6	90.1
Construction and calibration									
Selecting indicators and weights, and associating scores with likelihoods	Rate	Households	5,385	47.5	70.5	83.0	22.7	53.7	85.9
	Rate	People	5,385	54.5	76.9	87.8	27.7	60.9	90.0
Validation									
Measuring accuracy	Rate	Households	5,447	47.2	70.4	82.8	22.3	52.6	85.3
	Rate	People	5,447	54.9	77.6	88.1	26.8	60.4	90.1

Source: 2008/9 *Inquérito sobre Orçamento Familiar*. Poverty lines in MZN per person per day over July to August, 2009.

Figure 2: Poverty lines, and poverty rates at the household-level and person-level by poverty-line region

Poverty-line region	Line or Rate	Households or people	Poverty line					
			National			USAID	Intl. 2005 PPP	
			100%	150%	200%	'Extreme'	\$1.25/day	\$2.50/day
<u>All Mozambique</u>	Line		18.41	27.61	36.82	11.54	20.05	40.10
	Rate	Households	47.3	70.5	82.9	22.5	53.2	85.6
	Rate	People	54.7	77.3	88.0	27.3	60.6	90.1
<u>Niassa and Cabo Delgado, rural</u>	Line		15.95	23.92	31.89	11.17	17.37	34.75
	Rate	Households	26.6	53.5	72.1	12.5	33.2	75.9
	Rate	People	32.7	62.3	79.0	16.3	40.8	81.9
<u>Niassa and Cabo Delgado, urban</u>	Line		18.91	28.37	37.82	11.62	20.61	41.21
	Rate	Households	38.7	65.0	77.5	19.3	45.9	80.3
	Rate	People	43.4	71.2	82.2	21.7	51.6	84.7
<u>Nampula, rural</u>	Line		14.33	21.49	28.65	9.55	15.61	31.22
	Rate	Households	48.2	75.5	87.2	23.6	56.5	91.1
	Rate	People	56.7	82.2	91.6	28.2	65.4	94.7
<u>Nampula, urban</u>	Line		16.72	25.08	33.44	9.94	18.22	36.43
	Rate	Households	46.0	66.9	79.6	22.4	50.9	80.6
	Rate	People	49.9	70.5	82.5	24.8	54.2	83.6
<u>Sofala and Zambézia, rural</u>	Line		14.35	21.53	28.70	8.27	15.64	31.28
	Rate	Households	62.1	80.8	89.5	28.2	66.7	91.1
	Rate	People	69.7	86.8	93.8	34.8	74.1	94.9
<u>Sofala and Zambézia, urban</u>	Line		19.07	28.60	38.13	11.58	20.77	41.54
	Rate	Households	52.9	69.1	80.0	24.6	56.3	82.7
	Rate	People	56.7	72.2	83.7	28.2	59.6	85.8

Source: 2008/9 Inquérito sobre Orçamento Familiar. Poverty lines in MZN per person per day over July to August, 2009.

Figure 2 (cont.): Poverty lines, and poverty rates at the household-level and person-level by poverty-line region

Poverty-line region	Line or Rate	Households or people	Poverty line					
			National			USAID	Intl. 2005 PPP	
			100%	150%	200%	'Extreme'	\$1.25/day	\$2.50/day
<u>Manica and Tete, rural</u>	Line		19.39	29.08	38.78	12.22	21.13	42.25
	Rate	Households	41.5	69.8	85.9	21.0	47.8	88.9
	Rate	People	47.5	76.7	91.7	23.7	54.4	94.1
<u>Manica and Tete, urban</u>	Line		21.47	32.21	42.95	13.79	23.40	46.79
	Rate	Households	41.1	66.1	78.4	19.5	47.2	80.9
	Rate	People	48.7	74.8	85.0	24.2	55.2	86.4
<u>Gaza and Inhambane, rural</u>	Line		18.37	27.56	36.75	10.52	20.02	40.04
	Rate	Households	55.2	76.4	87.4	25.0	60.3	89.4
	Rate	People	65.2	84.5	92.0	32.5	69.9	93.9
<u>Gaza and Inhambane, urban</u>	Line		20.31	30.47	40.62	12.00	22.13	44.26
	Rate	Households	42.0	63.4	76.7	20.6	47.9	79.9
	Rate	People	44.9	65.6	79.2	22.4	50.4	82.3
<u>Maputo Province, rural</u>	Line		24.84	37.26	49.68	15.83	27.07	54.13
	Rate	Households	64.8	85.2	90.8	33.5	70.7	91.9
	Rate	People	76.3	91.5	94.1	37.9	80.9	94.6
<u>Maputo Province, urban</u>	Line		30.86	46.29	61.72	19.21	33.62	67.24
	Rate	Households	54.9	75.5	86.0	26.3	60.5	88.9
	Rate	People	63.7	31.7	90.2	31.8	68.6	92.4
<u>Maputo City</u>	Line		33.14	49.71	66.29	22.88	36.11	72.22
	Rate	Households	27.2	49.6	63.3	13.1	32.1	66.9
	Rate	People	36.2	60.8	73.3	18.0	41.6	76.5

Source: 2008/9 Inquérito sobre Orçamento Familiar. Poverty lines in MZN per person per day over July to August, 2009.

Figure 3: Poverty indicators by uncertainty coefficient

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
778	How many household members are 0 to 14 years old? (Five or more; Four; Three; Two; One; None)
769	How many household members are 0 to 13 years old? (Five or more; Four; Three; Two; One; None)
763	How many household members are 0 to 12 years old? (Four or more; Three; Two; One; None)
752	How many household members are 0 to 15 years old? (Five or more; Four; Three; Two; One; None)
750	How many household members are 0 to 17 years old? (Five or more; Four; Three; Two; One; None)
748	How many household members are 0 to 18 years old? (Six or more; Five; Four; Three; Two; One; None)
740	How many household members are 0 to 16 years old? (Five or more; Four; Three; Two; One; None)
717	How many household members are 0 to 11 years old? (Four or more; Three; Two; One; None)
661	How many members does the household have? (Eight or more; Seven; Six; Five; Four; Three; Two; One)
546	How many household members are 0 to 6 years old? (Three or more; Two; One; None)
406	Do all household members ages 6 to 13 currently go to school? (No; Yes; No members ages 6 to 13)
396	Do all household members ages 6 to 12 currently go to school? (No; Yes; No members ages 6 to 12)
385	Do all household members ages 6 to 11 currently go to school? (No; Yes; No members ages 6 to 11)
382	Do all household members ages 6 to 14 currently go to school? (No; Yes; No members ages 6 to 14)
375	Do all household members ages 6 to 15 currently go to school? (No; Yes; No members ages 6 to 15)
346	What toilet arrangement does the household use in its residence? (None, or other; Latrine of any kind; Toilet connected to a septic tank)
332	Do all household members ages 6 to 16 currently go to school? (No; Yes; No members ages 6 to 16)
327	Do all household members ages 6 to 17 currently go to school? (No; Yes; No members ages 6 to 17)
318	How many household members have their primary occupation (that is, the main job where they work) in agriculture, ranching/animal husbandry, forestry, fishing or hunting? (Five or more; Four; Three; Two; One; None)

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

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
318	What is the highest educational level that the female head/spouse has completed? (None, literacy, or grade school without completing any grades; First grade; Second grade; Third grade; Fourth grade; Fifth grade; Sixth grade; No female head/spouse; Seventh to ninth grade; Tenth grade, eleventh grade, technical school (elementary, basic, or middle), teacher's college, or higher)
313	Do all household members ages 6 to 18 currently go to school? (No; Yes; No members ages 6 to 18)
281	What is the main cooking fuel that the household uses? (For example, charcoal, coal, firewood, LPG, etc.)? (Firewood, dung, coal, or other; Oil/paraffin/kerosene, or charcoal; Electricity, or LPG)
246	What is the main source of energy for lighting in the residence? (Firewood, or batteries; LPG, oil/paraffin/kerosene, or candles; Other; Electricity, generator, or solar panel)
241	Does the household have a radio, stereo system, or cassette player? (No; Radio only; Stereo system or cassette player (regardless of radio))
235	How many beds does the household have (single, double, bunk beds, or for children)? (None; One; Two or more)
234	Does the household have a television? (No; Yes)
227	How many household members did any work (farming, selling something, or in some other economic activity) in the past seven days, or had a job, farm, company, or business in which they did not work but to which they plan to return? (Four or more; Three; Two; One, or none)
219	Does the household have a refrigerator or freezer? (No; Yes)
218	Does the household have a fan? (No; Yes)
202	In the last seven days, how many household members worked in agriculture? (Five or more; Four; Three; Two; One; None)
200	What is the highest educational level that the male head/spouse has completed? (None, literacy, or grade school without completing any grades; No male head/spouse; First grade; Second grade; Third grade; Fourth grade; Fifth grade; Sixth grade; Seventh grade; Eighth or ninth grade; Tenth grade, eleventh grade, technical school (elementary, basic, or middle), teacher's college, or higher)

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

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
196	Does the household have a non-electric or electric clothes iron? (No; Yes)
185	How many cellular telephones does the household have? (None; One; Two or more)
184	What type of residence does the household have? (Straw house, house made of improvised materials, part of a commercial building, or other; House of mixed materials; Basic house; Detached house, or flat/apartment)
180	Does the household have a gas, electric, or mixed stove? (No; Yes)
175	What is the main material of the floor of the residence (excluding the kitchen and bathroom)? (Uncovered, or other; Packed earth, wood/parquet, marble/granite, cement, or mosaic/tile)
174	Does the household have a bicycle, motorcycle, or car? (No; Bicycle only; Motorcycle or car (regardless of bicycle))
170	What is the main source of drinking water for the household? (Well water without a pump, rainwater, bottled water, or other; River/lake/pond; Standpipe; Hand-pumped from well or borehole; Piped outside the house into the yard or compound; Piped into the house)
164	Does the household have a clock (wall, wrist, or pocket)? (No; Yes)
162	How many minutes does it take to walk from the residence of the household to the nearest source of drinking water? (20 minutes or more; 11 to 19 minutes; 9 to 10 minutes; 6 to 8 minutes; 5 minutes; 3 to 4 minutes; 1 to 2 minutes; No minutes, or does have to walk to get drinking water)
159	What is the primary occupation of the female head/spouse? (That is, what is her main job where she works? (Agriculture, animal husbandry, forestry, fishing, or hunting; Manufacturing; Transport equipment operations; Laborer; Does not work; Services; No female head/spouse; Professional, technical, administrative, managerial, clerical, or sales)
154	Can the female head/spouse read and write? (No; Yes; No female head)
148	Does the household have a stereo system or cassette player? (No; Yes)

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

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
147	What is the main material of the roof of the house? (Grass/thatch/palm, or other; Metal sheets; Concrete slabs, tile, or Lusalite sheets)
122	Does the household treat its drinking water? (No; Yes)
120	What is the marital status of the male head/spouse? (Married, or widowed; No male head/spouse; Living together polygamously; Living together monogamously; Single/never-married, or divorced or separated)
120	Does the household have a car? (No; Yes)
112	How many years old was the female head/spouse on her last birthday? (32 to 36; 29 to 32; 22 to 28; 37 to 40; 41 to 46; 47 to 53; 54 to 60; 61 or older; 21 or younger; No female head/spouse)
112	What is the primary occupation of the male head/spouse? (That is, what is his main job where he works?) (Agriculture, ranching/animal husbandry, forestry, or hunting; Does not work; No male head/spouse; Manufacturing and related; Transport equipment operation and laborers; Sales, or services; Professional, technical, administrative, managerial, clerical, or related)
108	What is the main material of the walls of the residence? (Reeds/sticks/bamboo/palm, wood or metal sheets, tin/cardboard/paper/ sacks, or other; Adobe blocks, wattle and daub, cement blocks, or bricks)
99	For whom does the female head/spouse work in her primary occupation? (Unpaid family; Self-employed without employees; Does not work; No female head/spouse; Private sector, private person or household, cooperative, or NGO or other association; Government, public sector, or self-employed with employees)
96	For whom does the male head/spouse work in his primary occupation? (Unpaid family; Self-employed without employees; Does not work; No female head/spouse; Private sector, private person or household, cooperative, or NGO or other association; Government, public sector, or self-employed with employees)

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

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
95	Does the household have a radio? (No; Yes)
95	How many minutes does it take to walk from the residence of the household to the nearest bus stop? (40 minutes or more; There is no bus stop within walking distance; 30 to 39 minutes; 20 to 29 minutes; 15 to 19 minutes; 10 to 14 minutes; 5 to 9 minutes; 0 to 4 minutes)
92	Does the household have a bicycle or motorcycle? (No; Yes)
79	How many minutes does it take to walk from the residence of the household to the nearest market or grocery store? (41 minutes or more; There is no market or grocery store within walking distance; 26 to 40 minutes; 16 to 25 minutes; 11 to 15 minutes; 6 to 10 minutes; 4 to 5 minutes; 0 to 3 minutes)
79	In the last seven days, did the female head/spouse work in the fields, including in ranching/animal husbandry or fishing, whether for sale or for the consumption of the household? (Yes; No; No female head/spouse)
77	How many minutes does it take to walk from the residence of the household to the nearest grade school? (45 minutes or more; 31 to 44 minutes; 21 to 30 minutes; 16 to 20 minutes; 15 minutes; There is no grade school in walking distance; 8 to 14 minutes; 5 to 7 minutes; 0 to 4 minutes)
75	How many minutes does it take to walk from the residence of the household to the nearest police station? (60 minutes or more; There is no police station within walking distance; 31 to 59 minutes; 21 to 30 minutes; 11 to 20 minutes; 0 to 10 minutes)
72	How many household members have their primary occupation (that is, the main job where they work) in something other than agriculture, ranching/animal husbandry, forestry, fishing or hunting? (None; One; Two or more)
72	What is the marital status of the female head/spouse? (Married; Widowed; Divorced or separated; Living together polygamously; Living together monogamously; No female head/spouse; Single/never-married)

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

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
68	Does the household have a motorcycle? (No; Yes)
62	How many minutes does it take to walk from the residence of the household to the nearest health clinic? (61 minutes or more; 36 to 60 minutes; There is no health clinic within walking distance; 26 to 35 minutes; 16 to 25 minutes; 10 to 15 minutes; 0 to 9 minutes)
61	Is the female head/spouse a permanent, seasonal, or occasional worker? (Permanent; Does not work; Occasional; Seasonal; No female head/spouse)
58	Can the male head/spouse read and write? (No; No male head/spouse; Yes)
50	How many household members have a salaried job? (None; One or more)
49	How many years old was the male head/spouse on his last birthday? (25 or younger; 26 to 30; 31 to 35; No male head/spouse; 36 to 40; 41 to 50; 51 to 60; 61 or older)
41	Did the female head/spouse do any work (in the fields, selling something, or in some other economic activity) in the past seven days, or did she have a job, farm, company, or business in which she did not work but to which she plans to return? (Yes; No; No female head/spouse)
40	What is the tenancy status of the household in its residence? (Owned, or other; Rented, lent or borrowed temporarily)
39	How many household members can read and write? (None; One; Two; Three; Four or more)
38	How many rooms in the residence are used for sleeping? (One; Two; Three; Four or more)
37	What is the structure of household headship? (Female head/spouse only; Both male and female heads/spouses Male head/spouse only)
33	How many household members, in their primary occupation (that is, the main job where they work), are self-employed with employees? (None; One or more)

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

<u>Uncertainty coefficient</u>	<u>Indicator (Answers ordered starting with those most strongly linked with higher poverty likelihoods)</u>
31	How many household members, in their primary occupation (that is, the main job where they work), work for the government, a public-sector employer, a private-sector employer, a private person or household, a cooperative, or a NGO or other association? (None; One or more)
26	In the last seven days, did the male head/spouse work in the fields, including in ranching/animal husbandry or fishing, whether for sale or for the consumption of the household? (No male head/spouse; Yes; No)
26	Does the household have a bicycle? (No; Yes)
13	In the last seven days, how many household members worked in self-employment outside of farming and fishing or helped a family member in self-employment outside of farming and fishing? (None; One or more)
11	Is the male head/spouse a permanent, seasonal, or occasional worker? (Does not work, occasional; No male head/spouse; Permanent; Seasonal)
6	In the last seven days, how many household members worked for pay (in cash or in kind), including day labor? (None; One or more)
5	How many rooms does the residence have (excluding the kitchen and bathroom)? (One; Two; Three; Four; Five or more)
4	Did the male head/spouse do any work (in the fields, selling something, or in some other economic activity) in the past seven days, or did he have a job, farm, company, or business in which he did not work but to which he plans to return? (No; No male head/spouse; Yes)
4	How many household members, in their primary occupation (that is, the main job where they work), are seasonal or occasional workers? (One or more; None)

Source: 2008/9 *Inquérito sobre Orçamento Familiar*

**Tables for
100% of the National Poverty Line
(and Tables Pertaining to All Six Poverty Lines)**

Figure 4 (National line): Estimated poverty likelihoods associated with scores

If a household's score is then the likelihood (%) of being below the poverty line is:
0-4	97.1
5-9	93.0
10-14	89.9
15-19	79.4
20-24	76.1
25-29	72.0
30-34	60.8
35-39	50.8
40-44	31.7
45-49	28.8
50-54	21.4
55-59	8.5
60-64	7.2
65-69	3.2
70-74	0.6
75-79	0.0
80-84	0.0
85-89	0.0
90-94	0.0
95-100	0.0

Figure 5 (National line): Derivation of estimated poverty likelihoods associated with scores

Score	Households below poverty line		All households at score		Poverty likelihood (estimated, %)
0-4	59	÷	61	=	97.1
5-9	620	÷	667	=	93.0
10-14	2,137	÷	2,376	=	89.9
15-19	4,032	÷	5,076	=	79.4
20-24	7,251	÷	9,534	=	76.1
25-29	8,221	÷	11,418	=	72.0
30-34	7,534	÷	12,390	=	60.8
35-39	7,074	÷	13,914	=	50.8
40-44	4,297	÷	13,576	=	31.7
45-49	3,273	÷	11,373	=	28.8
50-54	1,675	÷	7,821	=	21.4
55-59	426	÷	5,006	=	8.5
60-64	216	÷	2,997	=	7.2
65-69	44	÷	1,361	=	3.2
70-74	6	÷	999	=	0.6
75-79	0	÷	750	=	0.0
80-84	0	÷	416	=	0.0
85-89	0	÷	147	=	0.0
90-94	0	÷	45	=	0.0
95-100	0	÷	73	=	0.0

Number of all households normalized to sum to 100,000.

Figure 6 Distribution of household poverty likelihoods across consumption ranges demarcated by poverty lines

Score	Likelihood of having consumption in range demarcated by poverty lines						
		=>USAID	=>100% Natl.	=>\$1.25/day	=>150% Natl.	=>200% Natl.	=>\$2.50/day
	<USAID	and	and	and	and	and	
	<100% Natl.	<\$1.25/day	<150% Natl.	<200% Natl.	<\$2.50/day		
	=>MNZ11.54	=>MNZ18.41	=>MZN24.25	=>MZN27.61	=>MZN36.82		=>MZN48.51
<MNZ11.54	and	and	and	and	and		
	<MNZ18.41	<MZN24.25	<MZN27.61	<MZN36.82	<MZN48.51		
0-4	77.7	19.4	2.9	0.0	0.0	0.0	0.0
5-9	65.6	27.5	3.8	1.8	1.4	0.0	0.0
10-14	62.9	27.1	2.7	4.9	2.1	0.4	0.0
15-19	52.3	27.1	4.7	9.2	4.4	0.7	1.5
20-24	42.9	33.2	5.5	10.3	5.4	0.8	1.9
25-29	35.0	37.0	6.3	12.8	6.2	0.8	1.9
30-34	27.0	33.9	7.7	19.7	8.7	0.9	2.2
35-39	19.9	30.9	8.4	19.1	10.7	2.6	8.2
40-44	12.9	18.7	9.8	25.6	17.2	3.7	12.0
45-49	9.7	19.0	4.2	19.1	21.7	4.4	21.8
50-54	5.7	15.7	4.8	18.8	22.8	5.6	26.6
55-59	3.2	5.3	3.4	18.7	20.1	7.8	41.4
60-64	0.0	7.2	2.9	14.7	18.7	8.1	48.4
65-69	0.0	3.2	1.8	10.6	11.6	4.6	68.3
70-74	0.0	0.6	0.8	3.4	10.8	5.4	79.1
75-79	0.0	0.0	0.0	1.3	8.7	3.5	86.5
80-84	0.0	0.0	0.0	0.0	0.0	0.0	100.0
85-89	0.0	0.0	0.0	0.0	0.0	0.0	100.0
90-94	0.0	0.0	0.0	0.0	0.0	0.0	100.0
95-100	0.0	0.0	0.0	0.0	0.0	0.0	100.0

All poverty likelihoods in percentage units.

Figure 7 (National line): Bootstrapped differences between estimated and true poverty likelihoods for households in a large sample ($n = 16,384$) with confidence intervals, scorecard applied to the validation sample

Score	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
0-4	-2.9	1.5	1.5	1.5
5-9	-7.0	3.5	3.5	3.5
10-14	+11.0	3.9	4.6	6.4
15-19	+12.4	3.6	4.1	5.7
20-24	-4.7	3.2	3.4	3.8
25-29	+0.7	2.0	2.3	2.9
30-34	-6.9	4.8	5.1	5.5
35-39	+4.1	2.0	2.5	3.5
40-44	+1.8	1.8	2.2	2.9
45-49	-22.8	13.2	13.5	14.1
50-54	+2.8	2.0	2.4	3.1
55-59	-4.2	3.2	3.4	3.9
60-64	-5.7	4.8	5.1	6.1
65-69	+1.5	1.1	1.3	1.8
70-74	+0.6	0.0	0.0	0.0
75-79	+0.0	0.0	0.0	0.0
80-84	+0.0	0.0	0.0	0.0
85-89	+0.0	0.0	0.0	0.0
90-94	+0.0	0.0	0.0	0.0
95-100	+0.0	0.0	0.0	0.0

Figure 8 (National line): Differences and precision of differences for bootstrapped estimates of poverty rates for groups of households at a point in time, by sample size, scorecard applied to the validation sample

Sample Size n	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
1	-1.0	70.2	73.6	90.7
4	+0.1	42.7	50.1	61.9
8	-0.2	33.4	39.1	50.3
16	-0.7	26.8	31.4	37.8
32	-1.6	20.2	23.9	30.5
64	-2.5	14.8	17.3	21.7
128	-2.8	10.7	13.0	16.3
256	-2.7	7.9	9.3	12.0
512	-2.9	5.3	6.3	8.5
1,024	-2.9	3.9	4.8	6.1
2,048	-2.9	2.8	3.3	4.2
4,096	-3.0	2.0	2.4	3.1
8,192	-3.0	1.4	1.7	2.2
16,384	-3.1	1.0	1.2	1.6

Figure 9 (All poverty lines): Differences, precision of differences, and the α factor for bootstrapped estimates of poverty rates for groups of households at a point in time, scorecard applied to the validation sample

	Poverty line					
	National			USAID	Intl. 2005 PPP	
	100%	150%	200%	'Extreme'	\$1.25/day	\$2.50/day
<u>Estimate minus true value (bias)</u>						
Scorecard applied to validation sample	-3.1	-2.0	-1.0	-1.7	-2.1	-0.4
<u>Precision of difference</u>						
Scorecard applied to validation sample	1.0	0.7	0.5	0.9	1.0	0.5
<u>α factor for sample size</u>						
Scorecard applied to validation sample	1.54	1.25	1.06	1.70	1.50	1.02

Precision is measured as 90-percent confidence intervals in units of $+/-$ percentage points.

Differences and precision estimated from 500 bootstraps of size $n = 16,384$.

α is estimated from 1,000 bootstrap samples of $n = 256, 512, 1,024, 2,048, 4,096, 8,192, \text{ and } 16,384$.

The USAID "extreme" line is in per-person units.

Figure 10 (All poverty lines): Possible types of outcomes from targeting by poverty score

		<u>Targeting segment</u>	
		<u>Targeted</u>	<u>Non-targeted</u>
<u>True poverty status</u>	<u>Below poverty line</u>	<u>Inclusion</u> Under poverty line Correctly Targeted	<u>Undercoverage</u> Under poverty line Mistakenly Non-targeted
	<u>Above poverty line</u>	<u>Leakage</u> Above poverty line Mistakenly Targeted	<u>Exclusion</u> Above poverty line Correctly Non-targeted

Figure 11 (National line): Households by targeting classification and score, along with “Total Accuracy” and BPAC, scorecard applied to the validation sample

Score	<u>Inclusion:</u>	<u>Undercoverage:</u>	<u>Leakage:</u>	<u>Exclusion:</u>	<u>Total Accuracy</u>	<u>BPAC</u>
	< poverty line correctly targeted	< poverty line mistakenly non-targeted	=> poverty line mistakenly targeted	=> poverty line non-targeted	Inclusion + Exclusion	See text
0–4	0.1	47.1	0.0	52.8	52.9	–99.7
5–9	0.7	46.4	0.0	52.8	53.6	–96.9
10–14	2.7	44.5	0.4	52.4	55.1	–87.7
15–19	6.5	40.7	1.7	51.1	57.6	–68.9
20–24	13.9	33.2	3.8	49.1	63.0	–32.9
25–29	21.8	25.4	7.4	45.5	67.2	+7.9
30–34	29.4	17.8	12.2	40.7	70.1	+50.3
35–39	36.3	10.9	19.2	33.7	69.9	+59.3
40–44	40.9	6.2	28.1	24.8	65.7	+40.4
45–49	44.4	2.7	36.0	16.9	61.3	+23.7
50–54	46.2	1.0	42.0	10.8	57.0	+10.9
55–59	46.8	0.3	46.4	6.5	53.3	+1.7
60–64	47.1	0.0	49.1	3.8	50.9	–4.1
65–69	47.2	0.0	50.4	2.4	49.6	–6.9
70–74	47.2	0.0	51.4	1.4	48.6	–9.0
75–79	47.2	0.0	52.2	0.7	47.8	–10.6
80–84	47.2	0.0	52.6	0.3	47.4	–11.5
85–89	47.2	0.0	52.7	0.1	47.3	–11.8
90–94	47.2	0.0	52.8	0.1	47.2	–11.9
95–100	47.2	0.0	52.8	0.0	47.2	–12.1

Inclusion, undercoverage, leakage, and exclusion normalized to sum to 100.

Figure 12 (National line): For a given score cut-off, the percentage of all households who are targeted (that is, have a score equal to or less than the cut-off), the percentage of targeted households who are poor (that is, below the poverty line), the percentage of poor households who are targeted, and the number of poor households who are successfully targeted (coverage) per non-poor household mistakenly targeted (leakage), scorecard applied to the validation sample

Targeting cut-off	% all households who are targeted	% targeted who are poor	% of poor who are targeted	Poor households targeted per non-poor household targeted
0-4	0.1	100.0	0.1	Only poor targeted
5-9	0.7	100.0	1.5	Only poor targeted
10-14	3.1	86.9	5.7	6.7:1
15-19	8.2	79.2	13.7	3.8:1
20-24	17.7	78.6	29.5	3.7:1
25-29	29.1	74.7	46.2	3.0:1
30-34	41.5	70.7	62.3	2.4:1
35-39	55.4	65.4	76.9	1.9:1
40-44	69.0	59.3	86.8	1.5:1
45-49	80.4	55.3	94.2	1.2:1
50-54	88.2	52.4	98.0	1.1:1
55-59	93.2	50.3	99.3	1.0:1
60-64	96.2	49.0	99.9	1.0:1
65-69	97.6	48.3	100.0	0.9:1
70-74	98.6	47.8	100.0	0.9:1
75-79	99.3	47.5	100.0	0.9:1
80-84	99.7	47.3	100.0	0.9:1
85-89	99.9	47.2	100.0	0.9:1
90-94	99.9	47.2	100.0	0.9:1
95-100	100.0	47.2	100.0	0.9:1

**Tables for
150% of the National Poverty Line**

Figure 4 (150% of the national line): Estimated poverty likelihoods associated with scores

If a household's score is then the likelihood (%) of being below the poverty line is:
0-4	100.0
5-9	98.6
10-14	97.5
15-19	93.4
20-24	91.8
25-29	91.1
30-34	88.2
35-39	78.4
40-44	67.1
45-49	52.1
50-54	45.1
55-59	30.6
60-64	24.9
65-69	15.6
70-74	4.8
75-79	1.3
80-84	0.0
85-89	0.0
90-94	0.0
95-100	0.0

Figure 7 (150% of the national line): Bootstrapped differences between estimated and true poverty likelihoods for households in a large sample ($n = 16,384$) with confidence intervals, scorecard applied to the validation sample

Score	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
0-4	+0.0	0.0	0.0	0.0
5-9	-1.4	0.7	0.7	0.7
10-14	+3.5	2.8	3.3	4.6
15-19	-2.4	1.8	1.9	2.1
20-24	-2.6	1.8	1.9	2.0
25-29	-2.6	1.8	1.8	2.0
30-34	+5.4	1.9	2.3	3.0
35-39	+1.1	1.8	2.1	2.9
40-44	+6.5	2.1	2.5	3.2
45-49	-19.4	10.9	11.1	11.5
50-54	-6.5	4.8	5.1	5.5
55-59	-0.5	3.2	3.7	4.9
60-64	-2.6	4.4	5.2	6.7
65-69	+6.0	3.2	3.9	5.0
70-74	-3.1	3.3	3.9	5.3
75-79	+1.0	0.4	0.4	0.6
80-84	-0.4	0.6	0.7	0.9
85-89	+0.0	0.0	0.0	0.0
90-94	+0.0	0.0	0.0	0.0
95-100	+0.0	0.0	0.0	0.0

Figure 8 (150% of the national line): Differences and precision of differences for bootstrapped estimates of poverty rates for groups of households at a point in time, by sample size, scorecard applied to the validation sample

Sample Size n	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
1	+0.8	66.7	78.8	85.8
4	+0.1	38.0	45.3	56.0
8	-0.9	28.1	33.6	42.4
16	-0.9	22.2	26.4	32.2
32	-1.3	15.4	17.8	23.4
64	-1.9	11.6	13.5	17.3
128	-1.9	7.8	9.5	11.5
256	-1.9	5.6	6.7	8.4
512	-1.9	4.1	4.8	5.9
1,024	-1.9	2.9	3.4	4.4
2,048	-1.9	2.1	2.5	3.2
4,096	-2.0	1.5	1.7	2.3
8,192	-2.0	1.1	1.3	1.6
16,384	-2.0	0.7	0.9	1.1

Figure 11 (150% of the national line): Households by targeting classification and score, along with “Total Accuracy” and BPAC, scorecard applied to the validation sample

Score	Inclusion:	Undercoverage:	Leakage:	Exclusion:	Total Accuracy	BPAC
	< poverty line correctly targeted	< poverty line mistakenly non-targeted	=> poverty line mistakenly targeted	=> poverty line non-targeted	Inclusion + Exclusion	See text
0-4	0.1	70.4	0.0	29.6	29.6	-99.8
5-9	0.7	69.7	0.0	29.6	30.3	-97.9
10-14	3.0	67.4	0.1	29.5	32.6	-91.3
15-19	7.9	62.5	0.3	29.3	37.2	-77.2
20-24	16.8	53.6	0.9	28.7	45.5	-51.0
25-29	27.3	43.1	1.8	27.8	55.1	-19.8
30-34	37.6	32.8	3.9	25.7	63.3	+12.4
35-39	48.6	21.8	6.9	22.7	71.3	+47.7
40-44	57.4	13.0	11.6	17.9	75.3	+79.5
45-49	63.9	6.5	16.5	13.1	77.0	+76.6
50-54	67.7	2.7	20.5	9.1	76.8	+70.9
55-59	69.4	1.0	23.8	5.7	75.1	+66.1
60-64	70.1	0.3	26.1	3.5	73.7	+63.0
65-69	70.3	0.1	27.3	2.3	72.6	+61.3
70-74	70.4	0.0	28.2	1.4	71.8	+60.0
75-79	70.4	0.0	28.9	0.7	71.1	+58.9
80-84	70.4	0.0	29.3	0.3	70.7	+58.4
85-89	70.4	0.0	29.5	0.1	70.5	+58.1
90-94	70.4	0.0	29.5	0.1	70.5	+58.1
95-100	70.4	0.0	29.6	0.0	70.4	+58.0

Inclusion, undercoverage, leakage, and exclusion normalized to sum to 100.

Figure 12 (150% of the national line): For a given score cut-off, the percentage of all households who are targeted (that is, have a score equal to or less than the cut-off), the percentage of targeted households who are poor (that is, below the poverty line), the percentage of poor households who are targeted, and the number of poor households who are successfully targeted (coverage) per non-poor household mistakenly targeted (leakage), scorecard applied to the validation sample

Targeting cut-off	% all households who are targeted	% targeted who are poor	% of poor who are targeted	Poor households targeted per non-poor household targeted
0-4	0.1	100.0	0.1	Only poor targeted
5-9	0.7	100.0	1.0	Only poor targeted
10-14	3.1	97.9	4.3	47.4:1
15-19	8.2	96.3	11.2	25.9:1
20-24	17.7	94.9	23.9	18.6:1
25-29	29.1	93.7	38.8	15.0:1
30-34	41.5	90.6	53.4	9.7:1
35-39	55.4	87.6	69.0	7.1:1
40-44	69.0	83.1	81.5	4.9:1
45-49	80.4	79.5	90.7	3.9:1
50-54	88.2	76.8	96.2	3.3:1
55-59	93.2	74.4	98.5	2.9:1
60-64	96.2	72.9	99.6	2.7:1
65-69	97.6	72.1	99.9	2.6:1
70-74	98.6	71.4	100.0	2.5:1
75-79	99.3	70.9	100.0	2.4:1
80-84	99.7	70.6	100.0	2.4:1
85-89	99.9	70.5	100.0	2.4:1
90-94	99.9	70.5	100.0	2.4:1
95-100	100.0	70.4	100.0	2.4:1

**Tables for
200% of the National Poverty Line**

Figure 4 (200% of the national line): Estimated poverty likelihoods associated with scores

If a household's score is then the likelihood (%) of being below the poverty line is:
0–4	100.0
5–9	100.0
10–14	99.6
15–19	97.7
20–24	97.3
25–29	97.3
30–34	96.9
35–39	89.2
40–44	84.3
45–49	73.8
50–54	67.8
55–59	50.7
60–64	43.5
65–69	27.1
70–74	15.6
75–79	9.9
80–84	0.0
85–89	0.0
90–94	0.0
95–100	0.0

Figure 7 (200% of the national line): Bootstrapped differences between estimated and true poverty likelihoods for households in a large sample ($n = 16,384$) with confidence intervals, scorecard applied to the validation sample

Score	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
0-4	+0.0	0.0	0.0	0.0
5-9	+0.0	0.0	0.0	0.0
10-14	-0.4	0.2	0.2	0.2
15-19	+0.4	1.1	1.3	1.7
20-24	-0.9	0.7	0.8	0.9
25-29	-1.0	0.7	0.8	0.9
30-34	+1.4	0.9	1.0	1.5
35-39	-0.6	1.4	1.7	2.1
40-44	+5.2	1.8	2.1	2.7
45-49	-11.6	6.5	6.7	6.9
50-54	+2.2	2.9	3.4	4.5
55-59	+0.9	3.5	4.1	5.4
60-64	-6.1	5.2	5.6	6.6
65-69	+7.3	4.5	5.3	6.7
70-74	-16.5	12.1	12.8	13.9
75-79	+3.9	3.9	4.5	5.9
80-84	-2.3	2.4	2.8	3.8
85-89	+0.0	0.0	0.0	0.0
90-94	+0.0	0.0	0.0	0.0
95-100	+0.0	0.0	0.0	0.0

Figure 8 (200% of the national line): Differences and precision of differences for bootstrapped estimates of poverty rates for groups of households at a point in time, by sample size, scorecard applied to the validation sample

Sample Size n	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
1	-0.9	64.2	66.8	85.0
4	-0.3	30.8	38.1	50.6
8	-0.8	21.8	26.8	35.0
16	-0.9	15.0	18.1	22.6
32	-0.8	11.0	13.2	17.5
64	-1.0	8.1	9.6	12.5
128	-1.0	5.5	6.6	8.6
256	-0.9	4.0	4.7	6.3
512	-0.9	2.9	3.4	4.4
1,024	-0.9	2.1	2.4	3.0
2,048	-0.9	1.4	1.7	2.2
4,096	-1.0	1.0	1.2	1.6
8,192	-1.0	0.7	0.9	1.2
16,384	-1.0	0.5	0.6	0.8

Figure 11 (200% of the national line): Households by targeting classification and score, along with “Total Accuracy” and BPAC, scorecard applied to the validation sample

Score	Inclusion:	Undercoverage:	Leakage:	Exclusion:	Total Accuracy	BPAC
	< poverty line correctly targeted	< poverty line mistakenly non-targeted	=> poverty line mistakenly targeted	=> poverty line correctly non-targeted	Inclusion + Exclusion	See text
0–4	0.1	82.8	0.0	17.2	17.2	–99.9
5–9	0.7	82.1	0.0	17.2	17.9	–98.2
10–14	3.1	79.7	0.0	17.2	20.3	–92.5
15–19	8.1	74.8	0.1	17.0	25.1	–80.4
20–24	17.4	65.5	0.3	16.8	34.2	–57.6
25–29	28.5	54.3	0.6	16.5	45.1	–30.4
30–34	40.3	42.5	1.2	16.0	56.3	–1.2
35–39	52.9	29.9	2.5	14.7	67.6	+30.8
40–44	64.2	18.7	4.8	12.3	76.5	+60.8
45–49	73.1	9.7	7.3	9.9	83.0	+85.3
50–54	78.3	4.6	10.0	7.2	85.5	+88.0
55–59	80.9	2.0	12.3	4.8	85.7	+85.1
60–64	82.2	0.7	14.0	3.1	85.3	+83.0
65–69	82.5	0.3	15.1	2.1	84.6	+81.8
70–74	82.8	0.1	15.8	1.4	84.1	+80.9
75–79	82.8	0.0	16.5	0.7	83.5	+80.1
80–84	82.8	0.0	16.9	0.3	83.1	+79.6
85–89	82.8	0.0	17.0	0.1	83.0	+79.4
90–94	82.8	0.0	17.1	0.1	82.9	+79.4
95–100	82.8	0.0	17.2	0.0	82.8	+79.3

Inclusion, undercoverage, leakage, and exclusion normalized to sum to 100.

Figure 12 (200% of the national line): For a given score cut-off, the percentage of all households who are targeted (that is, have a score equal to or less than the cut-off), the percentage of targeted households who are poor (that is, below the poverty line), the percentage of poor households who are targeted, and the number of poor households who are successfully targeted (coverage) per non-poor household mistakenly targeted (leakage), scorecard applied to the validation sample

Targeting cut-off	% all households who are targeted	% targeted who are poor	% of poor who are targeted	Poor households targeted per non-poor household targeted
0-4	0.1	100.0	0.1	Only poor targeted
5-9	0.7	100.0	0.9	Only poor targeted
10-14	3.1	100.0	3.7	Only poor targeted
15-19	8.2	98.6	9.7	72.1:1
20-24	17.7	98.1	21.0	51.5:1
25-29	29.1	97.9	34.4	46.0:1
30-34	41.5	97.1	48.7	33.5:1
35-39	55.4	95.5	63.9	21.1:1
40-44	69.0	93.0	77.5	13.2:1
45-49	80.4	90.9	88.2	10.0:1
50-54	88.2	88.7	94.5	7.9:1
55-59	93.2	86.8	97.6	6.6:1
60-64	96.2	85.4	99.2	5.8:1
65-69	97.6	84.5	99.6	5.5:1
70-74	98.6	84.0	99.9	5.2:1
75-79	99.3	83.4	100.0	5.0:1
80-84	99.7	83.1	100.0	4.9:1
85-89	99.9	82.9	100.0	4.9:1
90-94	99.9	82.9	100.0	4.8:1
95-100	100.0	82.8	100.0	4.8:1

**Tables for
the USAID “Extreme” Poverty Line**

Figure 4 (USAID “extreme” line): Estimated poverty likelihoods associated with scores

If a household's score is then the likelihood (%) of being below the poverty line is:
0–4	77.7
5–9	65.6
10–14	62.9
15–19	52.3
20–24	42.9
25–29	35.0
30–34	27.0
35–39	19.9
40–44	12.9
45–49	9.7
50–54	5.7
55–59	3.2
60–64	0.0
65–69	0.0
70–74	0.0
75–79	0.0
80–84	0.0
85–89	0.0
90–94	0.0
95–100	0.0

Figure 7 (USAID “extreme” line): Bootstrapped differences between estimated and true poverty likelihoods for households in a large sample ($n = 16,384$) with confidence intervals, scorecard applied to the validation sample

Score	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
0–4	–22.3	11.2	11.2	11.2
5–9	–15.8	10.9	11.4	12.7
10–14	+7.7	4.6	5.3	7.2
15–19	+12.8	3.8	4.7	5.8
20–24	–4.7	3.7	3.9	4.4
25–29	+1.9	2.3	2.8	3.8
30–34	–17.6	10.6	10.9	11.6
35–39	+1.6	1.6	1.9	2.5
40–44	+1.9	1.3	1.5	2.0
45–49	+0.2	1.4	1.6	2.1
50–54	+0.8	1.1	1.3	1.7
55–59	+2.4	0.4	0.4	0.6
60–64	–0.4	0.3	0.4	0.5
65–69	+0.0	0.0	0.0	0.0
70–74	+0.0	0.0	0.0	0.0
75–79	+0.0	0.0	0.0	0.0
80–84	+0.0	0.0	0.0	0.0
85–89	+0.0	0.0	0.0	0.0
90–94	+0.0	0.0	0.0	0.0
95–100	+0.0	0.0	0.0	0.0

Figure 8 (USAID “extreme” line): Differences and precision of differences for bootstrapped estimates of poverty rates for groups of households at a point in time, by sample size, scorecard applied to the validation sample

Sample Size n	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
1	-0.9	61.5	69.7	78.6
4	-0.2	38.7	45.8	56.7
8	+0.3	29.6	37.0	46.3
16	-0.2	25.1	28.6	35.4
32	-1.0	19.1	22.3	27.7
64	-1.3	13.0	15.1	20.3
128	-1.6	9.8	11.7	14.7
256	-1.5	7.0	8.2	10.6
512	-1.6	5.1	6.1	7.7
1,024	-1.6	3.6	4.2	5.6
2,048	-1.6	2.6	3.0	4.1
4,096	-1.7	1.8	2.2	2.9
8,192	-1.7	1.3	1.6	2.1
16,384	-1.7	0.9	1.1	1.4

Figure 11 (USAID “extreme” line): Households by targeting classification and score, along with “Total Accuracy” and BPAC, scorecard applied to the validation sample

Score	Inclusion:	Undercoverage:	Leakage:	Exclusion:	Total Accuracy	BPAC
	< poverty line correctly targeted	< poverty line mistakenly non-targeted	=> poverty line mistakenly targeted	=> poverty line correctly non-targeted	Inclusion + Exclusion	See text
0–4	0.1	22.2	0.0	77.7	77.8	–99.5
5–9	0.6	21.7	0.1	77.6	78.2	–94.0
10–14	1.9	20.4	1.2	76.5	78.4	–77.6
15–19	4.1	18.1	4.0	73.7	77.8	–44.7
20–24	8.6	13.6	9.1	68.6	77.3	+18.3
25–29	12.2	10.1	16.9	60.8	73.0	+24.1
30–34	16.0	6.3	25.5	52.2	68.1	–14.7
35–39	18.9	3.4	36.6	41.2	60.0	–64.1
40–44	20.3	1.9	48.7	29.1	49.4	–118.4
45–49	21.7	0.6	58.7	19.0	40.7	–163.6
50–54	22.2	0.1	66.0	11.7	33.9	–196.3
55–59	22.3	0.0	71.0	6.8	29.0	–218.5
60–64	22.3	0.0	73.9	3.8	26.1	–231.8
65–69	22.3	0.0	75.3	2.4	24.7	–237.9
70–74	22.3	0.0	76.3	1.4	23.7	–242.4
75–79	22.3	0.0	77.0	0.7	23.0	–245.8
80–84	22.3	0.0	77.5	0.3	22.5	–247.6
85–89	22.3	0.0	77.6	0.1	22.4	–248.3
90–94	22.3	0.0	77.6	0.1	22.4	–248.5
95–100	22.3	0.0	77.7	0.0	22.3	–248.8

Inclusion, undercoverage, leakage, and exclusion normalized to sum to 100.

Figure 12 (USAID “extreme” line): For a given score cut-off, the percentage of all households who are targeted (that is, have a score equal to or less than the cut-off), the percentage of targeted households who are poor (that is, below the poverty line), the percentage of poor households who are targeted, and the number of poor households who are successfully targeted (coverage) per non-poor household mistakenly targeted (leakage), scorecard applied to the validation sample

Targeting cut-off	% all households who are targeted	% targeted who are poor	% of poor who are targeted	Poor households targeted per non-poor household targeted
0–4	0.1	100.0	0.3	Only poor targeted
5–9	0.7	82.7	2.7	4.8:1
10–14	3.1	61.0	8.5	1.6:1
15–19	8.2	50.5	18.6	1.0:1
20–24	17.7	48.7	38.8	1.0:1
25–29	29.1	42.0	54.9	0.7:1
30–34	41.5	38.5	71.7	0.6:1
35–39	55.4	34.0	84.7	0.5:1
40–44	69.0	29.5	91.3	0.4:1
45–49	80.4	26.9	97.2	0.4:1
50–54	88.2	25.1	99.5	0.3:1
55–59	93.2	23.9	99.9	0.3:1
60–64	96.2	23.2	100.0	0.3:1
65–69	97.6	22.8	100.0	0.3:1
70–74	98.6	22.6	100.0	0.3:1
75–79	99.3	22.4	100.0	0.3:1
80–84	99.7	22.3	100.0	0.3:1
85–89	99.9	22.3	100.0	0.3:1
90–94	99.9	22.3	100.0	0.3:1
95–100	100.0	22.3	100.0	0.3:1

**Tables for
the \$1.25/day 2005 PPP Poverty Line**

Figure 4 (\$1.25/day 2005 PPP line): Estimated poverty likelihoods associated with scores

If a household's score is then the likelihood (%) of being below the poverty line is:
0–4	100.0
5–9	96.9
10–14	92.6
15–19	84.1
20–24	81.6
25–29	78.3
30–34	68.5
35–39	59.3
40–44	41.5
45–49	33.0
50–54	26.3
55–59	11.9
60–64	10.1
65–69	5.0
70–74	1.4
75–79	0.0
80–84	0.0
85–89	0.0
90–94	0.0
95–100	0.0

Figure 7 (\$1.25/day 2005 PPP line): Bootstrapped differences between estimated and true poverty likelihoods for households in a large sample ($n = 16,384$) with confidence intervals, scorecard applied to the validation sample

Score	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
0-4	+0.0	0.0	0.0	0.0
5-9	-3.1	1.6	1.6	1.6
10-14	+8.2	3.6	4.3	6.3
15-19	+15.4	3.5	4.1	5.8
20-24	-3.4	2.5	2.6	2.9
25-29	+1.8	1.9	2.2	2.8
30-34	-3.1	2.7	3.0	3.7
35-39	+2.4	2.0	2.4	3.2
40-44	+6.2	1.9	2.3	3.0
45-49	-20.9	12.1	12.4	13.1
50-54	-7.3	5.3	5.6	6.1
55-59	-5.5	3.9	4.2	4.6
60-64	-4.5	4.2	4.5	6.5
65-69	+2.5	1.5	1.7	2.1
70-74	+1.4	0.0	0.0	0.0
75-79	+0.0	0.0	0.0	0.0
80-84	+0.0	0.0	0.0	0.0
85-89	+0.0	0.0	0.0	0.0
90-94	+0.0	0.0	0.0	0.0
95-100	+0.0	0.0	0.0	0.0

Figure 8 (\$1.25/day 2005 PPP line): Differences and precision of differences for bootstrapped estimates of poverty rates for groups of households at a point in time, by sample size, scorecard applied to the validation sample

Sample Size n	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
1	+0.3	72.7	77.6	90.8
4	+0.7	42.4	51.2	60.8
8	+0.2	34.3	42.2	49.4
16	+0.3	26.2	30.9	38.7
32	-0.7	19.6	22.8	30.1
64	-1.6	14.0	17.1	21.5
128	-1.7	10.6	12.5	16.1
256	-1.7	7.7	8.9	11.4
512	-1.9	5.3	6.2	8.5
1,024	-1.9	3.8	4.5	5.8
2,048	-2.0	2.7	3.2	4.3
4,096	-2.1	1.9	2.2	3.0
8,192	-2.1	1.4	1.6	2.1
16,384	-2.1	1.0	1.2	1.5

Figure 11 (\$1.25/day 2005 PPP line): Households by targeting classification and score, along with “Total Accuracy” and BPAC, scorecard applied to the validation sample

Score	Inclusion:	Undercoverage:	Leakage:	Exclusion:	Total Accuracy	BPAC
	< poverty line correctly targeted	< poverty line mistakenly non-targeted	=> poverty line mistakenly targeted	=> poverty line correctly non-targeted	Inclusion + Exclusion	See text
0–4	0.1	52.6	0.0	47.4	47.4	–99.8
5–9	0.7	51.9	0.0	47.4	48.1	–97.2
10–14	2.8	49.8	0.3	47.1	50.0	–88.7
15–19	6.8	45.8	1.4	46.0	52.8	–71.5
20–24	14.7	37.9	3.0	44.4	59.1	–38.3
25–29	23.2	29.4	5.9	41.5	64.7	–0.5
30–34	31.5	21.1	10.0	37.3	68.8	+38.7
35–39	39.5	13.1	15.9	31.5	71.0	+69.8
40–44	45.0	7.6	24.0	23.4	68.4	+54.4
45–49	49.0	3.6	31.4	16.0	65.0	+40.3
50–54	51.3	1.3	36.9	10.5	61.8	+29.9
55–59	52.2	0.4	41.0	6.4	58.6	+22.1
60–64	52.6	0.1	43.6	3.7	56.3	+17.0
65–69	52.6	0.0	45.0	2.4	55.0	+14.6
70–74	52.6	0.0	46.0	1.4	54.0	+12.7
75–79	52.6	0.0	46.7	0.7	53.3	+11.2
80–84	52.6	0.0	47.1	0.3	52.9	+10.4
85–89	52.6	0.0	47.3	0.1	52.7	+10.2
90–94	52.6	0.0	47.3	0.1	52.7	+10.1
95–100	52.6	0.0	47.4	0.0	52.6	+9.9

Inclusion, undercoverage, leakage, and exclusion normalized to sum to 100.

Figure 12 (\$1.25/day 2005 PPP line): For a given score cut-off, the percentage of all households who are targeted (that is, have a score equal to or less than the cut-off), the percentage of targeted households who are poor (that is, below the poverty line), the percentage of poor households who are targeted, and the number of poor households who are successfully targeted (coverage) per non-poor household mistakenly targeted (leakage), scorecard applied to the validation sample

Targeting cut-off	% all households who are targeted	% targeted who are poor	% of poor who are targeted	Poor households targeted per non-poor household targeted
0-4	0.1	100.0	0.1	Only poor targeted
5-9	0.7	100.0	1.4	Only poor targeted
10-14	3.1	91.4	5.4	10.7:1
15-19	8.2	83.1	12.9	4.9:1
20-24	17.7	83.1	28.0	4.9:1
25-29	29.1	79.7	44.1	3.9:1
30-34	41.5	75.8	59.8	3.1:1
35-39	55.4	71.3	75.2	2.5:1
40-44	69.0	65.3	85.6	1.9:1
45-49	80.4	61.0	93.1	1.6:1
50-54	88.2	58.2	97.5	1.4:1
55-59	93.2	56.0	99.2	1.3:1
60-64	96.2	54.6	99.9	1.2:1
65-69	97.6	53.9	100.0	1.2:1
70-74	98.6	53.4	100.0	1.1:1
75-79	99.3	53.0	100.0	1.1:1
80-84	99.7	52.8	100.0	1.1:1
85-89	99.9	52.7	100.0	1.1:1
90-94	99.9	52.7	100.0	1.1:1
95-100	100.0	52.6	100.0	1.1:1

**Tables for
the \$2.50/day 2005 PPP Poverty Line**

Figure 4 (\$2.50/day 2005 PPP line): Estimated poverty likelihoods associated with scores

If a household's score is then the likelihood (%) of being below the poverty line is:
0–4	100.0
5–9	100.0
10–14	100.0
15–19	98.5
20–24	98.1
25–29	98.1
30–34	97.8
35–39	91.8
40–44	88.0
45–49	78.2
50–54	73.4
55–59	58.6
60–64	51.6
65–69	31.7
70–74	21.0
75–79	13.5
80–84	0.0
85–89	0.0
90–94	0.0
95–100	0.0

Figure 7 (\$2.50/day 2005 PPP line): Bootstrapped differences between estimated and true poverty likelihoods for households in a large sample ($n = 16,384$) with confidence intervals, scorecard applied to the validation sample

Score	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
0-4	+0.0	0.0	0.0	0.0
5-9	+0.0	0.0	0.0	0.0
10-14	+0.0	0.0	0.0	0.0
15-19	+1.1	1.1	1.3	1.7
20-24	-0.1	0.6	0.7	0.9
25-29	-1.0	0.6	0.7	0.7
30-34	+1.3	0.8	1.0	1.3
35-39	+0.0	1.2	1.5	1.9
40-44	+4.0	1.6	2.0	2.6
45-49	-8.8	5.1	5.2	5.5
50-54	+2.0	2.6	3.2	4.0
55-59	+3.8	3.5	4.2	5.8
60-64	-2.3	4.2	5.0	6.9
65-69	+2.0	5.3	6.4	8.8
70-74	-11.9	9.7	10.4	11.4
75-79	+7.4	3.9	4.5	5.9
80-84	-2.3	2.4	2.8	3.8
85-89	+0.0	0.0	0.0	0.0
90-94	+0.0	0.0	0.0	0.0
95-100	+0.0	0.0	0.0	0.0

Figure 8 (\$2.50/day 2005 PPP line): Differences and precision of differences for bootstrapped estimates of poverty rates for groups of households at a point in time, by sample size, scorecard applied to the validation sample

Sample Size n	Difference between estimate and true value			
	Diff.	Confidence interval (\pm percentage points)		
		90-percent	95-percent	99-percent
1	-0.8	59.8	68.2	83.0
4	+0.0	27.3	34.5	46.0
8	-0.4	19.4	24.0	32.4
16	-0.3	13.6	16.4	21.1
32	-0.2	10.4	12.2	17.2
64	-0.4	7.5	8.8	11.7
128	-0.3	5.1	6.2	8.0
256	-0.2	3.7	4.4	5.8
512	-0.3	2.6	3.1	4.1
1,024	-0.3	1.8	2.2	2.8
2,048	-0.3	1.3	1.6	2.0
4,096	-0.3	0.9	1.1	1.4
8,192	-0.4	0.7	0.8	1.0
16,384	-0.4	0.5	0.6	0.7

Figure 11 (\$2.50/day 2005 PPP line): Households by targeting classification and score, along with “Total Accuracy” and BPAC, scorecard applied to the validation sample

Score	Inclusion:	Undercoverage:	Leakage:	Exclusion:	Total Accuracy	BPAC
	< poverty line correctly targeted	< poverty line mistakenly non-targeted	=> poverty line mistakenly targeted	=> poverty line correctly non-targeted	Inclusion + Exclusion	See text
0–4	0.1	85.2	0.0	14.7	14.8	–99.9
5–9	0.7	84.6	0.0	14.7	15.4	–98.3
10–14	3.1	82.2	0.0	14.7	17.8	–92.7
15–19	8.1	77.2	0.1	14.6	22.6	–81.0
20–24	17.4	67.9	0.3	14.4	31.7	–58.9
25–29	28.7	56.7	0.5	14.2	42.9	–32.3
30–34	40.6	44.7	0.9	13.8	54.4	–3.7
35–39	53.5	31.8	1.9	12.8	66.3	+27.7
40–44	65.3	20.0	3.7	11.0	76.3	+57.5
45–49	74.6	10.7	5.8	8.9	83.5	+81.6
50–54	80.1	5.2	8.1	6.6	86.7	+90.5
55–59	83.0	2.3	10.2	4.5	87.5	+88.0
60–64	84.5	0.8	11.7	3.0	87.4	+86.2
65–69	84.9	0.4	12.6	2.1	87.0	+85.2
70–74	85.2	0.1	13.3	1.4	86.6	+84.4
75–79	85.3	0.0	14.0	0.7	85.9	+83.6
80–84	85.3	0.0	14.4	0.3	85.6	+83.1
85–89	85.3	0.0	14.6	0.1	85.4	+82.9
90–94	85.3	0.0	14.6	0.1	85.4	+82.9
95–100	85.3	0.0	14.7	0.0	85.3	+82.8

Inclusion, undercoverage, leakage, and exclusion normalized to sum to 100.

Figure 12 (\$2.50/day 2005 PPP line): For a given score cut-off, the percentage of all households who are targeted (that is, have a score equal to or less than the cut-off), the percentage of targeted households who are poor (that is, below the poverty line), the percentage of poor households who are targeted, and the number of poor households who are successfully targeted (coverage) per non-poor household mistakenly targeted (leakage), scorecard applied to the validation sample

Targeting cut-off	% all households who are targeted	% targeted who are poor	% of poor who are targeted	Poor households targeted per non-poor household targeted
0-4	0.1	100.0	0.1	Only poor targeted
5-9	0.7	100.0	0.9	Only poor targeted
10-14	3.1	100.0	3.6	Only poor targeted
15-19	8.2	98.6	9.5	72.1:1
20-24	17.7	98.1	20.4	51.5:1
25-29	29.1	98.4	33.6	59.6:1
30-34	41.5	97.9	47.6	46.0:1
35-39	55.4	96.5	62.7	27.9:1
40-44	69.0	94.7	76.6	17.8:1
45-49	80.4	92.8	87.4	12.8:1
50-54	88.2	90.8	93.9	9.9:1
55-59	93.2	89.1	97.3	8.1:1
60-64	96.2	87.8	99.0	7.2:1
65-69	97.6	87.1	99.6	6.7:1
70-74	98.6	86.5	99.9	6.4:1
75-79	99.3	85.9	100.0	6.1:1
80-84	99.7	85.5	100.0	5.9:1
85-89	99.9	85.4	100.0	5.9:1
90-94	99.9	85.4	100.0	5.8:1
95-100	100.0	85.3	100.0	5.8:1