Simple Poverty Scorecard® Tool
Peru

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The Scorocs Simple Poverty Scorecard-brand poverty-assessment tool is a low-cost, transparent way for pro-poor programs in Peru to get to know their participants better so as to prove and improve their social performance. Responses to the scorecard's 12 questions can be used to:

— Check poverty rates and numbers of poor people among in-coming participants
— Track changes in poverty among on-going participants
— Segment participants for differentiated treatment based on poverty

Version note

The new scorecard for Peru is based on data from 2019. It replaces old scorecards for Peru in Schreiner (**2012a**, **2009**, and **2008**) based on data from 2010, 2007, and 2003. Given the time that has passed, it is not recommended that users estimate changes with a baseline from an old scorecard and a follow-up from the new scorecard.

Acknowledgements

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Scorocs® Simple Poverty Scorecard® Tool

			Name	Identifier
Interview ID:				
Interview date:		Direct participant:		
Country:	PER	Field agent:		
Scorecard:	004	Service point:		
Sampling weight:		Number of household members:		

Question	Response	Points
1. In which region does the household live?	A. Lima, Callao, La Libertad, Ayacucho, or Pasco	0
	B. Cajamarca, Piura, or Puno	2
	C. Cusco, Junín, Apurímac, Huánuco, San Martín, Huancavelica, Amazonas, Tacna, Tumbes, or Moquegua	4
	D. Arequipa, Ancash, Loreto, or Madre de Díos	8
	E. Lambayeque, Ica, or Ucayali	14
2. How many members does the household have?	A. Six or more	0
	B. Five	4
	C. Four	8
	D. Three	13
	E. Two	19
	F. One	29
3. What is the main material of the floors?	A. Earth	0
	B. Wood (bamboo, planks, and so on), or cement	4
	C. Tile and so on; linoleum, vinyl and so on; parquet, polished wood, or other	11
4. How many rooms are used only as bedrooms?	A. None, or one	0
	B. Two or more	4
5. What cooking fuel does the household use more than any other?	A. Dung, or other	0
	B. Firewood, or charcoal	3
	C. Gas (LPG in a tank), natural gas (piped from network), electricity, or does not cook	5
6. Does the household have a microwave?	A. No	0
	B. Yes	3
7. Does the household have a food processor/blender?	A. No	0
	B. Yes	4
8. How many TVs (color or black and white) does the household have?	A. None	0
	B. One	3
	C. Two or more	6
9. Does the household have an internet connection?	A. No	0
	B. Yes	8
10. Does the household have a personal computer or laptop?	A. No	0
	B. Yes	5
11. Does the household have a cell phone or a land-line phone?	A. No	0
	B. Yes	6
12. In the last 15 days from . . . to . . ., has any member of the household obtained, consumed, bought, or received as a gift any milk (evaporated, powdered, fresh, evaporated with iron, evaporated light, or soy milk with lactose)?	A. No	0
	B. Yes	5

Score:

Back-page Worksheet: Members of the Household

Fill out the scorecard header first. Include the interview's unique identifier (if known), the interview date, and the sampling weight of the participating household (if known). Then record the full name and the unique identification number of the direct participant (who may differ from the respondent), of the direct participant's field agent (who may differ from you the enumerator), and of the service point that the direct participant uses (if any and if known). Circle the response to the first scorecard question based on your own knowledge of the region where the participating household lives.

Then read to the respondent: *Please tell me the first name or nickname of each household member. A* household *is the group of people—regardless of kinship ties (parents, single children, married children, brothers, uncles, etc.)—who occupy all or part of a residence, who share their main meals, and who cooperate to meet their basic needs. This group of household members also includes whomever the head of the household considers it to include (such as adopted children, good friends, godparents, etc.). A household can be made up of just one person*.

Write down the first name or nickname of each member, beginning with the head and the spouse of the head (if there is one). Mark the head and his/her spouse (if there is one). Record the number of household members in the scorecard header next to "Number of household members:". Then circle the response to the second scorecard question about the number of household members. Read the remaining 10 questions aloud.

Always keep in mind and apply the detailed instructions in the "**Interview Guide**".

First name or nickname?	Head or spouse of head?
1.	Head (male) Head (female)
2.	Wife of male head Husband of female head Other
3.	Other
4.	Other
5.	Other
6.	Other
7.	Other
8.	Other
9.	Other
10.	Other
11.	Other
12.	Other
13.	Other
Number of members:	—

Figure 1: Conversion of scores to poverty likelihoods

	Poverty likelihood (%)													
	National			Intl. 2011 PPP				Percentile-based lines						
Score	100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
0–19	81.2	98.5	99.9	4.5	36.7	87.4	100.0	69.3	88.2	98.3	99.2	99.5	100.0	100.0
20–22	68.9	93.7	99.1	2.4	23.6	75.5	100.0	52.6	76.8	93.5	96.5	98.7	99.9	100.0
23–25	62.5	91.7	97.9	1.7	17.0	67.0	100.0	41.1	67.9	90.6	94.5	97.3	99.7	100.0
26–27	57.8	87.3	97.4	0.7	10.1	59.7	100.0	32.1	63.1	87.4	92.1	96.6	99.7	100.0
28–29	44.8	84.8	97.3	0.3	7.6	50.1	99.9	22.6	52.2	83.0	89.9	96.0	99.7	99.9
30–31	41.7	83.8	94.2	0.2	6.6	40.8	99.7	19.4	41.9	78.3	89.0	93.8	98.8	99.7
32–33	35.1	76.7	93.7	0.1	4.4	35.6	99.7	16.9	36.9	73.5	84.1	91.9	98.5	99.7
34–35	32.9	75.5	93.0	0.1	2.6	29.2	99.6	10.2	30.8	66.9	80.8	89.1	98.3	99.5
36–37	27.2	68.9	88.7	0.1	2.6	27.5	99.3	10.0	28.9	62.4	75.8	85.9	97.3	99.2
38–39	17.9	60.9	85.5	0.1	1.6	18.0	99.1	6.1	19.2	51.7	68.2	80.9	95.8	98.9
40–41	15.4	53.6	81.4	0.1	1.1	15.7	99.1	4.1	16.3	46.2	60.9	73.6	94.9	98.9
42–43	11.5	46.3	78.0	0.1	0.4	8.9	98.8	3.1	9.6	35.4	52.0	67.5	92.6	98.4
44–45	10.6	44.3	75.0	0.0	0.4	7.3	98.1	2.6	8.1	33.1	50.1	67.5	90.1	97.1
46–47	7.4	37.7	66.2	0.0	0.2	4.3	96.6	1.4	4.3	26.9	40.4	56.5	86.3	95.0
48–49	4.6	31.8	61.4	0.0	0.1	3.5	95.8	0.6	3.8	22.7	35.9	52.3	83.7	94.1
50–51	3.2	25.3	52.8	0.0	0.1	1.5	93.9	0.4	1.7	15.0	27.7	42.4	76.0	92.6
52–53	2.0	17.6	45.0	0.0	0.0	1.3	92.7	0.4	1.5	10.5	19.4	31.6	71.5	89.8
54–55	1.6	15.1	41.7	0.0	0.0	1.1	88.6	0.1	1.1	7.9	15.5	28.9	65.4	86.4
56–57	0.8	9.5	30.2	0.0	0.0	0.5	85.6	0.1	0.5	6.2	10.7	20.2	58.9	82.3
58–100	0.2	3.4	13.8	0.0	0.0	0.1	58.8	0.0	0.1	1.5	3.6	7.8	29.9	54.0

Figure 2: Errors in estimated snapshot head-count poverty rates in a single time period, along with margins of error and the α factor for finding margins of error and sample sizes

	Poverty lines													
	National			Intl. 2011 PPP				Percentile-based lines						
	100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
Estimation error	–2.7	–6.5	–6.5	0.0	+0.7	+2.3	–3.1	+1.4	+2.0	+0.3	–1.9	–3.2	–3.3	–3.1
Margin of error	2.6	3.1	2.5	0.3	1.0	2.3	1.2	1.8	2.4	2.8	2.9	2.8	2.1	1.4
α factor	1.34	1.20	1.00	0.93	1.21	1.20	0.72	1.25	1.22	1.16	1.15	1.09	0.94	0.75

Estimation errors from the scorecard with 1,000 bootstrap samples of n = 16,384 households from the validation sample.
Estimation errors are average differences between estimates and observed values, in percentage points.
Margins of error are ± percentage points with 90-percent confidence for samples of n = 1,024.
α is an average across 1,000 bootstrap samples of n = 256, 512, 1,024, 2,048, 4,096, 8,192, and 16,384.

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Scorocs® Simple Poverty Scorecard® Tool
Peru

1. Introduction

The Scorocs Simple Poverty Scorecard-brand poverty-assessment tool for Peru is a low-cost, transparent way for pro-poor programs to get know their participants better so as to prove and improve their social performance.

1.1 Questions addressed by the scorecard

To address the question of “How many poor people does our program attract?”, the scorecard can take a snapshot in a single time period with a census or a sample of in-coming households to estimate both head-count poverty rates and the number of poor people.

To address the question of “How has poverty changed for on-going participants?”, the scorecard can be applied across two time periods with samples from a given population of on-going participants to estimate both net changes in head-count poverty rates and net changes in the number of poor people.

The scorecard can also be used for targeting, that is, to segment participants for differentiated treatment based on poverty.

It is difficult and costly for pro-poor programs to address these questions with the traditional direct approach to poverty assessment via consumption surveys. A case in point is the 2019 National Household Survey (*Encuesta Nacional de Hogares*, ENAHO) by Peru’s Instituto Nacional de Estadística e Informática (INEI). The 2019 ENAHO asked more than 800 top-level questions, many of which had several follow-up questions or were repeated (for example, for each household member, expenditure item, parcel of land, or crop).

1.2 How the scorecard works

The scorecard has 12 factual questions that are drawn from the exhaustive 2019 ENAHO survey. Examples include: “What is the main material of the floors?” and “What cooking fuel does the household use more than any other?”.

The 12 questions are selected to be:

- Inexpensive to collect, easy to answer quickly, and straightforward to verify
- Strongly and intuitively linked with poverty
- Liable to change over time as poverty changes
- Applicable in all regions of Peru

Each question has multiple-choice response options, and points are assigned to each possible response. The points are zeroes or positive whole numbers. The points are derived from the statistical links between responses and consumption-based poverty in the 2019 ENAHO.

Adding up the points for a given household gives a *score* that ranges from 0 to 100. The lower the score, the poorer the household.

Given 12 factual questions and easy-to-add-up points, an enumerator can interview a household, record its responses on paper or **on a hand-held device**, and tally the household's score (if needed for on-the-spot segmentation) in about ten minutes.[1]

Back at the office or in the cloud, a household's score is converted into an estimated probability (the *poverty likelihood*) that the household is poor for a given poverty line, again based on ENAHO data.

The average of poverty likelihoods across the members of sampled households is an estimate of the head-count poverty rate among people in the sampled population.

This estimated poverty rate may then be used to estimate:

- The number of poor people in in-coming households in a single time period
- The net number of poor people in households of on-going participants who rise above a poverty line across two time periods

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[1] Responses on paper are entered in a spreadsheet or database later at an office.

1.3 Targeting

The scorecard can also be used to segment participating households for differentiated services. Unlike some other targeting tools—such as the World Bank's "proxy-means tests"[2]—the scorecard is transparent, freely available,[3] and tailored to the capabilities and purposes not of national governments but rather of local pro-poor programs. The feasible poverty-assessment tools for such programs are typically blunt (such as rules based on land ownership or housing quality) or subjective and relative (such as community-based, participatory wealth ranking facilitated by skilled field workers). Poverty assessments based on these approaches may be costly, their accuracy is unknown, and they are not comparable across places, programs, nor time.

1.4 Consumption-based poverty

Peru's scorecard is a quantitative way to assess whether a program's participants have consumption below any of 14 poverty lines, for example:

- Peru's national line of PEN11.56 per person per day, giving a head-count poverty rate of 20.2 percent for all-Peru in 2019
- The World Bank's "international upper-middle-income poverty line" of $5.50 per person per day 2011 PPP (PEN10.91), giving a poverty rate of 19.2 percent

A program uses only the poverty line(s) that fit its context and mission. For example, a program may report poverty estimates to funders based on a World-Bank international line while internally using a national line or percentile-based line.

1.5 Transparency

The scorecard's design aims to make its workings clear to program managers. Its adoption in Peru and around the world stems from the low cost of its short interviews and from the fact that managers can see for themselves how the scorecard works and that its approach makes sense. Similar tools have been around for decades, but pro-poor programs have rarely used them. This is not because these tools are inaccurate, but because *how* they work is unclear or hidden.

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[2] **Coady, Grosh, and Hoddinott**, 2004.

[3] Peru's scorecard is not in the public domain; it is copyright © 2023 Scorocs.

When scorecard projects fail, the cause is not usually statistical inaccuracy but rather a program's failure to commit to the work-a-day project management needed to integrate the scorecard in the program's processes and to train and convince employees to use the tool properly.[4] In terms of tool-based estimates of social outcomes such as poverty, data scientists have long known that there is almost no trade-off between the straightforward and transparent versus the complex and opaque.[5] Project risk is less technical and more human, not statistics but organizational-change management.

1.6 Assumptions and estimation errors

Like all predictive tools, the scorecard makes two fundamental assumptions:

- The scored sample is representative of the same population as that whose data was used to construct the scorecard
- The links between responses and poverty are the same in the scored sample as in the population whose data was used to construct the scorecard

Of course, the assumptions do not hold to some unknown degree.[6] In particular:

- A given program's participants will not be representative of all-Peru
- Over time, the links between responses and poverty drift or shift

Scorecard estimates have errors because the scorecard incorrectly acts as if the links between responses and poverty in all scored samples and in all time periods are the same as in the construction data. Reality diverges further from assumptions as:

- More time passes since the collection of construction data
- A program's participants differ from the country's population as a whole
- Attrition has changed the composition of a cohort of on-going participants
- Change has been rapid (say, due to war, plague, or changes in the program itself)[7]

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[4] **Schreiner**, 2002.
[5] **Dupriez**, 2018; **Caire and Schreiner**, 2012; **Schreiner**, 2012b; **Hand**, 2006; **Lovie and Lovie**, 1986; **Kolesar and Showers**, 1985; **Stillwell, Barron, and Edwards**, 1983; **Dawes**, 1979; **Wainer**, 1976; **Myers and Forgy**, 1963.
[6] **Diamond *et al.***, 2016; **Tarozzi and Deaton**, 2009.
[7] For example, the 2020 economic downturn due to COVID–19 changed the links between poverty and questions, but the Peru scorecard still uses the 2019 links.

For any particular scorecard and scored sample, the estimation error due to migration away from the assumptions is unknown. It is known, however, that the scorecard's targeting is robust. That is, the extent to which assumptions diverge from reality is not strongly linked with the extent to which the scorecard gives lower scores to more-poor households and higher scores to less-poor households. It is also known that the scorecard's estimation errors are larger when estimating changes in poverty across two periods (or with two scorecards) than when estimating poverty in one period.

There are no rules nor formulas that automatically signal when estimation error is too large for estimates to be useful. Program managers must make their own judgments based on common sense and on what they know about their context and their participants from non-scorecard sources.

In practice, scorecard estimates often serve as a basic check on whether a pro-poor program is indeed *pro-poor*. The estimates address existential questions such as:

- "How many in-coming participants are below the national poverty line?"
- "Are in-coming participants poorer than the average person in our region?"
- "Are our poor participants more likely to rise above a poverty line than the average poor person in our region?"

For such existential checks on whether a program lives out its purported social mission, estimation errors will often be small enough to be immaterial.

1.7 Estimation errors when assumptions hold

If the scorecard's assumptions do hold, then all the scorecard estimators are statistically *unbiased*. That is, the true value in the population matches the average of estimates from repeated samples.

The assumptions do hold when the scorecard is tested against households in the validation sample from the 2019 ENAHO that is not used to construct the scorecard. Smaller errors in this ideal case imply smaller-than-otherwise errors in real-world use.

Even so, there are estimation errors on average in the validation sample because there is only one scorecard, and it is derived from one construction sample and applied to a single validation sample. **Annex 5** documents the error for snapshot estimates of poverty rates in one time period, allowing scorecard users to adjust for the error and to consider the margins of error.

1.8 What is next?

Section 2: **How to convert responses into poverty likelihoods**

Section 3: **How to calculate scorecard estimates**

- Snapshot estimates of:
  - **Head-count poverty rates in a single time period**
  - **Number of poor people in a single time period**
- Estimates of net changes across two time periods in:
  - **Net change in poverty rates with one sample scored twice**
  - **Annual net change in the number of poor people with one sample scored twice**
  - **Net change in poverty rates with two independent samples**
  - **Annual net change in the number of poor people with two independent samples**

Section 4: **How to design scorecard surveys and samples**

Section 5: **How to use scores for targeting**

After Section 5, the "**Interview Guide**" tells how to ask questions—and how to interpret responses—so as to mimic practice in Peru's 2019 ENAHO as closely as possible. The "Guide" (and the "Back-page Worksheet") are integral parts of the scorecard. Do not ignore them.

The annexes, figures, and references provide details for advanced users:

Annex 1	**Data used for construction and validation**
Annex 2	**Definitions of poverty and of poverty lines**
Annex 3	**Scorecard construction**
Annex 4	**Estimates of poverty likelihoods**
Annex 5	**Error and margins of error**
Annex 6	**Formulas for sample size**

References cited appear at the end.

2. How to convert responses to poverty likelihoods

This section tells how to:

- Collect a household's responses to scorecard questions
- Convert responses to points
- Add up points to get scores
- Convert scores to poverty likelihoods

The next section tells how to combine poverty likelihoods from a sample of households to estimate poverty.

2.1 Instructions for enumerators

An *enumerator* asks a scorecard's questions to a respondent and then records the responses. An enumerator may or may not be same as the program's field agent (if any) associated with a participating household.

Enumerators should interview a sampled household at the household's residence using an app **on a hand-held device** or a paper scorecard along with the "Back-page Worksheet". Following the "**Interview Guide**", enumerators should:

- Record administrative information in the scorecard header:
  - — Interview identifier (if known)
  - — Interview date (required)
  - — Country code ("PER", pre-filled)
  - — Scorecard code ("004", pre-filled)
  - — Sampling weight assigned to the household by the survey design (if any and if known)
- Record names and identifiers (if known) in the scorecard header:
  - — *Direct participant*. This is the household member who directly interacts with the pro-poor program. He/she may or may not be the same as the respondent who answers the scorecard questions. For example, a direct participant with a microfinance program is a borrower or a saver, and a direct participant with a child-health program is a child's parent or guardian
  - — *Field agent* (if there is one). This is the direct participant's main, repeated point of contact with the program. The field agent may or may not be the same as the enumerator. For example, the field agent in a microfinance program is a loan officer or savings collector, and the field agent in a child-health program is a village health-care worker

— *Service point* (if there is one). This is the program office that is relevant to the direct participant. The service point is usually the base of operations of the direct participant's field agent (if there is one) or where the direct participant usually goes to do program business. For example, the service point for a microfinance program is a branch, and the service point for a child-health program is a health post

- Mark the response to the first scorecard question ("In what region does the household live?"). If the enumerator already knows the region, then the question does not need to asked directly of the respondent
- Complete the "Back-page Worksheet" with each household member's first name or nickname, marking the head and his/her sex, and also marking the spouse of the head and his/her sex (if the head has a spouse)
- If using a paper scorecard, then use the "Back-page Worksheet" to record:
  — The number of household members in the header next to "Number of household members:"
  — The response to the second scorecard question ("How many members does the household have?")
- Read the remaining 10 questions aloud one-by-one and in order, marking the responses
- When marking a response on paper, write each point value in the far right-hand column. Then make single circle around the pre-printed response, the pre-printed points, and the hand-written points. This helps to reduce later data-entry mistakes
- Add up the points to get the score (if needed on-the-spot and if using a paper scorecard)
- Implement targeting policy (if any) based on the score
- Upload the data with a **mobile data-collection tool**, or deliver the filled-out paper scorecard to a central office for data entry, reporting, and analysis

2.2 Header, 'Back-page Worksheet', 'Interview Guide', and audits

Fill out the scorecard header as best you can; do not skip it. Scorecard estimates are more useful if they can be linked—via names or identifiers—to a program's existing data on direct participants, field agents, or service points. Record the types of identifiers that are used in the program's databases, be they program-specific or government-issued. Be sure to record the number of household members not only indirectly via the scorecard's second question but also directly in the header.

Do not leave fields in the header blank. If the data is unknown, does not exist, or is not applicable, then write "UNKNOWN", "DOES NOT EXIST" or "NOT APPLICABLE" instead of leaving a space blank.

Likewise, do not skip the “Back-page Worksheet”. Take the time to read the definition of *household* to the respondent and to fill out the roster member-by-member. If you cut corners by only asking, “How many members does the household have?”, many respondents will miscount or apply the wrong definition of *household*. Completing the “Back-page Worksheet” improves data quality because it mimics the practice of Peru’s INEI in the 2019 ENAHO. The accuracy of the scorecard’s estimates depends on the quality of recorded responses, and especially strongly on the count of household members. Working through the “Back-page Worksheet” gives the best count.

Throughout the interview, apply the instructions in the “**Interview Guide**”. Enumerators must be thoroughly trained on the “Guide” before they do any interviews, and they should carry a copy of the “Guide” with them to each interview.[8] Even though the scorecard is less difficult than other poverty-assessment tools, training and explicit definitions of the scorecard’s terms and concepts are still essential.[9] Enumerators must scrupulously study and follow the “Guide”.

Finally, on-going quality-control audits are wise if a program or its field agents gather their own data and if they believe that they have an incentive to exaggerate participants’ poverty (for example, if they are rewarded for higher poverty rates).[10]

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[8] The “**Interview Guide**” is the only guidance that programs should give to enumerators. All other issues of interpretation should be left to the judgment of enumerators and respondents, as this seems to be what Peru’s INEI did in the 2019 ENAHO.

[9] Merely reading through the scorecard with enumerators is not adequate training.

[10] **Matul and Kline**, 2003. If a program does not want enumerators or respondents to know the scorecard’s points, then it can use a **mobile data-collection app** or a paper version of the scorecard that omits the points, with scores computed later at an office. Even if points are hidden, however, enumerators and respondents can use common sense to guess how responses are linked with poverty.

Figure 3: First example household, filled-in scorecard

			Name	Identifier
Interview ID:	A123			
Interview date:	13JUN2020	Direct participant:	ANNA JACKSON	1V0276FZ7
Country:	PER	Field agent:	UNKNOWN	UNKNOWN
Scorecard:	004	Service point:	NORTHWEST CLINIC	NWC
Sampling weight:	UNKNOWN	Number of household members:		NINE

Question	Response	Points	
1. In which region does the household live?	A. Lima, Callao, La Libertad, Ayacucho, or Pasco	0	
	B. Cajamarca, Piura, or Puno	2	2
	C. Cusco, Junín, Apurímac, Huánuco, San Martín, Huancavelica, Amazonas, Tacna, Tumbes, or Moquegua	4	
	D. Arequipa, Ancash, Loreto, or Madre de Díos	8	
	E. Lambayeque, Ica, or Ucayali	14	
2. How many members does the household have?	A. Six or more	0	0
	B. Five	4	
	C. Four	8	
	D. Three	13	
	E. Two	19	
	F. One	29	
3. What is the main material of the floors?	A. Earth	0	0
	B. Wood (bamboo, planks, and so on), or cement	4	
	C. Tile and so on; linoleum, vinyl and so on; parquet, polished wood, or other	11	
4. How many rooms are used only as bedrooms?	A. None, or one	0	
	B. Two or more	4	4
5. What cooking fuel does the household use more than any other?	A. Dung, or other	0	
	B. Firewood, or charcoal	3	3
	C. Gas (LPG in a tank), natural gas (piped from network), electricity, or does not cook	5	
6. Does the household have a microwave?	A. No	0	0
	B. Yes	3	
7. Does the household have a food processor/blender?	A. No	0	0
	B. Yes	4	
8. How many TVs (color or black and white) does the household have?	A. None	0	
	B. One	3	3
	C. Two or more	6	
9. Does the household have an internet connection?	A. No	0	0
	B. Yes	8	
10. Does the household have a personal computer or laptop?	A. No	0	0
	B. Yes	5	
11. Does the household have a cell phone or a land-line phone?	A. No	0	0
	B. Yes	6	
12. In the last 15 days from . . . to . . ., has any member of the household obtained, consumed, bought, or received as a gift any milk (evaporated, powdered, fresh, evaporated with iron, evaporated light, or soy milk with lactose)?	A. No	0	
	B. Yes	5	5

Score: 2 + 0 + 0 + 4 + 3 + 0 + 0 + 3 + 0 + 0 + 0 + 5 = 17

Figure 4: First example household, filled-in "Back-page Worksheet"

First name or nickname?	Head or spouse of head?
1. **ANNA**	Head (male) Head (female)
2. **BILLY**	Wife of male head Husband of female head Other
3. **CHARLES**	Other
4. **DARLA**	Other
5. **EUGENE**	Other
6. **FREDA**	Other
7. **GRETA**	Other
8. **HANK**	Other
9. **IRIS**	Other
10.	Other
11.	Other
12.	Other
13.	Other
Number of members: **NINE**	—

2.3 First example household

The points for the first example household's responses add up to a score of 17 (**Figure 3** and **Figure 4**).

For a given poverty line, **Figure 1** lists poverty likelihoods by score range. A score of 17 falls in the first range of 0–19. For 100% of the national poverty line, the poverty likelihood for scores of 0–19 is 81.2 percent. That is, the scorecard estimates that 81.2 percent of households in Peru with a score of 0–19 have consumption below 100% of the national line.

Figure 5: The first example household's score of 17 implies a poverty likelihood of 81.2 percent for 100% of the national line (excerpted from Figure 1)

	Poverty likelihood (%)		
	National		
Score	**100%**	**150%**	**200%**
0–19	81.2	98.5	99.9
20–22	68.9	93.7	99.1
23–25	62.5	91.7	97.9
26–27	57.8	87.3	97.4
28–29	44.8	84.8	97.3
30–31	41.7	83.8	94.2
32–33	35.1	76.7	93.7
34–35	32.9	75.5	93.0
36–37	27.2	68.9	88.7
. . .	. . .	. . .	. . .

Figure 6: Second example household, filled-in scorecard

Interview ID:	B456		**Name**	**Identifier**
Interview date:	30JUN2020	Direct participant:	JOHN BROWN	2W3120ZG8
Country:	PER	Field agent:	UNKNOWN	UNKNOWN
Scorecard:	004	Service point:	NORTHWEST CLINIC	NWC
Sampling weight:	UNKNOWN	Number of household members:		FIVE

Question	Response		Points
1. In which region does the household live?	A. Lima, Callao, La Libertad, Ayacucho, or Pasco	0	
	B. Cajamarca, Piura, or Puno	2	
	C. Cusco, Junín, Apurímac, Huánuco, San Martín, Huancavelica, Amazonas, Tacna, Tumbes, or Moquegua	4	4
	D. Arequipa, Ancash, Loreto, or Madre de Díos	8	
	E. Lambayeque, Ica, or Ucayali	14	
2. How many members does the household have?	A. Six or more	0	
	B. Five	4	4
	C. Four	8	
	D. Three	13	
	E. Two	19	
	F. One	29	
3. What is the main material of the floors?	A. Earth	0	
	B. Wood (bamboo, planks, and so on), or cement	4	4
	C. Tile and so on; linoleum, vinyl and so on; parquet, polished wood, or other	11	
4. How many rooms are used only as bedrooms?	A. None, or one	0	
	B. Two or more	4	4
5. What cooking fuel does the household use more than any other?	A. Dung, or other	0	
	B. Firewood, or charcoal	3	3
	C. Gas (LPG in a tank), natural gas (piped from network), electricity, or does not cook	5	
6. Does the household have a microwave?	A. No	0	0
	B. Yes	3	
7. Does the household have a food processor/blender?	A. No	0	0
	B. Yes	4	
8. How many TVs (color or black and white) does the household have?	A. None	0	
	B. One	3	3
	C. Two or more	6	
9. Does the household have an internet connection?	A. No	0	0
	B. Yes	8	
10. Does the household have a personal computer or laptop?	A. No	0	0
	B. Yes	5	
11. Does the household have a cell phone or a land-line phone?	A. No	0	
	B. Yes	6	6
12. In the last 15 days from . . . to . . ., has any member of the household obtained, consumed, bought, or received as a gift any milk (evaporated, powdered, fresh, evaporated with iron, evaporated light, or soy milk with lactose)?	A. No	0	
	B. Yes	5	5

Score: 4 + 4 + 4 + 4 + 3 + 0 + 0 + 3 + 0 + 0 + 6 + 5 = 33

Figure 7: Second example household, filled-in "Back-page Worksheet"

First name or nickname?	**Head or spouse of head?**
1. **JOHN**	Head (male) Head (female)
2. **MARY**	Wife of male head Husband of female head Other
3. **SUE**	Other
4. **KIM**	Other
5. **MONICA**	Other
6.	Other
7.	Other
8.	Other
9.	Other
10.	Other
11.	Other
12.	Other
13.	Other
Number of members: **FIVE**	—

2.4 Second example household

The points for the second example household's responses add up to a score of 33 (**Figure 6** and **Figure 7**).

In **Figure 1**, a score of 33 falls in the range of 32–33. For 100% of the national poverty line, the poverty likelihood for scores of 32–33 is 35.1 percent. The scorecard estimates that 35.1 percent of households in Peru with a score of 32–33 have consumption below 100% of the national line.

Figure 8: The second example household's score of 33 implies a poverty likelihood of 35.1 percent for 100% of the national line (excerpt from Figure 1)

	Poverty likelihood (%)		
	National		
Score	**100%**	**150%**	**200%**
0–19	81.2	98.5	99.9
20–22	68.9	93.7	99.1
23–25	62.5	91.7	97.9
26–27	57.8	87.3	97.4
28–29	44.8	84.8	97.3
30–31	41.7	83.8	94.2
32–33	35.1	76.7	93.7
34–35	32.9	75.5	93.0
36–37	27.2	68.9	88.7
. . .	. . .	. . .	. . .

3. How to calculate scorecard estimates

This section tells how to estimate:

- Head-count poverty rates for a single time period for in-coming participants
- Net changes in poverty rates across two time periods for on-going participants

It also tells how to use these estimated poverty rates to estimate the:

- Number of poor people in the households of in-coming participants
- Net number of poor people in the households of on-going participants who rose above a poverty line

3.1 Head-count poverty rates in a single time period

The *head-count poverty rate* is the share of people in participating households in which total household consumption (divided by the number of household members) is below a given poverty line.

The scorecard estimates head-count poverty rates as the household-size-weighted average of poverty likelihoods from a scored sample, adjusted for the scorecard's known estimation error.

To illustrate the calculation, suppose that a pro-poor program opens a new service point in rural Cusco in 2020. In that calendar year, it enrolls 1,000 in-coming households, from which it scores a simple random sample[11] of two households.[12]

The program judges that 100% of the national poverty line is the most-relevant line for its purposes. For that line and for snapshot estimates of poverty rates in one period, the scorecard's known estimation error is –2.7 percentage points (**Figure 2**).

The first example household has nine members and is interviewed on June 13, 2020. With a score of 17, it has a poverty likelihood for 100% of the national line of 81.2 percent.

The second example household has five members and is interviewed on June 30, 2020. Its score of 33 corresponds with a poverty likelihood of 35.1 percent.

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[11] In a *simple random sample*, all households in the population have the same selection probability. This paper does not discuss samples in which selection probabilities vary.

[12] Of course, estimates based on such an unrealistically small sample have wide margins of error, but a small sample facilitates the arithmetic in the examples.

The estimated head-count poverty rate for the population of in-coming households in the 2020 calendar-year cohort in rural Cusco is the household-size-weighted average of the estimated poverty likelihoods of the sampled households, less the known estimation error. Expressing poverty likelihoods and the estimation error as proportions between 0 and 1 rather than percentages between 0 and 100, this is:

$$\frac{9 \cdot 0.812 + 5 \cdot 0.351}{9+5} - (-0.027) \approx \frac{9.06}{14} + 0.027 \approx 0.674 = 67.4 \text{ percent.}$$

The nine in the "$9 \cdot 0.812$" term in the numerator is the number of members (household size) in the first household, and 0.812 is the first household's estimated poverty likelihood.

In the same way, the five in the numerator's "$5 \cdot 0.351$" is the number of members in the second household, and 0.351 is the second household's estimated poverty likelihood.

The "9 + 5" in the denominator is the sum of the weights—that is, the number of household members—for the two sampled households.

The "–0.027" is the scorecard's estimation error for this poverty line from **Figure 2**. Because unadjusted estimates tend to be too low by 2.7 percentage points, they are adjusted upwards by subtracting –2.7 (which is equivalent to adding 2.7). This is akin to how an archer whose arrows tend to miss a little to the left of the bulls-eye will adjust his/her aim to be a little to the right of the bulls-eye.

The estimated head-count poverty rate for the population is 67.4 percent. Again, this is the household-size-weighted average of the two sampled households' poverty likelihoods, adjusted for the known estimation error.[13]

For real-world samples with hundreds or thousands of interviewed households, the calculations would be done by the **ProveIt™-brand reporting and analysis tool** or in a spreadsheet (**Figure 9**).

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[13] Be careful; the estimated poverty rate is *not* the single poverty likelihood associated with the household-size-weighted average score, which here is (9·17 + 5·33) ÷ (9 + 5) ≈ 23. This average score of 23 corresponds to a poverty likelihood of 62.5 percent (**Figure 1**), giving an error-adjusted poverty rate of 62.5 – (–2.7) = 65.2 percent. This differs from the 67.4 percent found as the household-size-weighted average of the two individual likelihoods associated with each of the two scores. Unlike likelihoods, scores are ordinal symbols, like colors in the spectrum or syllables in a solfège scale. Because scores are ordinal, they cannot be added up nor averaged. Only three operations are valid for scores: conversion to likelihoods, analysis of distributions, or comparison with a cut-off for segmentation (**Schreiner**, 2012b). In general, analyze likelihoods, not scores.

Figure 9: Spreadsheet calculation to estimate the head-count poverty rate and number of poor people in a population of in-coming participants in a period

	A	B	C	D	E	F	G
1	**Survey**	**Interview date**	**ID of direct participant**	**Number of household members**	**Score**	**Poverty likelihood (%)**	**Estimated number of poor household members**
2	Baseline	13-Jun-20	1V0276FZ7	9	17	81.2	7.31 = (D2*F2)/100
3	Baseline	30-Jun-20	2W3120ZG8	5	33	35.1	1.76 = (D3*F3)/100
4			**Sum:**	14 = SUM(D2:D3)			9.06 = SUM(G2:G3)
5			**Average:**	7.0 = AVERAGE(D2:D3)			
6							
7	**Estimated scorecard error for this poverty line (percentage points):**						-2.7
8							
9				**Estimated head-count poverty rate (%):**			67.4 = (G4/D4)*100-G7
10							
11				**Households in the population:**			1,000
12							
13				**People in households in the population:**			7,000 = G11*D5
14							
15				**Number of poor people in population:**			4,721 = (G9/100)*G13
16	Rows of data are sorted by Round, then by Interview date, then by Direct participant ID.						

This snapshot estimate in a single time period tends to be more relevant for in-coming participants who joined in the current period than for on-going participants who joined in past periods. This is because fulfilling a pro-poor mission implies that some share of new participants be poor by some definition of *poverty*.[14] To be pro-poor, a bare-minimum standard is that the poverty rate of in-coming participants exceed that of the country as a whole or that of the region where the program works.

To help with benchmarking poverty-rate estimates, **Figure 10** reports head-count poverty rates from the 2019 ENAHO for all 14 poverty lines by urban/rural/all for Peru as a whole and for each of Peru's regions. In the example of rural Cusco, the head-count poverty rate for 100% of the national line is 35.4 percent. Thus, the example program is pro-poor in the sense that its in-coming participants have an above-average poverty rate (67.4 percent).

The text that illustrates the calculation of the scorecard estimate of the number of poor people in a single time period follows after **Figure 10**, which stretches across the next nine pages. **Figure 10** begins with all-Peru first and then is, followed by the 24 regions (plus Callao) in alphabetical order.

[14] The scorecard uses a consumption-based definition of *poverty*. Common non-consumption definitions include: being rural, agricultural, landless, or unemployed; living in a given region; having a head who is illiterate, female, or an ethnic minority; or having a member who is pregnant, handicapped, elderly, or very young.

Figure 10 (All-Peru, Amazonas, and Ancash): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	National 100%	National 150%	National 200%	Intl. 2011 PPP $1.90	Intl. 2011 PPP $3.20	Intl. 2011 PPP $5.50	Intl. 2011 PPP $21.70	Percentile-based 10th	20th	40th	50th	60th	80th	90th
Peru	**Urban**	Line	21,493	12.39	18.59	24.78	3.87	6.52	11.20	44.19	8.75	11.37	16.11	18.56	21.47	31.07	41.47
		Rate		14.6	40.6	61.7	0.0	1.0	10.3	89.4	4.1	10.9	29.8	40.6	51.9	75.4	87.5
	Rural	Line	13,072	8.54	12.80	17.07	3.39	5.72	9.82	38.76	7.67	9.98	14.13	16.28	18.83	27.25	36.37
		Rate		40.8	72.2	86.6	1.5	13.5	52.0	99.2	31.7	53.3	77.6	84.4	89.8	97.0	99.0
	All	Line	34,565	11.56	17.35	23.13	3.77	6.34	10.91	43.03	8.52	11.07	15.68	18.07	20.90	30.26	40.38
		Rate		20.2	47.4	67.1	0.4	3.7	19.2	91.5	10.0	20.0	40.0	50.0	60.0	80.0	90.0
Amazonas	**Urban**	Line	434	10.45	15.67	20.89	3.52	5.92	10.18	40.17	7.95	10.34	14.64	16.87	19.52	28.25	37.69
		Rate		21.9	50.2	68.0	0.6	2.6	22.1	92.4	11.8	22.5	45.4	54.2	66.4	81.0	91.0
	Rural	Line	795	8.21	12.31	16.42	3.51	5.90	10.15	40.03	7.93	10.30	14.59	16.82	19.45	28.15	37.57
		Rate		39.3	71.3	86.8	0.4	11.9	58.6	99.2	36.2	59.6	81.8	88.2	91.9	97.3	98.7
	All	Line	1,229	9.34	14.01	18.69	3.51	5.91	10.16	40.10	7.94	10.32	14.62	16.84	19.48	28.20	37.63
		Rate		30.5	60.7	77.3	0.5	7.2	40.1	95.8	23.8	40.8	63.3	71.0	79.0	89.0	94.8
Ancash	**Urban**	Line	767	10.97	16.45	21.93	3.58	6.03	10.37	40.92	8.10	10.53	14.92	17.19	19.88	28.78	38.40
		Rate		6.6	29.4	54.1	0.0	0.9	5.1	91.3	1.9	5.6	22.3	33.4	46.3	74.9	88.5
	Rural	Line	654	8.56	12.83	17.11	3.32	5.59	9.62	37.94	7.51	9.76	13.83	15.94	18.43	26.68	35.60
		Rate		36.5	67.4	84.3	0.1	7.6	46.2	98.7	25.3	47.6	72.1	80.6	86.9	95.8	98.4
	All	Line	1,421	10.09	15.13	20.17	3.49	5.87	10.10	39.83	7.89	10.25	14.52	16.73	19.35	28.01	37.38
		Rate		17.5	43.3	65.2	0.1	3.4	20.1	94.0	10.5	21.0	40.5	50.7	61.1	82.5	92.1

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Apurímac, Arequipa, and Ayacucho): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region	Area	Line or Rate	*n*	National 100%	National 150%	National 200%	Intl. 2011 PPP $1.90	Intl. 2011 PPP $3.20	Intl. 2011 PPP $5.50	Intl. 2011 PPP $21.70	Percentile 10th	Percentile 20th	Percentile 40th	Percentile 50th	Percentile 60th	Percentile 80th	Percentile 90th
Apurímac	**Urban**	Line	253	10.05	15.08	20.11	3.53	5.94	10.20	40.26	7.97	10.36	14.67	16.91	19.56	28.31	37.78
		Rate		19.9	49.2	67.4	0.5	3.5	19.9	94.8	12.3	20.6	48.5	54.6	64.6	85.3	93.4
	Rural	Line	706	8.46	12.68	16.91	3.18	5.35	9.20	36.30	7.19	9.34	13.23	15.25	17.64	25.53	34.06
		Rate		36.3	70.7	88.8	0.0	6.3	42.6	99.4	19.5	43.9	74.7	82.4	89.8	96.2	99.2
	All	Line	959	9.16	13.74	18.32	3.33	5.61	9.64	38.04	7.53	9.79	13.87	15.98	18.48	26.75	35.70
		Rate		29.1	61.2	79.4	0.2	5.1	32.7	97.4	16.3	33.7	63.2	70.2	78.7	91.4	96.6
Arequipa	**Urban**	Line	1,230	10.53	15.79	21.06	3.55	5.97	10.27	40.51	8.02	10.43	14.77	17.02	19.68	28.49	38.02
		Rate		4.3	24.0	45.9	0.0	0.1	3.4	88.2	1.3	3.8	18.1	29.8	39.5	69.6	85.7
	Rural	Line	330	8.87	13.31	17.74	3.35	5.65	9.71	38.31	7.58	9.86	13.96	16.09	18.61	26.94	35.95
		Rate		23.9	46.6	63.0	0.1	4.8	27.2	95.1	15.4	27.8	48.3	56.2	66.7	86.9	94.2
	All	Line	1,560	10.39	15.58	20.77	3.53	5.95	10.22	40.32	7.98	10.38	14.70	16.94	19.59	28.36	37.84
		Rate		6.0	25.9	47.4	0.0	0.5	5.4	88.8	2.6	5.9	20.7	32.1	41.8	71.1	86.4
Ayacucho	**Urban**	Line	472	10.32	15.48	20.64	3.30	5.56	9.56	37.70	7.46	9.71	13.74	15.84	18.32	26.51	35.38
		Rate		27.5	57.3	77.4	0.0	2.1	21.3	95.0	9.4	22.8	46.8	58.7	70.0	84.6	94.2
	Rural	Line	697	8.59	12.88	17.17	3.29	5.54	9.52	37.56	7.44	9.67	13.69	15.78	18.25	26.41	35.25
		Rate		55.7	84.2	94.4	0.6	16.9	64.5	99.9	39.8	65.8	86.7	92.2	96.3	99.2	99.9
	All	Line	1,169	9.59	14.39	19.18	3.30	5.55	9.54	37.64	7.45	9.69	13.72	15.81	18.29	26.47	35.33
		Rate		39.4	68.6	84.5	0.2	8.3	39.5	97.1	22.2	40.9	63.6	72.8	81.0	90.7	96.6

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Cajamarca, Callao, and Cusco): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	National 100%	National 150%	National 200%	Intl. 2011 PPP $1.90	Intl. 2011 PPP $3.20	Intl. 2011 PPP $5.50	Intl. 2011 PPP $21.70	Percentile-based lines 10th	20th	40th	50th	60th	80th	90th
Cajamarca	**Urban**	Line	478	10.07	15.10	20.14	3.53	5.94	10.22	40.31	7.98	10.38	14.69	16.93	19.59	28.35	37.83
		Rate		15.4	38.0	57.6	0.0	2.0	15.4	89.5	5.5	16.4	36.8	46.0	56.4	77.6	86.5
	Rural	Line	964	8.30	12.44	16.59	3.33	5.60	9.63	37.99	7.52	9.78	13.85	15.96	18.46	26.72	35.65
		Rate		51.9	79.9	90.1	2.9	20.5	63.5	99.4	43.5	64.7	84.3	89.3	92.0	97.4	99.3
	All	Line	1,442	8.97	13.46	17.94	3.40	5.73	9.85	38.88	7.70	10.01	14.17	16.33	18.89	27.34	36.48
		Rate		38.0	63.9	77.7	1.8	13.5	45.1	95.6	29.0	46.2	66.1	72.8	78.4	89.8	94.4
Callao	**Urban**	Line	1,009	14.50	21.76	29.01	4.34	7.30	12.55	49.52	9.80	12.75	18.05	20.80	24.06	34.82	46.47
		Rate		14.3	42.7	67.1	0.0	0.5	7.1	92.8	2.0	8.2	28.4	39.2	52.0	78.4	91.7
	Rural	Line	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
		Rate		—	—	—	—	—	—	—	—	—	—	—	—	—	—
	All	Line	1,009	14.50	21.76	29.01	4.34	7.30	12.55	49.52	9.80	12.75	18.05	20.80	24.06	34.82	46.47
		Rate		14.3	42.7	67.1	0.0	0.5	7.1	92.8	2.0	8.2	28.4	39.2	52.0	78.4	91.7
Cusco	**Urban**	Line	500	10.41	15.62	20.83	3.52	5.94	10.20	40.25	7.97	10.36	14.67	16.91	19.55	28.30	37.77
		Rate		14.3	40.3	62.2	0.0	1.9	13.1	90.1	3.9	14.3	35.1	48.5	57.4	79.4	88.8
	Rural	Line	778	8.64	12.96	17.28	3.24	5.46	9.39	37.06	7.34	9.54	13.51	15.57	18.00	26.06	34.78
		Rate		35.4	71.6	87.0	0.2	7.7	43.8	99.2	22.7	45.0	74.3	81.8	89.2	96.7	99.0
	All	Line	1,278	9.68	14.52	19.37	3.41	5.74	9.87	38.93	7.71	10.02	14.19	16.35	18.92	27.38	36.53
		Rate		23.0	53.2	72.4	0.1	4.3	25.8	93.9	11.7	26.9	51.3	62.2	70.5	86.5	93.0

Poverty lines and poverty rates

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Huancavelica, Huánuco, and Ica): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	National			Intl. 2011 PPP				Percentile-based lines						
				100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
Huancavelica	**Urban**	Line	207	10.01	15.02	20.03	3.28	5.53	9.50	37.48	7.42	9.65	13.66	15.75	18.21	26.36	35.18
		Rate		19.0	49.8	77.7	0.0	0.0	16.5	96.2	2.1	17.6	40.6	56.9	68.9	90.7	95.7
	Rural	Line	825	8.43	12.64	16.85	3.27	5.50	9.45	37.30	7.38	9.60	13.59	15.67	18.12	26.23	35.00
		Rate		43.1	78.2	92.5	0.4	8.9	53.3	99.6	30.8	55.1	83.8	89.9	94.3	98.7	99.4
	All	Line	1,032	8.83	13.25	17.67	3.27	5.51	9.47	37.34	7.39	9.61	13.61	15.69	18.14	26.26	35.04
		Rate		36.9	70.9	88.7	0.3	6.6	43.8	98.7	23.4	45.5	72.7	81.4	87.8	96.6	98.4
Huánuco	**Urban**	Line	449	10.37	15.56	20.75	3.34	5.62	9.66	38.13	7.55	9.81	13.90	16.02	18.53	26.81	35.78
		Rate		17.5	42.0	59.7	0.0	0.0	15.7	89.8	6.5	16.6	33.8	43.3	50.5	74.5	88.0
	Rural	Line	828	8.52	12.78	17.04	3.32	5.59	9.61	37.93	7.51	9.76	13.83	15.93	18.43	26.68	35.60
		Rate		37.3	73.6	88.2	0.1	7.6	49.4	99.3	26.9	50.6	78.0	85.0	91.0	97.5	99.2
	All	Line	1,277	9.26	13.89	18.53	3.33	5.61	9.63	38.01	7.53	9.78	13.85	15.97	18.47	26.73	35.67
		Rate		29.4	60.9	76.8	0.0	4.6	35.9	95.5	18.8	37.0	60.3	68.3	74.7	88.3	94.7
Ica	**Urban**	Line	1,271	12.13	18.20	24.27	3.71	6.25	10.74	42.38	8.39	10.91	15.45	17.80	20.59	29.80	39.77
		Rate		2.6	24.0	55.2	0.0	0.0	1.3	91.9	0.0	1.6	11.3	21.8	36.1	73.4	89.6
	Rural	Line	292	9.62	14.43	19.23	3.83	6.45	11.08	43.71	8.65	11.25	15.93	18.36	21.24	30.74	41.02
		Rate		1.9	21.6	44.0	0.0	0.0	6.3	98.8	1.2	7.3	28.9	39.6	56.2	88.1	97.8
	All	Line	1,563	11.98	17.96	23.95	3.72	6.26	10.76	42.47	8.41	10.93	15.48	17.84	20.63	29.86	39.85
		Rate		2.6	23.8	54.5	0.0	0.0	1.6	92.3	0.1	1.9	12.4	22.9	37.3	74.4	90.1

Poverty lines and poverty rates

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Junín, La Libertad, and Lambayeque): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region	Area	Line or Rate	*n*	Poverty lines and poverty rates													
				National			Intl. 2011 PPP				Percentile-based lines						
				100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
Junín	**Urban**	Line	781	10.21	15.31	20.42	3.32	5.60	9.62	37.97	7.52	9.77	13.84	15.95	18.45	26.70	35.63
		Rate		15.1	40.9	61.7	0.0	0.8	10.5	90.1	4.0	11.4	33.4	42.9	55.4	76.6	88.4
	Rural	Line	790	8.37	12.55	16.73	3.42	5.76	9.90	39.05	7.73	10.05	14.23	16.40	18.97	27.46	36.65
		Rate		32.3	64.3	81.7	1.3	10.2	43.4	99.2	24.8	45.8	72.7	80.3	87.6	96.9	98.9
	All	Line	1,571	9.61	14.42	19.22	3.36	5.65	9.71	38.32	7.59	9.86	13.97	16.10	18.62	26.95	35.96
		Rate		20.7	48.5	68.2	0.4	3.8	21.2	93.0	10.7	22.5	46.1	55.0	65.8	83.2	91.8
La Libertad	**Urban**	Line	1,129	11.35	17.02	22.70	3.45	5.81	9.99	39.42	7.80	10.15	14.37	16.56	19.15	27.72	36.99
		Rate		16.4	42.4	62.9	0.1	1.4	11.4	88.8	4.5	12.2	29.2	40.8	50.0	74.8	86.1
	Rural	Line	456	8.67	13.00	17.33	3.30	5.56	9.55	37.67	7.46	9.70	13.73	15.82	18.30	26.49	35.35
		Rate		58.5	81.3	90.4	6.5	28.5	66.6	99.3	45.5	67.2	83.8	87.7	91.8	97.6	98.9
	All	Line	1,585	10.82	16.22	21.63	3.42	5.76	9.90	39.07	7.74	10.06	14.24	16.41	18.98	27.48	36.67
		Rate		24.7	50.2	68.3	1.4	6.8	22.4	90.9	12.7	23.2	40.1	50.1	58.3	79.3	88.6
Lambayeque	**Urban**	Line	1,064	11.43	17.15	22.86	3.45	5.80	9.97	39.35	7.79	10.13	14.34	16.53	19.12	27.67	36.93
		Rate		8.8	31.9	57.5	0.0	0.5	4.1	86.6	1.3	4.5	19.5	28.7	39.9	69.8	85.1
	Rural	Line	364	9.08	13.62	18.16	3.49	5.87	10.10	39.84	7.89	10.25	14.52	16.73	19.36	28.01	37.39
		Rate		17.3	50.8	74.1	0.0	1.3	23.2	98.9	11.5	24.3	54.9	67.7	78.5	94.7	98.8
	All	Line	1,428	11.04	16.56	22.08	3.45	5.81	9.99	39.43	7.81	10.15	14.37	16.56	19.16	27.73	37.00
		Rate		10.2	35.0	60.2	0.0	0.6	7.3	88.6	3.0	7.8	25.4	35.2	46.3	74.0	87.4

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Lima, Loreto, and Madre de Díos): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	National 100%	National 150%	National 200%	Intl. 2011 PPP $1.90	Intl. 2011 PPP $3.20	Intl. 2011 PPP $5.50	Intl. 2011 PPP $21.70	Percentile 10th	Percentile 20th	Percentile 40th	Percentile 50th	Percentile 60th	Percentile 80th	Percentile 90th
Lima	**Urban**	Line	4,010	14.26	21.39	28.52	4.29	7.22	12.41	48.96	9.69	12.60	17.84	20.56	23.79	34.43	45.94
		Rate		14.1	40.7	60.5	0.0	0.4	7.8	86.4	2.9	8.4	26.1	37.5	49.1	71.5	84.5
	Rural	Line	504	8.80	13.21	17.61	3.56	6.00	10.30	40.66	8.05	10.47	14.82	17.08	19.75	28.59	38.15
		Rate		23.2	53.7	72.9	0.4	6.2	33.1	98.5	17.0	34.7	60.2	71.0	79.3	94.0	97.8
	All	Line	4,514	14.17	21.25	28.33	4.27	7.20	12.37	48.81	9.66	12.57	17.79	20.51	23.72	34.33	45.81
		Rate		14.2	40.9	60.8	0.0	0.5	8.3	86.6	3.2	8.9	26.6	38.1	49.6	71.9	84.7
Loreto	**Urban**	Line	865	10.62	15.92	21.23	4.01	6.75	11.60	45.78	9.06	11.78	16.69	19.23	22.24	32.19	42.96
		Rate		22.0	47.3	66.1	0.7	5.1	26.5	95.3	14.7	27.9	50.9	59.7	69.0	85.3	93.9
	Rural	Line	603	8.12	12.18	16.24	4.14	6.97	11.98	47.25	9.35	12.16	17.22	19.85	22.96	33.23	44.34
		Rate		55.2	85.6	94.4	7.6	38.9	85.3	99.8	66.4	85.6	95.6	98.1	98.9	99.5	99.8
	All	Line	1,468	9.85	14.78	19.70	4.05	6.82	11.72	46.23	9.15	11.90	16.85	19.42	22.46	32.51	43.38
		Rate		32.2	59.0	74.7	2.8	15.5	44.5	96.7	30.5	45.6	64.6	71.5	78.1	89.7	95.7
Madre de Díos	**Urban**	Line	406	10.50	15.75	21.00	4.01	6.75	11.60	45.78	9.06	11.78	16.69	19.23	22.24	32.19	42.96
		Rate		9.6	25.0	44.5	0.0	0.3	12.0	92.9	3.3	12.4	27.8	38.1	47.7	78.6	90.8
	Rural	Line	236	8.04	12.06	16.08	4.14	6.97	11.98	47.25	9.35	12.16	17.22	19.85	22.96	33.23	44.34
		Rate		7.2	21.1	36.9	0.1	5.1	21.1	96.6	9.0	21.7	42.9	54.5	62.9	86.6	95.3
	All	Line	642	10.08	15.12	20.15	4.03	6.79	11.67	46.03	9.11	11.85	16.78	19.34	22.37	32.37	43.20
		Rate		9.2	24.4	43.2	0.0	1.1	13.5	93.6	4.2	14.0	30.4	40.9	50.3	80.0	91.6

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Moquegua, Pasco, and Piura): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	Poverty lines and poverty rates													
				National			Intl. 2011 PPP				Percentile-based lines						
				100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
Moquegua	Urban	Line	749	11.27	16.90	22.53	3.69	6.22	10.68	42.15	8.35	10.85	15.36	17.71	20.48	29.64	39.56
		Rate		4.4	19.0	40.0	0.0	0.2	4.1	83.6	1.5	4.6	14.8	22.8	34.3	62.6	80.9
	Rural	Line	222	8.57	12.86	17.15	3.24	5.45	9.37	36.99	7.32	9.52	13.48	15.54	17.97	26.01	34.71
		Rate		29.3	55.1	72.2	1.2	4.9	33.2	96.3	21.5	33.6	56.6	66.8	74.1	90.0	96.3
	All	Line	971	10.75	16.12	21.50	3.60	6.07	10.43	41.16	8.15	10.59	15.00	17.29	20.00	28.94	38.62
		Rate		9.2	26.0	46.2	0.2	1.1	9.7	86.1	5.4	10.2	22.9	31.3	42.0	67.8	83.9
Pasco	Urban	Line	513	10.23	15.34	20.46	3.32	5.59	9.60	37.89	7.50	9.75	13.81	15.92	18.41	26.64	35.55
		Rate		26.1	61.7	81.7	0.0	0.3	20.7	98.8	9.1	21.6	51.7	64.0	75.6	95.5	98.5
	Rural	Line	376	8.39	12.59	16.79	3.42	5.76	9.90	39.05	7.73	10.05	14.23	16.40	18.97	27.46	36.65
		Rate		39.2	73.3	87.1	0.5	13.7	52.5	99.4	34.8	53.5	80.8	87.2	90.9	98.2	99.1
	All	Line	889	9.64	14.45	19.27	3.35	5.64	9.70	38.26	7.58	9.85	13.95	16.07	18.59	26.91	35.91
		Rate		30.3	65.4	83.5	0.2	4.7	31.0	99.0	17.4	31.9	61.1	71.5	80.5	96.4	98.7
Piura	Urban	Line	1,157	11.60	17.40	23.21	3.45	5.80	9.98	39.36	7.79	10.13	14.35	16.53	19.12	27.68	36.94
		Rate		19.2	48.5	72.6	0.0	1.0	10.7	93.6	4.2	11.0	33.6	44.9	57.1	81.3	92.1
	Rural	Line	498	9.06	13.59	18.12	3.42	5.76	9.91	39.08	7.74	10.06	14.24	16.42	18.99	27.48	36.67
		Rate		43.1	73.3	87.4	1.6	13.5	51.0	98.9	30.3	53.3	77.5	84.1	89.3	96.9	98.8
	All	Line	1,655	11.07	16.61	22.15	3.44	5.80	9.96	39.30	7.78	10.12	14.33	16.51	19.10	27.64	36.88
		Rate		24.2	53.7	75.7	0.3	3.6	19.1	94.7	9.7	19.8	42.7	53.1	63.8	84.5	93.5

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Puno, San Martín, and Tacna): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	National 100%	National 150%	National 200%	Intl. 2011 PPP $1.90	Intl. 2011 PPP $3.20	Intl. 2011 PPP $5.50	Intl. 2011 PPP $21.70	Percentile-based 10th	20th	40th	50th	60th	80th	90th
Puno	**Urban**	Line	433	10.53	15.80	21.06	3.53	5.94	10.20	40.26	7.97	10.36	14.67	16.91	19.56	28.31	37.78
		Rate		27.2	54.7	70.7	0.0	5.8	25.1	96.4	11.4	25.4	51.7	58.5	68.6	84.1	94.6
	Rural	Line	769	8.79	13.18	17.58	3.20	5.38	9.25	36.50	7.23	9.40	13.30	15.33	17.73	25.67	34.25
		Rate		45.4	78.3	92.4	0.4	12.5	50.2	99.7	28.1	51.1	79.2	86.9	92.6	98.0	99.5
	All	Line	1,202	9.81	14.72	19.63	3.39	5.71	9.81	38.71	7.66	9.96	14.11	16.26	18.81	27.22	36.33
		Rate		34.7	64.4	79.7	0.2	8.6	35.4	97.8	18.3	36.0	63.0	70.2	78.5	89.8	96.6
San Martín	**Urban**	Line	784	10.49	15.74	20.99	3.51	5.91	10.16	40.07	7.93	10.32	14.61	16.83	19.47	28.18	37.61
		Rate		23.7	47.8	65.3	0.0	2.0	22.0	90.8	9.5	22.4	43.7	51.3	61.4	80.2	88.6
	Rural	Line	551	8.03	12.05	16.07	3.61	6.07	10.44	41.18	8.15	10.60	15.01	17.30	20.01	28.96	38.64
		Rate		28.9	65.5	82.4	1.1	10.2	51.1	99.4	31.1	52.2	79.6	87.8	92.1	98.3	99.1
	All	Line	1,335	9.72	14.57	19.43	3.54	5.96	10.25	40.42	8.00	10.40	14.73	16.98	19.64	28.43	37.93
		Rate		25.4	53.4	70.7	0.3	4.6	31.2	93.5	16.3	31.8	55.0	62.9	71.1	85.9	91.9
Tacna	**Urban**	Line	1,044	11.45	17.17	22.90	3.70	6.23	10.71	42.24	8.36	10.87	15.40	17.74	20.52	29.70	39.64
		Rate		11.6	35.8	58.8	0.0	0.9	6.9	90.7	2.6	7.0	26.9	38.3	51.3	75.5	88.4
	Rural	Line	304	8.92	13.38	17.84	3.50	5.90	10.14	40.02	7.92	10.30	14.59	16.81	19.44	28.14	37.56
		Rate		25.4	51.5	66.5	0.8	7.7	31.4	96.7	17.9	32.0	54.3	63.3	71.1	91.6	96.0
	All	Line	1,348	11.14	16.71	22.28	3.67	6.19	10.64	41.97	8.31	10.80	15.30	17.63	20.39	29.51	39.38
		Rate		13.3	37.8	59.8	0.1	1.7	9.9	91.4	4.5	10.0	30.2	41.4	53.7	77.5	89.3

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

Figure 10 (Tumbes and Ucayali): Poverty lines and head-count poverty rates by urban/rural/all in 2019

Region/ Area		Line or Rate	*n*	Poverty lines and poverty rates														
				National			Intl. 2011 PPP				Percentile-based lines							
				100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
Tumbes	Urban	Line	678	11.50	17.25	23.00	3.45	5.80	9.97	39.35	7.79	10.13	14.34	16.53	19.12	27.67	36.93
		Rate		13.6	45.9	68.2	0.0	0.7	7.8	93.8	3.0	8.0	31.2	41.0	53.5	80.1	92.2
	Rural	Line	176	9.20	13.80	18.40	3.52	5.93	10.19	40.21	7.96	10.35	14.66	16.89	19.54	28.28	37.73
		Rate		16.4	36.9	67.2	0.0	3.5	22.1	98.0	10.8	23.4	43.3	57.3	72.2	94.3	97.4
	All	Line	854	11.43	17.14	22.85	3.45	5.81	9.98	39.38	7.80	10.14	14.35	16.54	19.13	27.69	36.95
		Rate		13.7	45.6	68.1	0.0	0.8	8.3	93.9	3.3	8.5	31.6	41.6	54.1	80.6	92.4
Ucayali	Urban	Line	810	10.82	16.22	21.63	4.01	6.75	11.60	45.78	9.06	11.78	16.69	19.23	22.24	32.19	42.96
		Rate		9.6	40.7	66.7	0.1	0.8	15.0	96.8	4.4	15.9	42.5	54.9	68.7	89.9	95.9
	Rural	Line	354	8.26	12.39	16.52	4.14	6.97	11.98	47.25	9.35	12.16	17.22	19.85	22.96	33.23	44.34
		Rate		24.2	62.7	85.5	1.5	16.6	60.4	99.9	33.2	61.2	89.0	94.8	97.4	99.7	99.9
	All	Line	1,164	10.34	15.52	20.69	4.03	6.79	11.67	46.05	9.12	11.85	16.79	19.34	22.37	32.38	43.22
		Rate		12.3	44.7	70.2	0.4	3.7	23.4	97.4	9.7	24.3	51.1	62.3	74.0	91.7	96.6

Source: 2019 ENAHO.

All poverty lines are PEN in prices in Metropolitan Lima on average during the 2019 ENAHO fieldwork.

Poverty rates are percentages.

3.2 Number of poor people in a single time period

Fulfilling a pro-poor mission depends not only on the *poverty rate* of in-coming participants but also on the *number* of poor in-coming participants. After all, a smaller program whose few participants have a higher poverty rate may serve fewer poor people than a larger program whose many participants have a lower poverty rate.[15]

The first step in estimating the number of poor people in one period is to estimate the number of household members in the population of in-coming households. In our two-household example with simple random sampling, this is the equal-weighted average of the number of people in the sampled households:

$$\frac{9+5}{1+1} = \frac{14}{2} = 7.0 \text{ people.}$$

The second step is to estimate the total number of people in the population of in-coming households. The example program has 1,000 in-coming households in its first year, each with an estimated 7.0 members. The estimated number of in-coming participants is then 1,000 · 7.0 = 7,000 people.

The third and final step is to multiply the estimated poverty rate (here, 67.4 percent, or 0.674) by the estimated number of people in in-coming households (here, 7,000). This gives 7,000 · 0.674 ≈ 4,721 people.

All else constant, the *number* of in-coming participants who are poor is more important than the *share* of in-coming participants who are poor. Both estimates are useful,[16] but increasing the share who are poor is only a means to the end of increasing the number who are poor.

In turn, increasing the number of in-coming participants who are poor is only a means to the end of increasing the net number of on-going participants who rise above a poverty line.

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[15] **Navajas *et al***. (2000).

[16] **Schreiner** (2014) tells how to report and analyze scorecard estimates.

3.3 Net changes in poverty rates across two time periods for on-going participants

The estimated net change in a population's poverty rate is the difference between estimated poverty rates at follow-up versus baseline.

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

- *One sample scored twice*: Score the same sample that was scored at baseline
- *Two independent samples*: Score a new sample from the same population that was scored at baseline

Given the scorecard's assumptions, both approaches are unbiased, but scoring one sample twice has smaller margins of error.

3.3.1 Net change in poverty rates with one sample scored twice

When the follow-up sample is made up of the same households as the baseline sample,[17] then the estimated annual net change in the poverty rate of the population of on-going participants is the average-household-size-weighted average of the change in each scored household's poverty likelihood, divided by the household-size-weighted average of the years between each household's interviews.[18]

Continuing our example, suppose that the first household at follow-up has eight members (rather than nine as at baseline) and is scored a second time on August 13, 2023, which is 1,156 days (about 3.17 years) after its first interview on June 13, 2020. Its score is now 22 (rather than 17), so its poverty likelihood for 100% of the national line has decreased from 81.2 to 68.9 percent (**Figure 1**).

Suppose also that the second household now has four members (rather than five as at baseline) and is scored a second time on May 15, 2023, which is 1,049 days (about 2.87 years) after its first interview on June 30, 2020. Its score is now 36 (rather than 33), so its poverty likelihood has decreased from 35.1 to 27.2 percent.

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[17] Or when the follow-up sample is a random sample of the baseline sample.

[18] Estimates of change do not directly adjust for the estimation error in snapshot estimates because—given the scorecard's assumptions—this error washes out when comparing follow-up with baseline. Error due to divergence from assumptions is unknown, and there is no direct way to adjust for it.

With poverty likelihoods expressed as proportions between 0 and 1, the average-household-size-weighted average of the change in each scored household's poverty likelihood is:

$$\frac{\left(\frac{9+8}{2}\right)\cdot(0.689-0.812\ )+\left(\frac{5+4}{2}\right)\cdot(0.272-0.351)}{\left(\frac{9+8}{2}\right)+\left(\frac{5+4}{2}\right)} \approx \frac{-1.046-0.356}{13} \approx -0.108 = -10.8 \text{ percentage points.}$$

The head-count poverty rate decreased (improved) by 10.8 percentage points (not by 10.8 percent) between baseline and follow-up.

For clarity—and because the time between interviews varies across scored households—this estimate should be annualized by dividing it by the average-household-size-weighted average of years between the two interviews:

$$\frac{\left(\frac{9+8}{2}\right)\cdot 3.17+\left(\frac{5+4}{2}\right)\cdot 2.87}{\left(\frac{9+8}{2}\right)+\left(\frac{5+4}{2}\right)} \approx \frac{26.92+12.91}{13} \approx 3.07 \text{ years.}$$

The annual, non-compounded rate of net change is then the percentage-point change in the poverty rate, divided by the average years between interviews: –10.8 ÷ 3.07 ≈ –3.5 percentage points per year.[19] The negative change means that poverty decreased.[20]

In practice, the calculations would be done with the **ProveIt™-brand reporting and analysis tool** or spreadsheet (**Figure 11**).

[19] *Percentage points* are distinct from *percentages* (or *percents*). On the one hand, if the baseline poverty rate is 50.0 percent, and if there is a *10.0-percent* annual reduction in the poverty rate, then the poverty rate after one year is 0.50·(1 – 0.10) = 0.450 = 45.0 percent, and the poverty rate after two years is 0.45·(1 – 0.10) = 0.405 = 40.5 percent. On the other hand, if there is a *10.0-percentage-point* annual reduction in poverty, then the rate after one year is 0.50 – 0.10 = 0.40 = 40 percent, and the rate after two years is 0.40 – 0.10 = 0.30 = 30 percent.

[20] Of course, such a large annual reduction in poverty is unrealistic, but this is just an example to show how the scorecard can be used to estimate change.

Figure 11: Spreadsheet calculation of estimated annual net change in a head-count poverty rate and in the annual net number of poor people who rose above a poverty line with one sample scored twice

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	ID of direct	Interview date		Years between	Number of household members			Member-years	Score		Poverty likelihood (%)		Estimated net change in
2	participant	Baseline	Follow-up	interviews	Baseline	Follow-up	Average	between	Baseline	Follow-up	Baseline	Follow-up	number of poor
3	1V0276FZ7	13-Jun-2020	13-Aug-2023	3.17 = (C3-B3)/365	9	8	8.50 = (E3+F3)/2	26.92 = D3*G3	17	22	81.2	68.9	-1.046 = G3*(L3-K3)/100
4	2W3120ZG8	30-Jun-2020	15-May-2023	2.87 = (C4-B4)/365	5	4	4.50 = (E4+F4)/2	12.93 = D4*G4	33	36	35.1	27.2	-0.356 = G4*(L4-K4)/100
5				**Average:**	7.0 = AVERAGE(E3:E4)	6.0 = AVERAGE(F3:F4)	**Sum:**	39.85 = SUM(H3:H4)					-1.401 = SUM(M3:M4)
6													
7						**Estimated net change in head-count poverty rate (percentage points), follow-up versus baseline:**							-10.8 = M5/(E5+F5)*100
8													
9								**Household-size-weighted average years between interviews:**					3.07 = H6/(E5+F5)
10													
11							**Estimated annual net change in head-count poverty rate (percentage points):**						-3.5 = M7/M9*100
12													
13									**Participating households at baseline:**				1,000
14									**Participating households at follow-up:**				700
15													
16								**Estimated average number of on-going participating people:**					5,600 = (E5*M13+F5*M14)/2
17													
18								**Estimated annual net change in the number of poor people:**					-197 = M16*M11/100
19	Rows of data are sorted by the ID of the direct participant.												

3.3.2 Annual net change in the number of poor people with one sample scored twice

For a pro-poor program, the bottom line is not the annual net change in the poverty rate but rather the annual net change in the number of poor participants who rise above a poverty line.

To calculate this, the first step is to estimate the average number of household members in the population of on-going households from baseline to follow-up, accounting for drop-out. In our example, the population of the in-coming households in the 2020 cohort was 1,000. By the end of the follow-up period of calendar-year 2023, 300 had dropped out, leaving 700. If drop-out took place at a constant pace and was unrelated to changes in poverty,[21] then an estimate of the average number of on-going participating people is the equal-weighted average of the number of participating people among households interviewed at baseline and

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[21] This assumption rarely holds. On the one hand, the households that benefit most from the program—and thus those for whom participation is most likely to cause a faster-than-otherwise decrease in poverty—may also be the least-likely to drop out, leading to too-high estimates of the reduction in poverty due to participation. On the other hand, households whose poverty decreases may be more likely to drop out because the benefits of continued participation fall as poverty decreases, leading to too-low estimates of impact. Unfortunately, there is no general way to adjust scorecard estimates to account for drop out that is related to changes in poverty. As in all decision-making, managers must use their experience and judgment to detect deviations from assumptions and then to adjust for them as best they can. This is true even though scorecard estimates are based on data and math. “Hard numbers” may not represent reality as accurately as they seem to, and only a manager’s knowledge of context can detect and adjust for this. Managers should discount unreliable estimates when they have reasoned, explicit arguments to do so (**Schreiner**, 2016a). Of course, discretion also opens the door to abuse; faced with unexpectedly low estimates of poverty reduction, managers might quietly sweep them under the rug or attribute them to a slow economy (even though they would not attribute high estimates of poverty reduction to a roaring economy). Ironically and sadly, such attempts to make a program look good by hiding or excusing undesired results destroys the results’ value as feedback, harming the program’s ability to fulfill its mission. If a program’s funders fail to act like owners, then its employees—not its participants—often become its *de facto* beneficiaries (**Schreiner**, 1997).

follow-up. In a given round, the number of participating people is the average household size for that round's interviewed households (in the example, 7.0 at baseline and 6.0 at follow-up), multiplied by the number of participating households in the population in the given round (1,000 at baseline and 700 at follow-up), divided by the number of survey rounds (two). This is $\frac{7.0 \cdot 1{,}000 + 6.0 \cdot 700}{1+1} = 5{,}600$ people.

The second and last step is to multiply the estimated annual change in the poverty rate (here, –3.5 percentage points, or –0.035) by the estimated average number of on-going participants (here, 5,600). This gives an annual net change in the number of poor people by 100% of the national line of –0.035·5,600 ≈ –197 people.[22] This negative change is a reduction (improvement) in poverty; there are 197 fewer poor people in participating households each year.

3.3.3 Estimating a program's impact

Estimating *change* is not the same as an estimating a program's *impact*. It stands to reason that program participation is a force that does cause some share of the reduction (or increase) in the poverty of its participants. At the same time, it is equally logical to expect that a large share of any change is caused by the many non-program forces that affect participants' lives. On its own, the scorecard is like a bathroom scale; it can tell whether you lost weight in the past month, but not how much of the loss is due to eating right and exercising versus removing your coat and shoes.

This point is often forgotten, confused, or ignored, so it bears repeating: the scorecard estimates change, but it does not—on its own—identify the causes of change. In particular, estimating the impact of program participation requires knowledge or assumptions about what would have happened to participants if they had not been participants. This must come from beyond the scorecard.

What is a program to do? All decision-making hinges on forecasts of the expected impacts of possible choices, so a program cannot pretend that merely estimating change is helpful without also inferring some impact. Yet there are diminishing returns to improving inferences of impact. At a minimum, a program should compare its estimated annual net change in the poverty rate of its on-going participants to third-party estimates for the country as a whole or for the region

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

where it works. A program can also look for signs that participants value (or expect to value) its services. Is the number of in-coming participants growing? Is the drop-out rate low? Are drop-outs due to dissatisfaction or graduation? Is participation voluntary, without being a condition for some other linked benefit? Is the program the sole provider in its niche and region?

In short, decision-makers in pro-poor programs are called to do what good decision-makers always do: triangulate and weigh data and knowledge from a number of angles and sources—including scorecard estimates, but not *only* scorecard estimates—to inform reasoned guesses as to more or less what share of observed changes are due to program participation. Of course, the inevitable need for human wisdom/art may be disingenuously invoked as a cover for decision processes that do not take a program's pro-poor mission to heart. This is why the "scientific method"—that is, being transparent about inputs and reasoning so as to facilitate the productive review and debate of a conclusion—makes sense even (or perhaps especially) for business problems.[23]

3.3.4 Net change in poverty rates with two independent samples

Instead of interviewing the same sample of households at both baseline and follow-up, a program could draw a second, independent sample of households from the same population as that from which the baseline sample was drawn.[24] The head-count poverty rate for on-going participants in this new follow-up sample is estimated in the same way as for the baseline sample.

Continuing our example, suppose that a third household and a fourth household are sampled at follow-up. The third household is interviewed on March 3, 2023. It has six members, a score of 27, and a poverty likelihood by 100% of the national line of 57.8 percent (**Figure 1**).

The fourth household is interviewed on April 4, 2023. It has seven members, a score of 34, and a poverty likelihood of 32.9 percent.

As at baseline, the estimated head-count poverty rate at follow-up is the household-size-weighted average of the poverty likelihoods of the sampled households: $\frac{6 \cdot 0.578 + 7 \cdot 0.329}{6+7} \approx \frac{3.47 + 2.30}{13} \approx 0.444 = 44.4$ percent.

[23] **Schreiner** (2016a) and **Schreiner** (2014).

[24] By chance, some households may end up in both samples.

The estimated annual net change in the head-count poverty rate of on-going participants is then the difference between the poverty-rate estimates at follow-up (44.4 percent) versus at baseline (64.7 percent),[25] divided by the difference (in years) between the household-size-weighted average of follow-up interview dates (March 19, 2023) versus the household-size-weighted average of baseline interview dates (June 21, 2020). These two average dates differ by about 1,001 days or 2.74 years.

The estimated annual net change in the head-count poverty rate is the difference between the poverty-rate estimates at follow-up versus baseline, divided by the difference in the average years between interviews in the two rounds. For 100% of the national line, this is (44.4 – 64.7) ÷ 2.74 ≈ –7.4 percentage points per year.

In practice, the calculations would be done in the **ProveIt™-brand reporting and analysis tool** or a spreadsheet (**Figure 12**).

[25] With two independent samples, the estimation error in each of the two snapshot estimates washes out, so it is not explicitly included in the calculation.

Figure 12: Spreadsheet calculation of estimated annual net change in a head-count poverty rate and in the annual net number of poor people who rise above a poverty line with two independent samples

	A	B	C	D	E	F	G
1	**Survey**	**ID of direct participant**	**Interview date**	**Number of household members**	**Score**	**Poverty likelihood (%)**	**Estimated number of poor household members**
2	Baseline	1V0276FZ7	13-Jun-2020	9	17	81.2	7.31 = D2*F2/100
3	Baseline	2W3120ZG8	30-Jun-2020	5	33	35.1	1.76 = D3*F3/100
4	Follow-up	3XA76T21L	3-Mar-2023	6	27	57.8	3.47 = D4*F4/100
5	Follow-up	4Y8Y3EQS9	4-Apr-2023	7	34	32.9	2.30 = D5*F5/100
6		**Sum baseline:**		14 = SUM(D2:D3)			9.06 = SUM(G2:G3)
7		**Sum follow-up:**		13 = SUM(D4:D5)			5.77 = SUM(G4:G5)
8		**Average baseline:**	21-Jun-2020 = AVERAGE(C2:C3)	7.0 = AVERAGE(D2:D3)			
9		**Average follow-up:**	19-Mar-2023 = AVERAGE(C4:C5)	6.5 = AVERAGE(D4:D5)			
10							
11						**Estimated baseline poverty rate (%):**	64.7 = G6/D6*100
12						**Estimated follow-up poverty rate (%):**	44.4 = G7/D7*100
13							
14						**Average years between follow-up and baseline interviews:**	2.74 = (C9-C8)/365
15							
16						**Estimated annual net change in head-count poverty rate (percentage points):**	-7.4 = (G12-G11)/G14
17							
18						**Participating households at baseline:**	1,000
19						**Participating households at follow-up:**	700
20							
21						**Estimated average number of on-going participating people:**	5,775 = (D8*G18+D9*G19)/2
22							
23						**Estimated annual net change in the number of poor people:**	-429 = G21*G16/100
24	Rows of data are sorted by Round, then by Interview date, then by Direct participant ID.						

3.3.5 Annual net change in the number of poor people with two independent samples

For a pro-poor program, the bottom line is not the annual net change in the poverty rate but rather the annual net change in the number of poor participants who rise above a poverty line.

To calculate this, the first step is to estimate the average number of household members in the population of on-going households from baseline to follow-up, accounting for drop-out. In our example, the population of the baseline 2020 cohort is 1,000 in-coming households. By the end of the follow-up period 2023, 300 dropped out, leaving 700. If drop-out took place at a constant pace and was unrelated to changes in poverty, then an estimate of the average number of on-going participating people is the equal-weighted average of the number of participating people among households interviewed at baseline and follow-up. In a given round, the number of participating people is the average household size for that round's interviewed households (in our example, 7.0 at baseline and 6.5 at follow-up), multiplied by the number of participating households in the population in the given round (1,000 at baseline and 700 at follow-up), and divided by two (the number of rounds). This is $\frac{7.0 \cdot 1{,}000 + 6.5 \cdot 700}{1+1} = 5{,}775$ people.

The second and last step is to multiply the estimated annual net change in the head-count poverty rate (here, –7.4 percentage points, or –0.074) by the estimated number of on-going participants (here, 5,775). For 100% of the national line, this gives an annual net change in the number of poor people of –0.074·5,775 ≈ –429 people. This negative change is a (non-compounded) reduction in poverty; the number of poor people in participating households decreases (improves) by 429 each year.

Given the scorecard's assumptions, both approaches to estimating change over time—one sample scored twice, and two independent samples—are unbiased. In general, the two approaches give different estimates (as in this example) because they interview different households at different times. All else constant, scoring one sample twice has smaller margins of error, but there may be context-specific reasons (related to costs or non-sampling errors) to score two independent samples.

4. How to design scorecard surveys and samples

To design a scorecard survey and its sample, a program must decide:[26]

- Who will do interviews
- Where and how to do interviews
- How to record responses and scores
- How to calculate estimates and report/analyze them
- Which participating households to interview
- How many participating households to interview
- How frequently to do surveys
- Whether to track a population across multiple time periods
- Whether to interview the same participants twice

Decisions should follow from the program's goals, the business problems to be addressed, and the budget. The central goals of the design are to:

- Inform issues that matter to the program
- Make sure that the sample is representative of a well-defined population

4.1 Who will do interviews

The enumerators who interview participating households must be trained to follow the "**Interview Guide**". Enumerators may be:

- Program employees
- Contractors

4.2 Where and how to do interviews

Interviews should be:

- In-person, and
- At the sampled household's residence, and
- With an enumerator trained to follow the "**Interview Guide**"

This is the only recommended way. It follows Peru's INEI in the 2019 ENAHO, so it provides the most-accurate and most-consistent data (and thus the best estimates).

[26] **IRIS Center** (2007) and **Toohig** (2008) also discuss this topic, covering sampling, budgeting, training, logistics, interviewing, piloting, and recording data.

Of course, it is possible to do interviews in non-recommended ways such as:

- Without an enumerator (such as by asking respondents to fill out paper or web forms on their own or to answer questions sent via e-mail, texts, or robo-calls)
- Away from home (such as a program's service point or a local meeting place)
- Not in-person (such as with an enumerator by phone)

While non-recommended methods may reduce costs, they also affect responses[27] and thus reduce the accuracy of estimates. This is why interviewing by a trained enumerator at the residence is recommended.

In some contexts—such as when a program's field agents do not already visit participants at home anyway as part of their normal work—a program might be willing to trade accuracy for a lower-cost, non-recommended approach. The business wisdom of this depends on context-specific factors that each program must judge for itself. To judge carefully, a program that is considering a non-recommended method should do a small test to see how responses differ versus with a trained enumerator at the residence. Furthermore, all reporting should discuss the possible consequences of using a non-recommended method.

4.3 How to record responses and scores

Responses and scores can be recorded by enumerators on:

- Paper, and then keyed into a database or spreadsheet at an office
- **Mobile devices**, and then uploaded to a database[28]

4.4 How to calculate estimates and report/analyze them

Analysts can calculate estimates by plugging data into spreadsheets (following the examples in Section 3) or with the **ProveIt™-brand reporting and analysis tool**. **Schreiner** (2014) describes how to report and analyze scorecard estimates.

[27] **Schreiner**, 2015.

[28] **Scorocs** can help set up a system to collect data with mobile devices or to transfer data from paper forms into a database at the office. Support is also available for calculating estimates as well as for reporting and analysis.

4.5 Which participating households to interview

Given a population relevant for a particular business question, the participating households to be interviewed can be:

- All relevant participants (a census)
- A representative sample of relevant participants
- All relevant participants in a representative sample of relevant service points and/or in a representative sample of relevant field agents
- A representative sample of relevant participants in a representative sample of relevant service points and/or in a representative sample of relevant field agents

A census is rarely necessary, except for very small programs. Nevertheless, it may be easier to interview all in-coming households as a standard part of in-take rather than managing who gets scored and who does not.

4.6 How many participating households to interview

If not determined by other factors, the number of participating households to interview can be derived from sample-size formulas to achieve a desired confidence level for a desired margin of error (**Annex 6**).

The focus of sample design, however, should be less on having enough interviews to achieve some arbitrary level of statistical significance and more on having a representative sample from a well-defined population that is relevant for informing business questions that matter to the program.

In practice, non-sampling errors in implementation and in the definition of the population often matter at least as much as errors due to smaller samples. Program managers sometimes are too concerned about sample size, as there is no point in deriving the ideal sample size unless just as much effort goes to mitigating other sources of error and then accounting for margins of error in the analysis stage. Of course, smaller samples produce less-reliable estimates. In practice, however, almost no one reports or considers margins of error (even though they should), and estimates derived from at least 1,000 interviews will rarely raise eyebrows (**Annex 6**).

4.7 How frequently to do surveys

The frequency of scorecard surveys can be:

- As a once-off project (precluding estimating change)
- Every three years (or at any other fixed or variable time interval, allowing estimating change)
- Each time a field agent visits a participant at home (allowing estimating change)

4.8 Whether to track a population across periods

The scorecard can estimate changes in poverty across periods, but not all programs want to do this. Many programs want to check poverty only for in-coming participants.

4.9 Whether to interview the same participants twice

If a scorecard is applied more than once in order to estimate changes in poverty, then it can be applied with:

- One sample of participants, all of whom are scored at both baseline and follow-up
- Two samples of participants from the same population, with the first sample scored at baseline and the second sample scored at follow-up.

Scoring one sample twice gives estimates with smaller margins of error. It may also be less costly at follow-up, given that the households have already been tracked down at home at baseline. Furthermore, the follow-up round could be based on a random sample of the households interviewed at baseline.

4.10 Survey design and implementation in Bangladesh

An example set of choices is illustrated by the microfinance arms of BRAC and ASA, two pro-poor titans in Bangladesh who each have about 7 million participating households and who made plans to apply the scorecard for Bangladesh[29] with a sample of about 25,000 participants each.

Their design is that all loan officers in a random sample of branches score all participants each time the loan officers visit a homestead (about once a year) as part of their standard due diligence prior to loan disbursement. The loan officers record responses on paper in the field before sending the forms to a central office to be entered into a database and converted to poverty likelihoods for further analysis.

[29] **Schreiner**, 2013.

5. How to use scores for targeting

When a program uses the scorecard for segmenting (*targeting*) participants for differentiated treatment based on poverty, people in households with scores at or below a cut-off are labeled *targeted* and given one type of treatment. People in households with scores above a cut-off are labeled *non-targeted* and given another type of treatment.[30]

Households that score at or below a given cut-off should be labeled as *targeted*,[31] not as *poor*.[32]

Targeting is successful to the extent to which people truly below a poverty line are targeted (*inclusion*) or people truly above a poverty line are not targeted (*exclusion*). Of course, no poverty-assessment tool is perfect, and targeting is unsuccessful to the extent to which people truly below a poverty line are not targeted (*undercoverage*) or people truly above a poverty line are targeted (*leakage*).

Figure 13 below depicts these four possible targeting outcomes. Targeting accuracy varies by the cut-off score. A higher cut-off has better inclusion and better undercoverage (but worse exclusion and worse leakage). In contrast, a lower cut-off has worse inclusion and worse undercoverage (but better exclusion and better leakage).

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[30] *Targeting status* (having a score at or below a targeting cut-off) is not the same concept as *poverty status* (having consumption below a poverty line). Poverty status is a fact that is defined by 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.

[31] Other labels can be meaningful as long as they describe the segment and do not confuse targeting status (having a score below a program-selected cut-off) with poverty status (having consumption below an externally-defined poverty line). Examples include: *Groups A, B, and C*; *People with scores of 29 or less, 30 to 69, or 70 or more*; and *People that qualify for reduced fees, or that do not qualify*.

[32] After all, unless all targeted households have poverty likelihoods of 100 percent, it is likely that some of them are non-poor (their consumption is above a given poverty line). In the context of the scorecard, the terms *poor* and *non-poor* have specific definitions. Using these same terms for targeting status is incorrect and misleading.

Figure 13: Possible targeting outcomes

		Targeting segment	
		Targeted	**Non-targeted**
Observed poverty status	**Poor**	**Inclusion** Poor correctly targeted	**Undercoverage** Poor mistakenly not targeted
	Non-poor	**Leakage** Non-poor mistakenly targeted	**Exclusion** Non-poor correctly not targeted

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 the sum of net benefits.[33]

The five tables below show the scorecard's targeting outcomes by poverty line and by score cut-off for people in Peru:

- **Figure 14:** Inclusion (% people who are poor and correctly targeted)
- **Figure 15:** Undercoverage (% of people who are poor but mistakenly not targeted)
- **Figure 16:** Leakage (% people who are not poor but mistakenly targeted)
- **Figure 17:** Exclusion (% people who are not poor and correctly not targeted)
- **Figure 18:** Hit rate (% people correctly targeted, that is, inclusion plus exclusion)

For a given score cut-off, each of the five figures below also show the share of all people who are targeted.

[33] Adams and Hand, 2000; Hoadley and Oliver, 1998.

Figure 14: Inclusion (% people who are poor and correctly targeted)

Targeting cut-off	% all people who are targeted	Inclusion (%)													
		National			Intl. 2011 PPP				Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	2.4	3.0	3.1	0.2	1.2	2.6	3.1	2.0	2.6	3.1	3.1	3.1	3.1	3.1
<=22	5.9	4.3	5.6	5.8	0.3	1.9	4.7	5.9	3.4	4.8	5.7	5.8	5.8	5.9	5.9
<=25	9.3	6.5	8.7	9.2	0.4	2.4	6.9	9.3	4.9	7.0	8.8	9.0	9.2	9.3	9.3
<=27	12.8	8.5	11.8	12.6	0.4	2.8	8.8	12.8	6.0	9.0	11.7	12.2	12.5	12.8	12.8
<=29	15.9	10.0	14.5	15.7	0.4	3.1	10.5	15.9	6.9	10.7	14.5	15.1	15.6	15.9	15.9
<=31	20.5	12.0	18.4	20.1	0.4	3.2	12.5	20.5	7.7	12.8	18.0	19.3	20.0	20.4	20.5
<=33	24.1	13.1	21.2	23.6	0.4	3.4	13.7	24.1	8.3	14.0	20.6	22.4	23.4	24.1	24.1
<=35	29.4	14.8	25.2	28.6	0.4	3.4	15.1	29.4	8.8	15.5	23.9	26.6	28.0	29.2	29.4
<=37	33.3	15.7	27.9	32.1	0.4	3.5	16.0	33.3	9.1	16.5	26.4	29.5	31.3	33.1	33.3
<=39	39.2	16.9	31.8	37.2	0.4	3.6	16.9	39.1	9.4	17.5	29.5	33.6	36.2	38.8	39.1
<=41	43.3	17.7	34.3	40.5	0.4	3.6	17.4	43.2	9.5	18.1	31.5	36.4	39.3	42.6	43.2
<=43	48.5	18.3	36.7	44.3	0.4	3.6	18.0	48.4	9.6	18.7	33.5	39.1	42.8	47.1	48.3
<=45	53.2	18.7	38.7	47.8	0.4	3.6	18.3	53.0	9.8	19.0	35.1	41.3	45.8	51.4	52.9
<=47	58.4	19.1	40.4	51.2	0.4	3.6	18.6	58.0	9.8	19.3	36.2	42.8	48.5	55.8	57.8
<=49	62.2	19.3	41.9	53.9	0.4	3.6	18.8	61.7	9.9	19.5	37.3	44.4	50.7	59.1	61.4
<=51	67.4	19.7	43.4	57.0	0.4	3.6	18.9	66.8	9.9	19.7	38.3	46.0	53.1	63.2	66.5
<=53	71.0	19.7	44.2	58.9	0.4	3.6	19.0	70.1	10.0	19.8	38.6	46.9	54.4	65.9	69.8
<=55	75.4	19.9	45.0	60.9	0.4	3.6	19.1	74.1	10.0	19.9	39.1	47.7	55.9	69.1	73.6
<=57	79.1	19.9	46.0	62.6	0.4	3.6	19.1	77.5	10.0	19.9	39.5	48.7	57.2	71.6	76.9
<=100	100.0	20.0	47.0	66.6	0.4	3.6	19.2	91.5	10.0	20.0	40.0	49.7	59.5	79.5	89.9

Scorecard applied to the validation sample.

Figure 15: Undercoverage (% of people who are poor but mistakenly not targeted)

Targeting cut-off	% all people who are targeted	Undercoverage (%)														
		National			Intl. 2011 PPP				Percentile-based lines							
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th	
<=19	3.1	17.6	44.0	63.5	0.2	2.4	16.6	88.4	8.1	17.4	36.9	46.6	56.4	76.4	86.8	
<=22	5.9	15.7	41.3	60.7	0.1	1.7	14.5	85.6	6.6	15.3	34.2	43.9	53.7	73.7	84.1	
<=25	9.3	13.5	38.3	57.4	0.0	1.2	12.3	82.2	5.2	13.0	31.2	40.7	50.3	70.2	80.6	
<=27	12.8	11.5	35.2	53.9	0.0	0.8	10.3	78.7	4.0	11.0	28.2	37.5	47.0	66.7	77.1	
<=29	15.9	10.0	32.4	50.9	0.0	0.6	8.7	75.5	3.1	9.3	25.5	34.6	43.9	63.6	74.0	
<=31	20.5	8.0	28.6	46.4	0.0	0.4	6.7	71.0	2.3	7.2	22.0	30.4	39.5	59.1	69.4	
<=33	24.1	6.9	25.8	43.0	0.0	0.3	5.5	67.3	1.7	6.0	19.3	27.3	36.2	55.5	65.8	
<=35	29.4	5.2	21.8	38.0	0.0	0.2	4.1	62.1	1.3	4.5	16.0	23.1	31.6	50.3	60.5	
<=37	33.3	4.4	19.1	34.5	0.0	0.1	3.2	58.1	0.9	3.5	13.6	20.2	28.2	46.4	56.6	
<=39	39.2	3.1	15.2	29.4	0.0	0.1	2.3	52.3	0.6	2.5	10.5	16.1	23.3	40.8	50.8	
<=41	43.3	2.3	12.7	26.1	0.0	0.0	1.7	48.2	0.5	1.9	8.4	13.3	20.2	36.9	46.7	
<=43	48.5	1.7	10.3	22.2	0.0	0.0	1.2	43.1	0.4	1.3	6.4	10.6	16.7	32.4	41.6	
<=45	53.2	1.3	8.3	18.8	0.0	0.0	0.9	38.4	0.2	1.0	4.8	8.4	13.8	28.1	37.0	
<=47	58.4	0.9	6.6	15.4	0.0	0.0	0.6	33.4	0.2	0.7	3.8	6.9	11.0	23.8	32.1	
<=49	62.2	0.7	5.1	12.7	0.0	0.0	0.4	29.8	0.1	0.5	2.6	5.3	8.8	20.4	28.5	
<=51	67.4	0.3	3.6	9.6	0.0	0.0	0.3	24.7	0.1	0.3	1.7	3.7	6.5	16.3	23.5	
<=53	71.0	0.3	2.8	7.7	0.0	0.0	0.2	21.3	0.1	0.2	1.3	2.8	5.1	13.6	20.2	
<=55	75.4	0.1	2.0	5.7	0.0	0.0	0.1	17.4	0.0	0.1	0.8	2.0	3.6	10.5	16.3	
<=57	79.1	0.1	1.0	3.9	0.0	0.0	0.1	13.9	0.0	0.1	0.4	1.0	2.3	7.9	13.0	
<=100	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

Scorecard applied to the validation sample.

Figure 16: Leakage (% people who are not poor but mistakenly targeted)

Targeting cut-off	% all people who are targeted	Leakage (%)													
		National			Intl. 2011 PPP				Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	0.7	0.1	0.0	2.9	1.9	0.5	0.0	1.2	0.5	0.0	0.0	0.0	0.0	0.0
<=22	5.9	1.5	0.2	0.0	5.5	3.9	1.2	0.0	2.5	1.1	0.1	0.0	0.0	0.0	0.0
<=25	9.3	2.7	0.6	0.1	8.9	6.9	2.4	0.0	4.4	2.3	0.5	0.3	0.1	0.0	0.0
<=27	12.8	4.3	1.0	0.2	12.4	9.9	3.9	0.0	6.8	3.8	1.0	0.6	0.3	0.0	0.0
<=29	15.9	6.0	1.4	0.2	15.5	12.9	5.4	0.0	9.0	5.2	1.4	0.8	0.3	0.0	0.0
<=31	20.5	8.5	2.1	0.3	20.1	17.2	8.0	0.0	12.8	7.7	2.5	1.2	0.5	0.0	0.0
<=33	24.1	11.0	2.9	0.6	23.7	20.8	10.5	0.0	15.8	10.1	3.5	1.8	0.8	0.1	0.0
<=35	29.4	14.6	4.2	0.8	29.0	26.0	14.3	0.0	20.7	13.9	5.5	2.8	1.5	0.2	0.0
<=37	33.3	17.7	5.4	1.2	32.9	29.8	17.4	0.0	24.2	16.9	7.0	3.8	2.0	0.2	0.0
<=39	39.2	22.3	7.4	2.0	38.8	35.6	22.3	0.1	29.8	21.7	9.7	5.6	3.0	0.4	0.1
<=41	43.3	25.7	9.1	2.8	42.9	39.7	25.9	0.1	33.8	25.2	11.8	7.0	4.0	0.7	0.2
<=43	48.5	30.2	11.8	4.2	48.1	44.9	30.5	0.1	38.9	29.8	15.0	9.4	5.7	1.4	0.2
<=45	53.2	34.5	14.6	5.4	52.8	49.6	34.9	0.2	43.5	34.2	18.1	12.0	7.5	1.8	0.4
<=47	58.4	39.3	18.0	7.2	58.0	54.8	39.8	0.4	48.6	39.1	22.2	15.6	9.9	2.7	0.6
<=49	62.2	42.8	20.3	8.3	61.8	58.5	43.4	0.5	52.3	42.6	24.9	17.8	11.5	3.1	0.7
<=51	67.4	47.7	24.0	10.4	67.0	63.8	48.5	0.6	57.5	47.7	29.1	21.4	14.3	4.2	0.9
<=53	71.0	51.3	26.9	12.2	70.6	67.4	52.0	0.9	61.1	51.3	32.4	24.2	16.6	5.1	1.3
<=55	75.4	55.5	30.4	14.5	75.0	71.7	56.3	1.3	65.4	55.4	36.2	27.7	19.5	6.3	1.7
<=57	79.1	59.2	33.1	16.5	78.7	75.5	60.0	1.6	69.1	59.2	39.6	30.5	21.9	7.5	2.2
<=100	100.0	80.0	53.0	33.4	99.6	96.4	80.8	8.5	90.0	80.0	60.0	50.3	40.5	20.5	10.1

Scorecard applied to the validation sample.

Figure 17: Exclusion (% people who are not poor and correctly not targeted)

Targeting cut-off	% all people who are targeted	Exclusion (%)													
		National			Intl. 2011 PPP				Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	79.3	52.9	33.4	96.7	94.5	80.3	8.5	88.8	79.5	60.0	50.3	40.5	20.5	10.1
<=22	5.9	78.4	52.8	33.4	94.1	92.4	79.7	8.5	87.5	78.9	59.9	50.3	40.5	20.5	10.1
<=25	9.3	77.2	52.4	33.3	90.7	89.5	78.5	8.5	85.6	77.7	59.6	50.0	40.4	20.5	10.1
<=27	12.8	75.7	52.0	33.3	87.2	86.4	76.9	8.5	83.2	76.2	59.0	49.7	40.2	20.5	10.1
<=29	15.9	74.0	51.6	33.2	84.1	83.5	75.4	8.5	81.0	74.8	58.6	49.5	40.1	20.5	10.1
<=31	20.5	71.5	50.9	33.1	79.5	79.1	72.8	8.5	77.2	72.3	57.5	49.1	40.0	20.5	10.1
<=33	24.1	69.0	50.1	32.9	75.9	75.6	70.4	8.5	74.2	69.9	56.5	48.5	39.7	20.4	10.1
<=35	29.4	65.4	48.8	32.6	70.6	70.4	66.5	8.5	69.3	66.1	54.6	47.5	39.0	20.3	10.1
<=37	33.3	62.3	47.6	32.2	66.7	66.6	63.4	8.5	65.8	63.1	53.1	46.5	38.5	20.3	10.1
<=39	39.2	57.7	45.6	31.4	60.8	60.7	58.5	8.5	60.2	58.3	50.3	44.7	37.5	20.0	10.0
<=41	43.3	54.3	44.0	30.6	56.7	56.6	54.9	8.4	56.2	54.8	48.2	43.3	36.4	19.8	9.9
<=43	48.5	49.8	41.2	29.3	51.5	51.5	50.3	8.4	51.1	50.2	45.1	40.9	34.8	19.1	9.9
<=45	53.2	45.5	38.5	28.0	46.8	46.7	45.9	8.3	46.5	45.8	41.9	38.3	33.0	18.6	9.7
<=47	58.4	40.7	35.0	26.2	41.6	41.6	41.0	8.1	41.4	40.9	37.8	34.7	30.6	17.8	9.5
<=49	62.2	37.1	32.7	25.1	37.8	37.8	37.4	8.1	37.7	37.4	35.2	32.5	29.0	17.4	9.3
<=51	67.4	32.3	29.0	23.0	32.6	32.6	32.3	7.9	32.5	32.3	30.9	28.9	26.1	16.3	9.1
<=53	71.0	28.7	26.1	21.3	29.0	28.9	28.8	7.6	28.9	28.7	27.6	26.1	23.9	15.3	8.8
<=55	75.4	24.5	22.6	18.9	24.6	24.6	24.5	7.3	24.6	24.6	23.8	22.6	21.0	14.2	8.4
<=57	79.1	20.8	19.9	17.0	20.9	20.9	20.8	6.9	20.9	20.8	20.5	19.8	18.6	13.0	7.9
<=100	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Scorecard applied to the validation sample.

Figure 18: Hit rate (% people correctly targeted, that is, inclusion plus exclusion)

Targeting cut-off	% all people who are targeted	Hit rate (= Inclusion + Exclusion) (%)													
		National			Intl. 2011 PPP				Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	81.7	55.9	36.5	97.0	95.7	82.9	11.6	90.8	82.1	63.1	53.4	43.6	23.6	13.2
<=22	5.9	82.8	58.4	39.2	94.4	94.3	84.4	14.4	90.9	83.6	65.7	56.1	46.3	26.3	15.9
<=25	9.3	83.8	61.2	42.5	91.0	91.9	85.4	17.8	90.4	84.7	68.3	59.1	49.6	29.7	19.4
<=27	12.8	84.1	63.8	45.9	87.6	89.2	85.7	21.3	89.2	85.2	70.8	61.9	52.8	33.3	22.9
<=29	15.9	84.0	66.2	48.9	84.4	86.5	85.9	24.5	87.9	85.5	73.1	64.6	55.7	36.4	26.0
<=31	20.5	83.5	69.3	53.2	79.9	82.3	85.3	29.0	84.9	85.1	75.5	68.3	60.0	40.9	30.6
<=33	24.1	82.1	71.3	56.5	76.2	79.0	84.0	32.7	82.5	83.9	77.2	70.9	63.1	44.4	34.2
<=35	29.4	80.1	74.0	61.2	71.0	73.8	81.6	37.9	78.1	81.6	78.5	74.1	67.0	49.5	39.5
<=37	33.3	78.0	75.5	64.3	67.0	70.1	79.4	41.8	74.9	79.6	79.4	76.0	69.8	53.4	43.4
<=39	39.2	74.6	77.4	68.6	61.2	64.3	75.3	47.6	69.6	75.8	79.8	78.3	73.6	58.8	49.1
<=41	43.3	72.0	78.2	71.1	57.1	60.2	72.4	51.7	65.7	72.9	79.8	79.7	75.7	62.4	53.1
<=43	48.5	68.1	77.8	73.6	51.9	55.1	68.2	56.8	60.7	68.8	78.6	80.0	77.6	66.2	58.2
<=45	53.2	64.2	77.1	75.8	47.2	50.4	64.2	61.3	56.3	64.8	77.1	79.6	78.8	70.1	62.6
<=47	58.4	59.7	75.4	77.4	42.0	45.2	59.6	66.2	51.2	60.2	74.0	77.6	79.2	73.6	67.3
<=49	62.2	56.5	74.6	79.0	38.2	41.5	56.2	69.8	47.6	56.9	72.5	76.9	79.7	76.5	70.8
<=51	67.4	52.0	72.3	80.0	33.0	36.2	51.2	74.7	42.4	52.0	69.2	75.0	79.2	79.5	75.6
<=53	71.0	48.4	70.3	80.2	29.4	32.6	47.8	77.8	38.8	48.5	66.2	73.0	78.3	81.2	78.5
<=55	75.4	44.4	67.6	79.8	25.0	28.3	43.7	81.4	34.6	44.5	62.9	70.4	76.9	83.2	82.0
<=57	79.1	40.7	65.9	79.6	21.3	24.5	40.0	84.5	30.9	40.8	60.0	68.5	75.8	84.6	84.8
<=100	100.0	20.0	47.0	66.6	0.4	3.6	19.2	91.5	10.0	20.0	40.0	49.7	59.5	79.5	89.9

Scorecard applied to the validation sample.

For an example cut-off of 31 or less and referring to the previous figures, 20.5 percent of all people are targeted, and outcomes for 100% of the national line in the validation sample are:

- Inclusion: 12.0 percent are below the line and correctly targeted
- Undercoverage: 8.0 percent are below the line and mistakenly not targeted
- Leakage: 8.5 percent are above the line and mistakenly targeted
- Exclusion: 71.5 percent are above the line and correctly not targeted

Increasing the cut-off to 33 or less changes the share of of all people targeted to 24.1 percent. Raising the cut-off improves inclusion and undercoverage but worsens leakage and exclusion:

- Inclusion: 13.1 percent are below the line and correctly targeted
- Undercoverage: 6.9 percent are below the line and mistakenly not targeted
- Leakage: 11.0 percent are above the line and mistakenly targeted
- Exclusion: 69.0 percent are above the line and correctly not targeted

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

Benefit per person correctly included	x	People correctly included	–
Cost per person mistakenly not covered	x	People mistakenly not covered	–
Cost per person mistakenly leaked	x	People mistakenly leaked	+
Benefit per person correctly excluded	x	People 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 the figures above for a chosen 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 pro-poor program that uses targeting—with or without the scorecard—should thoughtfully consider how it values successful inclusion and exclusion versus errors of undercoverage and leakage. It is healthy to go through a process of thinking explicitly and intentionally about how targeting outcomes are valued.

A common choice of benefits and costs is the *hit rate*, where total net benefit is the number of people correctly included or correctly excluded:

Hit rate =	1	x	People correctly included	–
	0	x	People mistakenly undercovered	–
	0	x	People mistakenly leaked	+
	1	x	People correctly excluded.	

Figure 18 shows the scorecard's hit rate for all cut-offs and poverty lines. For the example of 100% of the national line in the validation sample, total net benefit under the hit rate for a cut-off of 31 or less is 83.5 percent. Among the 20.5 percent of all Peruvians targeted, about five in six people are correctly classified.

The hit rate weighs successful inclusion of people below a poverty line the same as successful exclusion of people above the line. If a program values inclusion more (say, twice as much) than exclusion, then it can reflect this by setting the benefit for inclusion to 2 and the benefit for exclusion to 1. Then the chosen cut-off will maximize (2 x people correctly included) + (1 x people correctly excluded).

As an alternative to assigning benefits and costs to targeting outcomes and then setting a score cut-off to maximize net benefits, a pro-poor program could set cut-offs based on aspects of targeting accuracy from the three figures below:

- **Figure 19:** Share of targeted people who are poor
- **Figure 20:** Poor people correctly targeted per non-poor person mistakenly targeted
- **Figure 21:** Share of poor people who are targeted

Figure 19: Share of targeted people who are poor

Targeting cut-off	% all people who are targeted	% targeted people who are poor																
		National			Intl. 2011 PPP							Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$8.00	$11.00	$15.00	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	78.1	96.6	100.0	7.9	38.9	84.3	99.1	100.0	100.0	100.0	62.9	84.6	99.1	100.0	100.0	100.0	100.0
<=22	5.9	73.7	96.1	99.4	5.6	32.8	80.3	98.0	99.6	100.0	100.0	58.0	81.1	98.0	99.6	99.6	100.0	100.0
<=25	9.3	70.5	93.8	99.0	3.9	26.1	74.6	94.7	99.2	99.9	100.0	52.2	75.2	94.7	97.3	98.9	99.9	100.0
<=27	12.8	66.2	92.3	98.8	3.0	22.2	69.2	91.9	98.3	99.9	100.0	47.1	70.4	91.8	95.5	97.9	99.9	100.0
<=29	15.9	62.6	91.3	98.6	2.4	19.2	66.0	91.0	98.3	100.0	100.0	43.4	67.1	90.9	95.0	97.9	100.0	100.0
<=31	20.5	58.5	89.9	98.4	1.9	15.7	61.0	88.2	98.2	99.9	100.0	37.6	62.5	87.8	94.1	97.6	99.9	100.0
<=33	24.1	54.4	87.9	97.7	1.6	14.0	56.7	86.0	97.5	99.7	100.0	34.6	58.1	85.4	92.7	96.7	99.7	100.0
<=35	29.4	50.3	85.6	97.1	1.3	11.7	51.3	82.4	96.2	99.3	100.0	29.8	52.7	81.4	90.5	95.0	99.4	99.9
<=37	33.3	47.0	83.7	96.3	1.2	10.6	47.8	79.9	95.3	99.2	99.9	27.4	49.4	79.1	88.6	94.0	99.3	99.9
<=39	39.2	43.1	81.1	94.9	1.0	9.2	43.0	76.2	93.6	98.8	99.8	23.9	44.6	75.2	85.8	92.3	98.9	99.7
<=41	43.3	40.8	79.1	93.5	0.9	8.3	40.3	73.7	92.1	98.3	99.8	22.0	41.8	72.8	83.9	90.7	98.4	99.7
<=43	48.5	37.8	75.6	91.4	0.8	7.5	37.0	70.2	89.9	96.8	99.7	19.8	38.5	69.1	80.6	88.3	97.1	99.6
<=45	53.2	35.2	72.6	89.8	0.8	6.8	34.4	67.2	87.9	96.3	99.6	18.3	35.7	66.0	77.5	85.9	96.6	99.3
<=47	58.4	32.7	69.1	87.6	0.7	6.2	31.8	63.1	85.3	95.1	99.3	16.8	33.1	62.0	73.4	83.1	95.4	98.9
<=49	62.2	31.1	67.3	86.7	0.6	5.9	30.2	61.2	83.9	94.7	99.2	15.9	31.4	60.0	71.4	81.5	95.0	98.8
<=51	67.4	29.2	64.3	84.6	0.6	5.4	28.1	57.8	81.2	93.4	99.1	14.7	29.2	56.8	68.3	78.7	93.8	98.6
<=53	71.0	27.8	62.1	82.9	0.6	5.1	26.8	55.4	79.1	92.3	98.7	14.0	27.9	54.4	66.0	76.6	92.8	98.2
<=55	75.4	26.4	59.7	80.8	0.5	4.8	25.3	53.0	76.8	91.1	98.3	13.3	26.4	51.9	63.3	74.1	91.6	97.7
<=57	79.1	25.2	58.1	79.2	0.5	4.6	24.2	51.1	75.0	90.0	98.0	12.7	25.2	50.0	61.5	72.3	90.5	97.2
<=100	100.0	20.0	47.0	66.6	0.4	3.6	19.2	40.8	62.2	78.9	91.5	10.0	20.0	40.0	49.7	59.5	79.5	89.9

Scorecard applied to the validation sample.

Figure 20: Poor people correctly targeted per non-poor person mistakenly targeted

Targeting cut-off	% all people who are targeted	Poor people targeted per non-poor person targeted													
		National			Intl. 2011 PPP				Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	3.6:1	28.6:1	All poor	0.1:1	0.6:1	5.4:1	All poor	1.7:1	5.5:1	111.5:1	All poor	All poor	All poor	All poor
<=22	5.9	2.8:1	24.6:1	167.6:1	0.1:1	0.5:1	4.1:1	All poor	1.4:1	4.3:1	48.4:1	222.5:1	222.5:1	All poor	All poor
<=25	9.3	2.4:1	15.1:1	102.6:1	0.0:1	0.4:1	2.9:1	All poor	1.1:1	3.0:1	17.8:1	36.1:1	90.1:1	1,222.6:1	All poor
<=27	12.8	2.0:1	12.0:1	81.7:1	0.0:1	0.3:1	2.2:1	All poor	0.9:1	2.4:1	11.3:1	21.3:1	47.6:1	1,684.5:1	All poor
<=29	15.9	1.7:1	10.5:1	70.5:1	0.0:1	0.2:1	1.9:1	All poor	0.8:1	2.0:1	10.0:1	19.1:1	45.7:1	2,098.4:1	All poor
<=31	20.5	1.4:1	8.9:1	60.4:1	0.0:1	0.2:1	1.6:1	All poor	0.6:1	1.7:1	7.2:1	15.9:1	40.0:1	792.7:1	All poor
<=33	24.1	1.2:1	7.3:1	42.4:1	0.0:1	0.2:1	1.3:1	4,338.2:1	0.5:1	1.4:1	5.9:1	12.7:1	29.6:1	286.3:1	4,338.2:1
<=35	29.4	1.0:1	6.0:1	34.1:1	0.0:1	0.1:1	1.1:1	2,950.2:1	0.4:1	1.1:1	4.4:1	9.6:1	19.1:1	161.8:1	1,731.6:1
<=37	33.3	0.9:1	5.1:1	26.0:1	0.0:1	0.1:1	0.9:1	1,619.7:1	0.4:1	1.0:1	3.8:1	7.7:1	15.7:1	146.7:1	1,126.3:1
<=39	39.2	0.8:1	4.3:1	18.5:1	0.0:1	0.1:1	0.8:1	575.9:1	0.3:1	0.8:1	3.0:1	6.0:1	11.9:1	86.6:1	371.1:1
<=41	43.3	0.7:1	3.8:1	14.4:1	0.0:1	0.1:1	0.7:1	504.4:1	0.3:1	0.7:1	2.7:1	5.2:1	9.7:1	60.0:1	285.7:1
<=43	48.5	0.6:1	3.1:1	10.7:1	0.0:1	0.1:1	0.6:1	356.5:1	0.2:1	0.6:1	2.2:1	4.2:1	7.5:1	33.7:1	238.7:1
<=45	53.2	0.5:1	2.7:1	8.8:1	0.0:1	0.1:1	0.5:1	239.2:1	0.2:1	0.6:1	1.9:1	3.4:1	6.1:1	28.1:1	149.7:1
<=47	58.4	0.5:1	2.2:1	7.1:1	0.0:1	0.1:1	0.5:1	148.7:1	0.2:1	0.5:1	1.6:1	2.8:1	4.9:1	21.0:1	93.7:1
<=49	62.2	0.5:1	2.1:1	6.5:1	0.0:1	0.1:1	0.4:1	129.1:1	0.2:1	0.5:1	1.5:1	2.5:1	4.4:1	19.1:1	82.2:1
<=51	67.4	0.4:1	1.8:1	5.5:1	0.0:1	0.1:1	0.4:1	106.5:1	0.2:1	0.4:1	1.3:1	2.2:1	3.7:1	15.1:1	70.4:1
<=53	71.0	0.4:1	1.6:1	4.8:1	0.0:1	0.1:1	0.4:1	78.1:1	0.2:1	0.4:1	1.2:1	1.9:1	3.3:1	12.8:1	54.0:1
<=55	75.4	0.4:1	1.5:1	4.2:1	0.0:1	0.1:1	0.3:1	58.6:1	0.2:1	0.4:1	1.1:1	1.7:1	2.9:1	11.0:1	42.9:1
<=57	79.1	0.3:1	1.4:1	3.8:1	0.0:1	0.0:1	0.3:1	48.9:1	0.1:1	0.3:1	1.0:1	1.6:1	2.6:1	9.6:1	35.2:1
<=100	100.0	0.3:1	0.9:1	2.0:1	0.0:1	0.0:1	0.2:1	10.7:1	0.1:1	0.3:1	0.7:1	1.0:1	1.5:1	3.9:1	8.9:1

Scorecard applied to the validation sample. "All poor" means "Only poor targeted".

Figure 21: Share of poor people who are targeted

Targeting cut-off	% all people who are targeted	% poor people who are targeted													
		National			Intl. 2011 PPP				Percentile-based lines						
		100%	150%	200%	$1.90	$3.20	$5.50	$21.70	10th	20th	40th	50th	60th	80th	90th
<=19	3.1	12.1	6.4	4.7	61.0	33.1	13.6	3.4	19.5	13.1	7.7	6.2	5.2	3.9	3.5
<=22	5.9	21.6	12.0	8.8	81.3	52.7	24.5	6.4	33.9	23.8	14.4	11.7	9.8	7.4	6.5
<=25	9.3	32.7	18.5	13.8	89.7	66.5	36.1	10.1	48.4	34.9	22.0	18.2	15.4	11.7	10.3
<=27	12.8	42.3	25.1	19.0	95.1	77.8	46.1	14.0	60.2	45.0	29.4	24.6	21.0	16.1	14.2
<=29	15.9	49.8	31.0	23.6	95.6	83.8	54.8	17.4	69.0	53.5	36.3	30.5	26.2	20.0	17.7
<=31	20.5	59.9	39.2	30.2	96.8	88.3	65.1	22.4	76.9	63.9	45.0	38.8	33.6	25.7	22.8
<=33	24.1	65.6	45.2	35.4	97.5	92.6	71.3	26.4	83.3	70.1	51.6	45.0	39.2	30.2	26.8
<=35	29.4	73.9	53.6	42.9	97.5	94.6	78.6	32.2	87.5	77.5	59.9	53.6	47.0	36.8	32.7
<=37	33.3	78.2	59.4	48.2	97.9	97.2	83.1	36.4	91.2	82.4	66.0	59.4	52.7	41.6	37.0
<=39	39.2	84.5	67.7	55.9	98.7	98.5	87.9	42.8	93.7	87.4	73.8	67.7	60.8	48.7	43.5
<=41	43.3	88.3	72.9	60.9	98.7	98.9	90.9	47.3	95.1	90.5	78.9	73.2	66.0	53.6	48.0
<=43	48.5	91.6	78.1	66.6	99.6	99.2	93.6	52.9	96.0	93.3	83.9	78.7	71.9	59.2	53.7
<=45	53.2	93.6	82.3	71.8	99.8	99.6	95.4	58.0	97.6	95.1	88.0	83.0	76.9	64.7	58.8
<=47	58.4	95.3	85.9	76.9	100.0	99.9	96.8	63.4	98.2	96.6	90.6	86.2	81.6	70.1	64.3
<=49	62.2	96.6	89.1	81.0	100.0	99.9	97.8	67.5	98.8	97.7	93.4	89.4	85.2	74.3	68.3
<=51	67.4	98.4	92.3	85.6	100.0	99.9	98.6	73.0	99.1	98.5	95.7	92.6	89.1	79.5	73.9
<=53	71.0	98.7	94.0	88.5	100.0	99.9	99.1	76.7	99.4	98.9	96.7	94.3	91.4	82.9	77.6
<=55	75.4	99.4	95.7	91.4	100.0	100.0	99.5	81.0	100.0	99.6	98.0	96.0	93.9	86.8	81.9
<=57	79.1	99.6	97.9	94.1	100.0	100.0	99.7	84.8	100.0	99.7	98.9	97.9	96.2	90.1	85.6
<=100	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Scorecard applied to the validation sample.

For example, a pro-poor program could set a score cut-off to achieve a desired poverty rate—say, 50 percent—among targeted people. Given 100% of the national line, targeting Peruvians who score 35 or less would target 29.4 percent of people in Peru and give a head-count poverty rate among those targeted of 50.3 percent (**Figure 19**).

Figure 20 is a different way of looking at this same aspect of targeting accuracy. It shows the number of poor people correctly targeted (included) for each non-poor person mistakenly included (leakage). For 100% of the national line and a score cut-off of 35 or less, one (1.0) poor person is targeted for every non-poor person targeted.

Alternatively, a pro-poor program might seek to target a desired share—such as half—of poor Peruvians. **Figure 21** shows that a score cut-off of 29 or less would target 15.9 percent of all Peruvians, a group in which 49.8 percent are poor by 100% of the national line.

Interview Guide

The excerpts quoted here are from:

Instituto Nacional de Estadística e Informática (2019) *Manual del/la Encuestador/a: Encuesta Nacional de Hogares 2019, Condiciones de Vida y Pobreza*, [the *Manual*], **link**

G1. Basic interview instructions

The scorecard can be filled out on paper in the field, with responses entered later in a spreadsheet or in your own database. Alternatively, Scorocs' cloud-based data-collection tool works in a web browser or as an app on Android phones, allowing data entry in the field or in the office. If there is no connection, then data is stored on the phone until it can be uploaded. **Try** the data-collection tool, or **ask** about a private account.

The scorecard should be administered by an enumerator trained to follow this "**Interview Guide**".

Fill out the scorecard header and the "Back-page Worksheet" first, following the directions on the "Back-page Worksheet".

In the scorecard header, fill in the number of household members in the space "Number of household members:" based on the list that you the enumerator made as part of the "Back-page Worksheet".

Do not directly ask the first scorecard question ("In what region does the household live?"). Instead, fill in the answer based on your knowledge of the region where the household lives.

In the same way, do not directly ask the second scorecard question ("How many members does the household have?"). Instead, mark the answer based on the number of household members that you listed on the "Back-page Worksheet".

Ask all of the remaining questions directly of the respondent.

G1.1 General interviewing guidance

Study this “Guide” carefully, and carry it with you while you work. Follow the instructions in this “Guide” (including this one).

Remember that the respondent for the interview need not be the household member who is the direct participant with your program.

Likewise, the field agent to be recorded in the scorecard header is not necessarily the same as you the enumerator who does the interview. Rather, the field agent is the employee of the pro-poor program with whom the direct participant has an on-going relationship. If there is no such field agent, then write “UNKNOWN” in those spaces in the scorecard header.

In general, do not leave fields in the header blank. If the information is unknown, does not exist, or is not applicable, then write “UNKNOWN”, “DOES NOT EXIST”, or “NOT APPLICABLE” in the blanks of the header. This shows that you the enumerator tried to obtain the data and thus may help prevent wasted time and effort to try to get the data later.

Read each question aloud word-for-word, in the order presented in the scorecard.

When you mark a response to a scorecard question, write the point value in the “Score” column and then circle the spelled-out response option, the pre-printed point value, and the hand-written points, like this:

3. What is the main material of the floors?	A. Earth	0	
	B. Wood (bamboo, planks, and so on), or cement	4	**4**
	C. Tile and so on; linoleum, vinyl and so on; parquet, polished wood, or other	11	

When an issue comes up that is not addressed in this “**Interview Guide**”, its resolution should be left to the unaided judgment of the enumerator and the respondent, as that apparently was the practice of Peru’s INEI in the 2019 ENAHO. That is, a program should not promulgate any definitions or rules (other than those in this “**Interview Guide**”) to be used by all its enumerators. Anything not explicitly addressed in this “**Interview Guide**” is to be left to the unaided judgment of each individual enumerator and the respondent.

Do not read the response options to the respondent. Instead, read the question, and then stop; wait for a response. If the respondent asks for clarification or otherwise hesitates or seems confused, then read the question again or provide additional assistance based on this "**Interview Guide**" or as you the enumerator deem appropriate.

In general, you should accept the responses given by the respondent. Nevertheless, if the respondent says something—or if you see or sense something—that suggests that the response may not be accurate, that the respondent is uncertain, or that the respondent desires assistance in figuring out how to respond, then you should read the question again and provide whatever help you deem appropriate based on this "Guide".

While most responses to questions in the scorecard are verifiable, in most cases you do not need to verify responses. You should verify only if something suggests to you that a response may be inaccurate and thus that verification might improve data quality. For example, you might choose to verify if the respondent hesitates, seems nervous, or otherwise gives signals that he/she may be lying, confused, or uncertain. Likewise, verification is probably appropriate if a child in the interviewed household or if a neighbor says something that does not square with a respondent's response. Verification is also a good idea if you can see something yourself that suggests that a response may be inaccurate, such as a consumer durable that the respondent claims not to possess, or a child eating in the room who has not been counted as a member of the household.

In general, the application of the scorecard should mimic as closely as possible the application of the 2019 ENAHO by Peru's INEI. For example, interviews should done in-person by a trained enumerator at the participating household's residence because that is what INEI did in the 2019 ENAHO.

G1.2 Translation

As of this writing, the scorecard itself, the "Back-page Worksheet", and this "**Interview Guide**" are available only in English, Spanish, and Quechua. There are not yet official, professional translations to Aymara nor other languages spoken in Peru. Users should check **scorocs.com** to see what translations have been done since this writing.

If there is not yet an official, professional translation to a desired language, then please contact **Scorocs**.

G2. General interview guidance from the *Manual*

G2.1 Who should be the respondent?

Remember that the respondent does not need to be the household member who is the direct participant with your program (although the respondent may be the direct participant).

According to p. 127 of the *Manual*, the preferred respondent is the head of the household. “If the head is absent on the day of the interview, then the preferred respondent is the spouse of the head, followed by any other adult member of the household.”

G2.2 Who is the head of the household?

Note that the head of the household may or may not be the household member who is the direct participant with your program (although the head may be the direct participant).

According to p. 128 of the *Manual*, the *head of the household* “is the member of the household who is acknowledged as the head by the other members of the household. The head must be a member of the household. If there is no consensus, then use the following criteria to determine who is the head:

- “The main breadwinner, and/or
- “The one with the most responsibility for the household”

G2.3 How to conduct an interview

According to pp. 20–21 of the *Manual*, the enumerator must:

- “Strictly follow the instructions in this *Manual* [including this one]
- “Review the recorded responses once the interview is complete so as to detect and correct possible errors or inconsistencies and to make sure all the data has been recorded correctly
- “Conduct face-to-face interviews with each interviewed household in its residence, carrying this [“Guide”] with you and carefully following its instructions [including this one]
- “Personally do your assigned duties without delegating them to someone else and without being accompanied on the interviews by anyone who has no business being there
- “Maintain the highest standards of behavior so as to respect and protect your program’s important mission”

According to p. 21 of the *Manual*, the enumerator must not:

- “Change data or make up data
- “Arrange for someone else to do your work for you
- “Take with you to the field anyone who has no business being there
- “Relate data provided by an interviewed household to anyone who is not affiliated with the program’s survey work
- “Ask for or accept gifts or payments—whether in cash or in kind—from the interviewed household
- “Miss appointments made with interviewed households
- “Misbehave in any way while in the course your work
- “Threaten respondents or discuss religion, politics, and so on.”

G2.4 Tips for interviewing

According to pp. 22–23 of the *Manual*, “An interview is a dialog between the enumerator and the respondent. Successful interviewing is an art, and as an art it should not be done mechanically. Rather, it should unfold like a normal conversation between two people.

“When the interview begins, you the enumerator and the respondent do not know each other. Therefore, winning the respondent’s good-faith cooperation depends critically on first impressions: your physical appearance, the first things you do, and your first words.

“For example, you should be self-confident and always stay in control of the situation. At the same time, avoid intimidating the respondent, for example, by overemphasizing the official nature of the survey.

“You should be friendly and respectful. Always remember that the respondents are important people and that the data that they provide are invaluable for [your program].

“You should introduce yourself to the respondent, for example, as follows: ‘Good morning, my name is <NAME>, and I work for [my program]. Here is my identification badge. I would like to speak with you, Sir/Madam.’

“Some specific issues that may arise in an interview are discussed below:

- “*Respondent is too busy to be interviewed*. If the respondent declares that he/she does not have time to be interviewed, then you should immediately offer to come back later, and attempt to arrange a specific time and date
- “*Refuses to cooperate*. Some respondents will refuse to participate in the survey. When this happens, you should use all of your skill to change his/her mind
- “*Presence of people who are not members of the interviewed household*. The presence of third parties can reduce the quality of responses. Do what you can to avoid this situation. The risk is that the presence of third parties may induce the respondent to give answers that are in accord with the respondent’s beliefs and perceptions about what others in society would expect, rather than the reality of his/her own experiences and perspectives

“Briefly explain that you are doing a survey of participants of [your program] for the purpose of . . . better understanding how they live, . . . and that you therefore would like to request his/her cooperation in providing accurate responses.

G2.5 How to ask questions

According to pp. 23–25 of the *Manual*, “To conduct the interview quickly and smoothly, you should study [the scorecard] until you know it forwards and backwards. To ensure that the responses are not influenced by your own particular point of view or your own personality, be sure to follow the following procedures:

- “Read the questions exactly as they are written in [the scorecard]
- “Read the questions in the order that they appear in [the scorecard]
- “Do not lead the respondent toward any particular response, for example, by suggesting one of several alternatives

“*Confidentiality of the data*. “Before asking any questions, you should assure the respondent that you will keep all data that you collect strictly confidential. Explain that under no circumstances will their names, addresses, or other identifying information be associated with their responses, and that any data collected will be used [to improve the management of your program]. You should never—for any reason—show the information that you collect to anyone who is not authorized to see it.

“*Neutrality*. The questionnaire has been carefully designed to avoid suggesting responses to the respondent. It is, therefore, critical that you remain neutral with respect to the content of the survey.

“If you do not read each question carefully, completely, and exactly as it is written, then you might destroy this neutrality.

“If the respondent gives a vague or imprecise response, then you should gently probe—in a neutral way—saying ‘Could you repeat that?’ or ‘I could not hear what you said.’ You should never record something that differs from the response given by the respondent.

“You should never suggest—whether by the expression on your face or by the tone of your voice—that the respondent has made a mistake or has said something that is wrong. Sometimes, a respondent will ask you, the enumerator, for your opinion or point of view. When this happens, you should say, ‘Your opinion is what matters for this survey.’ After the interview is over, you can talk about your opinions with the respondent for a few minutes, if you would like.

“*Managing the interview*. Be serious about the quality of your work, but do not be so anxious and rigid that you seem inflexible to the respondent.

“From the point of view of the respondent, the interview should seem like an opportunity to share information and to discuss his/her own perspectives. Thus, your remarks as an enumerator should be as brief as possible and should serve mainly to encourage the respondent to continue responding to the questions.

“If the respondent rambles on without answering the question, or if the respondent talks about things that do not pertain to the survey, it is wise to refrain from interrupting. Nevertheless, use tact and try to bring the discussion back to the interview as soon as you can.

“*How to deal with vague or evasive responses*. Be prepared for evasive answers. Sometimes, a respondent will give vague, imprecise, or self-contradictory answers or just say, ‘I don’t know’ or refuse to answer outright. When this happens, try to encourage the respondent, build up his/her confidence, and help him/her feel more comfortable before continuing with the next question.

“*Probe incomplete or inadequate responses*. Sometimes, the respondent will give an answer that, from the point of view of the survey, is inadequate. This might happen, for example, if the response is incomplete, off-topic, or if the respondent simply does not know the answer.

“In order to obtain a better response, you should use follow-up questions. This process of digging deeper is called *probing*. When you do it, be sure to use neutral words so as not to suggest specific answers.

“*Do not assume that you know what responses will be*. Regardless of the socio-economic or sociological characteristics of the respondent or the location or quality of the residence, you should not assume that you know any answers without actually asking the question of the respondent.

"*Do not rush the interview*. Ask questions slowly so that the respondent understands them. After asking a question, wait; give the respondent time to think.

"*Ending the interview*. Once you have completed the survey, do not rush out the door so quickly that the respondent gets the feeling that he/she has been 'used'. In most cases, a few minutes of polite, pleasant conversation is enough to maintain the respondent's good will. After a little while, thank the respondent for his/her cooperation and take your leave."

G3. Guidelines for each question in the scorecard

G3.1 In which region does the household live?

A. Lima, Callao, La Libertad, Ayacucho, or Pasco
B. Cajamarca, Piura, or Puno
C. Cusco, Junín, Apurímac, Huánuco, San Martín, Huancavelica, Amazonas, Tacna, Tumbes, or Moquegua
D. Arequipa, Ancash, Loreto, or Madre de Díos
E. Lambayeque, Ica, or Ucayali

Unless you have to, do not directly ask this question of the respondent. Instead, fill in the answer based on your knowledge of the region where the household lives.

G3.2 How many members does the household have?

A. Six or more
B. Five
C. Four
D. Three
E. Two
F. One

Do not directly ask this question of the respondent. Instead, mark the response based on the number of household members that you listed on the “Back-page Worksheet”.

According to the cover page of the survey instrument for the 2019 ENAHO, a *household* is “a person or group of people who eat from the same pot and who cooperate to fulfill their other basic needs.”

According to p. 67 of the *Manual*, a *household* “is the group of people—regardless of their blood relationship (parents, single children, married children, brothers, uncles, etc.)—who occupy all or part of a residence, who share their main meals, and who cooperate to meet their basic needs. This group of household members also includes whomever the head of the household considers it to include (such as adopted children, good friends, godparents, etc.). A household can be made up of a single person.”

According to Section 200 of the questionnaire for the 2019 ENAHO, the enumerator should “remember to record absent household members and newborns.”

According to p. 129 of the *Manual*, the definition of *household* excludes “domestic servants who stay overnight in the household, as well as all lodgers.”

Nevertheless, pp. 127 and 128 of the *Manual* says that “domestic servants who sleep in the household’s residence, regardless of whether they are paid cash for their work“ count as members of the household.

According to p. 127 of the *Manual*, “Do not count as household members those people who usually live abroad but who happen to be present temporarily at the residence on the day of the interview. On the other hand, do count as household members those who are temporarily absent from the residence due to travel for work, studies, or vacation and who have a planned date of return.”

G3.3 What is the main material of the floors?

A. Earth
B. Wood (bamboo, planks, and so on), or cement
C. Tile and so on; linoleum, vinyl and so on; parquet, polished wood, or other

According to pp. 80–81 of the *Manual*, the *main material of the floors* "is the material that covers the largest share of the floors of the rooms of the residence (the greatest surface area).

"If 60 percent of the floors of the residence are cement and 40 percent are earth, then mark 'B. Wood (bamboo, planks, and so on), or cement'.

"If 50 percent of the floors are tile and 50 percent are cement, then mark 'C. Tile and so on, linoleum, vinyl and so on, parquet, polished wood, or other' because tile is higher quality than cement.

G3.4 How many rooms are used only as bedrooms?

A. None, or one
B. Two or more

According to p. 78 of the *Manual*, a *residence* "is any building that is structurally separate and independent, made up of one room or a group of rooms that is used to shelter people."

According to p. 84 in the *Manual*, "If more than one household lives in a residence, . . . then count all the rooms in the residence that are used exclusively for sleeping by all of the households. Remember to count the room(s) used for sleeping by any domestic servants."

According to p. 84 of the *Manual*, a *room used only as a bedroom* is "a space in a residence that is used only as a bedroom and that is enclosed by walls that reach from the floor to the ceiling/roof and that has at least enough space for an adult-size bed.

"The concept of 'rooms used only as bedrooms' includes rooms which may be used not only for sleeping but also for other daily activities (such as doing homework or watching television) that do not dominate the room's basic function as a bedroom. For example:

- "A room is considered to be used only as a bedroom if a student sleeps there, even if he/she also has a television and a computer there which is used for studying, entertainment, or communication
- "Rooms are not considered to be used only as bedrooms if they are used as a kitchen, a dining room, or a living room, even if someone sleeps there, if the bed being slept on is brought in at night and removed or put up during the day
- "In rural areas, a space is not counted as a room used only for sleeping if the respondent reports that it is used not only for sleeping but also for storing farm produce and tools for work"

G3.5 What cooking fuel does the household use more than any other?

A. Dung, or other
B. Firewood, or charcoal
C. Gas (LPG in a tank), natural gas (piped from network), electricity, or does not cook

According to pp. 108–109 of the *Manual*, the following definitions are used:

- "*Dung* is manure from cattle or horses
- "*Manure* is excrement from any animal
- "*Other* encompasses all fuels that are not included in other response options, such as kerosene, saw dust, wood chips, dry leaves, dry sticks, and so on
- "*LPG* is liquid petroleum gas that is produced via an industrial process and that is used mainly in homes for cooking and heating and as a fuel for vehicles
- "*Natural gas* is a fossil fuel made up of a simpler type of hydrocarbon [than LPG] that is found in deposits deep underground. It is used mainly in homes for cooking and heating to which it is delivered via a network of pipes, and as a fuel for powering vehicles, factories, and electrical plants
- "*Electricity*: When the household uses electrical energy for cooking. Count the use of an electric rice cooker if it is used daily
- "*Does not cook* means that the household does not prepare food of any kind."

G3.6 Does the household have a microwave?

A. No
B. Yes

According to p. 181–182 of the *Manual*, “Count the interviewed household as having a microwave if any member of the household owns one.

“Count broken microwaves only if they will be repaired in the near future.

“Do not count microwaves that are not owned by the interviewed household (regardless of whether the household is using them). The key is *ownership*, [not possession].

“Do not count microwaves that the interviewed household has borrowed in or rented in. [Do count microwaves that are lent out or rented out.]

“If the interviewed household owns a microwave but keeps it at a different residence, then count it as being owned.”

“Count microwaves that the interviewed household owns that are used in businesses that the household runs from its residence. [Do not count microwaves that the household owns that are used in businesses that are run outside of the residence.]”

G3.7 Does the household have a food processor/blender?

A. No
B. Yes

According to p. 181–182 of the *Manual*, “Count the interviewed household as having a food processor/blender if any member of the household owns one.

“Count broken food processors/blenders only if they will be repaired in the near future.

“Do not count food processors/blenders that are not owned by the interviewed household (regardless of whether the household is using them). The key is *ownership*, [not possession].

“Do not count food processors/blenders that the interviewed household has borrowed in or rented in. [Do count food processors/blenders that are lent out or rented out.]

“If the interviewed household owns a food processor/blender but keeps it at a different residence, then count it as being owned.

Count food processors/blenders that the interviewed household owns that are used in businesses that the household runs from its residence. [Do not count food processors/blenders that the household owns that are used in businesses that are run outside of the residence.]”

G3.8 How many TVs (color or black and white) does the household have?

A. None
B. One
C. Two or more

According to p. 181–182 of the *Manual*, “Count the interviewed household as having a TV if any member of the household owns one.

“Count broken TVs only if they will be repaired in the near future.

“Do not count TVs that are not owned by the interviewed household (regardless of whether the household is using them). The key is *ownership*, [not possession].

“Do not count TVs that the interviewed household has borrowed in or rented in. [Do count TVs that are lent out or rented out.]

“If the interviewed household owns a TV but keeps it at a different residence, then count it as being owned.

“Count TVs that the interviewed household owns that are used in businesses that the household runs from its residence. [Do not count TVs that the household owns that are used in businesses that are run outside of the residence.]”

G3.9 Does the household have an internet connection?

A. No
B. Yes

According to p. 109 of the *Manual*, "The interviewed household is considered to have an internet connection when:

- "The interviewed household has internet service for the use of all household members (contracted unlimited service by cable or wireless)
- "Any member of the interviewed household has a 'smartphone' or other cell phone with an unlimited data contract

"The interviewed household is not considered to have an internet connection if it only has pre-paid data on a smartphone, cell phone, USB modem, or other electronic device that only lasts until the pre-paid, limited data is used up."

G3.10 Does the household have a personal computer or laptop?

A. No
B. Yes

According to pp. 181–182 of the *Manual*, "Count the interviewed household as having a personal computer or laptop if any member of the household owns one.

"Count broken personal computers or laptops only if they will be repaired in the near future.

"Do not count personal computers or laptops that are not owned by the interviewed household (regardless of whether the household is using them). The key is *ownership*, [not possession].

"Do not count personal computers or laptops that the interviewed household has borrowed in or rented in. [Do count personal computers or laptops that are lent out or rented out.]

"If the interviewed household owns a personal computer or laptop but keeps it at a different residence, then count it as being owned.

"Count personal computers or laptops that the interviewed household owns that are used in businesses that the household runs from its residence. [Do not count personal computers or laptops that the household owns that are used in businesses that are run outside of the residence.]"

G3.11 Does the household have a cell phone or a land-line phone?

A. No
B. Yes

According to p. 181–182 of the *Manual*, “Count the interviewed household as having a cell phone or a land-line phone if any member of the household owns one.

“Count broken cell phones or land-line phones only if they will be repaired in the near future.

“Do not count cell phones or land-line phones that are not owned by the interviewed household (regardless of whether the interviewed household is using them). The key is *ownership*, [not possession].

“Do not count cell phones or land-line phones that the interviewed household has borrowed in or rented in. [Do count cell phones or land-line phones that are lent out or rented out.]

“If the interviewed household owns a cell phone or a land-line phone but keeps it at a different residence, then count it as being owned.

“Count cell phones or land-line phones that the interviewed household owns that are used in businesses that the household runs from its residence. [Do not count cell phones or land-line phones that the household owns that are used in businesses that are run outside of the residence.]”

Landline phone. According to p. 108–109 of the *Manual*, if more than one household lives in a residence, if more than one household (including the interviewed household) shares a single land-line phone, and if the interviewed household pays for all or part of the costs of the shared land-line phone, then the interviewed household is considered to have a land-line phone. What matters is paying at least part of the costs.

However, if the interviewed household does not pay anything to the neighbor who owns the shared land-line phone, then the interviewed household is not considered to have a land-line phone.

If the interviewed household makes and receives calls via a coin-operated land-line phone, then the interviewed household is not counted as having a land-line phone”

Cell phone. The interviewed household counts as having a cell phone when:

- “The interviewed household has a cell phone that is available for use by all household members, or
- “Any member of the interviewed household reports having a cell phone for his/her personal use

G3.12 In the last 15 days from . . . to . . ., has any member of the household obtained, consumed, bought, or received as a gift any milk (evaporated, powdered, fresh, evaporated with iron, evaporated light, or soy milk with lactose)?

A. No
B. Yes

According to p. 143 of the *Manual*, the amount obtained, consumed, purchased, or received as a gift does not matter. What matters is whether any at all was obtained, consumed, purchased, or received as a gift.

Technical Annexes: Overview

The technical annexes cover aspects of the scorecard for advanced users or other specialists. While programs can skip the annexes and still benefit from the scorecard, understanding the details will increase the usefulness of scorecard estimates and improve implementation, interpretation, and analysis.

The annexes cover:

Annex 1 Data used for construction and validation

Peru's Instituto Nacional de la Estadística e Informática (INEI) fielded the 2019 Encuesta Nacional de Hogares (ENAHO, the National Household Survey) with 34,565 households from January 1 to December 31, 2019. The 2019 ENAHO is Peru's most-recent national household consumption survey.

Questions and points for the scorecard are selected (*constructed*) based on data from a random three-fifths of the 34,565 households in the 2019 ENAHO. These same three-fifths of households are also used to associate (*calibrate*) scores with poverty likelihoods for all poverty lines.

Data from the other two-fifths of households from the 2019 ENAHO is used to test (*validate*) the scorecard's accuracy for one-period, snapshot estimates of poverty rates *out-of-sample*, that is, with data that is not used in construction nor calibration. Data from those same two-fifths of households are also used for out-of-sample tests of targeting accuracy.

Annex 2 Definitions of poverty and of poverty lines

A household's *poverty status* as poor or non-poor depends on whether its consumption expenditure (PEN per person per day) is below a given poverty line. Thus, a definition of *poverty* is a poverty line together with a measure of consumption.

The definition of *consumption* for the 2019 ENAHO is the same as that documented in **Schreiner, 2012a** for the old scorecard based on data from the 2010 ENAHO.

Even though the old 2010 scorecard and the new 2019 scorecard here use the same definition of *poverty*, the nine elapsed years mean that the scorecards' two basic assumptions (of an unchanging population and of unchanging relationships between scorecard questions and poverty) are unlikely to hold well. Therefore, users are warned against estimating changes in poverty with a baseline estimate from the old 2010 scorecard (or from the old 2003 or 2007 scorecards) and a follow-up estimate from the new 2019 scorecard. Changes may be estimated with both a baseline and a follow-up from the new 2019 scorecard.

Because pro-poor programs in Peru may want to use different or various poverty lines, the scorecard supports 14 lines:

- 100% of the national line
- 150% of the national line
- 200% of the national line
- $1.90/day 2011 PPP
- $3.20/day 2011 PPP
- $5.50/day 2011 PPP
- $21.70/day 2011 PPP
- First-decile (10th-percentile) line
- First-quintile (20th-percentile) line
- Second-quintile (40th-percentile) line
- Median (50th-percentile) line
- Third-quintile (60th-percentile) line
- Fourth-quintile (80th-percentile) line
- Tenth-decile (90th-percentile) line

A2.1 National poverty lines

Schreiner, 2012a documents the derivation of Peru's national poverty lines. The derivation is the same as that used for "new-definition" lines supported by the old 2010 scorecard, adjusted price changes since 2010. The lines are also adjusted for price differences over time during field work for the 2019 ENAHO as well as price differences across geographical regions.[34] Prices are in units for Metropolitan Lima on average during calendar-year 2019.

The national poverty line (usually called here "100% of the national line") is PEN11.56 per person per day. The corresponding all-Peru head-count poverty rate is 20.2 percent (**Figure 10**).[35]

A2.2 International 2011 PPP poverty lines

The World Bank tracks world-wide poverty with four poverty lines:[36]

- $1.90/day   Low-income countries (the international "extreme poverty" line)
- $3.20/day   Lower-middle income countries
- $5.50/day   Upper-middle income countries
- $21.70/day   High-income countries

For Peru, the most relevant is the $5.50/day 2011 PPP line.

These lines control for differences in purchasing power across countries. PPP factors adjust for the fact that non-tradable services are usually less costly in poorer countries while tradable goods are more costly. The goal of PPP-adjusted poverty lines is to make poverty estimates as comparable across countries as possible.

[34] Metropolitan Lima, urban coast, rural coast, urban sierra, rural sierra, urban jungle, and rural jungle.
[35] This rate for this line matches INEI (2020, p. 36), suggesting that this paper uses the same data and calculations as INEI did.
[36] **Jolliffe and Prydz**, 2016; **Ferreira *et al.***, 2016.

International 2011 PPP lines for Peru are derived from:

- 2011 PPP (revised) exchange rate for Peru for "individual consumption expenditure by households":[37] PEN1.57918 per $1.00
- Average all-Peru Consumer Price Index[38] (CPI) in calendar-year:
  - 2011: 104.95
  - 2019: 131.77
- Average all-Peru temporal and spatial price deflator in 2019: 0.8688431
- Household-level temporal and geographic price deflators provided by INEI with the 2019 ENAHO data

Given this, the $5.50/day 2011 PPP line for a given household is:

$$\$5.50 \cdot 2011 \text{ PPP factor} \cdot \frac{\text{Deflator}_{\text{HH}}}{\text{Ave. deflator}_{\text{Peru}}} \cdot \frac{\text{CPI}_{2019}}{\text{CPI}_{2011}}.$$

For Peru as a whole and in prices in Metropolitan Lima in calendar-year 2019, the $5.50/day 2011 PPP line is:

$$\$5.50 \cdot 1.57918 \cdot \frac{0.8849}{0.8849} \cdot \frac{131.77}{104.95} = \text{PEN}10.91.$$

The corresponding all-Peru head-count poverty rate is 20.2 percent (**Figure 10**).

The 2011 PPP poverty lines for $1.90/day, $3.20/day, and $21.70/day are multiples of the $5.50/day line.

The 2011 PPP lines and rates here are not directly comparable with those from the World Bank's PovcalNet because PovcalNet does not report 2011 PPP estimates for the 2019 ENAHO.

For the 2018 ENAHO, PovcalNet reports a head-count poverty rate for $5.50/day 2011 PPP of 22.3 percent[39]. The poverty line by 100% of the national line in 2019 exceeded $5.50/day 2011 PPP by 11.56 – 10.91 = PEN0.65/day (**Figure 10**). The poverty rate by 100% of the national line is almost identical in 2018 and 2019 (20.5 percent versus 20.2 percent in 2019.[40] Given that Peru's national line is close to $5,50/day 2011 PPP and that this paper and PovcalNet use the same deflator for inflation, PovcalNet's eventual estimates for 2019 for $5,50/day 2011 PPP will likely exceed the estimates here by about 3 percentage points. The difference probably

[37] **World Bank**, 2020, Table E.3, column 13.
[38] Base = 100 in calendar-year 2009, **link**.
[39] **PovcalNet**, 2020.
[40] **INEI**, 2020, p. 39.

results from PovcalNet's not adjusting for the fact that the person-weighted average temporal and geographic price deflator in the 2018 ENAHO is not 1.0000. This would lead to PPP lines that are too high by about (1.000 ÷ 0.8849) – 1 ≈ 13.0 percent everywhere outside of Metropolitan Lima, in turn giving too-high poverty rates.

A2.3 Percentile-based poverty lines

The scorecard for Peru also supports percentile-based poverty lines.[41] This facilitates a number of types of analyses. For example, the second-quintile (40th-percentile) line might be used to help track Peru's progress toward the **World Bank's** (2013) goal of "shared prosperity/inclusive economic growth", defined as income growth among the bottom 40 percent of the world's people.

The four quintile lines (or all seven percentile lines), analyzed together, can also be used to look at the relationship of consumption with health outcomes (or anything else related with the distribution of consumption). The scorecard thus offers an alternative for health-equity analyses that typically have used an asset index such as that supplied with the data from the Demographic and Health Surveys to compare an estimate of socio-economic status with health outcomes.[42]

Of course, relative-wealth analyses were always possible (and still are possible) with scores from the scorecard. But support for relative consumption lines allows for a more straightforward use of a single tool to analyze any or all of:

- Relative wealth (via scores)
- Absolute consumption (via poverty likelihoods and absolute poverty lines)
- Relative consumption (via poverty likelihoods and percentile-based poverty lines)

Unlike the scorecard, asset indexes serve only to analyze relative wealth. Furthermore, the scorecard—unlike asset indexes based on Principal Component Analysis or similar approaches—uses a straightforward, well-understood standard for socio-economic status whose definition is external to the tool itself (consumption expenditure relative to a poverty line defined in monetary units).

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[41] Percentiles are defined in terms of all people in Peru. For example, the all-Peru head-count poverty rate for the first-quintile (20th-percentile) poverty line is 20 percent (**Figure 10**).
[42] **Rutstein and Johnson**, 2004.

In contrast, an asset index defines *poverty* in terms of its own questions and points, without reference to an external standard. This means that two asset indexes with different questions or different points—even if derived from the same data for a given country—imply two distinct definitions of *poverty*. In the same set-up, two scorecards would provide comparable estimates under a single definition of *poverty*.

Annex 3 Scorecard construction

For Peru, about 90 candidate questions are prepared in these areas:

- Household composition (such as the number of household members)
- Education (such as the educational attainment of the female head (or spouse of the male head))
- Employment (such as the number of household members who work)
- Housing (such as the main material of the floor)
- Ownership of consumer durables (such as microwaves or telephones)
- Location of residence (such as region)
- Food consumption in the past 15 days (such as eggs or milk)
- Participation in social programs (such as *Vaso de Leche* or *Qali Warma*)

To facilitate the estimation of change over time, preference is given to questions that are more sensitive to changes in poverty. For example, the number of TVs owned is probably more responsive to changes in poverty than is the age of the head of the household.

The scorecard itself is built using 100% of the national poverty line and Logit regression on the construction sub-sample. Questions are selected based on both judgment and statistics.

The first step is to use Logit to build one draft scorecard for each candidate question. The power of each one-question draft scorecard to rank households by poverty status is assessed via the concentration index.[43]

One of the one-question draft scorecards is then selected based on:[44]

- Improvement in accuracy
- Likelihood of acceptance by users according to:
  - — Simplicity
  - — Cost of collection
  - — Concordance with:
    - ▪ Experience
    - ▪ Theory
    - ▪ Common sense

[43] **Ravallion**, 2009.
[44] **Schreiner *et al.***, 2014; **Zeller**, 2004.

- Sensitivity to changes in consumption
- Variety among types of questions
- Applicability across regions
- Tendency to have a slow-changing relationship with poverty
- Relevance for distinguishing among people at the poorer end of the distribution of consumption
- Verifiability

A series of two-question draft scorecards are then built, each adding a second question to the one-question scorecard selected from the first stage. The best two-question draft scorecard is then selected, again using judgment to balance statistical accuracy with non-statistical criteria. These steps are repeated until the scorecard has 12 questions that work well together.

The last step is to transform the Logit coefficients into non-negative integers such that scores range from 0 to 100, with lower scores corresponding with greater poverty.

This algorithm is similar to common R^2-based stepwise least-squares regression. It differs from naïve stepwise in that the selection of questions considers both statistical[45] and non-statistical criteria. The use of non-statistical criteria can improve robustness through time and across non-nationally representative groups. It also helps to ensure that questions are straightforward, common-sense, inexpensive-to-collect, and acceptable to users.

The single scorecard here applies to all of Peru. Customizing poverty-assessment tools by urban/rural does not improve targeting accuracy much.[46] Segment-specific tools may improve the accuracy of estimates of poverty rates,[47] but:

- They are also at greater risk of overfitting[48]
- Most of their benefit can be had in a single scorecard with a question about the segment (such as, in the case of Peru, the region of residence)[49]

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[45] The statistical criterion is not the *p* values of coefficients but rather a question's contribution to the ranking of households by poverty status in the context of a scorecard with 11 other questions.
[46] **Brown, Ravallion, and van de Walle**, 2018; **World Bank**, 2012; **Sharif**, 2009; **Schreiner**, 2006; **Schreiner**, 2005; **Narayan and Yoshida**, 2005; and **Grosh and Baker**, 1995.
[47] **Diamond *et al.***, 2016; **Tarozzi and Deaton**, 2009.
[48] **Haslett**, 2012.
[49] **Schreiner**, 2016b.

Annex 4 Estimates of poverty likelihoods

This annex tells how scores are converted into estimated poverty likelihoods.

Scores are on an ordinal scale from 0 to 100. Higher scores signal less poverty, but not how much less. The ordered symbols used to represent scores are numbers, but those symbols are not the normal cardinal numbers that you can do math on. For example, a score of 20 plus a score of 10 is not 30 of anything, just as the letter "A" plus the letter "B" is not the letter "C" (nor anything else).

To get cardinal units, a look-up table is used to convert scores to *poverty likelihoods*, that is, probabilities of being below a poverty line. For the example of 100% of the national line, scores of 30–31 correspond with a poverty likelihood of 41.7 percent, and scores of 32–33 correspond with a poverty likelihood of 35.1 percent (**Figure 1**).

The poverty likelihood associated with a score varies by poverty line. For example, scores of 30–31 are associated with a likelihood of 41.7 percent for 100% of the national line but with a likelihood of 83.8 percent for the 150% of the national line.

A4.1 Calibrating scores with poverty likelihoods

A given score is associated ("calibrated") with an estimated poverty likelihood that is defined as the share of people in the construction sub-sample who have the score and who live in households with per-capita consumption below a given poverty line.

For the example of 100% of the national line and a score of 30–31 (**Figure 22** below), there are 3,437 (normalized) people in the construction sample. Of these, 1,432 (normalized) are below the poverty line. The estimated poverty likelihood associated with a score of 30–31 is then 41.7 percent, because 1,432 ÷ 3,437 ≈ 0.417 = 41.7 percent.

The same method is used to calibrate all scores with poverty likelihoods for all 14 poverty lines.[50]

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[50] To ensure that likelihoods never increase as scores increase, likelihoods across pairs of adjacent scores may be iteratively averaged before grouping scores into ranges. This preserves unbiasedness while keeping users from balking when higher scores would otherwise be associated with higher likelihoods.

Figure 22: Estimation of poverty likelihoods (100% of national line)

Score	Households in range and < poverty line		All households in range		Poverty likelihood (%)
0–19	1,632	÷	2,011	=	81.2
20–22	1,269	÷	1,842	=	68.9
23–25	1,604	÷	2,567	=	62.5
26–27	1,356	÷	2,347	=	57.8
28–29	1,099	÷	2,453	=	44.8
30–31	1,432	÷	3,437	=	41.7
32–33	1,239	÷	3,527	=	35.1
34–35	1,688	÷	5,131	=	32.9
36–37	1,166	÷	4,289	=	27.2
38–39	922	÷	5,154	=	17.9
40–41	654	÷	4,240	=	15.4
42–43	582	÷	5,052	=	11.5
44–45	539	÷	5,099	=	10.6
46–47	412	÷	5,538	=	7.4
48–49	199	÷	4,309	=	4.6
50–51	161	÷	5,036	=	3.2
52–53	91	÷	4,454	=	2.0
54–55	74	÷	4,496	=	1.6
56–57	33	÷	3,941	=	0.8
58–100	44	÷	25,076	=	0.2

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

A4.2 Objectivity of estimates of poverty likelihoods

Even though scorecard questions are selected partly based on judgment related to non-statistical criteria, the calibration process produces estimates of poverty likelihoods that are objective, that is, derived from monetary poverty lines and from survey data on consumption.[51] Acknowledging that some choices in scorecard construction are informed by judgment in no way impugns the objectivity of the estimated likelihoods; their objectivity depends on using data in score calibration, not on using data (and nothing else) in scorecard construction.

A4.3 Why not use the Logit formula?

The scorecard is based on a Logit regression (**Annex 3**). This means that poverty likelihoods could be estimated not with a calibrated look-up table (**Figure 1**) but rather with the Logit formula of $2.718281828^{\beta X}$ x $(1 + 2.718281828^{\beta X})^{-1}$, where β are the Logit coefficients and X is a household's responses.

The scorecard uses the calibration approach is because the Logit formula is difficult to compute by hand and looks frightening. Program managers can understand poverty likelihoods defined as the share of people with a given score in the construction sample from Peru's 2019 ENAHO who are below a poverty line. A calibrated look-up table also allows program analysts to convert scores to likelihoods without any arithmetic at all. This calibration approach can also improve accuracy, especially with large samples.

[51] The calibrated likelihoods would be objective even if scorecard construction did not use any data at all. In fact, objective scorecards of proven accuracy are often constructed using only expert judgment (**Caire**, 2004; **Schreiner *et al.***, 2014).

Annex 5 Error and margins of error

This annex reports the scorecard's estimation error for head-count poverty rates in a single time period. It also discusses margins of error.

A5.1 Estimation errors

A5.1.1 What is estimation error?

Estimation error is the distance and direction by which a scorecard's estimate tends to miss the true value in the population.

For example, the estimation error of Peru's scorecard for snapshot estimates of head-count poverty rates in a single time period by 100% of the national poverty line is –2.7 percentage points (**Figure 2**).

An unadjusted estimate can usually be improved—that is, moved closer to the true value—by subtracting off the known estimation error. For example, if the unadjusted estimate is 64.7 percent and the error is –2.7 percentage points, then an improved estimate is 64.7 – (–2.7) = 67.4 percent.

A5.1.2 What estimation errors are reported here?

Estimation errors are reported for snapshot estimates of head-count poverty rates in a single time period for all 14 poverty lines. Errors are derived *out-of-sample*; the scorecard (made from the construction sample from the 2019 ENAHO, **Annex 1**) is tested with repeated sub-samples from the validation sample that was not used to construct the scorecard. The estimation error is the average of the differences between scorecard estimates and observed poverty rates in these repeated sub-samples.

There is no data today on consumption-based poverty in the future, so it is impossible to report estimation error for annual net changes in head-count poverty rates across two time periods. The scorecard cannot be not tested *out-of-time* because it is both constructed and validated with data from a single time period (2019).

In practice, the scorecard—like all poverty-assessment tools—is always applied both out-of-sample and out-of-time. Being out-of-sample violates the assumption that the scorecard is applied to a sample from the same population whose data was used to construct the scorecard. Being out-of-time violates the assumption that the relationships between poverty and scorecard questions are the same as in the population whose data was used to construct the scorecard.

The unknown degree of these inevitable violations of the scorecard's assumptions means that actual estimation errors will differ from those reported here in unknowable ways.[52] Still, the errors (and margins of error) reported here are the best available, and it makes sense to account for them.

A5.1.3 How to estimate estimation errors

Given the scorecard's standard assumptions, an unbiased estimator of *estimation error* is the average of differences between scorecard estimates and observed values in repeated sub-samples from the validation sample.[53]

It is possible to compare estimated and observed poverty rates because the validation sample from the 2019 ENAHO records actual (not estimated) consumption-based poverty status. The observed poverty likelihood in the 2019 ENAHO is 100 percent for poor households and 0 percent for non-poor households. For a given poverty line, the observed (not estimated) head-count poverty rate is the household-size-weighted average of observed poverty statuses.

The scorecard can also be applied to the same validation sub-sample (ignoring that actual poverty status is observed) to estimate the poverty rate as the household-size-weighted average of estimated poverty likelihoods from the scorecard (Section 3).

The scorecard's estimation error in a given validation sub-sample is then the difference between the scorecard estimate versus the observed value.

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[52] Estimation errors due to being out-of-time can be measured with post-2019 data (say, from the 2020 ENAHO). Of course, 2020 ENAHO data will not be available until after 2020, so there will still be some unknown out-of-time error (and out-of-sample error will still be completely unknown).

[53] This is the *bootstrap approach*. The average of the estimated values in repeated samples from the validation sample is an unbiased estimator of the true value in the population of Peru as a whole. The population's true value is taken as the value in the 2019 ENAHO (even though the ENAHO is itself only a sample).

Different sub-samples from the validation sample result in different errors. The estimate of the scorecard's general *estimation error* is the average of these errors across many sub-samples.[54] In turn, the scorecard estimate's margin of error reflects the extent of the spread of the distribution of all the sub-samples' errors around their average.[55]

A5.1.4 Errors for snapshot estimates of poverty rates in one time period

The first line in **Figure 2** ("Estimation error") presents errors for snapshot estimates of poverty rates in one time period for Peru's 14 poverty lines.

The average of the absolute value of each error across all poverty lines is about 2.6 percentage points. The largest absolute error is 6.5 percentage points. The error for 100% of the national line is –2.7 percentage points.

A5.2 Margins of error

A5.2.1 What are margins of error?

Like any statistic, a scorecard estimate depends on a particular sample from a population. Because samples are drawn at random, each sample is different, and different samples give different scorecard estimates. Scorecard estimates are unbiased—under the standard assumptions—because the average estimate across repeated samples is the same as the single true value in the population.

Unusual luck in any single sample, however, may push an estimate far from the true value. Larger samples provide more chances for luck to even out, so large errors are less likely in larger samples.[56]

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[54] Households in a sub-sample are drawn *with replacement*; each draw comes from the full pool, including households who have already been drawn. Thus, a given household may appear in a given sub-sample once, more than once, or not at all.
[55] Schreiner, 2020 discusses the derivation of errors.
[56] When flipping a fair coin, the true probability of "heads" is 50 percent. *Unbiasedness* means that the average of the share of "heads" in many samples will be close to 50 percent. In a single sample of 10 tosses, however, the chances of at least six "heads" (60 percent of tosses, with an error of at least 10 percentage points) is about 37 percent. In a single sample of 100 tosses, the chances of such a large error is about 3 percent. Larger samples reduce the risk that estimates will be far from true values.

For a given estimate, sample size, and confidence level, the *margin of error* is the range of true population values that are reasonably consistent with the estimate.

A margin of error has two parts:

- The margin of error itself (such as ±2.0 percentage points), centered on the estimate
- A confidence level (such as 90 percent) that the true value is in the margin of error

All else constant, narrower margins of error or higher confidence levels mean that is more likely that the sample-based estimate is closer to the true population value.

To illustrate, suppose that the adjusted estimate of the head-count poverty rate for 100% of the national line is 67.4 percent and that the sample size is n = 1,024. Given 90-percent confidence, the margin of error is then ±2.6 percentage points (**Figure 2**).[57] Absent other sources of error and given the scorecard's standard assumptions, this means that there is a 90-percent chance that the true population value is in the range of 67.4 – 2.6 = 64.8 percent to 67.4 + 2.6 = 70.0 percent, with the most-likely true value being the center of the range (the 67.4-percent estimate).

Said another way, "With 90-percent confidence, the estimate has a margin of error from 64.8 to 70.0 percent." This means that the true population value has a:

- 5-percent chance of being less than 64.8 percent
- 90-percent chance of being between 64.8 and 70.0 percent
- 5-percent chance of being greater than 70.0 percent

A5.2.2 Why do margins of error matter?

Managers should put less weight on estimates with wider margins of error.

For example, a pro-poor program in Peru probably is indeed pro-poor if the scorecard estimate of the poverty rate for in-coming participants by 100% of the national poverty line with 80-percent confidence is 30.0 percent with a margin of error of ±5.0 percentage points, that is, from 25.0 to 35.0 percent. The estimate and its margin of error suggest that the true poverty rate of in-coming participants is unlikely to be less than or about the same as the all-Peru rate for this line (20.2 percent, **Figure 10**).

[57] Most real-world decisions are made with much less than 90-percent confidence.

If, however, the margin of error were ±15.0 percentage points (that is, from 15.0 to 45.0 percent), then there would be a non-negligible chance that the poverty rate of in-coming participants is less than or about the same as the average Peruvian and thus that the program may not actually be pro-poor.

To date, almost all analyses of scorecard estimates have ignored margins of error. This deficient practice increases the risk of bad decisions.

A5.2.3 Margins of error for snapshot estimates of poverty rates in one time period for the Peru scorecard

For sample sizes of *n* = 1,024 and 90-percent confidence and across all supported poverty lines, the margins of error for snapshot estimates of head-count poverty rates in a single time period are ±3.1 percentage points or smaller (**Figure 2**). Given the scorecard's standard assumptions, this means that in 90 of 100 samples of this size, the true population value is within ±3.1 percentage points or less of the error-adjusted estimate.

A5.2.4 How to calculate margins of error

The **ProveIt™-brand reporting and analysis tool** calculates margins of error for all scorecard estimates discussed here. Analysts may also use the formulas that follow.[58]

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[58] Schreiner (2020) discusses the derivation of the formulas.

A5.2.5 Formula for margins of error for snapshot estimates of head-count poverty rates in a single time period

All formulas for margins of error involve the following elements:

$\pm c$ is a margin of error as a proportion (*e.g.*, ±0.020 for ±2.0 percentage points),

z is from the Normal distribution and is $\begin{cases} 1.04 \text{ for confidence levels of 70 percent} \\ 1.28 \text{ for confidence levels of 80 percent} \\ 1.64 \text{ for confidence levels of 90 percent} \end{cases}$,

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

$\hat{p}$ is the estimated proportion of sampled people below a poverty line,

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

N is the population size in terms of households (not members of households),

n is the sample size (in terms of interviewed households,

not members of interviewed households), and

α is an adjustment factor specific to the scorecard, estimator, and poverty line.

Given a confidence level that corresponds with z, a sample-based estimate $\hat{p}$, a population N, a sample n, and an adjustment factor α for a specific poverty line from **Figure 2**, the formula[59] for the margin of error $\pm c$ is $\pm z\cdot\alpha\cdot\sqrt{\frac{\hat{p}\cdot(1-\hat{p})}{n}}\cdot\sqrt{\frac{N-n}{N-1}}$.

[59] This formula ignores how sampling variability affects the derivation of the scorecard. It also ignores that interviewed households have different numbers of

To illustrate, Peru's 2019 ENAHO gives a direct-measure head-count poverty rate for 100% of the national line of $\hat{p}$ = 20.2 percent (**Figure 10**). The adjustment factor α is 1.00 by definition because $\hat{p}$ is a direct-measure estimate, not an indirect-scorecard estimate. Peru in 2019 had a population of households (not people) of N = 3,556,832, and the ENAHO sample size was n = 34,565. Given a desired confidence level of 90 percent, z is 1.64. The margin of error ±c is then about ±0.4 percentage points:

$$\pm z \cdot \alpha \cdot \sqrt{\frac{\hat{p} \cdot (1-\hat{p})}{n}} \cdot \sqrt{\frac{N-n}{N-1}} = \pm 1.64 \cdot 1.00 \cdot \sqrt{\frac{0.202 \cdot (1-0.202)}{34{,}565}} \cdot \sqrt{\frac{3{,}556{,}832 - 34{,}565}{3{,}556{,}832 - 1}}.$$

This implies a 90-percent chance that Peru's true head-count poverty rate for 100% of the national line in 2019 is in the range of 20.2 – 0.4 = 19.8 percent to 20.2 + 0.4 = 20.6 percent.

A5.2.6 Margins of error for snapshot estimates of numbers of poor people in a single time period

The lower (upper) limit of the margin of error for a snapshot estimate of numbers of poor people is the number of people in participating households, multiplied by the lower (upper) limit of the margin of error of the poverty-rate estimate.

To illustrate, the baseline example in Section 23 has an estimated snapshot poverty rate of 67.4 percent. With 70-percent confidence, the margin of error is about ±39.5 percentage points,[60] from 67.4 – 39.5 = 27.9 percent to 67.4 + 39.5 = 106.9 percent ≈ 100 percent (because a poverty rate cannot exceed 100 percent). The margin of error is huge because the sample size of n = 2 interviewed households is exceedingly small.[61]

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members, and that larger households are more likely to have higher poverty likelihoods. This leads to an understatement of the margin of error.

[60] The example in Section 3 has N = 1,000, n = 2, and α = 1.34. For 70-percent confidence, z = 1.04. The margin of error ±c for the head-count poverty-rate estimate is then about ±0.395 ≈ $\pm 1.04 \cdot 1.34 \cdot \sqrt{\frac{0.202 \cdot (1-0.202)}{2}} \cdot \sqrt{\frac{1{,}000-2}{1{,}000-1}}$.

[61] Yet the formulas for margin of error still apply, and the estimator is still unbiased.

The estimated number of people in participating households in the example in Section 3 is 7,000,[62] so the lower limit of the 70-percent margin of error for the estimated number of poor people is 7,000·0.279 = 1,953. The upper limit is 7,000·1.00 = 7,000.

A5.2.7 Margins of error for estimates of the annual net change in head-count poverty rates across two periods for one sample, scored twice

In this case, the formula for the margin of error ±*c* is:

$$\pm \frac{z \cdot \alpha}{y} \cdot \sqrt{\frac{\hat{p}_{up} \cdot (1 - \hat{p}_{up}) + \hat{p}_{down} \cdot (1 - \hat{p}_{down}) + 2 \cdot \hat{p}_{up} \cdot \hat{p}_{down}}{n}} \cdot \sqrt{\frac{N - n}{N - 1}},$$

where:

- *z*, α, *N*, and *n* are defined as above
- $\hat{p}_{up}$ is the share of members of sampled households that rise above the poverty line
- $\hat{p}_{down}$ is the share of members of sampled households that fall below the poverty line
- *y* is the household-size-weighted average of years between interviews

Illustrating with the earlier example of one sample scored twice (Section **3.3.1**), $\hat{p}_{up}$ is the proportion of household members estimated to rise above a poverty line. This is the absolute value of the sum of the estimated *negative* changes in the number of members in poor households (from column M in **Figure 11**, here |–1.046 + (–0.356)| = +1.401), divided by the sum across all sampled households of each household's average household size across baseline and follow-up of 7.0 + 6.0 = 13.0 (from columns E and F). Thus, $\hat{p}_{up}$ = 1.401 ÷ 13 ≈ 0.108.

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[62] The formula for margin of error for the estimated number of poor people ignores that the estimated number of people in participating households has its own margin of error.

In turn, $\hat{p}_{down}$ is the share of household members estimated to fall below a poverty line. This is the sum of the estimated *positive* net changes in the number of members in poor households (from column M in **Figure 11**), which is zero in this example because there are no positive changes. Dividing this by the sum across all sampled households of each household's average household size across baseline and follow-up gives $\hat{p}_{down} = 0 \div 13 = 0.000$.[63]

The household-size-weighted average of the number of years between interviews *y* is 3.07.

With sample size $n = 2$ interviewed households, population N of 1,000 households, confidence level of 70 percent ($z = 1.04$), and the α adjustment factor for this estimator of 1.14,[64] the margin of error $\pm c$ is about

$$\pm 0.085 \approx \pm \frac{1.04 \cdot 1.14}{3.07} \cdot \sqrt{\frac{0.108 \cdot (1 - 0.108) + 0 \cdot (1 - 0) + 2 \cdot 0.108 \cdot 0}{2}} \cdot \sqrt{\frac{1{,}000 - 2}{1{,}000 - 1}}.$$

The example's estimated net annual poverty-rate change is –3.5 percentage points (**Figure 11**), so the 70-percent margin of error is –3.5 – 8.5 = –12.0 percentage points to –3.5 + 8.5 = +5.0 percentage points. The estimate from this tiny sample of *n* = 2 is uninformative; the true net change could easily be negative, close to zero, or positive.

This example shows why margins of error are useful. Without them, program managers might believe that there was evidence that poverty rates fell by 3.5 percentage points per year even though the data in this sample is also consistent with widely different rates and directions of change.

[63] $\hat{p}_{up} - \hat{p}_{down}$ is the estimated net poverty-rate change. In this particular example, $\hat{p}_{down}$ happens to be zero, so $\hat{p}_{up}$ equals the estimated net poverty-rate change.

[64] Schreiner, 2020.

A5.2.8 Margins of error for estimates of the annual net change in the number of poor people across two periods for one sample, scored twice

The lower (upper) limit of the margin of error for an estimate of annual net change in the number of poor people for one sample, scored twice is the average number of people in participating households from baseline to follow-up, multiplied by the lower (upper) limit of the margin of error of the estimated annual net change in the poverty rate.

To illustrate with the example in Section **3.3.4** for one sample scored twice, the estimated annual net change in the poverty rate is –3.5 percentage points. As just shown, the small sample size of $n = 2$ means that the 70-percent margin of error runs from –12.0 to +5.0 percentage points.

The estimated average number of on-going participating people is 5,600.[65] Thus, the lower limit of the 70-percent margin of error for the estimated annual net change in the number of poor people is $5{,}600 \cdot (-0.120) = -672$ (a net decrease in poor people), and the upper limit is $5{,}600 \cdot (+0.050) = +280$ (a net increase in poor people).

[65] The formula for margin of error for the estimated number of poor people ignores that the estimated number of people in participating households has its own margin of error.

A5.2.9 Margins of error for estimates of the annual net change in head-count poverty rates across two periods for two independent samples

The formula for the margin of error ±*c* is $\pm\frac{z\cdot\alpha}{y}\cdot\sqrt{\frac{2\cdot\hat{p}\cdot(1-\hat{p})}{n}}\cdot\sqrt{\frac{N-n}{N-1}}$,

where *z*, α, *y*, $\hat{p}$ and *N* are defined as above, and *n* is the sample size of interviewed households at both baseline and follow-up.

Illustrating with the example for two independent samples in Section 23:

- *z* = 1.04, assuming a desired confidence level is 70 percent
- α = 1.10, the adjustment factor for this estimator[66]
- *y* = 2.74, the years between the average interview at baseline and follow-up
- $\hat{p}$ = 0.647, the estimation-error-adjusted estimate of the poverty rate at baseline
- *N* = 850, the average number of households across baseline (1,000) and follow-up (700)
- *n* = 2, the sample size for the example in both baseline and follow-up

The margin of error ±*c* is ±0.199 ≈ $\pm\frac{1.04\cdot1.10}{2.74}\cdot\sqrt{\frac{2\cdot0.647\cdot(1-0.647)}{2}}\cdot\sqrt{\frac{850-2}{850-1}}$.

The example's estimated net annual poverty-rate change is –7.4 percentage points (**Figure 12**). Thus, the 70-percent margin of error is –7.4 – 19.9 = –27.3 percentage points to –7.4 + 19.9 = +12.5 percentage points. The tiny sample is again gives almost no information about whether the true value in the population negative, close to zero, or positive. This shows why margins of error matter.

[66] Schreiner, 2020.

A5.2.10 Margins of error for estimates of the annual net change in the number of poor people across two periods for two independent samples

The lower (upper) limit of the margin of error for an estimate of annual net change in the number of poor people for two independent samples is the average number of people in participating households from baseline to follow-up, multiplied by the lower (upper) limit of the margin of error of the estimated annual net change in the poverty rate.

To illustrate, the example in Section 2 for two independent samples estimates the annual net change in the poverty rate as –7.4 percentage points. As just shown, the 70-percent margin of error runs from –27.3 to +12.5 percentage points.

The estimated average number of on-going participating people is 5,775.[67] Thus, the lower limit of the 70-percent margin of error for the estimated annual net change in the number of poor people per year is 5,775 · (–0.273) ≈ –1,577 (a net decrease in poor people), and the upper limit is 5,775 · (+0.125) ≈ +722 (a net increase in poor people).

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[67] The formula for margin of error for the estimated number of poor people ignores that the estimated number of people in participating households has its own margin of error.

Annex 6 Formulas for sample size

Before drawing a sample of households to interview, the formulas here can be used to calculate the sample size that corresponds to a program's:

- Desired margin of error for the eventual scorecard estimate
- Desired confidence level for the margin of error, and
- Pre-estimation guess of the true population value to be estimated

These formulas may or may not be useful, for several reasons.

First, programs often collect scorecard data but then fail to report and analyze it. In such cases, the entire project is a waste, so there is no point in worrying about sample size. A solution is to plan and budget for reporting and analysis. If the remaining budget will not cover at least 1,000 interviews, then ignore the formulas and do as many interviews as the budget allows.

Second, both psychological sample size and statistical sample size matter. On the one hand, samples smaller than n = 300 often seem too small. On the other hand, samples of at least n = 1,000 usually seem large enough.

Third, calculating an optimal sample size makes sense only if a program:

- Has reason to desire a particular margin of error or level of confidence[68]
- Plans to report and analyze margins of error

If margins of error are not understood or will not be reported and analyzed, then just interview as many participating households as the budget allows.

Fourth, sample-size calculations are sometimes unneeded. For example, using the scorecard for segmenting requires interviewing all relevant participants. Likewise, doing a basic check on the fulfillment of a pro-poor mission is usually easier if all in-coming participants are scored as a routine step of the in-take process rather than repeatedly deciding at the moment whether to score a given enrollee.

[68] Academic conventions, applied to business, often imply unnecessarily large samples.

In sum, go ahead with the formulas below if you:

- Reserve resources for reporting and analysis
- Understand margins of error and will report and analyze them
- Plan to estimate net changes in poverty over time, and
- Have enough budget for at least 1,000 interviews at both baseline and follow-up

Otherwise:

- If checking a pro-poor mission, then score all in-coming participants at in-take
- If segmenting by poverty, then score all relevant participants
- If estimating changes in poverty, then score as many participants as the budget allows

A6.1 Sample-size formula for snapshot estimates of head-count-poverty rates in a single time period

In this case, the formula for the sample size n (the number of participating households to be interviewed) is $n = N \cdot \left(\frac{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p})}{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p}) + c^2 \cdot (N-1)} \right)$,

where n, c, z, α, and N are defined as in **Annex 5**, and $\tilde{p}$ is a before-estimation expectation for the poverty rate to be estimated.[69]

The illustration below of the calculation of the sample size n uses these values:

- The population of participating households is N = 10,000
- The desired confidence level for the margin of error is 80 percent, so z = 1.28
- The poverty line is 100% of the national line, so α = 1.34 (**Figure 2**)
- The pre-estimation expected poverty rate is the all-Peru rate for 100% of the national line, so $\tilde{p}$ = 20.2 percent = 0.202 (**Figure 10**)
- The desired margin of error $\pm c$ = ±3.0 percentage points = ±0.030

Given these hypothetical values,

$$n = 10{,}000 \cdot \left(\frac{1.28^2 \cdot 1.34^2 \cdot 0.202 \cdot (1-0.202)}{1.28^2 \cdot 1.34^2 \cdot 0.202 \cdot (1-0.202) + 0.03^2 \cdot (10{,}000-1)} \right) \approx 501.$$

[69] If the population N is "large" relative to the expected sample size n, then the formula can be taken as $n = \left(\frac{\alpha \cdot z}{c} \right)^2 \cdot \tilde{p} \cdot (1-\tilde{p})$.

A6.2 Sample-size formula for estimates of annual net changes in head-count-poverty rates across two time periods with two independent samples

This formula is two (2), multiplied by the formula for sample size for a snapshot estimate at a point in time. If n and $\tilde{p}$ are the same at both baseline and follow-up, then $n = 2 \cdot N \cdot \left(\dfrac{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p})}{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p}) + c^2 \cdot (N-1)} \right)$.[70]

There are n interviews at baseline, and n interviews at follow-up. For this estimator and regardless of the scorecard or poverty line, $\alpha = 1.10$.[71]

To illustrate with the same hypothetical values as in the example just above (except that $\alpha = 1.10$), the sample size at baseline n is:

$$2 \cdot 10{,}000 \cdot \left(\frac{1.28^2 \cdot 1.10^2 \cdot 0.202 \cdot (1-0.202)}{1.28^2 \cdot 1.10^2 \cdot 0.202 \cdot (1-0.202) + 0.03^2 \cdot (10{,}000-1)} \right) \approx 686.$$

The sample size at follow-up is also $n = 686$.

[70] If N is large relative to n, then the formula is $n = 2 \cdot \left(\dfrac{\alpha \cdot z}{c} \right)^2 \cdot \tilde{p} \cdot (1-\tilde{p})$.

[71] Schreiner, 2020.

A6.3 Sample-size formula for estimates of annual net changes in head-count-poverty rates across two time periods with one sample scored twice

The formula for the number of households to interview at both baseline and follow-up n is:[72]

$$2 \cdot \left(\frac{\alpha \cdot z}{c}\right)^2 \cdot [-0.01 + 0.016 \cdot y + 0.56 \cdot p_{\text{pre-baseline}} \cdot (1 - p_{\text{pre-baseline}})] \cdot \sqrt{\frac{N-n}{N-1}},$$

where n, α, z, c, and N are defined as above, y is the number of years between baseline and follow-up, and $p_{\text{pre-baseline}}$ is the population's expected head-count poverty rate prior to the baseline interviews.

The illustration below for this formula uses the following values:

- The poverty line is 100% of the national line
- α = 1.14 (regardless of the scorecard or poverty line, Schreiner, 2020)
- The desired confidence level for the margin of error is 80 percent, so z = 1.28
- The desired margin of error ±c = ±3.0 percentage points = ±0.030
- The number of years between baseline and follow-up is y = 3
- The pre-estimation expected pre-baseline poverty rate is the all-Peru rate for 100% of the national line: $p_{\text{pre-baseline}}$ = 20.2 percent = 0.202 (**Figure 10**)
- The population of participating households is N = 10,000

Assuming N is large relative to n so that $\sqrt{\frac{N-n}{N-1}} \approx 1$, the baseline sample size n is:

$$2 \cdot \left(\frac{1.14 \cdot 1.28}{0.03}\right)^2 \cdot [-0.01 + 0.016 \cdot 3 + 0.56 \cdot 0.202 \cdot (1 - 0.202)] \cdot 1 \approx 607.$$

The follow-up sample size is also 607.

[72] Schreiner, 2020.

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