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# Simple Poverty Scorecard® Tool
# Cambodia

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ឯកសារនេះ និង**ឧបករណ៍ប្រមូលទិន្នន័យ** ជាភាសាខ្មែរមាននៅគេហទំព័រ **scorocs.com**
This document and a **data-collection tool** are in English at **scorocs.com**

The Scorocs Simple Poverty Scorecard-brand poverty-assessment tool is a low-cost, transparent way for pro-poor programs in Cambodia to get to know their participants better so as to prove and improve their social performance. Responses to the scorecard's 10 questions can be used to:

- Assess poverty rates and numbers of poor people among in-coming participants
- Track changes in poverty among on-going participants
- Estimate daily per-capita consumption expenditure
- Segment participants for differentiated treatment based on poverty

## Version note

This new scorecard is based on data from **2019/20**. It replaces old scorecards based on data from **2004**, **2011**, and **2017**. The new scorecard should be used from now on. Because Cambodia changed its definition of *poverty* in 2019, it is not possible to estimate changes with a baseline from an old scorecard and a follow-up from the new scorecard. Both baseline and follow-up estimates must come from the new scorecard.

## Acknowledgements

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# Scorocs® Simple Poverty Scorecard® Poverty Assessment Tool

| | | | Full name | Identifier |
|---|---|---|---|---|
| Interview ID: | | | | |
| Interview date: | | Participant of record: | | |
| Country: | KHM | Service agent: | | |
| Scorecard: | 004 | Service point: | | |
| Sampling weight: | | Number of household members: | | |

| Question | Response | Points |
|---|---|---|
| 1. In which province does the household live? (*record without asking*) | A. Phnom Penh, Tboung Khmum, Kampong Thom, Pailin, Mondulkiri, or Ratanakiri | 0 |
| | B. Kandal, Siem Reap, Banteay Meanchey, Kampong Chhnang, Kratié, or Preah Vihear | 1 |
| | C. Prey Veng, Battambang, Kampong Cham, Takéo, Svay Rieng, Pursat, Oddar Meanchey, or Stung Treng | 2 |
| | D. Kampong Speu, Preah Sihanouk, Kampot, Koh Kong, or Kep | 7 |
| 2. How many members does the household have? (*from* ***Back-page Worksheet***) | A. Seven or more | 0 |
| | B. Six | 6 |
| | C. Five | 13 |
| | D. Four | 18 |
| | E. Three | 22 |
| | F. One or two | 30 |
| 3. How many rooms in the dwelling are used by the household (other than kitchen, toilet, and bathrooms)? | A. One | 0 |
| | B. Two | 4 |
| | C. Three or more | 9 |
| 4. What is the primary construction material of the floor of the dwelling occupied by the household? | A. Bamboo strips, earth, clay, or wooden planks | 0 |
| | B. Cement, brick, stone, parquet, polished wood, polished stone, marble, or other | 2 |
| | C. Vinyl, or ceramic tiles | 4 |
| 5. What kind of toilet facility does the household usually use? | A. None | 0 |
| | B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other | 3 |
| | C. Pour flush (or flush) to sewer | 4 |
| 6. Does the household own any gas or electric stoves? | A. No | 0 |
| | B. Yes | 3 |
| 7. How many cell phones does the household own? | A. None, or one | 0 |
| | B. Two, or three | 3 |
| | C. Four or more | 7 |
| 8. How many motorcycles (including electric motorcycles) does the household own? | A. None | 0 |
| | B. One | 6 |
| | C. Two or more | 12 |
| 9. Does the household own any cars, jeeps, or vans? | A. No | 0 |
| | B. Yes | 20 |
| 10. In the past 7 days, did anyone in the household eat any bananas, apples, oranges, lemons, or tangerines? | A. No | 0 |
| | B. Yes | 4 |




**Score:**

# Back-page Worksheet

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 unique identification number for the participant of record (who may differ from the interview's respondent), for the service agent of the participant of record (who may differ from you the enumerator), and for the service point that the participant of record uses (if any and if known). Without asking the respondent, circle the response to the first scorecard question based on the province where the household lives.

Then read to the respondent: *Please tell me the first name or nickname of each household member, starting with the head and his/her spouse partner (if there is one). A* household *is one or more people—regardless of kinship ties—who usually live together and who share an arrangement for food, such as using a common kitchen or sharing a food budget. The members do not have another permanent residence, and their actual or planned stay with the household is at least 12 months. Migrant or commuting workers (such as garment workers) count if they visit the household at least once a month.*

Write down the name (or nickname) of each member, first for the head and then for his/her spouse (if there is one). Record the sex of the head and of his/her spouse (if there is one).

After recording all household members, write down the exact number of members in the scorecard header next to "Number of household members". Then circle the response to the second scorecard question.

Read aloud the remaining eight questions. Always apply the instructions in the **Interview Guide**.

| **First name or nickname?** | **Head or spouse of head?** |
|---|---|
| 1. | Head (male)<br>Head (female) |
| 2. | Wife (eldest) of male head<br>Husband of female head<br>Other member |
| 3. | Other |
| 4. | Other |
| 5. | Other |
| 6. | Other |
| 7. | Other |
| 8. | Other |
| 9. | Other |
| 10. | Other |
| 11. | Other |
| 12. | Other |
| **# Household members**: | — |

## Figure 1: Conversion of scores to estimated poverty likelihoods

| | Poverty likelihood (%) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | National (2019/20 | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| Score | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| 0–17 | 80.3 | 98.4 | 100.0 | 78.1 | 100.0 | 59.4 | 82.5 | 92.1 | 96.8 | 98.4 | 100.0 | 100.0 | 100.0 | 100.0 |
| 18–22 | 57.9 | 93.5 | 98.1 | 57.3 | 100.0 | 36.8 | 62.5 | 79.0 | 87.3 | 94.1 | 95.9 | 98.1 | 98.9 | 99.8 |
| 23–25 | 43.8 | 86.8 | 95.5 | 41.9 | 99.9 | 28.5 | 50.8 | 67.9 | 82.5 | 87.9 | 93.5 | 96.0 | 97.9 | 99.8 |
| 26–27 | 39.5 | 86.3 | 95.1 | 36.0 | 99.8 | 18.6 | 42.2 | 63.8 | 78.0 | 87.0 | 91.4 | 95.3 | 97.9 | 99.8 |
| 28–29 | 27.5 | 81.9 | 95.1 | 24.2 | 99.8 | 13.4 | 32.8 | 53.2 | 73.3 | 85.5 | 90.3 | 95.3 | 97.9 | 99.8 |
| 30–31 | 19.1 | 72.4 | 92.2 | 17.1 | 99.8 | 7.7 | 22.1 | 40.8 | 59.6 | 75.2 | 86.7 | 93.8 | 97.8 | 99.8 |
| 32–33 | 13.7 | 69.7 | 92.2 | 12.2 | 99.7 | 5.5 | 16.9 | 34.3 | 56.8 | 72.4 | 86.4 | 93.7 | 97.7 | 99.7 |
| 34–35 | 11.7 | 58.4 | 84.9 | 10.4 | 99.0 | 4.1 | 16.0 | 29.8 | 46.2 | 60.8 | 74.9 | 87.0 | 92.3 | 98.3 |
| 36–37 | 10.2 | 56.4 | 81.0 | 9.7 | 98.1 | 3.9 | 12.5 | 26.1 | 40.9 | 57.9 | 70.5 | 82.7 | 90.8 | 97.6 |
| 38–39 | 6.5 | 39.6 | 76.4 | 6.0 | 97.3 | 2.7 | 7.4 | 14.8 | 25.8 | 43.5 | 63.0 | 78.4 | 88.9 | 96.9 |
| 40–41 | 3.4 | 32.2 | 70.0 | 3.4 | 97.3 | 0.7 | 4.8 | 10.0 | 21.6 | 34.8 | 55.0 | 72.7 | 88.2 | 96.9 |
| 42–43 | 1.5 | 25.0 | 63.0 | 1.5 | 95.0 | 0.4 | 2.7 | 7.6 | 14.4 | 28.2 | 45.1 | 68.7 | 81.4 | 93.7 |
| 44–45 | 1.5 | 18.7 | 54.9 | 1.5 | 94.2 | 0.3 | 1.7 | 4.7 | 10.8 | 21.4 | 38.6 | 57.9 | 77.9 | 91.9 |
| 46–47 | 0.8 | 14.7 | 49.9 | 0.8 | 93.4 | 0.0 | 1.0 | 4.0 | 8.0 | 16.1 | 33.2 | 53.3 | 76.5 | 91.3 |
| 48–50 | 0.0 | 8.8 | 36.3 | 0.0 | 89.7 | 0.0 | 0.0 | 0.7 | 3.1 | 10.5 | 22.3 | 41.2 | 65.8 | 86.2 |
| 51–54 | 0.0 | 4.5 | 22.0 | 0.0 | 87.4 | 0.0 | 0.0 | 0.0 | 1.3 | 5.4 | 11.5 | 25.0 | 49.0 | 83.9 |
| 55–60 | 0.0 | 2.0 | 12.8 | 0.0 | 74.9 | 0.0 | 0.0 | 0.0 | 0.2 | 2.6 | 5.2 | 13.9 | 35.8 | 69.3 |
| 61–68 | 0.0 | 0.4 | 5.0 | 0.0 | 54.0 | 0.0 | 0.0 | 0.0 | 0.2 | 1.0 | 1.6 | 6.1 | 19.8 | 47.4 |
| 69–100 | 0.0 | 0.0 | 0.2 | 0.0 | 21.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.2 | 3.9 | 18.2 |

## Figure 2: Conversion of scores to estimated daily per-capita consumption expenditure

| Score | KHR | Score | KHR | Score | KHR | Score | KHR | Score | KHR |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 6,657 | 20 | 10,980 | 40 | 20,273 | 60 | 38,081 | 80 | 68,179 |
| 1 | 6,657 | 21 | 11,294 | 41 | 20,925 | 61 | 39,259 | 81 | 70,160 |
| 2 | 6,657 | 22 | 11,609 | 42 | 21,626 | 62 | 40,462 | 82 | 72,140 |
| 3 | 7,062 | 23 | 11,923 | 43 | 22,327 | 63 | 41,665 | 83 | 74,120 |
| 4 | 7,265 | 24 | 12,238 | 44 | 23,028 | 64 | 42,868 | 84 | 76,097 |
| 5 | 7,470 | 25 | 12,603 | 45 | 23,730 | 65 | 44,205 | 85 | 78,074 |
| 6 | 7,675 | 26 | 12,969 | 46 | 24,431 | 66 | 45,543 | 86 | 80,051 |
| 7 | 7,880 | 27 | 13,335 | 47 | 25,185 | 67 | 46,880 | 87 | 82,052 |
| 8 | 8,089 | 28 | 13,756 | 48 | 25,940 | 68 | 48,218 | 88 | 84,053 |
| 9 | 8,298 | 29 | 14,177 | 49 | 26,695 | 69 | 49,555 | 89 | 86,055 |
| 10 | 8,507 | 30 | 14,599 | 50 | 27,526 | 70 | 50,987 | 90 | 86,055 |
| 11 | 8,731 | 31 | 15,113 | 51 | 28,357 | 71 | 52,419 | 91 | 90,057 |
| 12 | 8,954 | 32 | 15,627 | 52 | 29,188 | 72 | 53,851 | 92 | 92,058 |
| 13 | 9,178 | 33 | 16,141 | 53 | 30,208 | 73 | 55,458 | 93 | 92,058 |
| 14 | 9,414 | 34 | 16,655 | 54 | 31,229 | 74 | 57,065 | 94 | 92,058 |
| 15 | 9,651 | 35 | 17,169 | 55 | 32,250 | 75 | 58,672 | 95 | 92,058 |
| 16 | 9,888 | 36 | 17,769 | 56 | 33,408 | 76 | 60,573 | 96 | 92,058 |
| 17 | 10,147 | 37 | 18,370 | 57 | 34,566 | 77 | 62,475 | 97 | 92,058 |
| 18 | 10,406 | 38 | 18,970 | 58 | 35,725 | 78 | 64,376 | 98 | 92,058 |
| 19 | 10,665 | 39 | 19,621 | 59 | 36,903 | 79 | 66,278 | 99 | 92,058 |
| | | | | | | | | 100 | 92,058 |

KHR in 2019/20 in prices in Phnom Phen on average during the CSES fieldwork.
For total household figures, multiply the per-capita figure from the table by household size.
For monthly figures, multiple a per-capita or total figure by 30.417.

## Figure 3: Estimation errors in head-count poverty rates in a time period, along with margins of error and the α factor for finding margins of error and sample sizes

| | Poverty lines | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | National (2019 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| Estimation error | +1.7 | –1.8 | –3.1 | +1.6 | –1.8 | +1.8 | +2.1 | –2.3 | –1.2 | –2.2 | –3.0 | –3.0 | –2.9 | –1.5 |
| Margin of error | 2.4 | 2.3 | 1.8 | 2.4 | 1.2 | 1.7 | 2.7 | 2.4 | 2.2 | 2.3 | 2.0 | 1.8 | 1.5 | 1.3 |
| α factor | 1.20 | 0.93 | 0.77 | 1.17 | 0.84 | 1.11 | 1.25 | 1.01 | 0.92 | 0.92 | 0.82 | 0.77 | 0.74 | 0.85 |

Estimation errors and margins of error are estimated from 1,000 bootstraps with n = 16,384.
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.
The α factor is used to calculate margins of error and sample sizes.
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 Cambodia

## 1. Introduction

The Scorocs Simple Poverty Scorecard-brand poverty-assessment tool for Cambodia 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 "How many poor people does our program attract?", the scorecard can take a snapshot in a single time period with a census or sample of the households of in-coming participants to estimate:

- Head-count poverty rates
- Number of poor people

To address "How has poverty changed for our program's participants?", the scorecard can be applied across two time periods with samples of households from a given cohort of on-going participants to estimate net annual changes in:

- Head-count poverty rates
- Number of poor people

The scorecard also estimates daily per-capita consumption expenditure in Cambodian riel (KHR).

Finally, the scorecard can be used for targeting, that is, to segment participants for differentiated treatment based on their socio-economic level.

It is difficult and costly for pro-poor programs to address these questions with the traditional direct approach to poverty assessment via consumption-expenditure surveys. A case in point is Cambodia's 2019/20 Socio-Economic Survey (CSES) by the National Institute of Statistics (NIS). That questionnaire has about 60 pages and more than 600 top-level questions, most of which have several follow-up questions or are repeated (for example, for each household member, each consumer durable, or each food or non-food expenditure item).

## 1.2 How the scorecard works

The scorecard has 10 factual questions that are drawn from the exhaustive 2019/20 CSES. Examples include: "What kind of toilet facility does the household usually use?" and "Does the household own any gas or electric stoves?".

The 10 questions are selected to be:

- Inexpensive to collect, easy to answer quickly, and straightforward to verify
- Strongly and intuitively linked with socio-economic level
- Liable to change over time as socio-economic level changes
- Applicable in all provinces of Cambodia

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

Adding up the points that correspond to a household's responses gives a *score* that ranges from 0 to 100. The lower the score, the poorer the household.

A trained enumerator can interview a household, record its responses on paper or **on a device**, and add up 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. The links between scores, poverty likelihoods, and consumption expenditure are based on CSES data.

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

### 1.2.1 Estimated levels and changes in poverty rates and in numbers of poor people

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.

Estimated poverty rates may be used to estimate:

- The number of poor people in in-coming households in a single time period
- The change in the net number of poor people in households of on-going participants across two time periods

### 1.2.2 Estimates of consumption expenditure

A household's score can be converted into an estimate of its daily (or monthly or annual) per-capita (or total) consumption expenditure in KHR.

Estimates of the level of consumption expenditure in KHR might be useful, for example, for a microfinance lender who wants to assess the repayment capacity of a household that has applied for a loan.

### 1.2.3 Targeting

The scorecard can also be used to segment (target) 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 available to 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.

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

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

## 1.3 Poverty status based on consumption expenditure

Cambodia's scorecard is a quantitative way to assess whether people in the households of a program's participants have consumption expenditure below any of 14 supported poverty lines. The most-relevant poverty line is Cambodia's official line of KHR10,951 per person per day in average prices in Phnom Phen during CSES fieldwork. This line gives a country-wide head-count poverty rate in 2019/20 of 17.8 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 the official line while internally using a percentile-based line.

*Consumption expenditure* is the monetary value of tradable goods and services used up by a household in a time period. Compared with income, consumption expenditure is a better indicator of a household's well-being.

Cambodia's CSES measures poverty in terms of consumption expenditure, as does the scorecard here. Other common definitions of *poverty* include:

- Being rural, agricultural, landless, or unemployed
- Living in a given area
- Having a head who is illiterate, female, or an ethnic minority, or
- Having a member who is pregnant, handicapped, elderly, or young.

## 1.4 Transparency

The scorecard's design aims to make its workings clear to program managers. The tool's value stems from the low cost of its quick 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 they are inaccurate, but because *how* they work is unclear or hidden.

When scoring projects fail, the cause is not usually inaccuracy but rather a program's failure to:

- Commit to the work-a-day project management needed to integrate the scorecard in its processes
- Train and convince employees to use the tool properly[4]

[4] **Schreiner**, 2002.

For tool-based estimates of social outcomes such as poverty, data scientists have long known that there is almost no trade-off in accuracy between the straightforward and transparent (a glass box) versus the complex and opaque (a black box).[5] Project risk is less technical and more human, not statistics but organizational-change management.

## 1.5 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, these assumptions do not hold to some unknown degree.[6] In particular:

- A given program's participants are not representative of Cambodia overall
- Over time, the links between responses and poverty shift or drift

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 sample from the 2019/20 CSES. Reality diverges further from assumptions as:

- More time passes since the collection of construction data
- A program's participants differ from the country's general population
- 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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[5] **Dupriez**, 2018; **Caire and Schreiner**, 2012; **Schreiner**, 2012; **Hand**, 2006; **Lovie and Lovie**, 1986; **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 2020−23 economic upheaval due to COVID−19 and Russia's invasion of Ukraine changed the links between poverty and responses to scorecard questions, but the Cambodia scorecard still uses the links observed in 2019/20.

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 smaller when estimating poverty in one period or across two periods with a single scorecard than when estimating changes in poverty across two periods (or across two scorecards).

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 people who are members of the households of in-coming participants are below the official poverty line?"
- "Are the members of the households of our in-coming participants poorer than average people in our work area?"
- "Are people in the households of our on-going participants more likely to rise above a poverty line than average people in our work area?"

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

## 1.6 Estimation errors when assumptions hold

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

The assumptions do hold when the new scorecard is tested against households in the validation sample from the 2019/20 CSES that are 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 derived from one construction sample and applied to a single validation sample. **Figure 3** reports estimation error for estimates of poverty rates in one time period, allowing scorecard users to at least partially adjust for it.

## 1.7 What is next?

Section 2: How to convert responses to poverty likelihoods

Section 3: How to calculate scorecard estimates

— Poverty in a single time period for in-coming participants
  - Head-count poverty rate
  - Number of poor people

— Annual net changes in poverty across two time periods for on-going participants:
  - Poverty rate with one sample scored twice
  - Number of poor people with one sample scored twice
  - Poverty rate with two independent samples
  - 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 Cambodia's CSES as closely as possible. The **Interview Guide** and the **Back-page Worksheet** are integral parts of the scorecard tool. Do not ignore them.

The annexes provide details for advanced users:

Annex 1 Data used for construction and validation

Annex 2 Definition of poverty

Annex 3 Scorecard construction

Annex 4 Estimates of poverty likelihoods and consumption expenditure

Annex 5 Error and margins of error

Annex 6 Formulas for sample size

**References** to cited works 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 estimates of:
  - Poverty likelihoods
  - Consumption expenditure

**Section 3** below tells how to use poverty likelihoods for a sample of households to estimate poverty rates and numbers of poor people.

## 2.1 Instructions for enumerators

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

Enumerators should interview a sampled household at the household's dwelling using a **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 ("KHM", 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:
  - *Participant of record*. This is the member of the participating household whose identifying information is kept on-file with the pro-poor program. Often, the participant of record is the adult member of the household who interacts directly with the program. He or she may or may not be the same as the respondent who responds to the scorecard questions. For example, a participant of record for a microfinance program is often a borrower or a saver, and a participant of record with a child-health program might be a child or a child's parent or guardian

- *Service agent* (if there is one and if known). This is the participant of record's main, on-going point of contact with the program. The service agent may or may not be the same as the enumerator. For example, the service agent in a microfinance program is often a loan officer or savings collector, and the service agent in a child-health program might be a community health-care worker or a nurse practitioner
- *Service point* (if there is one). This is the program office that is relevant to the participant of record. The service point is usually the base of operations for the service agent (if there is one) who serves the participant of record or where the participant of record usually goes to do program business. For example, the service point for a microfinance program is often a branch, and the service point for a child-health program might be a community health post

- Mark the response to the first scorecard question ("In what province does the household live?"). If the enumerator already knows the province (as is almost always the case), then the question does not need to be asked directly of the respondent
- Use the **Back-page Worksheet** to record:
  - First name (or nickname) for each household member, starting with the head and the spouse of the head (if there is one)
  - The sex of the head and of the spouse of the head (if there is one)
- 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 aloud the remaining eight questions one-by-one, word-for-word as printed in the scorecard questionnaire, and in order, marking the responses given by the respondent
- Do not read the response options for any scorecard question to the respondent
- When marking a response on paper, write each point value in the far right-hand column of the scorecard questionnaire. To help reduce later data-entry mistakes, then make single circle that encompasses all of:
  - The text of the pre-printed response, and
  - The pre-printed points, and
  - The hand-written points
- 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

## 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 much more useful if they can be linked—via names or identifiers—to a program's existing data on the participant of record, service agent, and service point. 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 scorecard's header.

Do not leave fields in the header blank. If the data is unknown, does not exist, or is not applicable, then write "UNKNOWN" or "NONE".

Likewise, do not skip the **Back-page Worksheet**. Take the time to read the full definition of *household* word-for-word to the respondent and to fill out the roster member-by-member. If you cut corners, 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 Cambodia's NIS in the CSES. The accuracy of the scorecard's estimates depends on the quality of recorded responses and especially strongly on an accurate count of household members. Working through the **Back-page Worksheet** provides the best data.

Throughout the interview, apply the instructions in the **Interview Guide**. Enumerators must be thoroughly trained on the **Interview Guide** before they do any interviews, and they should carry a copy of the **Interview 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 study the **Interview Guide** and scrupulously follow it.

[8] The **Interview Guide** is the only source of guidance for enumerators. All other issues of interpretation should be left to the judgment of enumerators and respondents, as this seems to be what Cambodia's NIS did in the CSES.

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

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

[10] **Matul and Kline**, 2003. If a program does not want enumerators to know the scorecard's points, then it can use a **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 socio-economic status.

## Figure 4: First example household, filled-in scorecard

| | | | Full name | Identifier |
|---|---|---|---|---|
| Interview ID: | A123 | | | |
| Interview date: | 13JUN2023 | Participant of record: | ANNA JACKSON | 1V0276FZ7 |
| Country: | KHM | Service agent: | UNKNOWN | UNKNOWN |
| Scorecard: | 004 | Service point: | EAST CLINIC | NONE |
| Sampling weight: | UNKNOWN | | Number of household members: | SIX |

| Question | Response | Points | |
|---|---|---|---|
| 1. In which province does the household live? (*record without asking*) | A. Phnom Penh, Tboung Khmum, Kampong Thom, Pailin, Mondulkiri, or Ratanakiri | 0 | |
| | B. Kandal, Siem Reap, Banteay Meanchey, Kampong Chhnang, Kratié, or Preah Vihear | 1 | |
| | C. Prey Veng, Battambang, Kampong Cham, Takéo, Svay Rieng, Pursat, Oddar Meanchey, or Stung Treng | 2 | 2 |
| | D. Kampong Speu, Preah Sihanouk, Kampot, Koh Kong, or Kep | 7 | |
| 2. How many members does the household have? (*from* ***Back-page Worksheet***) | A. Seven or more | 0 | |
| | B. Six | 6 | 6 |
| | C. Five | 13 | |
| | D. Four | 18 | |
| | E. Three | 22 | |
| | F. One or two | 30 | |
| 3. How many rooms in the dwelling are used by the household (other than kitchen, toilet, and bathrooms)? | A. One | 0 | |
| | B. Two | 4 | 4 |
| | C. Three or more | 9 | |
| 4. What is the primary construction material of the floor of the dwelling occupied by the household? | A. Bamboo strips, earth, clay, or wooden planks | 0 | 0 |
| | B. Cement, brick, stone, parquet, polished wood, polished stone, marble, or other | 2 | |
| | C. Vinyl, or ceramic tiles | 4 | |
| 5. What kind of toilet facility does the household usually use? | A. None | 0 | |
| | B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other | 3 | 3 |
| | C. Pour flush (or flush) to sewer | 4 | |
| 6. Does the household own any gas or electric stoves? | A. No | 0 | 0 |
| | B. Yes | 3 | |
| 7. How many cell phones does the household own? | A. None, or one | 0 | 0 |
| | B. Two, or three | 3 | |
| | C. Four or more | 7 | |
| 8. How many motorcycles (including electric motorcycles) does the household own? | A. None | 0 | |
| | B. One | 6 | 6 |
| | C. Two or more | 12 | |
| 9. Does the household own any cars, jeeps, or vans? | A. No | 0 | 0 |
| | B. Yes | 20 | |
| 10. In the past 7 days, did anyone in the household eat any bananas, apples, oranges, lemons, or tangerines? | A. No | 0 | 0 |
| | B. Yes | 4 | |



**Score: 2 + 6 + 4 + 0 + 3 + 0 + 0 + 6 + 0 + 0 = 21**

## Figure 5: First example household, filled-in Back-page Worksheet

| First name or nickname? | Head or spouse of head? |
|---|---|
| 1. **ANNA** | Head (male)<br>Head (female) |
| 2. **BILLY** | Wife (eldest) of male head<br>Husband of female head<br>Other member |
| 3. **CHARLES** | Other |
| 4. **DARLA** | Other |
| 5. **EUGENE** | Other |
| 6. **FRANK** | Other |
| 7. | Other |
| 8. | Other |
| 9. | Other |
| 10. | Other |
| **# Household members**: **SIX** | — |

## 2.3 First example household

The points for the first example household's responses add up to a score of 21 (**Figure 4** and **Figure 5**).

For all supported poverty lines, **Figure 1** lists poverty likelihoods by score range. A score of 21 falls in the second range of 18−22. For the official line (called here "100% of the national line"), the poverty likelihood for scores of 18−22 is 57.9 percent. That is, the scorecard estimates that 57.9 percent of households in Cambodia with a score of 18–22 have consumption expenditure below 100% of the national line.

### Figure 6: The first example household's score of 21 corresponds with a poverty likelihood of 57.9 percent for 100% of the national line

| | National (2019 def.) | | |
|---|---|---|---|
| **Score** | **100%** | **150%** | **200%** |
| 0–17 | 80.3 | 98.4 | 100.0 |
| 18–22 | 57.9 | 93.5 | 98.1 |
| 23–25 | 43.8 | 86.8 | 95.5 |
| 26–27 | 39.5 | 86.3 | 95.1 |
| 28–29 | 27.5 | 81.9 | 95.1 |
| 30–31 | 19.1 | 72.4 | 92.2 |
| 32–33 | 13.7 | 69.7 | 92.2 |
| 34–35 | 11.7 | 58.4 | 84.9 |
| 36–37 | 10.2 | 56.4 | 81.0 |
| 38–39 | 6.5 | 39.6 | 76.4 |

Source: Excerpted from **Figure 1**

## Figure 7: Second example household, filled-in scorecard

| | | | Full name | Identifier |
|---|---|---|---|---|
| Interview ID: | B456 | | | |
| Interview date: | 30JUN2023 | Participant of record: | JOHN BROWN | 2W3120ZG8 |
| Country: | KHM | Service agent: | UNKNOWN | UNKNOWN |
| Scorecard: | 004 | Service point: | EAST CLINIC | NONE |
| Sampling weight: | UNKNOWN | Number of household members: | | FIVE |

| Question | Response | Points | |
|---|---|---|---|
| 1. In which province does the household live? (*record without asking*) | A. Phnom Penh, Tboung Khmum, Kampong Thom, Pailin, Mondulkiri, or Ratanakiri | 0 | |
| | B. Kandal, Siem Reap, Banteay Meanchey, Kampong Chhnang, Kratié, or Preah Vihear | 1 | |
| | C. Prey Veng, Battambang, Kampong Cham, Takéo, Svay Rieng, Pursat, Oddar Meanchey, or Stung Treng | 2 | 2 |
| | D. Kampong Speu, Preah Sihanouk, Kampot, Koh Kong, or Kep | 7 | |
| 2. How many members does the household have? (*from* ***Back-page Worksheet***) | A. Seven or more | 0 | |
| | B. Six | 6 | |
| | C. Five | 13 | 13 |
| | D. Four | 18 | |
| | E. Three | 22 | |
| | F. One or two | 30 | |
| 3. How many rooms in the dwelling are used by the household (other than kitchen, toilet, and bathrooms)? | A. One | 0 | |
| | B. Two | 4 | 4 |
| | C. Three or more | 9 | |
| 4. What is the primary construction material of the floor of the dwelling occupied by the household? | A. Bamboo strips, earth, clay, or wooden planks | 0 | 0 |
| | B. Cement, brick, stone, parquet, polished wood, polished stone, marble, or other | 2 | |
| | C. Vinyl, or ceramic tiles | 4 | |
| 5. What kind of toilet facility does the household usually use? | A. None | 0 | |
| | B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other | 3 | 3 |
| | C. Pour flush (or flush) to sewer | 4 | |
| 6. Does the household own any gas or electric stoves? | A. No | 0 | 0 |
| | B. Yes | 3 | |
| 7. How many cell phones does the household own? | A. None, or one | 0 | 0 |
| | B. Two, or three | 3 | |
| | C. Four or more | 7 | |
| 8. How many motorcycles (including electric motorcycles) does the household own? | A. None | 0 | 0 |
| | B. One | 6 | |
| | C. Two or more | 12 | |
| 9. Does the household own any cars, jeeps, or vans? | A. No | 0 | 0 |
| | B. Yes | 20 | |
| 10. In the past 7 days, did anyone in the household eat any bananas, apples, oranges, lemons, or tangerines? | A. No | 0 | |
| | B. Yes | 4 | 4 |



**Score:** 2 + 13 + 4 + 0 + 3 + 0 + 0 + 0 + 0 + 4 = 26

## Figure 8: Second example household, filled-in Back-page Worksheet

| First name or nickname? | Head or spouse of head? |
|---|---|
| 1. **ALBERT** | Head (male)<br>Head (female) |
| 2. **BERNITA** | Wife (eldest) of male head<br>Husband of female head<br>Other member |
| 3. **CARLOS** | Other |
| 4. **DARLENE** | Other |
| 5. **EVELYN** | Other |
| 6. | Other |
| 7. | Other |
| 8. | Other |
| 9. | Other |
| 10. | Other |
| **# Household members**: **FIVE** | — |

Source: Excerpted from **Figure 1**

## 2.4 Second example household

The points for the second example household's responses add up to a score of 26 (**Figure 7**).

For all supported poverty lines, **Figure 1** lists poverty likelihoods by score range. A score of 26 falls in the fourth range of 26–27. For 100% of the national poverty line, the poverty likelihood for scores of 26–27 is 39.5 percent. That is, the scorecard estimates that 39.5 percent of households in Cambodia with a score of 26–27 have consumption expenditure below 100% of the national line.

### Figure 9: The second example household's score of 26 corresponds with a poverty likelihood of 39.5 percent for 100% of the national line

| | National (2019 def.) | | |
|---|---|---|---|
| **Score** | **100%** | **150%** | **200%** |
| 0–17 | 80.3 | 98.4 | 100.0 |
| 18–22 | 57.9 | 93.5 | 98.1 |
| 23–25 | 43.8 | 86.8 | 95.5 |
| 26–27 | 39.5 | 86.3 | 95.1 |
| 28–29 | 27.5 | 81.9 | 95.1 |
| 30–31 | 19.1 | 72.4 | 92.2 |
| 32–33 | 13.7 | 69.7 | 92.2 |
| 34–35 | 11.7 | 58.4 | 84.9 |
| 36–37 | 10.2 | 56.4 | 81.0 |
| 38–39 | 6.5 | 39.6 | 76.4 |

# 3. How to calculate scorecard estimates

This section tells how to estimate:

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

It also tells how to use these estimated levels and changes in poverty rates to estimate:

- The number of poor people in the households of in-coming participants in a single time period
- The net change in the number of poor people in the households of on-going participants across two time periods

Finally, this section tells how to convert a household's score into an estimate of consumption expenditure.

## 3.1 Poverty in a single time period for in-coming participants

### 3.1.1 Head-count poverty rate

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

An estimate of the head-count poverty rate is 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 that operates throughout Cambodia enrolls 1,000 in-coming households in calendar-year 2023, from which it scores a simple random sample[11] of two households.[12]

The program chooses 100% of the national poverty line as relevant for its purposes. For that line and for estimates of poverty rates in one period, the scorecard's known estimation error is +1.7 percentage points (**Figure 3**).

The first example household has six members and is interviewed on June 13, 2023 (**Figure 4** and **Figure 5**). Its score of 21 corresponds with a poverty likelihood of 57.9 percent.

The second example household has five members and is interviewed on June 30, 2023 (**Figure 7** and **Figure 8**). Its score of 26 corresponds with a poverty likelihood of 39.5 percent.

The estimated head-count poverty rate for the population of people who are members of in-coming households in the 2023 calendar-year cohort 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:

$$\frac{6 \cdot 0.579 + 5 \cdot 0.395}{6+5} - (+0.017) \approx \frac{3.48 + 1.98}{11} - 0.017 \approx 0.479 = 47.9 \text{ percent.}$$

The "6" in the "$6 \cdot 0.579$" term is the number of members (household size) in the first household. The "0.579" is the first household's estimated poverty likelihood as a proportion.

In the same way, the "5" in "$5 \cdot 0.395$" is the number of members in the second household. The "0.395" is the second household's estimated poverty likelihood.

The "6 + 5" is the sum of the weights—that is, the number of household members—in the two sampled households.

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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 different households have different selection probabilities.

[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 here.

The “+0.017” is the scorecard’s estimation error for this poverty line (**Figure 3**). Because unadjusted estimates tend to be too high by 1.7 percentage points, they are adjusted downwards by subtracting +1.7. This is akin to how an archer whose arrows tend to miss a little to the right of the bulls-eye will adjust his or her aim to be a little to the left of the bulls-eye.

The estimated head-count poverty rate for the population is 47.9 percent. Again, this is the household-size-weighted average of the two sampled households’ poverty likelihoods, adjusted for the known estimation error.[13]

In practice, there are hundreds or thousands of interviewed households, so the calculations are done with the **ProveIt™-brand reporting and analysis tool** or in a spreadsheet, following the model in **Figure 10** below.

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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 $(6 \cdot 21 + 5 \cdot 26) \div (6 + 5) \approx 23$. This average score of 23 corresponds to a poverty likelihood for 100% of the national line of 43.8 percent (**Figure 1**), giving an error-adjusted poverty rate of $43.8 - (+1.7) = 42.1$ percent. This differs from the 47.9 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**, 2012). In general, programs should analyze likelihoods, not scores.

**Figure 10: Spreadsheet calculation to estimate the head-count poverty rate and number of poor people in households 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-23 | 1V0276FZ7 | 6 | 21 | 57.9 | 3.48 = (D2*F2)/100 |
| **3** | Baseline | 30-Jun-23 | 2W3120ZG8 | 5 | 26 | 39.5 | 1.98 = (D3*F3)/100 |
| **4** | | | **Sum:** | 11 = SUM(D2:D3) | | | 5.45 = SUM(G2:G3) |
| **5** | | | **Average:** | 5.5 = AVERAGE(D2:D3) | | | |
| **6** | | | | | | | |
| **7** | | **Estimated scorecard error for this poverty line (percentage points):** | | | | | +1.7 |
| **8** | | | | | | | |
| **9** | | | | **Estimated head-count poverty rate (%):** | | | 47.9 = (G4/D4)*100–G7 |
| **10** | | | | | | | |
| **11** | | | | **Households in the population:** | | | 1,000 |
| **12** | | | | | | | |
| **13** | | | | **People in households in the population:** | | | 5,500 = G11*D5 |
| **14** | | | | | | | |
| **15** | | | | **Number of poor people in population:** | | | 2,633 = (G9/100)*G13 |
| **16** | Rows of data are sorted by Survey, then by Interview date, then by the ID of the participant of record. | | | | | | |

This estimate in a single time period tends to be more relevant for in-coming participating households who joined a program in the current period than for on-going participating households who joined in past periods. This is because fulfilling a pro-poor mission implies that some share of new participants must be poor by some definition of *poverty*. To be pro-poor, a bare-minimum standard is that the poverty rate of people in the households in-coming participants exceed that for people in the country as a whole or for the program's work area.

To help with benchmarking poverty-rate estimates, **Figure 11** reports head-count poverty rates from the 2019/20 CSES for all 14 supported poverty lines by urban/rural/all for Cambodia overall and for each of its 25 provinces.

For Cambodia overall, the head-count poverty rate for 100% of the national line is 17.8 percent. Thus, the example program is pro-poor in the sense that people in the households of its in-coming participants have an above-average estimated poverty rate (47.9 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 11**, which stretches across the next nine pages.

The areas in **Figure 11** begin with Cambodia overall, followed by the 25 provinces in the order in which the NIS reports them.

## Figure 11: (Cambodia overall, Banteay Meanchey, and Battambang): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ | Area | Line or Rate | *n* | Poverty lines and poverty rates | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | National (2019 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | | | | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| Cambodia | Urban | Line | 3,745 | 11,812 | 17,718 | 23,625 | 11,647 | 41,420 | 10,125 | 12,285 | 14,175 | 16,082 | 18,160 | 20,845 | 24,427 | 29,129 | 38,873 |
| | | Rate | | 9.6 | 32.8 | 52.9 | 9.1 | 83.9 | 4.6 | 10.8 | 18.0 | 25.1 | 34.5 | 43.8 | 55.0 | 67.0 | 81.3 |
| | Rural | Line | 6,330 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 22.8 | 57.2 | 77.3 | 21.7 | 96.0 | 13.2 | 25.5 | 37.1 | 48.9 | 59.2 | 69.6 | 78.9 | 87.8 | 95.2 |
| | All | Line | 10,075 | 10,951 | 16,426 | 21,902 | 10,798 | 38,400 | 9,387 | 11,389 | 13,141 | 14,910 | 16,836 | 19,325 | 22,646 | 27,005 | 36,039 |
| | | Rate | | 17.8 | 48.1 | 68.2 | 17.0 | 91.5 | 10.0 | 20.0 | 30.0 | 40.0 | 50.0 | 60.0 | 70.0 | 80.0 | 90.0 |
| Banteay | Urban | Line | 220 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 13.0 | 42.3 | 63.7 | 13.0 | 93.7 | 8.6 | 16.3 | 28.3 | 33.5 | 43.2 | 55.5 | 64.8 | 78.5 | 91.0 |
| | Rural | Line | 280 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 26.1 | 64.4 | 81.4 | 25.7 | 97.0 | 15.6 | 28.4 | 42.0 | 55.4 | 65.4 | 77.2 | 82.8 | 89.9 | 96.5 |
| | All | Line | 500 | 10,702 | 16,053 | 21,405 | 10,553 | 37,528 | 9,174 | 11,130 | 12,843 | 14,571 | 16,453 | 18,886 | 22,131 | 26,392 | 35,220 |
| | | Rate | | 21.7 | 57.0 | 75.4 | 21.4 | 95.9 | 13.2 | 24.3 | 37.4 | 48.0 | 57.9 | 69.9 | 76.7 | 86.1 | 94.6 |
| Battambang | Urban | Line | 140 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 16.2 | 43.7 | 69.2 | 16.2 | 88.7 | 10.8 | 16.2 | 26.7 | 34.3 | 46.9 | 60.2 | 72.1 | 77.4 | 88.7 |
| | Rural | Line | 440 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 21.4 | 56.0 | 78.2 | 18.8 | 98.0 | 11.0 | 23.0 | 35.3 | 47.4 | 57.5 | 69.8 | 79.6 | 88.1 | 97.1 |
| | All | Line | 580 | 10,598 | 15,897 | 21,195 | 10,450 | 37,161 | 9,084 | 11,021 | 12,717 | 14,429 | 16,293 | 18,701 | 21,915 | 26,134 | 34,876 |
| | | Rate | | 20.3 | 53.5 | 76.4 | 18.3 | 96.1 | 11.0 | 21.6 | 33.6 | 44.7 | 55.3 | 67.8 | 78.1 | 86.0 | 95.4 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Kampong Cham, Kampong Chhnang, and Kampong Speu): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ | Area | Line or Rate | *n* | National (2019 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | **100%** | **150%** | **200%** | **$6.85** | **$24.36** | **10th** | **20th** | **30th** | **40th** | **50th** | **60th** | **70th** | **80th** | **90th** |
| Kampong Cham | **Urban** | Line | 80 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 22.2 | 54.9 | 72.7 | 21.3 | 87.9 | 3.7 | 23.3 | 31.3 | 45.7 | 55.5 | 59.2 | 72.7 | 77.1 | 86.6 |
| | **Rural** | Line | 490 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 19.8 | 55.8 | 77.2 | 18.5 | 96.4 | 11.1 | 21.7 | 34.5 | 45.5 | 58.6 | 69.5 | 77.9 | 86.7 | 95.4 |
| | **All** | Line | 570 | 10,538 | 15,807 | 21,077 | 10,391 | 36,953 | 9,033 | 10,960 | 12,646 | 14,348 | 16,201 | 18,597 | 21,792 | 25,987 | 34,680 |
| | | Rate | | 20.1 | 55.7 | 76.6 | 18.9 | 95.3 | 10.2 | 21.9 | 34.1 | 45.6 | 58.2 | 68.2 | 77.2 | 85.5 | 94.3 |
| Kampong | **Urban** | Line | 110 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 25.5 | 55.3 | 76.6 | 24.4 | 93.4 | 16.0 | 26.9 | 36.5 | 46.9 | 56.8 | 66.6 | 79.6 | 89.5 | 93.4 |
| | **Rural** | Line | 280 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 28.7 | 63.7 | 85.4 | 28.4 | 98.0 | 20.3 | 31.7 | 44.8 | 55.4 | 65.4 | 78.9 | 86.1 | 94.3 | 97.6 |
| | **All** | Line | 390 | 10,604 | 15,905 | 21,207 | 10,456 | 37,182 | 9,089 | 11,028 | 12,724 | 14,437 | 16,302 | 18,712 | 21,927 | 26,148 | 34,896 |
| | | Rate | | 28.0 | 61.9 | 83.6 | 27.6 | 97.0 | 19.4 | 30.7 | 43.1 | 53.6 | 63.6 | 76.3 | 84.7 | 93.3 | 96.7 |
| Kampong Speu | **Urban** | Line | 260 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 12.4 | 36.1 | 60.3 | 12.4 | 91.4 | 7.0 | 14.2 | 18.8 | 27.2 | 37.8 | 49.7 | 63.6 | 76.3 | 91.0 |
| | **Rural** | Line | 220 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 14.3 | 44.1 | 67.7 | 13.3 | 96.4 | 8.5 | 15.0 | 29.7 | 39.3 | 45.3 | 59.4 | 72.5 | 84.1 | 95.3 |
| | **All** | Line | 480 | 10,893 | 16,339 | 21,786 | 10,741 | 38,196 | 9,337 | 11,328 | 13,071 | 14,830 | 16,746 | 19,222 | 22,525 | 26,862 | 35,847 |
| | | Rate | | 13.2 | 39.5 | 63.4 | 12.8 | 93.5 | 7.6 | 14.5 | 23.3 | 32.2 | 40.9 | 53.7 | 67.3 | 79.5 | 92.8 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Kampong Thom, Kampot, and Kandal): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ Area | | Line or Rate | *n* | National (2019 def.) 100% | National (2019 def.) 150% | National (2019 def.) 200% | Intl. 2017 PPP (2019 def.) $6.85 | Intl. 2017 PPP (2019 def.) $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Kampong Thom | **Urban** | Line | 70 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 15.5 | 41.9 | 72.5 | 14.1 | 90.4 | 7.1 | 19.3 | 26.4 | 31.5 | 41.9 | 61.9 | 74.4 | 82.1 | 85.3 |
| | **Rural** | Line | 390 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 30.8 | 65.7 | 82.7 | 29.7 | 96.9 | 17.5 | 33.2 | 45.9 | 59.8 | 68.0 | 77.2 | 84.6 | 89.9 | 95.6 |
| | **All** | Line | 460 | 10,524 | 15,786 | 21,048 | 10,377 | 36,902 | 9,021 | 10,945 | 12,629 | 14,328 | 16,179 | 18,571 | 21,762 | 25,951 | 34,633 |
| | | Rate | | 29.2 | 63.1 | 81.6 | 28.0 | 96.2 | 16.4 | 31.7 | 43.8 | 56.8 | 65.2 | 75.6 | 83.5 | 89.0 | 94.5 |
| Kampot | **Urban** | Line | 50 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 11.6 | 28.2 | 49.0 | 11.6 | 78.8 | 11.6 | 11.6 | 21.4 | 24.1 | 30.3 | 39.1 | 49.0 | 61.3 | 77.8 |
| | **Rural** | Line | 370 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 10.1 | 40.6 | 67.5 | 10.1 | 94.2 | 5.9 | 11.9 | 20.0 | 30.7 | 43.1 | 54.6 | 69.5 | 81.2 | 92.9 |
| | **All** | Line | 420 | 10,520 | 15,781 | 21,041 | 10,373 | 36,890 | 9,018 | 10,941 | 12,625 | 14,323 | 16,174 | 18,565 | 21,755 | 25,943 | 34,622 |
| | | Rate | | 10.3 | 39.4 | 65.6 | 10.3 | 92.6 | 6.5 | 11.9 | 20.1 | 30.0 | 41.7 | 53.0 | 67.4 | 79.2 | 91.4 |
| Kandal | **Urban** | Line | 420 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 8.7 | 40.6 | 64.0 | 7.7 | 94.1 | 2.2 | 9.0 | 17.0 | 28.3 | 42.9 | 54.1 | 66.4 | 77.5 | 92.2 |
| | **Rural** | Line | 210 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 18.7 | 56.2 | 75.0 | 18.3 | 94.6 | 8.2 | 20.1 | 34.2 | 50.3 | 58.3 | 66.0 | 76.6 | 85.0 | 93.8 |
| | **All** | Line | 630 | 10,946 | 16,418 | 21,891 | 10,793 | 38,381 | 9,382 | 11,383 | 13,135 | 14,902 | 16,827 | 19,315 | 22,634 | 26,991 | 36,021 |
| | | Rate | | 12.2 | 46.0 | 67.9 | 11.4 | 94.2 | 4.3 | 12.9 | 23.0 | 36.0 | 48.3 | 58.2 | 70.0 | 80.1 | 92.8 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Koh Kong, Kratié, and Mondulkiri): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province | Area | Line or Rate | *n* | Natl. (2019/20 def.) 100% | Natl. (2019/20 def.) 150% | Natl. (2019/20 def.) 200% | Intl. 2017 PPP (2019 def.) $6.85 | Intl. 2017 PPP (2019 def.) $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Koh Kong | **Urban** | Line | 110 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 9.4 | 34.5 | 56.1 | 9.4 | 86.8 | 6.5 | 10.1 | 13.7 | 24.0 | 38.5 | 48.4 | 56.9 | 71.6 | 85.1 |
| | **Rural** | Line | 100 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 6.6 | 29.2 | 50.4 | 6.6 | 85.8 | 3.5 | 9.5 | 17.6 | 23.2 | 31.2 | 40.5 | 52.3 | 73.3 | 82.2 |
| | **All** | Line | 210 | 10,789 | 16,184 | 21,579 | 10,639 | 37,833 | 9,248 | 11,221 | 12,947 | 14,689 | 16,587 | 19,040 | 22,311 | 26,606 | 35,506 |
| | | Rate | | 7.9 | 31.6 | 53.0 | 7.9 | 86.3 | 4.8 | 9.8 | 15.9 | 23.5 | 34.5 | 44.1 | 54.4 | 72.5 | 83.5 |
| Kratié | **Urban** | Line | 40 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 5.1 | 27.1 | 36.3 | 5.1 | 76.1 | 0.0 | 5.1 | 19.6 | 23.1 | 27.1 | 33.5 | 40.4 | 53.7 | 73.1 |
| | **Rural** | Line | 270 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 34.1 | 66.2 | 83.1 | 32.9 | 97.9 | 21.8 | 34.9 | 46.0 | 57.2 | 70.3 | 76.2 | 85.6 | 92.3 | 95.9 |
| | **All** | Line | 310 | 10,519 | 15,779 | 21,039 | 10,372 | 36,886 | 9,017 | 10,940 | 12,623 | 14,322 | 16,172 | 18,563 | 21,753 | 25,940 | 34,618 |
| | | Rate | | 31.2 | 62.2 | 78.3 | 30.1 | 95.7 | 19.6 | 31.9 | 43.3 | 53.7 | 65.9 | 71.9 | 81.0 | 88.3 | 93.6 |
| Mondulkiri | **Urban** | Line | 70 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 9.4 | 26.6 | 43.0 | 9.4 | 82.9 | 7.7 | 9.4 | 14.0 | 23.6 | 28.7 | 36.0 | 45.6 | 58.5 | 78.2 |
| | **Rural** | Line | 130 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 35.3 | 59.9 | 76.7 | 33.6 | 95.5 | 22.9 | 35.9 | 47.6 | 54.7 | 62.0 | 73.0 | 79.2 | 83.6 | 93.7 |
| | **All** | Line | 200 | 10,726 | 16,089 | 21,452 | 10,576 | 37,611 | 9,194 | 11,155 | 12,871 | 14,603 | 16,490 | 18,928 | 22,180 | 26,450 | 35,298 |
| | | Rate | | 25.8 | 47.7 | 64.3 | 24.7 | 90.9 | 17.4 | 26.2 | 35.2 | 43.2 | 49.7 | 59.4 | 66.9 | 74.4 | 88.0 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

# Figure 11: (Phnom Penh, Preah Vihear, and Prey Veng): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ | Area | Line or Rate | *n* | Poverty lines and poverty rates | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | National (2019 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | | | | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| Phnom Penh | Urban | Line | 925 | 12,835 | 19,252 | 25,670 | 12,656 | 45,006 | 11,002 | 13,348 | 15,402 | 17,474 | 19,732 | 22,649 | 26,541 | 31,650 | 42,238 |
| | | Rate | | 4.2 | 20.4 | 37.7 | 4.1 | 74.0 | 1.9 | 5.1 | 10.1 | 15.0 | 21.7 | 29.6 | 39.6 | 53.2 | 70.0 |
| | Rural | Line | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| | | Rate | | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| | All | Line | 925 | 12,835 | 19,252 | 25,670 | 12,656 | 45,006 | 11,002 | 13,348 | 15,402 | 17,474 | 19,732 | 22,649 | 26,541 | 31,650 | 42,238 |
| | | Rate | | 4.2 | 20.4 | 37.7 | 4.1 | 74.0 | 1.9 | 5.1 | 10.1 | 15.0 | 21.7 | 29.6 | 39.6 | 53.2 | 70.0 |
| Preah Vihear | Urban | Line | 40 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 15.2 | 31.3 | 71.5 | 15.2 | 93.7 | 15.2 | 15.2 | 17.6 | 22.0 | 33.0 | 51.4 | 71.5 | 77.2 | 91.3 |
| | Rural | Line | 200 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 20.2 | 57.8 | 78.2 | 20.2 | 97.0 | 9.4 | 24.8 | 37.0 | 49.5 | 60.7 | 71.4 | 78.9 | 87.9 | 96.5 |
| | All | Line | 240 | 10,522 | 15,783 | 21,044 | 10,375 | 36,896 | 9,019 | 10,943 | 12,626 | 14,325 | 16,176 | 18,568 | 21,758 | 25,947 | 34,627 |
| | | Rate | | 19.6 | 55.0 | 77.5 | 19.6 | 96.6 | 10.0 | 23.8 | 34.9 | 46.6 | 57.8 | 69.3 | 78.1 | 86.7 | 95.9 |
| Prey Veng | Urban | Line | 30 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 28.1 | 39.8 | 62.5 | 20.9 | 82.5 | 16.9 | 28.1 | 35.1 | 35.1 | 39.8 | 46.5 | 65.8 | 78.6 | 82.5 |
| | Rural | Line | 540 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 23.4 | 57.4 | 78.1 | 22.1 | 95.9 | 12.5 | 27.3 | 37.4 | 50.6 | 59.2 | 70.1 | 80.2 | 89.7 | 95.6 |
| | All | Line | 570 | 10,481 | 15,722 | 20,963 | 10,335 | 36,754 | 8,984 | 10,901 | 12,578 | 14,270 | 16,114 | 18,496 | 21,675 | 25,847 | 34,493 |
| | | Rate | | 23.6 | 56.5 | 77.3 | 22.1 | 95.2 | 12.8 | 27.4 | 37.3 | 49.8 | 58.2 | 68.9 | 79.4 | 89.1 | 94.9 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Pursat, Ratanakiri, and Siem Reap): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| | | | | Poverty lines and poverty rates | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Line | | National (2019 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | |
| Province/ | Area | or Rate | *n* | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| **Pursat** | **Urban** | Line | 80 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 13.4 | 39.0 | 57.4 | 13.4 | 86.4 | 6.2 | 13.4 | 26.6 | 31.1 | 40.3 | 49.3 | 61.0 | 72.7 | 86.4 |
| | **Rural** | Line | 290 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 26.8 | 60.6 | 78.2 | 25.7 | 96.6 | 14.3 | 29.6 | 38.5 | 50.5 | 61.3 | 69.3 | 80.8 | 90.3 | 96.4 |
| | **All** | Line | 370 | 10,578 | 15,866 | 21,155 | 10,430 | 37,090 | 9,067 | 11,000 | 12,693 | 14,401 | 16,262 | 18,666 | 21,873 | 26,084 | 34,810 |
| | | Rate | | 24.4 | 56.8 | 74.5 | 23.5 | 94.8 | 12.9 | 26.8 | 36.4 | 47.0 | 57.6 | 65.8 | 77.3 | 87.2 | 94.6 |
| **Ratanakiri** | **Urban** | Line | 40 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 5.2 | 37.2 | 61.2 | 5.2 | 89.7 | 1.5 | 7.6 | 14.5 | 23.0 | 37.2 | 53.7 | 61.2 | 75.7 | 86.7 |
| | **Rural** | Line | 170 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 38.0 | 68.7 | 89.2 | 34.9 | 98.3 | 25.1 | 41.6 | 53.3 | 58.0 | 71.9 | 83.6 | 90.4 | 94.1 | 97.8 |
| | **All** | Line | 210 | 10,553 | 15,830 | 21,107 | 10,406 | 37,006 | 9,046 | 10,975 | 12,664 | 14,368 | 16,225 | 18,623 | 21,824 | 26,025 | 34,730 |
| | | Rate | | 33.2 | 64.2 | 85.2 | 30.6 | 97.0 | 21.6 | 36.7 | 47.7 | 52.9 | 66.9 | 79.3 | 86.2 | 91.4 | 96.1 |
| **Siem Reap** | **Urban** | Line | 190 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 10.1 | 37.6 | 57.7 | 10.1 | 85.4 | 4.4 | 11.4 | 16.3 | 28.9 | 42.4 | 50.1 | 58.2 | 70.6 | 82.3 |
| | **Rural** | Line | 380 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 27.9 | 66.7 | 82.3 | 26.2 | 96.6 | 15.8 | 32.3 | 45.5 | 55.9 | 69.1 | 76.8 | 82.5 | 88.6 | 95.9 |
| | **All** | Line | 570 | 10,669 | 16,003 | 21,338 | 10,520 | 37,410 | 9,145 | 11,095 | 12,803 | 14,525 | 16,402 | 18,827 | 22,062 | 26,309 | 35,110 |
| | | Rate | | 22.7 | 58.1 | 75.1 | 21.4 | 93.3 | 12.5 | 26.1 | 36.9 | 48.0 | 61.3 | 68.9 | 75.3 | 83.3 | 91.9 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Preah Sihanouk, Stung Treng, and Svay Rieng): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ Area | | Line or Rate | *n* | National (2019 def.) 100% | National 150% | National 200% | Intl. 2017 PPP (2019 def.) $6.85 | Intl. $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Preah Sihanouk | **Urban** | Line | 170 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 6.3 | 26.3 | 40.5 | 5.8 | 76.3 | 1.6 | 8.7 | 12.2 | 18.9 | 27.7 | 32.5 | 43.5 | 56.7 | 74.1 |
| | **Rural** | Line | 80 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 2.1 | 40.3 | 60.6 | 2.1 | 90.9 | 2.1 | 7.4 | 19.5 | 34.2 | 40.3 | 48.5 | 62.5 | 73.9 | 89.3 |
| | **All** | Line | 250 | 11,003 | 16,504 | 22,005 | 10,849 | 38,581 | 9,431 | 11,443 | 13,203 | 14,980 | 16,915 | 19,416 | 22,752 | 27,132 | 36,209 |
| | | Rate | | 5.1 | 30.2 | 46.1 | 4.7 | 80.4 | 1.7 | 8.3 | 14.2 | 23.1 | 31.1 | 36.9 | 48.8 | 61.5 | 78.3 |
| Stung Treng | **Urban** | Line | 50 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 9.0 | 19.9 | 37.9 | 7.5 | 74.4 | 3.7 | 9.0 | 11.0 | 17.6 | 19.9 | 26.5 | 39.8 | 54.2 | 70.0 |
| | **Rural** | Line | 140 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 37.3 | 68.8 | 87.7 | 35.6 | 98.6 | 27.7 | 41.5 | 50.0 | 64.6 | 71.4 | 83.2 | 88.1 | 95.4 | 98.4 |
| | **All** | Line | 190 | 10,630 | 15,945 | 21,260 | 10,482 | 37,275 | 9,112 | 11,055 | 12,756 | 14,473 | 16,342 | 18,759 | 21,982 | 26,214 | 34,983 |
| | | Rate | | 30.4 | 56.8 | 75.6 | 28.7 | 92.7 | 21.9 | 33.6 | 40.5 | 53.1 | 58.8 | 69.4 | 76.3 | 85.3 | 91.5 |
| Svay Rieng | **Urban** | Line | 130 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 10.5 | 37.5 | 59.4 | 9.9 | 92.8 | 6.5 | 16.3 | 26.9 | 32.6 | 40.2 | 47.3 | 62.4 | 72.0 | 90.9 |
| | **Rural** | Line | 290 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 16.6 | 50.1 | 71.6 | 15.4 | 94.2 | 6.9 | 20.2 | 29.5 | 43.7 | 52.4 | 62.4 | 72.6 | 85.5 | 93.5 |
| | **All** | Line | 420 | 10,667 | 16,001 | 21,335 | 10,518 | 37,406 | 9,144 | 11,094 | 12,801 | 14,523 | 16,400 | 18,825 | 22,059 | 26,306 | 35,105 |
| | | Rate | | 14.8 | 46.4 | 68.1 | 13.8 | 93.8 | 6.8 | 19.1 | 28.7 | 40.5 | 48.8 | 58.0 | 69.6 | 81.6 | 92.8 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Takéo, Oddar Meanchey, and Kep): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ | Area | Line or Rate | *n* | National (2019 def.) 100% | 150% | 200% | Intl. 2017 PPP (2019 def.) $6.85 | $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Takéo | **Urban** | Line | 130 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 10.6 | 49.5 | 69.0 | 10.1 | 93.2 | 4.0 | 12.5 | 31.1 | 37.6 | 51.5 | 59.3 | 71.9 | 82.6 | 89.4 |
| | **Rural** | Line | 380 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 12.2 | 46.8 | 70.9 | 12.2 | 96.1 | 5.7 | 14.7 | 25.9 | 36.5 | 49.5 | 62.0 | 72.7 | 85.1 | 94.2 |
| | **All** | Line | 510 | 10,684 | 16,026 | 21,368 | 10,535 | 37,463 | 9,158 | 11,111 | 12,821 | 14,546 | 16,425 | 18,854 | 22,093 | 26,346 | 35,160 |
| | | Rate | | 11.7 | 47.7 | 70.3 | 11.5 | 95.2 | 5.2 | 14.0 | 27.5 | 36.8 | 50.1 | 61.1 | 72.4 | 84.3 | 92.7 |
| Oddar Meanchey | **Urban** | Line | 90 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 26.6 | 49.8 | 57.9 | 25.3 | 88.4 | 9.8 | 29.3 | 39.0 | 42.2 | 49.8 | 54.2 | 59.7 | 71.1 | 88.4 |
| | **Rural** | Line | 160 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 25.9 | 68.1 | 82.7 | 25.3 | 95.6 | 19.3 | 31.9 | 47.9 | 62.8 | 69.2 | 74.6 | 83.5 | 91.1 | 95.6 |
| | **All** | Line | 250 | 10,689 | 16,034 | 21,378 | 10,540 | 37,482 | 9,162 | 11,116 | 12,827 | 14,553 | 16,433 | 18,863 | 22,104 | 26,359 | 35,177 |
| | | Rate | | 26.2 | 62.2 | 74.7 | 25.3 | 93.3 | 16.3 | 31.1 | 45.0 | 56.2 | 63.0 | 68.1 | 75.9 | 84.7 | 93.3 |
| Kep | **Urban** | Line | 80 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 5.0 | 20.3 | 55.2 | 5.0 | 88.3 | 1.5 | 5.0 | 12.3 | 16.7 | 22.2 | 42.0 | 57.6 | 70.9 | 88.3 |
| | **Rural** | Line | 20 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 0.0 | 25.8 | 67.2 | 0.0 | 87.7 | 0.0 | 0.0 | 0.0 | 6.4 | 25.8 | 46.3 | 67.2 | 70.9 | 81.0 |
| | **All** | Line | 100 | 11,067 | 16,600 | 22,133 | 10,912 | 38,805 | 9,486 | 11,509 | 13,280 | 15,067 | 17,013 | 19,529 | 22,885 | 27,290 | 36,419 |
| | | Rate | | 4.0 | 21.4 | 57.5 | 4.0 | 88.2 | 1.2 | 4.0 | 9.9 | 14.7 | 22.9 | 42.9 | 59.4 | 70.9 | 86.9 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

## Figure 11: (Pailin, and Tboung Khmum): Poverty lines and head-count poverty rates by urban/rural/all in 2019/20

| Province/ Area | | Line or Rate | *n* | National (2019 def.) 100% | National (2019 def.) 150% | National (2019 def.) 200% | Intl. 2017 PPP (2019 def.) $6.85 | Intl. 2017 PPP (2019 def.) $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Pailin** | **Urban** | Line | 160 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 29.7 | 50.5 | 67.0 | 29.7 | 87.1 | 20.1 | 30.4 | 37.6 | 45.5 | 50.5 | 60.4 | 68.0 | 73.0 | 84.4 |
| | **Rural** | Line | 60 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 13.9 | 48.3 | 81.6 | 13.9 | 94.6 | 9.0 | 17.5 | 31.7 | 41.7 | 56.1 | 64.7 | 82.5 | 88.1 | 93.2 |
| | **All** | Line | 220 | 11,027 | 16,541 | 22,055 | 10,873 | 38,668 | 9,452 | 11,468 | 13,233 | 15,014 | 16,953 | 19,460 | 22,804 | 27,193 | 36,290 |
| | | Rate | | 25.9 | 49.9 | 70.6 | 25.9 | 89.0 | 17.4 | 27.3 | 36.2 | 44.6 | 51.8 | 61.4 | 71.5 | 76.7 | 86.5 |
| **Tboung Khmum** | **Urban** | Line | 60 | 11,217 | 16,826 | 22,435 | 11,061 | 39,334 | 9,615 | 11,666 | 13,461 | 15,272 | 17,245 | 19,795 | 23,197 | 27,662 | 36,915 |
| | | Rate | | 16.5 | 34.3 | 71.0 | 16.5 | 82.0 | 9.1 | 16.5 | 24.9 | 32.7 | 34.3 | 54.7 | 71.0 | 74.5 | 81.3 |
| | **Rural** | Line | 440 | 10,440 | 15,661 | 20,881 | 10,295 | 36,610 | 8,949 | 10,858 | 12,528 | 14,214 | 16,051 | 18,424 | 21,590 | 25,746 | 34,358 |
| | | Rate | | 24.8 | 55.3 | 73.1 | 24.2 | 92.7 | 17.1 | 27.1 | 37.4 | 46.6 | 55.9 | 65.4 | 74.7 | 84.5 | 92.0 |
| | **All** | Line | 500 | 10,505 | 15,758 | 21,010 | 10,358 | 36,837 | 9,005 | 10,925 | 12,606 | 14,303 | 16,150 | 18,538 | 21,724 | 25,905 | 34,571 |
| | | Rate | | 24.2 | 53.6 | 72.9 | 23.6 | 91.8 | 16.4 | 26.2 | 36.3 | 45.5 | 54.1 | 64.5 | 74.4 | 83.6 | 91.1 |

Poverty rates are percentages.

All poverty lines are KHR per-person, per-day.

All poverty lines are KHR in average prices in Phnom Phen on average during the 2019/20 CSES fieldwork.

### 3.1.2 Number of poor people

Fulfilling a pro-poor mission depends not only on the *poverty rate* of the members of the households of in-coming participants but also on the *number* of poor people in those households. After all, a smaller program with a higher poverty rate may serve fewer poor people than a larger program with a lower poverty rate.[14]

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

$$\frac{6+5}{1+1} = \frac{11}{2} = 5.5 \text{ people.}$$

The second step is to estimate the total number of members in the households in the population of in-coming participants. The example program has 1,000 in-coming participants in its first calendar-year, with an estimated average of 5.5 members per participating household. The estimated number of members in the households in the population of in-coming participants is then 1,000 · 5.50 = 5,500.

The third and final step is to multiply the estimated poverty rate (here, 47.9 percent, or 0.479 as a proportion) by the estimated number of people in the population of in-coming households (here, 5,500). This gives 5,500 · 0.479 ≈ 2,633 poor people (**Figure 10**).

All else constant, the *number* of people in the households of in-coming participants who are poor is more important than the *share* of people in the households of in-coming participants who are poor. Both estimates are useful,[15] 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 members in the households of in-coming participants who are poor is only a means to the end of increasing the net reduction in the number of members in the households of on-going participants who are poor.

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[14] **Navajas, *et al*.** (2000).

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

## 3.2 Annual net changes in poverty across two time periods for on-going participants

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

Two sampling approaches are possible for the follow-up round after baseline:

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

Given the scorecard's assumptions, both approaches are unbiased. With all else held constant, however, scoring one sample twice has smaller margins of error than does scoring two independent samples.

### 3.2.1 Poverty rate with one sample scored twice

When the follow-up sample is made up of the same households as the baseline sample,[16] then the estimated annual net change in the poverty rate of the population of members in the households of on-going participants is the average of the change in each scored household's poverty likelihood (weighted by the average of each household's number of members between the two interviews), divided the average of the years between each household's interviews (weighted by the average of each household's number of members between the two interviews).[17]

Continuing the earlier example, suppose that the first household has seven members when re-interviewed at follow-up (rather than six as at baseline) and is scored a second time on August 13, 2026, which is 1,157 days (about 3.17 years) after the first household's first interview on June 13, 2023. Its score at follow-up is 24 (rather than 21), so its poverty likelihood for 100% of the national line has decreased from 57.9 percent at baseline to 43.8 percent at follow-up (**Figure 1**).

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

[17] Estimates of change across two periods do not need to directly adjust for the estimation error in estimates in each single period because—given the scorecard's assumptions—this error washes out when comparing follow-up with baseline. The remaining error (due to divergence from assumptions) is unknown, and there is no general nor direct way to adjust for it.

Suppose that the second household has six members at follow-up (rather than five as at baseline) and is re-interviewed on May 15, 2026, which is 1,050 days (about 2.88 years) after its first interview on June 30, 2023. Its score at follow-up is 29 (rather than 26), so its poverty likelihood has decreased from 39.5 percent at baseline to 27.5 percent at follow-up.

With poverty likelihoods expressed as proportions between 0 and 1, the average of the change in each scored household's poverty likelihood (weighted by the average of each household's number of members between the two interviews) is −13.2 percentage points:

$$\frac{\left(\frac{6+7}{2}\right)\cdot(0.438-0.579)+\left(\frac{5+6}{2}\right)\cdot(0.275-0.395)}{\left(\frac{6+7}{2}\right)+\left(\frac{5+6}{2}\right)}\approx\frac{-0.918+-0.664}{12.0}\approx-0.132.$$

The estimated head-count poverty rate decreased (improved) by 13.2 *percentage points* (not by 13.2 *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 of years between the two interviews (weighted by the average of each household's number of members between the two interviews):

$$\frac{\left(\frac{6+7}{2}\right)\cdot 3.17+\left(\frac{5+6}{2}\right)\cdot 2.88}{\left(\frac{6+7}{2}\right)+\left(\frac{5+6}{2}\right)}\approx\frac{20.60+15.82}{12}\approx 3.04\text{ years.}$$

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: −13.2 ÷ 3.04 ≈ −4.3 percentage points per year.[18] The negative change means that poverty decreased (improved).[19]

In practice, there are hundreds or thousands of interviewed households, so the calculations are done with the **ProveIt™-brand reporting and analysis tool** or in a spreadsheet, following the model in **Figure 12** below.

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[18] *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 compounded 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 non-compounded reduction in poverty, then the rate after one year is 0.50 − 0.10 = 0.40 = 40.0 percent, and the rate after two years is 0.40 − 0.10 = 0.30 = 30.0 percent.

[19] 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 12: Spreadsheet calculation of estimated annual net change in the head-count poverty rate and in the annual net number of poor people in a population of on-going participating households 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 | | Interview date | | | Number of household members | | | Member-years | Score | | Poverty likelihood (%) | | Estimated net change in |
| 2 | ID of direct participant | Baseline | Follow-up | Years between interviews | Baseline | Follow-up | Average: | between interviews | Baseline | Follow-up | Baseline | Follow-up | number of poor household members |
| 3 | 1V0276FZ7 | 13-Jun-2023 | 13-Aug-2026 | 3.17 = (C3-B3)/365 | 6 | 7 | 6.50 = (E3+F3)/2 | 20.60 = D3*G3 | 21 | 24 | 57.9 | 43.8 | –0.918 = G3*(L3-K3)/100 |
| 4 | 2W3120ZG8 | 30-Jun-2023 | 15-May-2026 | 2.88 = (C4-B4)/365 | 5 | 6 | 5.50 = (E4+F4)/2 | 15.82 = D4*G4 | 26 | 29 | 39.5 | 27.5 | –0.664 = G4*(L4-K4)/100 |
| 5 | | | | **Average:** | 5.5 = AVERAGE(E3:E4) | 6.5 = AVERAGE(F3:F4) | **Sum:** | 36.43 = SUM(H3:H4) | | | | | –1.582 = SUM(M3:M4) |
| 6 | | | | | | | | | | | | | |
| 7 | | | | | | **Estimated net change in head-count poverty rate (percentage points), follow-up versus baseline:** | | | | | | | –13.2 = M5/(E5+F5)*100 |
| 8 | | | | | | | | | | | | | |
| 9 | | | | | | | | **Household-size-weighted average years between interviews:** | | | | | 3.04 = H6/(E5+F5) |
| 10 | | | | | | | | | | | | | |
| 11 | | | | | | | **Estimated annual net change in head-count poverty rate (percentage points):** | | | | | | –4.3 = 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:** | | | | | 5,025 = (E5*M13+F5*M14)/2 |
| 17 | | | | | | | | | | | | | |
| 18 | | | | | | | | **Estimated annual net change in the number of poor people:** | | | | | –218 = M16*M11/100 |
| 19 | Rows of data are sorted by the ID of the direct participant. | | | | | | | | | | | | |

### 3.2.2 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* of people in participating households. Rather, the bottom line is the annual net change in the *number* of poor people in participating households.

To calculate this, the first step is to estimate the average number of household members in the population of on-going participants from baseline to follow-up, accounting for drop-out. In the example here, the population in 2023 of in-coming households in the calendar-year 2023 cohort is 1,000. By the end of the follow-up period of calendar-year 2026, 300 households have dropped out, leaving 700 on-going participating households from the 2023 cohort. If drop-out takes place at a constant pace and is unrelated to changes in poverty,[20] then an estimate of the average number of people in the households of on-going participants is the

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[20] This assumption rarely holds. On the one hand, the households that benefit most from a program—and thus those for whom participation is most likely to cause a faster-than-otherwise decrease in poverty—may be less likely to drop out than others, leading to an estimate of the change in poverty due to participation that is too high. If, on the other hand, the benefits of continued participation fall as poverty decreases, then households whose poverty decreases may be more likely to drop out, leading to an estimate of change that is too low. 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 account for them as best they can. This is the case even though scorecard estimates are based on data and math. "Hard numbers" may not represent reality as accurately as they may seem to, and only managers' knowledge of context can detect and account for this. Managers should discount 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 blame them on a slow economy (even though they might not attribute high estimates of poverty reduction to a roaring economy). Sadly and ironically, 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—commonly become its *de facto* beneficiaries (**Schreiner**, 1997).

equal-weighted average of the number of people in the participating households interviewed at baseline and of the number of people in the participating households interviewed at follow-up. In a given round, the number of people in participating households is the average household size for that round's interviewed households (in the example, 5.5 at baseline and 6.5 at follow-up), multiplied by the number of participating households in the population in the corresponding round (1,000 at baseline and 700 at follow-up), divided by the number of survey rounds (two). In the example, this is $\frac{5.5 \cdot 1{,}000 + 6.5 \cdot 700}{1+1} = 5{,}025$ people.

The second and last step is to multiply the estimated annual change in the poverty rate (here, about −4.3 percentage points, or −0.043 as a proportion) by the estimated average number of on-going participants (here, 5,025). This gives an estimate of the annual net change in the number of poor people in the households of on-going participants by 100% of the national line of $-0.043 \cdot 5{,}025 \approx -218$ people.[21]

This negative change is a decrease (improvement) in poverty; in each year between baseline and follow-up, the number of poor people in participating households from the 2023 cohort decreased by 218.

### 3.2.3 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 real force that does cause some change (be it an increase or decrease) in the poverty of participants. At the same time, it is equally logical to expect that a large share of any change in participants' poverty is caused by the many forces other than program participation that also affect participants. On its own, the scorecard is like a bathroom scale; it can tell whether you lost weight in the past year, but it does not reveal how much of the loss is due to eating better and exercising more 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 participating households if they had not been participants. This must come from beyond the scorecard.

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

What are program managers to do? After all, decision-making hinges on forecasts of the expected impacts of possible choices; managers cannot pretend that merely estimating change is helpful without also inferring some cause-and-effect relationship. Yet estimates of impact are always imperfect.

At a minimum, managers should compare their program's estimated annual net change in the poverty rate of people in the households of its on-going participants to third-party estimates for the country overall or for the program's particular work area.

Managers can also look for signs that participants value (or expect to value) its services. Is the number of in-coming participants high or increasing? Is the drop-out rate low or decreasing? Is drop-out mostly 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 area?

In short, managers in pro-poor programs are called to do what good managers must always do: weigh data and knowledge from a number of perspectives 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 or art may be disingenuously invoked as a cover for decision-making 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 productive review and debate—makes sense even (or perhaps especially) for business decisions.[22]

### 3.2.4 Poverty rate 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 cohort as that from which the baseline sample was drawn.[23] The head-count poverty rate for members of the households of on-going participants in this new follow-up sample is estimated in the same way as for the baseline sample.

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[22] Schreiner (**2016a** and **2014**).
[23] By chance, some households may end up in both samples, and that is fine.

Continuing the example, suppose that a third household and a fourth household are sampled at follow-up from among on-coming participants in the 2023 cohort. The third household is interviewed on March 3, 2026. It has four members, a score of 27, and a poverty likelihood by 100% of the national line of 39.7 percent (**Figure 1**).

The fourth household is interviewed on April 4, 2026. It has seven members, a score of 30, and a poverty likelihood of 19.1 percent.

At follow-up, the estimated head-count poverty rate is calculated in the same way as at baseline. That is, it is the household-size-weighted average of the poverty likelihoods of the sampled households:

$$\frac{4 \cdot 0.395 + 7 \cdot 0.191}{4+7} \approx \frac{1.58 + 1.34}{11} \approx 0.265 = 26.5 \text{ percent.}$$

The estimated annual net change in the head-count poverty rate of people in the households of on-going participants is then the difference between the (unadjusted) poverty-rate estimates at follow-up (26.5 percent) versus at baseline (49.6 percent),[24] divided by the difference (in years) between the household-size-weighted average of follow-up interview dates (March 23, 2026) versus the household-size-weighted average of baseline interview dates (June 20, 2023). These two average dates differ by about 1,007 days (about 2.76 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% percent of the national line, this is about (26.5 − 49.6) ÷ 2.76 ≈ −8.4 percentage points per year.

In practice, there are hundreds or thousands of interviewed households, so the calculations are done with the **ProveIt™-brand reporting and analysis tool** or in a spreadsheet, following the model in **Figure 13** below.

[24] With two independent samples, the estimation error in each of the two single-period estimates washes out, so it is not explicitly included in the calculation. Thus, the figure here is 49.6 percent, not 49.6 − (+1.7) = 47.9 percent.

**Figure 13: Spreadsheet calculation of estimated annual net change in the head-count poverty rate and in the annual net number of poor people who rise above a poverty line in a population of on-going participating households with two independent samples**

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | **Survey** | **ID of direct participant** | **Interview date** | **Number of household members** | **Interview date x Number of household members** | **Score** | **Poverty likelihood (%)** | **Estimated number of poor household members** |
| 2 | Baseline | 1V0276FZ7 | 13-Jun-2023 | 6 | 16-Sep-2640 = C2*D2 | 21 | 57.9 | 3.48 = D2*G2/100 |
| 3 | Baseline | 2W3120ZG8 | 30-Jun-2023 | 5 | 28-Jun-2517 = C2*D2 | 26 | 39.5 | 1.98 = D3*G3/100 |
| 4 | Follow-up | 3XA76T21L | 3-Mar-2026 | 4 | 09-Sep-2404 = C2*D2 | 27 | 39.5 | 1.58 = D4*G4/100 |
| 5 | Follow-up | 4Y8Y3EQS9 | 4-Apr-2026 | 7 | 29-Oct-2783 = C2*D2 | 30 | 19.1 | 1.34 = D5*G5/100 |
| 6 | **Sum baseline:** | | | 11 = SUM(D2:D3) | | | | 5.45 = SUM(H2:H3) |
| 7 | **Sum follow-up:** | | | 11 = SUM(D4:D5) | | | | 2.92 = SUM(H4:H5) |
| 8 | **Average baseline:** | | | 5.5 = AVERAGE(D2:D3) | 20-Jun-2023 = SUM(E2:E3)/D6 | | | |
| 9 | **Average follow-up:** | | | 5.5 = AVERAGE(D4:D5) | 23-Mar-2026 = SUM(E4:E5)/D7 | | | |
| 10 | | | | | | | | |
| 11 | | | | | | | **Estimated baseline poverty rate (%):** | 49.6 = H6/D6*100 |
| 12 | | | | | | | **Estimated follow-up poverty rate (%):** | 26.5 = H7/D7*100 |
| 13 | | | | | | | | |
| 14 | | | | | | | **Average years between follow-up and baseline interviews:** | 2.76 = (E9-E8)/365 |
| 15 | | | | | | | | |
| 16 | | | | | | | **Estimated annual net change in head-count poverty rate (percentage points):** | –8.4 = (H12-H11)/H14 |
| 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:** | 4,675 = (D8*H18+D9*H19)/2 |
| 22 | | | | | | | | |
| 23 | | | | | | | **Estimated annual net change in the number of poor people:** | –390 = H21*H16/100 |
| 24 | Rows of data are sorted by Survey, then by Interview date, then by the ID of the participant of record. | | | | | | | |

### 3.2.5 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* of people in the households of on-going participants but rather the annual net change in the *number* of poor people in the households of on-going participants.

To calculate this, the first step is to estimate the average number of people in households in the population of on-going participants from baseline to follow-up, accounting for drop-out. In the example here, there are 1,000 in-coming households in the population of the baseline 2023 cohort in 2023. By the end of the 2026 follow-up period, 300 households have dropped out, leaving 700 from the 2023 cohort.

If drop-out takes place at a constant pace and is unrelated with changes in poverty, then an estimate of the average number of people in the households of on-going participants is the equal-weighted average of the number of people in the households interviewed at baseline and of the number of people in the households interviewed at follow-up.

In a given round, the number of people in the households of on-going participants from the 2023 cohort is the average household size for that round's interviewed households (in our example, 5.5 at baseline and coincidentally also 5.5 at follow-up), multiplied by the number of participating households in the population in the corresponding round (1,000 at baseline and 700 at follow-up), divided by two (the number of rounds). This is

$$\frac{5.5 \cdot 1{,}000 + 5.5 \cdot 700}{1+1} = 4{,}675 \text{ people.}$$

The second and last step is to multiply the estimated annual net change in the head-count poverty rate (here, −8.4 percentage points, or −0.084 as a proportion) by the estimated number of people in the households of on-going participants between the two rounds (here, 4,675).

For 100% of the national line, this gives an annual, non-compounded net change in the number of poor people of about $-0.084 \cdot 4{,}675 \approx -390$ people per year. This negative change is a reduction (improvement) in poverty; the number of poor people in the households of on-going participants from the 2023 cohort decreased by about 390 each year between baseline and follow-up.

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. Still, there may be context-specific reasons (related to operational costs or non-sampling errors) to score two independent samples.

## 3.3 How to estimate consumption expenditure

A household's score from Cambodia's new scorecard is converted into an estimate of daily per-capita consumption expenditure in riel (KHR) via the look-up table in **Figure 2**.

To illustrate, the first example household (**Figure 4**) has a score of 21. In **Figure 2**, this score corresponds with an estimate of daily per-capita consumption expenditure of KHR11,294 in average prices in Phnom Phen during the 2019/20 CSES fieldwork.

To get an estimate of a household's total (not per-capita) daily consumption expenditure, multiply the per-capita estimate from the table by the number of household members.

Continuing the illustration, the first example household has six members at baseline. Thus, an estimate of the household's total daily consumption expenditure is KHR11,294 · 6 = KHR67,764.

A monthly estimate is found by multiplying a daily estimate (whether per-capita or total) by the average number of days in a month (30.417).

For an annual estimate, multiply a daily estimate by 365.

Do *not* estimate head-count poverty rates by directly comparing these estimates of consumption expenditure with poverty lines; the poverty-likelihood approach described earlier in this section is more accurate.

# 4. How to design scorecard surveys and samples

To design a scorecard survey and its sample, a program must decide:[25]

- **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 interview participating households**
- **Whether to track a population across multiple time periods**
- **Whether to interview the same participating households twice**

Decisions should follow from the program's goals, the business issues to be informed, 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, or
- Third-party contractors

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

## 4.2 Where and how to do interviews

Interviews should be:

- In-person, and
- At the sampled household's dwelling, and
- Done by an enumerator trained to follow the **Interview Guide**

This is the only recommended way. It mimics the practice of Cambodia's NIS in the CSES, so it provides the most accurate, reliable, and consistent data (and thus the best estimates).

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

- Without an enumerator (such as by respondents' filling out paper or web forms on their own or responding to questions on the web or sent via e-mail, texts, or robo-calls)
- Away from home (such as at 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[26] and thus reduce the accuracy of estimates. This is why interviewing by a trained enumerator at the dwelling is recommended.

In some contexts—such as when a program's service agents do not already visit participants at their dwelling anyway as part of their normal work—a program might be willing to trade some accuracy for a lower-cost, non-recommended approach. The business wisdom of this choice 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 when compared with a trained enumerator at the dwelling. Furthermore, all reporting should discuss the possible consequences of the non-recommended method.

## 4.3 How to record responses and scores

Responses and scores may be recorded by enumerators on:

- Paper, and then keyed into a database or spreadsheet later at an office
- A device running a **browser-based app** and then uploaded to a database[27]

[26] **Schreiner**, 2015.

## 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$^{TM}$-brand reporting and analysis tool**. **Schreiner** (2014) describes how to report and analyze scorecard estimates.

## 4.5 Which participating households to interview

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

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

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

## 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 decisions that matter to the program.

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[27] **Scorocs** can help users set up **a mobile, paper-less data-entry system** or to transfer data from paper forms into a database at the office. Support is also available for calculating estimates and for reporting and analysis.

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. Programs are often concerned about sample size, but there is no point in deriving the ideal sample size unless proportional effort goes to mitigating other sources of error and then accounting for margins of error in the analysis stage. Of course, larger samples produce more-reliable estimates. In practice, however, few analysts report or consider margins of error (even though all analysts should), and estimates based on at least 1,000 interviews will rarely raise eyebrows (**Annex 6**).

## 4.7 How frequently to interview participating households

The frequency of scorecard survey rounds 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 service agent visits a participant at home (allowing estimating change)

## 4.8 Whether to track a population across multiple time periods

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

## 4.9 Whether to interview the same participating households twice

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

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

All else constant, scoring one sample twice gives smaller margins of error. In addition, this approach may be less costly at follow-up, given that the sampled households have already been tracked down at baseline. Also, the follow-up round could be based on a random sample of the households interviewed at baseline.

## 4.10 Example of survey design 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[28] with a sample of about 25,000 participants each.

Their design is that all loan officers in a random sample of branches score all participating households each time these 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.

[28] **Schreiner**, 2013.

# 5. How to use scores for targeting

When a program uses the scorecard for segmenting (*targeting*) participants for differentiated treatment based on socio-econmic level, people in households with scores at or below a program-selected cut-off are labeled *targeted* and given one type of treatment. People in households with scores above the cut-off are labeled *non-targeted* and given another type of treatment.[29]

Households that score at or below a given cut-off should be labeled as *targeted*,[30] not as *poor*.[31]

Targeting is successful to the extent to which poor people truly below a poverty line are targeted (*inclusion*) or non-poor people truly above a poverty line are not targeted (*exclusion*).

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

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

[31] After all, it is very unlikely that all targeted households are poor (their consumption expenditure is below a given poverty line). In the context of the scorecard, the terms *poor* and *non-poor* have specific definitions that are based on consumption expenditure and a poverty line. Using these same terms for targeting status is incorrect and misleading.

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

[**Figure 14**](#) 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).

## Figure 14: Possible targeting outcomes

| | | Targeting segment | |
|---|---|---|---|
| | | **Targeted** | **Non-targeted** |
| **Observed poverty status** | **Poor** | **Inclusion** Poor correctly targeted | **Undercoverage** Poor mistakenly non-targeted |
| | **Non-poor** | **Leakage** Non-poor mistakenly targeted | **Exclusion** Non-poor correctly non-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.[32] The five tables below show the scorecard's targeting outcomes by poverty line and by score cut-off for people in Cambodia:

- **Figure 15: Inclusion (% people who are poor and correctly targeted)**
- **Figure 16: Undercoverage (% people who are poor but mistakenly not targeted)**
- **Figure 17: Leakage (% people who are not poor but mistakenly targeted)**
- **Figure 18: Exclusion (% people who are not poor and correctly not targeted)**
- **Figure 19: Hit rate (% people correctly targeted, that is, inclusion plus exclusion)**

For a given score cut-off, each figure also shows the share of all people who are targeted.

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

## Figure 15: Inclusion (% people who are poor and correctly targeted)

| Targeting cut-off | % all people who are targeted | Inclusion (%) Natl. (2019/20 def.) 100% | 150% | 200% | Intl. 2017 PPP (2019 def.) $6.85 | $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <=17 | 5.2 | 4.2 | 5.0 | 5.1 | 4.2 | 5.2 | 3.1 | 4.4 | 4.7 | 5.0 | 5.0 | 5.1 | 5.1 | 5.1 | 5.2 |
| <=22 | 10.9 | 7.6 | 10.3 | 10.7 | 7.4 | 10.9 | 5.2 | 8.1 | 9.4 | 10.0 | 10.3 | 10.6 | 10.7 | 10.8 | 10.9 |
| <=25 | 16.9 | 10.0 | 15.6 | 16.6 | 9.8 | 16.8 | 6.5 | 10.7 | 13.7 | 14.8 | 15.7 | 16.3 | 16.6 | 16.7 | 16.8 |
| <=27 | 21.5 | 11.4 | 19.0 | 20.8 | 11.1 | 21.4 | 7.2 | 12.2 | 15.9 | 17.6 | 19.3 | 20.4 | 20.8 | 21.2 | 21.4 |
| <=29 | 25.9 | 12.7 | 22.5 | 25.0 | 12.3 | 25.8 | 7.8 | 13.7 | 18.3 | 20.8 | 22.8 | 24.4 | 25.1 | 25.6 | 25.8 |
| <=31 | 31.4 | 13.9 | 26.6 | 30.3 | 13.4 | 31.3 | 8.3 | 15.0 | 20.9 | 24.5 | 27.1 | 29.3 | 30.4 | 31.1 | 31.3 |
| <=33 | 37.1 | 14.9 | 30.4 | 35.3 | 14.3 | 37.0 | 8.6 | 16.2 | 23.0 | 27.6 | 31.0 | 34.0 | 35.4 | 36.5 | 37.0 |
| <=35 | 43.2 | 15.5 | 34.5 | 40.7 | 14.9 | 43.1 | 8.8 | 17.1 | 25.0 | 30.7 | 35.3 | 39.0 | 40.9 | 42.4 | 42.9 |
| <=37 | 49.5 | 16.4 | 38.0 | 46.1 | 15.8 | 49.2 | 9.1 | 18.1 | 26.6 | 33.3 | 39.0 | 43.7 | 46.4 | 48.2 | 49.1 |
| <=39 | 55.8 | 17.1 | 41.1 | 51.1 | 16.5 | 55.3 | 9.4 | 18.9 | 28.1 | 35.7 | 42.3 | 48.1 | 51.5 | 53.9 | 55.1 |
| <=41 | 61.8 | 17.4 | 43.4 | 55.7 | 16.7 | 61.2 | 9.5 | 19.2 | 28.8 | 37.1 | 44.8 | 51.8 | 56.3 | 59.4 | 61.0 |
| <=43 | 66.8 | 17.6 | 44.8 | 59.0 | 16.9 | 66.1 | 9.6 | 19.5 | 29.3 | 38.1 | 46.6 | 54.2 | 59.7 | 63.6 | 65.7 |
| <=45 | 71.1 | 17.7 | 46.1 | 61.5 | 17.0 | 70.2 | 9.7 | 19.6 | 29.7 | 38.8 | 47.8 | 56.1 | 62.3 | 67.0 | 69.7 |
| <=47 | 75.6 | 17.7 | 46.7 | 63.9 | 17.0 | 74.5 | 9.7 | 19.6 | 29.9 | 39.1 | 48.6 | 57.4 | 64.8 | 70.6 | 74.0 |
| <=50 | 80.5 | 17.7 | 47.3 | 65.7 | 17.0 | 79.0 | 9.7 | 19.7 | 29.9 | 39.4 | 49.1 | 58.6 | 67.0 | 73.9 | 78.3 |
| <=54 | 85.3 | 17.7 | 47.4 | 66.9 | 17.0 | 83.3 | 9.7 | 19.7 | 30.0 | 39.6 | 49.3 | 59.3 | 68.5 | 76.5 | 82.5 |
| <=60 | 90.5 | 17.7 | 47.6 | 67.8 | 17.0 | 87.4 | 9.7 | 19.7 | 30.0 | 39.6 | 49.5 | 59.7 | 69.4 | 78.6 | 86.3 |
| <=68 | 95.2 | 17.7 | 47.8 | 68.1 | 17.0 | 90.4 | 9.7 | 19.7 | 30.0 | 39.7 | 49.6 | 59.9 | 69.9 | 79.7 | 88.9 |
| <=100 | 100.0 | 17.7 | 47.8 | 68.2 | 17.0 | 91.6 | 9.7 | 19.7 | 30.0 | 39.7 | 49.7 | 59.9 | 70.0 | 80.1 | 89.9 |

Scorecard applied to the validation sample.

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

| Targeting cut-off | % all people who are targeted | Undercoverage (%) Natl. (2019/20 def.) 100% | 150% | 200% | Intl. 2017 PPP (2019 def.) $6.85 | $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <=17 | 5.2 | 13.6 | 42.8 | 63.1 | 12.9 | 86.4 | 6.6 | 15.3 | 25.3 | 34.7 | 44.6 | 54.8 | 64.8 | 74.9 | 84.7 |
| <=22 | 10.9 | 10.2 | 37.5 | 57.5 | 9.6 | 80.7 | 4.5 | 11.7 | 20.6 | 29.7 | 39.3 | 49.3 | 59.3 | 69.3 | 79.0 |
| <=25 | 16.9 | 7.7 | 32.2 | 51.6 | 7.3 | 74.8 | 3.2 | 9.0 | 16.3 | 24.9 | 34.0 | 43.6 | 53.4 | 63.4 | 73.0 |
| <=27 | 21.5 | 6.3 | 28.8 | 47.4 | 5.9 | 70.2 | 2.5 | 7.5 | 14.1 | 22.1 | 30.4 | 39.5 | 49.1 | 58.8 | 68.4 |
| <=29 | 25.9 | 5.0 | 25.3 | 43.2 | 4.7 | 65.8 | 1.9 | 6.1 | 11.7 | 18.8 | 26.8 | 35.6 | 44.9 | 54.5 | 64.1 |
| <=31 | 31.4 | 3.8 | 21.2 | 37.9 | 3.6 | 60.3 | 1.4 | 4.7 | 9.2 | 15.2 | 22.6 | 30.6 | 39.6 | 48.9 | 58.5 |
| <=33 | 37.1 | 2.8 | 17.4 | 32.8 | 2.7 | 54.6 | 1.1 | 3.5 | 7.0 | 12.0 | 18.7 | 25.9 | 34.5 | 43.5 | 52.9 |
| <=35 | 43.2 | 2.2 | 13.3 | 27.5 | 2.1 | 48.5 | 0.9 | 2.7 | 5.0 | 9.0 | 14.4 | 20.9 | 29.1 | 37.7 | 46.9 |
| <=37 | 49.5 | 1.3 | 9.8 | 22.1 | 1.2 | 42.4 | 0.6 | 1.6 | 3.4 | 6.4 | 10.6 | 16.2 | 23.6 | 31.9 | 40.8 |
| <=39 | 55.8 | 0.6 | 6.7 | 17.1 | 0.6 | 36.3 | 0.3 | 0.9 | 1.9 | 4.0 | 7.4 | 11.9 | 18.4 | 26.2 | 34.8 |
| <=41 | 61.8 | 0.3 | 4.4 | 12.5 | 0.3 | 30.4 | 0.2 | 0.5 | 1.2 | 2.6 | 4.8 | 8.1 | 13.7 | 20.7 | 28.9 |
| <=43 | 66.8 | 0.2 | 2.9 | 9.2 | 0.2 | 25.5 | 0.0 | 0.3 | 0.7 | 1.6 | 3.1 | 5.7 | 10.3 | 16.4 | 24.1 |
| <=45 | 71.1 | 0.0 | 1.7 | 6.7 | 0.0 | 21.4 | 0.0 | 0.1 | 0.3 | 0.9 | 1.9 | 3.9 | 7.6 | 13.0 | 20.1 |
| <=47 | 75.6 | 0.0 | 1.0 | 4.3 | 0.0 | 17.1 | 0.0 | 0.1 | 0.2 | 0.5 | 1.1 | 2.5 | 5.2 | 9.5 | 15.9 |
| <=50 | 80.5 | 0.0 | 0.5 | 2.5 | 0.0 | 12.6 | 0.0 | 0.1 | 0.1 | 0.2 | 0.5 | 1.3 | 2.9 | 6.2 | 11.6 |
| <=54 | 85.3 | 0.0 | 0.3 | 1.3 | 0.0 | 8.3 | 0.0 | 0.0 | 0.0 | 0.1 | 0.3 | 0.6 | 1.5 | 3.6 | 7.4 |
| <=60 | 90.5 | 0.0 | 0.2 | 0.4 | 0.0 | 4.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.2 | 0.3 | 0.5 | 1.4 | 3.5 |
| <=68 | 95.2 | 0.0 | 0.0 | 0.1 | 0.0 | 1.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.4 | 1.0 |
| <=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 17: Leakage (% people who are not poor but mistakenly targeted)

| Targeting cut-off | % all people who are targeted | Leakage (%) Natl. (2019/20 def.) 100% | 150% | 200% | Intl. 2017 PPP (2019 def.) $6.85 | $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <=17 | 5.2 | 1.1 | 0.2 | 0.1 | 1.1 | 0.0 | 2.1 | 0.8 | 0.6 | 0.2 | 0.2 | 0.1 | 0.1 | 0.1 | 0.0 |
| <=22 | 10.9 | 3.3 | 0.6 | 0.2 | 3.5 | 0.0 | 5.7 | 2.8 | 1.5 | 0.9 | 0.6 | 0.3 | 0.2 | 0.1 | 0.0 |
| <=25 | 16.9 | 6.9 | 1.3 | 0.3 | 7.1 | 0.0 | 10.3 | 6.1 | 3.2 | 2.1 | 1.2 | 0.5 | 0.3 | 0.2 | 0.0 |
| <=27 | 21.5 | 10.1 | 2.5 | 0.7 | 10.3 | 0.0 | 14.2 | 9.2 | 5.6 | 3.8 | 2.2 | 1.0 | 0.6 | 0.2 | 0.0 |
| <=29 | 25.9 | 13.2 | 3.4 | 0.9 | 13.5 | 0.1 | 18.1 | 12.2 | 7.6 | 5.0 | 3.1 | 1.5 | 0.8 | 0.3 | 0.1 |
| <=31 | 31.4 | 17.6 | 4.8 | 1.2 | 18.0 | 0.1 | 23.2 | 16.4 | 10.6 | 6.9 | 4.4 | 2.1 | 1.1 | 0.3 | 0.1 |
| <=33 | 37.1 | 22.3 | 6.7 | 1.8 | 22.8 | 0.1 | 28.6 | 20.9 | 14.1 | 9.5 | 6.2 | 3.2 | 1.7 | 0.6 | 0.2 |
| <=35 | 43.2 | 27.7 | 8.7 | 2.5 | 28.3 | 0.1 | 34.4 | 26.1 | 18.2 | 12.5 | 7.9 | 4.2 | 2.3 | 0.8 | 0.3 |
| <=37 | 49.5 | 33.1 | 11.6 | 3.4 | 33.7 | 0.3 | 40.4 | 31.4 | 22.9 | 16.2 | 10.5 | 5.8 | 3.2 | 1.3 | 0.5 |
| <=39 | 55.8 | 38.7 | 14.7 | 4.7 | 39.3 | 0.5 | 46.4 | 36.9 | 27.7 | 20.1 | 13.5 | 7.7 | 4.2 | 1.9 | 0.7 |
| <=41 | 61.8 | 44.4 | 18.4 | 6.1 | 45.1 | 0.6 | 52.3 | 42.5 | 33.0 | 24.7 | 17.0 | 10.0 | 5.5 | 2.4 | 0.8 |
| <=43 | 66.8 | 49.2 | 22.0 | 7.8 | 49.9 | 0.7 | 57.2 | 47.3 | 37.4 | 28.7 | 20.3 | 12.6 | 7.1 | 3.2 | 1.0 |
| <=45 | 71.1 | 53.3 | 25.0 | 9.6 | 54.0 | 0.9 | 61.4 | 51.4 | 41.4 | 32.2 | 23.2 | 15.0 | 8.7 | 4.0 | 1.3 |
| <=47 | 75.6 | 57.9 | 28.9 | 11.7 | 58.6 | 1.1 | 65.9 | 55.9 | 45.7 | 36.5 | 27.0 | 18.2 | 10.8 | 5.0 | 1.6 |
| <=50 | 80.5 | 62.8 | 33.2 | 14.8 | 63.4 | 1.5 | 70.8 | 60.8 | 50.6 | 41.0 | 31.3 | 21.8 | 13.4 | 6.6 | 2.2 |
| <=54 | 85.3 | 67.6 | 37.8 | 18.3 | 68.2 | 2.0 | 75.6 | 65.5 | 55.3 | 45.7 | 36.0 | 25.9 | 16.8 | 8.8 | 2.8 |
| <=60 | 90.5 | 72.8 | 42.9 | 22.7 | 73.5 | 3.1 | 80.8 | 70.8 | 60.5 | 50.9 | 41.0 | 30.8 | 21.1 | 11.9 | 4.2 |
| <=68 | 95.2 | 77.5 | 47.4 | 27.1 | 78.2 | 4.8 | 85.5 | 75.5 | 65.2 | 55.5 | 45.6 | 35.3 | 25.3 | 15.5 | 6.3 |
| <=100 | 100.0 | 82.3 | 52.2 | 31.8 | 83.0 | 8.4 | 90.3 | 80.3 | 70.0 | 60.3 | 50.3 | 40.1 | 30.0 | 19.9 | 10.1 |

Scorecard applied to the validation sample.

## Figure 18: Exclusion (% people who are not poor and correctly not targeted)

| Targeting cut-off | % all people who are targeted | Exclusion (%) Natl. (2019/20 def.) 100% | 150% | 200% | Intl. 2017 PPP (2019 def.) $6.85 | $24.36 | Percentile lines (2019 def.) 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <=17 | 5.2 | 81.2 | 52.0 | 31.7 | 81.9 | 8.4 | 88.2 | 79.4 | 69.4 | 60.1 | 50.2 | 40.0 | 29.9 | 19.9 | 10.1 |
| <=22 | 10.9 | 79.0 | 51.6 | 31.6 | 79.5 | 8.4 | 84.6 | 77.4 | 68.5 | 59.4 | 49.8 | 39.8 | 29.9 | 19.8 | 10.1 |
| <=25 | 16.9 | 75.4 | 50.9 | 31.5 | 75.9 | 8.4 | 80.0 | 74.2 | 66.8 | 58.2 | 49.2 | 39.5 | 29.8 | 19.8 | 10.1 |
| <=27 | 21.5 | 72.2 | 49.8 | 31.2 | 72.7 | 8.4 | 76.1 | 71.0 | 64.4 | 56.5 | 48.2 | 39.0 | 29.4 | 19.7 | 10.1 |
| <=29 | 25.9 | 69.1 | 48.9 | 31.0 | 69.4 | 8.3 | 72.2 | 68.1 | 62.4 | 55.3 | 47.3 | 38.6 | 29.3 | 19.6 | 10.1 |
| <=31 | 31.4 | 64.7 | 47.4 | 30.7 | 64.9 | 8.3 | 67.1 | 63.9 | 59.4 | 53.4 | 46.0 | 38.0 | 29.0 | 19.6 | 10.0 |
| <=33 | 37.1 | 60.0 | 45.5 | 30.0 | 60.2 | 8.3 | 61.7 | 59.4 | 55.9 | 50.8 | 44.2 | 36.9 | 28.3 | 19.3 | 10.0 |
| <=35 | 43.2 | 54.6 | 43.5 | 29.3 | 54.7 | 8.3 | 55.9 | 54.2 | 51.8 | 47.9 | 42.4 | 35.9 | 27.7 | 19.1 | 9.9 |
| <=37 | 49.5 | 49.2 | 40.7 | 28.4 | 49.2 | 8.1 | 49.9 | 48.9 | 47.1 | 44.1 | 39.8 | 34.3 | 26.9 | 18.6 | 9.7 |
| <=39 | 55.8 | 43.6 | 37.6 | 27.1 | 43.7 | 7.9 | 43.9 | 43.4 | 42.3 | 40.2 | 36.9 | 32.4 | 25.8 | 18.1 | 9.4 |
| <=41 | 61.8 | 37.9 | 33.8 | 25.7 | 37.9 | 7.8 | 38.0 | 37.7 | 37.0 | 35.6 | 33.3 | 30.1 | 24.5 | 17.6 | 9.3 |
| <=43 | 66.8 | 33.0 | 30.3 | 24.0 | 33.0 | 7.7 | 33.2 | 32.9 | 32.5 | 31.6 | 30.1 | 27.5 | 22.9 | 16.8 | 9.1 |
| <=45 | 71.1 | 28.9 | 27.2 | 22.3 | 28.9 | 7.5 | 28.9 | 28.8 | 28.6 | 28.1 | 27.1 | 25.1 | 21.3 | 15.9 | 8.8 |
| <=47 | 75.6 | 24.4 | 23.4 | 20.1 | 24.4 | 7.3 | 24.4 | 24.3 | 24.2 | 23.9 | 23.3 | 21.9 | 19.2 | 14.9 | 8.5 |
| <=50 | 80.5 | 19.5 | 19.0 | 17.1 | 19.5 | 6.9 | 19.5 | 19.5 | 19.4 | 19.3 | 19.0 | 18.3 | 16.6 | 13.3 | 8.0 |
| <=54 | 85.3 | 14.7 | 14.4 | 13.5 | 14.7 | 6.4 | 14.7 | 14.7 | 14.7 | 14.6 | 14.4 | 14.1 | 13.2 | 11.1 | 7.4 |
| <=60 | 90.5 | 9.5 | 9.3 | 9.1 | 9.5 | 5.3 | 9.5 | 9.5 | 9.5 | 9.4 | 9.3 | 9.2 | 8.9 | 8.1 | 5.9 |
| <=68 | 95.2 | 4.8 | 4.8 | 4.7 | 4.8 | 3.6 | 4.8 | 4.8 | 4.8 | 4.8 | 4.8 | 4.8 | 4.7 | 4.4 | 3.8 |
| <=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 19: Hit rate (% people correctly targeted, that is, inclusion plus exclusion)

| Targeting cut-off | % all people who are targeted | Hit rate ( = Inclusion + Exclusion) (%) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Natl. (2019/20 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| <=17 | 5.2 | 85.4 | 57.0 | 36.8 | 86.1 | 13.5 | 91.4 | 83.8 | 74.1 | 65.1 | 55.2 | 45.1 | 35.1 | 25.0 | 15.3 |
| <=22 | 10.9 | 86.5 | 61.9 | 42.3 | 86.9 | 19.2 | 89.9 | 85.5 | 77.8 | 69.3 | 60.1 | 50.4 | 40.5 | 30.6 | 21.0 |
| <=25 | 16.9 | 85.4 | 66.5 | 48.1 | 85.7 | 25.2 | 86.5 | 84.9 | 80.5 | 73.0 | 64.8 | 55.9 | 46.3 | 36.5 | 26.9 |
| <=27 | 21.5 | 83.6 | 68.8 | 51.9 | 83.8 | 29.8 | 83.3 | 83.2 | 80.3 | 74.1 | 67.4 | 59.5 | 50.2 | 40.9 | 31.5 |
| <=29 | 25.9 | 81.8 | 71.4 | 56.0 | 81.8 | 34.1 | 80.0 | 81.7 | 80.7 | 76.1 | 70.1 | 63.0 | 54.3 | 45.2 | 35.9 |
| <=31 | 31.4 | 78.6 | 74.0 | 60.9 | 78.3 | 39.6 | 75.4 | 78.9 | 80.3 | 77.9 | 73.1 | 67.3 | 59.3 | 50.7 | 41.4 |
| <=33 | 37.1 | 74.9 | 75.9 | 65.3 | 74.5 | 45.3 | 70.3 | 75.6 | 78.9 | 78.4 | 75.1 | 70.9 | 63.8 | 55.9 | 47.0 |
| <=35 | 43.2 | 70.1 | 78.1 | 70.0 | 69.6 | 51.3 | 64.7 | 71.2 | 76.7 | 78.6 | 77.7 | 74.9 | 68.6 | 61.5 | 52.8 |
| <=37 | 49.5 | 65.6 | 78.6 | 74.5 | 65.0 | 57.3 | 59.1 | 67.0 | 73.7 | 77.3 | 78.8 | 78.0 | 73.2 | 66.8 | 58.7 |
| <=39 | 55.8 | 60.7 | 78.7 | 78.2 | 60.1 | 63.2 | 53.3 | 62.2 | 70.4 | 75.9 | 79.1 | 80.5 | 77.4 | 72.0 | 64.5 |
| <=41 | 61.8 | 55.3 | 77.2 | 81.3 | 54.6 | 69.1 | 47.6 | 56.9 | 65.8 | 72.7 | 78.2 | 81.8 | 80.8 | 77.0 | 70.3 |
| <=43 | 66.8 | 50.6 | 75.1 | 83.0 | 49.9 | 73.8 | 42.8 | 52.4 | 61.9 | 69.7 | 76.6 | 81.7 | 82.6 | 80.4 | 74.8 |
| <=45 | 71.1 | 46.7 | 73.3 | 83.7 | 46.0 | 77.7 | 38.6 | 48.5 | 58.3 | 66.9 | 74.9 | 81.1 | 83.7 | 83.0 | 78.5 |
| <=47 | 75.6 | 42.1 | 70.1 | 83.9 | 41.4 | 81.8 | 34.1 | 44.0 | 54.1 | 63.0 | 71.9 | 79.3 | 84.0 | 85.5 | 82.5 |
| <=50 | 80.5 | 37.2 | 66.3 | 82.8 | 36.6 | 85.9 | 29.2 | 39.2 | 49.3 | 58.7 | 68.2 | 76.9 | 83.6 | 87.2 | 86.3 |
| <=54 | 85.3 | 32.4 | 61.8 | 80.4 | 31.8 | 89.7 | 24.4 | 34.5 | 44.7 | 54.2 | 63.7 | 73.5 | 81.7 | 87.6 | 89.9 |
| <=60 | 90.5 | 27.2 | 56.9 | 76.9 | 26.5 | 92.7 | 19.2 | 29.2 | 39.5 | 49.1 | 58.8 | 68.9 | 78.4 | 86.7 | 92.3 |
| <=68 | 95.2 | 22.5 | 52.5 | 72.9 | 21.8 | 94.0 | 14.5 | 24.5 | 34.8 | 44.5 | 54.4 | 64.7 | 74.6 | 84.1 | 92.7 |
| <=100 | 100.0 | 17.7 | 47.8 | 68.2 | 17.0 | 91.6 | 9.7 | 19.7 | 30.0 | 39.7 | 49.7 | 59.9 | 70.0 | 80.1 | 89.9 |

Scorecard applied to the validation sample.

For an example cut-off of 31 or less in the previous figures, 31.4 percent of all people in Cambodia are targeted, and outcomes for 100% of the national line in the validation sample are:

- Inclusion: 13.9 percent are below the line and correctly targeted
- Undercoverage: 3.8 percent are below the line and mistakenly not targeted
- Leakage: 17.6 percent are above the line and mistakenly targeted
- Exclusion: 64.7 percent are above the line and correctly not targeted

Increasing the cut-off to 33 or less increases the share of of all people targeted to 37.1 percent. The higher cut-off improves inclusion and undercoverage but worsens leakage and exclusion:

- Inclusion: 14.9 percent are below the line and correctly targeted
- Undercoverage: 2.8 percent are below the line and mistakenly not targeted
- Leakage: 22.3 percent are above the line and mistakenly targeted
- Exclusion: 60.0 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 **Figure 15** to **Figure 18** 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 19** 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, the hit rate for a cut-off of 31 or less is 78.6 percent. That is, a little less than four in five people in Cambodia are correctly classified.

The hit rate weighs the successful inclusion of people below a poverty line the same as the 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 cut-off score to maximize net benefits, a pro-poor program could set cut-offs based on aspects of targeting accuracy from the three figures below:

- **Figure 20: Share of targeted people who are poor**
- **Figure 21: Poor people correctly targeted per non-poor person mistakenly targeted**
- **Figure 22: Share of poor people who are targeted**

## Figure 20: Share of targeted people who are poor

| Targeting cut-off | % all people who are targeted | % targeted people who are poor | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Natl. (2019/20 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| <=17 | 5.2 | 79.8 | 96.0 | 98.1 | 79.8 | 99.3 | 60.1 | 84.5 | 89.4 | 95.6 | 96.7 | 98.1 | 98.1 | 98.7 | 99.3 |
| <=22 | 10.9 | 69.3 | 94.5 | 98.2 | 68.1 | 99.7 | 47.9 | 74.2 | 86.0 | 91.4 | 94.9 | 97.6 | 98.2 | 98.9 | 99.7 |
| <=25 | 16.9 | 59.3 | 92.3 | 98.3 | 58.0 | 99.8 | 38.6 | 63.8 | 81.1 | 87.6 | 92.9 | 96.9 | 98.3 | 99.1 | 99.8 |
| <=27 | 21.5 | 53.0 | 88.5 | 96.9 | 51.9 | 99.8 | 33.7 | 56.9 | 73.9 | 82.1 | 89.8 | 95.2 | 97.1 | 99.0 | 99.8 |
| <=29 | 25.9 | 49.1 | 87.0 | 96.7 | 47.7 | 99.7 | 30.0 | 52.8 | 70.7 | 80.5 | 88.1 | 94.2 | 97.0 | 98.9 | 99.7 |
| <=31 | 31.4 | 44.1 | 84.6 | 96.3 | 42.6 | 99.7 | 26.3 | 47.8 | 66.3 | 77.9 | 86.1 | 93.3 | 96.6 | 99.0 | 99.7 |
| <=33 | 37.1 | 40.1 | 81.8 | 95.1 | 38.6 | 99.7 | 23.0 | 43.8 | 62.0 | 74.4 | 83.4 | 91.5 | 95.4 | 98.4 | 99.6 |
| <=35 | 43.2 | 35.8 | 79.9 | 94.2 | 34.6 | 99.7 | 20.3 | 39.6 | 57.8 | 71.1 | 81.6 | 90.3 | 94.7 | 98.1 | 99.4 |
| <=37 | 49.5 | 33.2 | 76.7 | 93.1 | 31.9 | 99.4 | 18.4 | 36.6 | 53.7 | 67.2 | 78.8 | 88.3 | 93.6 | 97.4 | 99.1 |
| <=39 | 55.8 | 30.7 | 73.7 | 91.6 | 29.5 | 99.2 | 16.8 | 33.8 | 50.4 | 64.0 | 75.8 | 86.2 | 92.4 | 96.7 | 98.7 |
| <=41 | 61.8 | 28.1 | 70.2 | 90.1 | 27.1 | 99.1 | 15.4 | 31.1 | 46.6 | 60.0 | 72.5 | 83.8 | 91.1 | 96.2 | 98.7 |
| <=43 | 66.8 | 26.3 | 67.1 | 88.3 | 25.3 | 99.0 | 14.4 | 29.1 | 43.9 | 57.0 | 69.7 | 81.2 | 89.3 | 95.3 | 98.4 |
| <=45 | 71.1 | 24.9 | 64.8 | 86.5 | 24.0 | 98.7 | 13.6 | 27.6 | 41.8 | 54.6 | 67.3 | 78.9 | 87.7 | 94.4 | 98.1 |
| <=47 | 75.6 | 23.4 | 61.8 | 84.5 | 22.5 | 98.5 | 12.8 | 26.0 | 39.5 | 51.8 | 64.2 | 76.0 | 85.7 | 93.4 | 97.9 |
| <=50 | 80.5 | 22.0 | 58.7 | 81.7 | 21.2 | 98.2 | 12.0 | 24.5 | 37.2 | 49.0 | 61.1 | 72.9 | 83.3 | 91.8 | 97.3 |
| <=54 | 85.3 | 20.8 | 55.6 | 78.5 | 20.0 | 97.7 | 11.4 | 23.2 | 35.2 | 46.4 | 57.8 | 69.6 | 80.3 | 89.7 | 96.8 |
| <=60 | 90.5 | 19.6 | 52.6 | 74.9 | 18.8 | 96.6 | 10.7 | 21.8 | 33.1 | 43.8 | 54.7 | 65.9 | 76.7 | 86.9 | 95.4 |
| <=68 | 95.2 | 18.6 | 50.2 | 71.6 | 17.9 | 94.9 | 10.2 | 20.7 | 31.5 | 41.7 | 52.1 | 62.9 | 73.4 | 83.7 | 93.4 |
| <=100 | 100.0 | 17.7 | 47.8 | 68.2 | 17.0 | 91.6 | 9.7 | 19.7 | 30.0 | 39.7 | 49.7 | 59.9 | 70.0 | 80.1 | 89.9 |

Scorecard applied to the validation sample.

# Figure 21: 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 | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Natl. (2019/20 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| <=17 | 5.2 | 3.9:1 | 24.2:1 | 52.8:1 | 3.9:1 | 151.2:1 | 1.5:1 | 5.4:1 | 8.5:1 | 21.9:1 | 29.4:1 | 52.8:1 | 52.8:1 | 78.3:1 | 151.2:1 |
| <=22 | 10.9 | 2.3:1 | 17.2:1 | 56.0:1 | 2.1:1 | 317.2:1 | 0.9:1 | 2.9:1 | 6.1:1 | 10.6:1 | 18.7:1 | 40.8:1 | 56.0:1 | 90.5:1 | 317.2:1 |
| <=25 | 16.9 | 1.5:1 | 12.0:1 | 58.1:1 | 1.4:1 | 491.5:1 | 0.6:1 | 1.8:1 | 4.3:1 | 7.1:1 | 13.1:1 | 30.9:1 | 58.1:1 | 104.9:1 | 491.5:1 |
| <=27 | 21.5 | 1.1:1 | 7.7:1 | 31.3:1 | 1.1:1 | 626.0:1 | 0.5:1 | 1.3:1 | 2.8:1 | 4.6:1 | 8.8:1 | 20.0:1 | 33.0:1 | 96.8:1 | 626.0:1 |
| <=29 | 25.9 | 1.0:1 | 6.7:1 | 29.2:1 | 0.9:1 | 371.9:1 | 0.4:1 | 1.1:1 | 2.4:1 | 4.1:1 | 7.4:1 | 16.3:1 | 31.9:1 | 93.7:1 | 371.9:1 |
| <=31 | 31.4 | 0.8:1 | 5.5:1 | 25.9:1 | 0.7:1 | 298.4:1 | 0.4:1 | 0.9:1 | 2.0:1 | 3.5:1 | 6.2:1 | 13.9:1 | 28.0:1 | 100.8:1 | 298.4:1 |
| <=33 | 37.1 | 0.7:1 | 4.5:1 | 19.5:1 | 0.6:1 | 311.9:1 | 0.3:1 | 0.8:1 | 1.6:1 | 2.9:1 | 5.0:1 | 10.7:1 | 20.7:1 | 61.1:1 | 232.3:1 |
| <=35 | 43.2 | 0.6:1 | 4.0:1 | 16.4:1 | 0.5:1 | 362.8:1 | 0.3:1 | 0.7:1 | 1.4:1 | 2.5:1 | 4.4:1 | 9.4:1 | 17.8:1 | 51.3:1 | 163.8:1 |
| <=37 | 49.5 | 0.5:1 | 3.3:1 | 13.6:1 | 0.5:1 | 159.4:1 | 0.2:1 | 0.6:1 | 1.2:1 | 2.0:1 | 3.7:1 | 7.6:1 | 14.7:1 | 36.8:1 | 107.3:1 |
| <=39 | 55.8 | 0.4:1 | 2.8:1 | 10.9:1 | 0.4:1 | 120.4:1 | 0.2:1 | 0.5:1 | 1.0:1 | 1.8:1 | 3.1:1 | 6.2:1 | 12.2:1 | 29.1:1 | 78.9:1 |
| <=41 | 61.8 | 0.4:1 | 2.4:1 | 9.1:1 | 0.4:1 | 107.9:1 | 0.2:1 | 0.5:1 | 0.9:1 | 1.5:1 | 2.6:1 | 5.2:1 | 10.2:1 | 25.2:1 | 74.8:1 |
| <=43 | 66.8 | 0.4:1 | 2.0:1 | 7.5:1 | 0.3:1 | 95.7:1 | 0.2:1 | 0.4:1 | 0.8:1 | 1.3:1 | 2.3:1 | 4.3:1 | 8.4:1 | 20.1:1 | 62.8:1 |
| <=45 | 71.1 | 0.3:1 | 1.8:1 | 6.4:1 | 0.3:1 | 78.6:1 | 0.2:1 | 0.4:1 | 0.7:1 | 1.2:1 | 2.1:1 | 3.7:1 | 7.1:1 | 16.7:1 | 52.2:1 |
| <=47 | 75.6 | 0.3:1 | 1.6:1 | 5.4:1 | 0.3:1 | 67.6:1 | 0.1:1 | 0.4:1 | 0.7:1 | 1.1:1 | 1.8:1 | 3.2:1 | 6.0:1 | 14.1:1 | 46.2:1 |
| <=50 | 80.5 | 0.3:1 | 1.4:1 | 4.5:1 | 0.3:1 | 53.5:1 | 0.1:1 | 0.3:1 | 0.6:1 | 1.0:1 | 1.6:1 | 2.7:1 | 5.0:1 | 11.2:1 | 36.2:1 |
| <=54 | 85.3 | 0.3:1 | 1.3:1 | 3.6:1 | 0.2:1 | 42.4:1 | 0.1:1 | 0.3:1 | 0.5:1 | 0.9:1 | 1.4:1 | 2.3:1 | 4.1:1 | 8.7:1 | 29.8:1 |
| <=60 | 90.5 | 0.2:1 | 1.1:1 | 3.0:1 | 0.2:1 | 28.1:1 | 0.1:1 | 0.3:1 | 0.5:1 | 0.8:1 | 1.2:1 | 1.9:1 | 3.3:1 | 6.6:1 | 20.6:1 |
| <=68 | 95.2 | 0.2:1 | 1.0:1 | 2.5:1 | 0.2:1 | 18.7:1 | 0.1:1 | 0.3:1 | 0.5:1 | 0.7:1 | 1.1:1 | 1.7:1 | 2.8:1 | 5.1:1 | 14.1:1 |
| <=100 | 100.0 | 0.2:1 | 0.9:1 | 2.1:1 | 0.2:1 | 10.9:1 | 0.1:1 | 0.2:1 | 0.4:1 | 0.7:1 | 1.0:1 | 1.5:1 | 2.3:1 | 4.0:1 | 8.9:1 |

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

## Figure 22: Share of poor people who are targeted

| Targeting cut-off | % all people who are targeted | % poor people who are targeted | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Natl. (2019/20 def.) | | | Intl. 2017 PPP (2019 def.) | | Percentile lines (2019 def.) | | | | | | | | |
| | | 100% | 150% | 200% | $6.85 | $24.36 | 10th | 20th | 30th | 40th | 50th | 60th | 70th | 80th | 90th |
| <=17 | 5.2 | 23.5 | 10.5 | 7.5 | 24.4 | 5.6 | 32.3 | 22.3 | 15.5 | 12.6 | 10.2 | 8.5 | 7.3 | 6.4 | 5.8 |
| <=22 | 10.9 | 42.6 | 21.5 | 15.7 | 43.5 | 11.9 | 53.8 | 40.9 | 31.2 | 25.1 | 20.8 | 17.7 | 15.3 | 13.5 | 12.1 |
| <=25 | 16.9 | 56.4 | 32.6 | 24.3 | 57.4 | 18.4 | 67.3 | 54.4 | 45.5 | 37.2 | 31.6 | 27.2 | 23.7 | 20.8 | 18.7 |
| <=27 | 21.5 | 64.2 | 39.8 | 30.5 | 65.5 | 23.4 | 74.6 | 61.8 | 52.8 | 44.4 | 38.8 | 34.1 | 29.8 | 26.5 | 23.8 |
| <=29 | 25.9 | 71.7 | 47.1 | 36.7 | 72.5 | 28.2 | 80.1 | 69.2 | 61.0 | 52.5 | 45.9 | 40.7 | 35.9 | 32.0 | 28.7 |
| <=31 | 31.4 | 78.4 | 55.7 | 44.4 | 78.7 | 34.2 | 85.2 | 76.1 | 69.5 | 61.7 | 54.5 | 49.0 | 43.4 | 38.9 | 34.9 |
| <=33 | 37.1 | 84.0 | 63.6 | 51.8 | 84.3 | 40.4 | 88.3 | 82.3 | 76.8 | 69.6 | 62.4 | 56.7 | 50.6 | 45.6 | 41.2 |
| <=35 | 43.2 | 87.4 | 72.2 | 59.7 | 87.6 | 47.0 | 90.5 | 86.5 | 83.2 | 77.4 | 71.0 | 65.1 | 58.4 | 52.9 | 47.8 |
| <=37 | 49.5 | 92.8 | 79.4 | 67.6 | 92.7 | 53.7 | 94.3 | 91.8 | 88.6 | 83.8 | 78.6 | 73.0 | 66.3 | 60.2 | 54.6 |
| <=39 | 55.8 | 96.6 | 86.0 | 74.9 | 96.6 | 60.4 | 96.9 | 95.5 | 93.6 | 89.9 | 85.2 | 80.2 | 73.7 | 67.3 | 61.3 |
| <=41 | 61.8 | 98.2 | 90.8 | 81.6 | 98.2 | 66.8 | 98.2 | 97.4 | 96.0 | 93.5 | 90.2 | 86.4 | 80.4 | 74.2 | 67.8 |
| <=43 | 66.8 | 99.1 | 93.8 | 86.5 | 99.1 | 72.2 | 99.6 | 98.5 | 97.8 | 96.0 | 93.8 | 90.5 | 85.3 | 79.5 | 73.2 |
| <=45 | 71.1 | 100.0 | 96.4 | 90.2 | 100.0 | 76.6 | 100.0 | 99.4 | 99.0 | 97.8 | 96.3 | 93.5 | 89.1 | 83.7 | 77.6 |
| <=47 | 75.6 | 100.0 | 97.8 | 93.7 | 100.0 | 81.3 | 100.0 | 99.5 | 99.5 | 98.6 | 97.8 | 95.8 | 92.6 | 88.1 | 82.3 |
| <=50 | 80.5 | 100.0 | 98.9 | 96.4 | 100.0 | 86.2 | 100.0 | 99.7 | 99.7 | 99.4 | 99.0 | 97.9 | 95.8 | 92.2 | 87.1 |
| <=54 | 85.3 | 100.0 | 99.3 | 98.2 | 100.0 | 91.0 | 100.0 | 100.0 | 100.0 | 99.7 | 99.3 | 99.0 | 97.9 | 95.5 | 91.8 |
| <=60 | 90.5 | 100.0 | 99.6 | 99.4 | 100.0 | 95.4 | 100.0 | 100.0 | 100.0 | 99.9 | 99.6 | 99.6 | 99.2 | 98.2 | 96.1 |
| <=68 | 95.2 | 100.0 | 100.0 | 99.9 | 100.0 | 98.7 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 99.9 | 99.5 | 98.9 |
| <=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.
For 100% of the national line, targeting those who score 29 or less would target 25.9 percent of people in Cambodia and give a head-count poverty rate among those targeted of 49.1percent (**Figure 20**).

**Figure 21** 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 targeted (leakage). For 100% of the national line and a score cut-off of 29 or less, about 1.0 poor people are successfully targeted for every one non-poor person mistakenly targeted.

Alternatively, a pro-poor program might seek to target a desired share—such as 80 percent—of poor people in Cambodia. For 100% of the national line, **Figure 22** shows that a score cut-off of 31 or less would target 31.4 percent of all people in Cambodia, a segment that includes 78.4 percent of all poor people.

# Interview Guide

Citations in this **Interview Guide** come from:

**National Institute of Statistics**. (2019) "Field-Operations Manual for Interviewers and Supervisors: Cambodia Socio-Economic Survey 2019/20" (*ឯកសារណែនាំ សម្រាប់ មន្ត្រីសម្ភាសន៍ និង មន្ត្រីត្រួតពិនិត្យនាំឆ្នាំ ២០១៩*) [*2019 Manual*]

and

**National Institute of Statistics**. (2012) "Field-Operations Manual for Interviewers and Supervisors: Cambodia Socio-Economic Survey 2012" (*ឯកសារណែនាំ សម្រាប់ មន្ត្រីសម្ភាសន៍ និង មន្ត្រីត្រួតពិនិត្យនាំឆ្នាំ ២០១២*) [*2012 Manual*], **link**

and

**National Institute of Statistics**. (2019) *Cambodia Population Census* (*ជំរឿនទូទៅនៃប្រជាជនកម្ពុជា*) [*Census*], តំណ

and

**National Institute of Statistics**. (2019) *Report of Cambodia Socio-Economic Survey, 2019/20*, (pages 206–270), [*the Questionnaire*], **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 on any device, allowing data entry in the field or in the office. If there is no connection, then data is stored on the device until it can be uploaded.

The scorecard should be administered by enumerators trained to follow this **Interview Guide**.

Fill out the scorecard header and the **Back-page Worksheet** first, following the directions found there.

In the scorecard header, fill in the exact 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 which province does the household live?"). Instead, fill in the response based on the knowledge that you the enumerator have of the province where the interviewed household lives.

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

Ask all eight remaining questions directly of the respondent.

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

Do not read the response options.

Study this **Interview Guide** carefully, and carry it with you while you work. Follow its instructions (including this one).

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

Likewise, the service agent to be recorded in the scorecard header is not necessarily the same as you the enumerator who does the interview. Rather, the service agent is the employee of the pro-poor program with whom the participant of record has an on-going relationship. If there is no such service agent, or if you the enumerator do not know if there is such a service agent, or if you do not know the name of the service agent, then write "NONE" or "UNKNOWN" in the relevant spaces in the scorecard header.

In general, do not leave blank spaces in the header. If the requested information is unknown, does not exist, or is not applicable, then write "NONE" or "UNKNOWN" in the blanks. This shows that you the enumerator tried to obtain the data. This may help avoid returning to the household later to try to collect uncollectible data.

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, as shown below.

| | | | |
|---|---|---|---|
| 8. How many cell phones does the household own? | A. None | 0 | |
| | B. One | 7 | 7 |
| | C. Two or more | 11 | |

When an issue comes up that is not addressed in this **Interview Guide**, its resolution should be left to the unaided judgment of you the enumerator and the respondent, as that apparently was the practice of Cambodia's NIS in the 2019/20 CSES. 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 needs or 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 **Interview Guide**.

While 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 or she may be lying, confused, or uncertain.

Likewise, verification may be called for if a child in the interviewed household or if a neighbor says something that does not square with a respondent's response.

Verification may also be 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 or in the yard 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 2019/20 CSES by Cambodia's NIS. For example, interviews should done in-person by a trained enumerator at the dwelling of the interviewed household because that is what the NIS did in the 2019/20 CSES.

## G2. Translation

You the enumerator should do the interview in a language which both you and the respondent speak and understand well.

The scorecard itself, the **Back-page Worksheet**, and this **Interview Guide** are available English and Khmer. There are not yet official, professional translations to other languages spoken in Cambodia. Users should check **scorocs.com** for translations that may have been done since this writing. If there is not yet an official, professional translation to a desired language, then please contact **Scorocs** to arrange to collaborate on one.

## G3. Who should be the respondent?

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

According to the *Questionnaire*, the scorecard questions "should be asked of the head of the interviewed household or of the head's spouse (if there is one). If both the head and his or her spouse are absent, then ask the questions of another adult member of the interviewed household."

According to p. 8 of the *2012 Manual*, "[You the enumerator] may interview any responsible member of the household who can provide accurate responses to the questions and who can give information on behalf of the household. The head of the household and/or his or her spouse (if there is one) are the most qualified to respond."

## G4. 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 participant of record with your program.

Every household has one (and only one) head. The head of the interviewed household must be a member of the interviewed household. A person cannot be the head of more than one household because no one can be a member of more than one household.

According to p. 186 of the *2019 Manual*, the *head of the household* is "the member of the interviewed household who the other members of the household acknowledge as the head. Frequently, household members report that the senior male member (if there is one) is their head. Nevertheless, you the enumerator should not assume that the senior male is the head. Instead, ask the members of the interviewed household who their head is. In most cases, they will answer without any difficulty."

According to p. 3 of the *2012 Manual*, the *head of the household* is "usually the member of the household who makes major economic and social decisions on behalf of the household and who is recognized as the head by the other members of the household.

"Usually the head of the household is the person who provides the resources to cover most of the needs of the household and who is familiar with all the activities and occupations of the household members. Note that the head is not necessarily the oldest member of the household, nor is the head necessarily the member who earns the most money from employment, from a business activity, or from the sale of farm produce. You the enumerator must listen carefully to the household members and allow them to point out to you the member who is the head of their household."

According to the *Census*, the *head of the household* is "the member of the interviewed household who is acknowledged as the head by the other members of the household. The head may be male or female. In general, the head is the member of the household who is responsible for the household's management and decision-making. The head may or may not be the oldest member of the household. In the same way, the head may or may not be a younger male or female member of the household. If person who is recognized as the head by the other members of the interviewed household is not a member of the interviewed household by the definition of *household* used for the scorecard, then count as the head the person who is a member of the interviewed household who is generally responsible for managing the interviewed household's affairs."

## G5. Guidelines for each question in the scorecard

### G5.1 In which province does the household live?

A. Phnom Penh, Tboung Khmum, Kampong Thom, Pailin, Mondulkiri, or Ratanakiri
B. Kandal, Siem Reap, Banteay Meanchey, Kampong Chhnang, Kratié, or Preah Vihear
C. Prey Veng, Battambang, Kampong Cham, Takéo, Svay Rieng, Pursat, Oddar Meanchey, or Stung Treng
D. Kampong Speu, Preah Sihanouk, Kampot, Koh Kong, or Kep

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

### G5.2 How many members does the household have?

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

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

According to p. 186 of the *Census*, a *household* is "a group of persons (or a single person) who usually live together and who have a common arrangement for food. People who do not usually eat with the interviewed household are not counted as members of the interview household."

According to p. 26 of the *2012 Manual*, a *household* is "a group of people (or a single person) who usually live together and who have a common arrangement for food, such as using a common kitchen or a common food budget. The people may or may not be related to each other by blood or marriage. They may include servants or other employees who live and eat with their employer (that is, with the interviewed household).

"Students, boarders, and employees who live in the interviewed household's residence and who have a common food arrangement with the interviewed household are considered to be members of the interviewed household if they have had that arrangement with the interviewed household for more than 12 months or if they have no other current place of residence.

"However, if there are five or more boarders or lodgers in a residence, then they should not be reported as members of the interviewed household from whom they buy room and board."

According to p. 27 of the *2012 Manual*, "A *member of the interviewed household* is any person who has been normally living in the residence of the interviewed household and who has shared arrangements for food for at least 12 months or who has no other residence.

“Thus, most students who board (that is, sleep and eat) in the residence of a household other than the residence of the household of their parents because the students attend a school that distant from the residence of the household of their parents are nevertheless considered to be members of the household of their parents unless the students have boarded continuously in the residence close to their school for more than 12 months.

“A person who has changed his or her residence less than 12 months ago is considered to be a member of the household at his or her current residence if he or she plans to remain at the current residence for a total duration of at least 12 months. Similarly, a person who has recently moved out of a residence and who has no intention to return is no longer considered to be a member of the household at the former residence.

“A person is counted as a member of the interviewed household if he or she currently lives there or has been absent for less than 12 months.

“A person who has moved out of the interviewed household more than 12 months ago and who still visits the interviewed household only occasionally (such as only during major holidays a few times a year) is not considered to be a member of the interviewed household. However, a person who has had a separate residence for more than 12 months but who comes home regularly (on average, once a month or more frequently) is still considered to be a member of the interviewed household (for example, garment workers).

“The following are also considered to be members of the interviewed household:

- Newly-wed spouses (for example, a son-in-law or a daughter-in-law) who recently joined the interviewed household
- New-born children of members of the interviewed household
- People who commute between the village and their jobs or who come home regularly from their jobs (for the weekend, or sometimes at the end of the month), such as garment workers

“Newly-weds who have moved out of the interviewed household, people who have died, and so on are not counted as members of the interviewed household.”

### G5.3 How many rooms in the dwelling are used by the household (other than kitchen, toilet, and bathrooms)?

A. One
B. Two
C. Three or more

According to p. 35 of the *2012 Manual*, "Ask for the number of rooms in the dwelling unit that is used by the interviewed household. A *room* must have four walls with a roof and a doorway. It must be wide enough and long enough for a person to sleep in. When counting the number of rooms occupied by the interviewed household, you the enumerator should exclude kitchens, storerooms, bathrooms, and toilets, as these are are not normally usable for living or sleeping.

"A room which is shared by more than one household is not to be counted as being occupied by any of the households that share it."

### G5.4 What is the primary construction material of the floor of the dwelling occupied by the household?

A. Bamboo strips, earth, clay, or wooden planks
B. Cement, brick, stone, parquet, polished wood, polished stone, marble, or other
C. Vinyl, or ceramic tiles

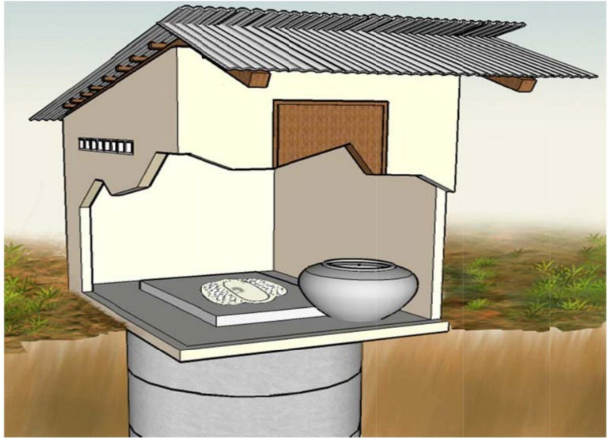
According to p. 35 of the *2012 Manual*, “This question can be answered via observation. If in doubt, however, then you the enumerator should ask the question of the respondent.

“If the floor of the interviewed household’s residence is made of more than one type of material, then record the type of material that accounts for the largest share of the floor area.”

## G5.5 What kind of toilet facility does the household usually use?

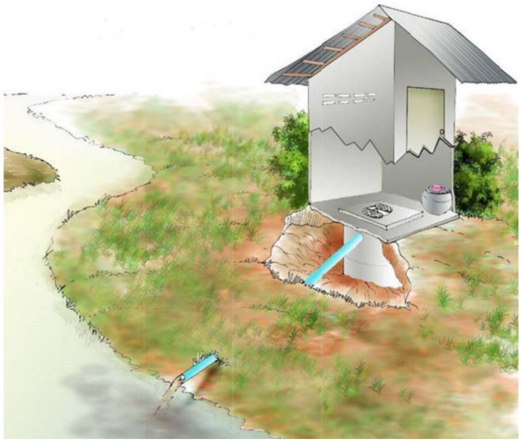
A. None
B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other
C. Pour flush (or flush) to sewer

**A. None**

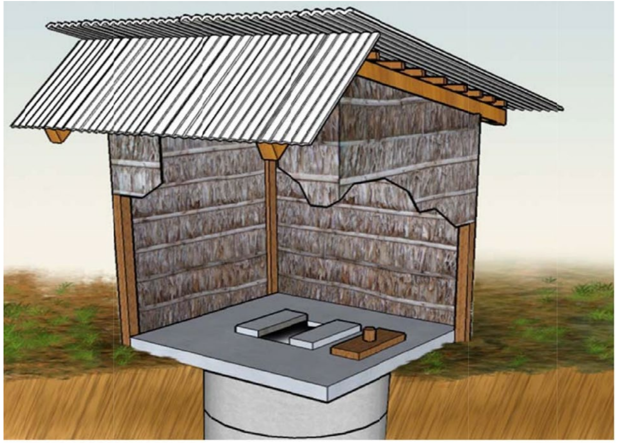


**B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other**

**B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other**

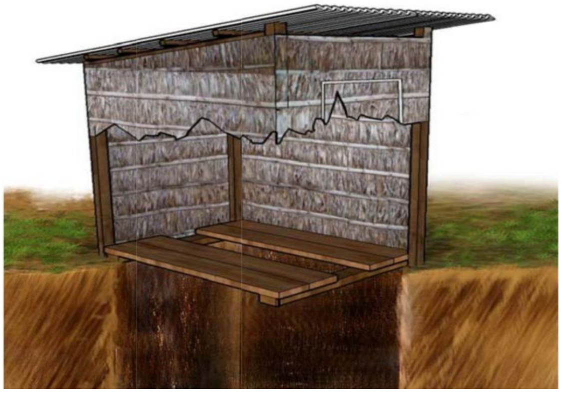


**B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other**



**B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other**

**B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other**



**B. Pour flush (or flush) to septic tank, pit, or somewhere else that is not a sewer; pit latrine with or without slab; open pit or latrine overhanging field or water (drop in field, pond, river, lake, or sea); or other**

**C. Pour flush (or flush) to sewer**

### G5.6 Does the household own any gas or electric stoves?

A. No
B. Yes

According to the NIS, a gas or electric stove that is broken-but-repairable should be counted for the purposes of this question. A borrowed gas or electric stove should not be counted.

There is no additional guidance for this question.

### G5.7 How many cell phones does the household own?

A. None, or one
B. Two, or three
C. Four or more

According to the NIS, a cell phone that is broken-but-repairable should be counted for the purposes of this question. A borrowed cell phone should not be counted.

There is no additional guidance for this question.

### G5.8 How many motorcycles (including electric motorcycles) does the household own?

A. None
B. One
C. Two or more

According to the NIS, a motorcycle (or electric motorcycle) that is broken-but-repairable should be counted for the purposes of this question. A borrowed motorcycle (or electric motorcycle) should not be counted.

There is no additional guidance for this question.

### G5.9 Does the household own any cars, jeeps, or vans?

A. No
B. Yes

According to the NIS, a car, jeep, or van that is broken-but-repairable should be counted for the purposes of this question. A borrowed car, jeep, or van should not be counted.

There is no additional guidance for this question.

### G5.10 In the past 7 days, did anyone in the household eat any bananas, apples, oranges, lemons, or tangerines?

A. No
B. Yes

There is no additional guidance for this question.

# Technical Annexes: Overview

The technical annexes cover advanced or technical aspects of the scorecard. While program managers can skip the annexes and still benefit from using the scorecard, understanding the details will increase the usefulness of scorecard estimates and improve implementation and interpretation.

# Annex 1 Data used for construction and validation

The National Institute of Statistics (NIS) fielded the 2019/20 Cambodia Socio-Economic Survey (CSES) with 10,075 households from July 1, 2019 to June 30, 2020. This is Cambodia's most-recent national household consumption-expenditure survey.

Questions and points for the scorecard are selected (*constructed*) based on data from a random three-fifths of the households in the 2019/20 CSES. These same three-fifths of households are also used to associate (*calibrate*) scores with poverty likelihoods for all supported poverty lines as well as to calibrate scores with daily per-capita consumption expenditure.

Data from the other two-fifths of households from the 2019/20 CSES are used to test (*validate*) the scorecard's accuracy for one-period 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 validation of targeting accuracy.

# Annex 2 Definition of *poverty*

A household's *poverty status* as poor or non-poor depends on whether its daily per-capita consumption expenditure in riel (KHR) is below a given poverty line. Thus, a definition of *poverty* is a poverty line together with a measure of consumption expenditure from the 2019/20 CSES.

For the 2019/20 CSES, Cambodia adopted a new definition of consumption expenditure.[33] It is better than the old definition because it:

- Records both quantities and values of expenditure items
- Imputes a rental value to owner-occupied housing
- Imputes a use value to durable goods
- Does not assign a fixed expense for clean water

In addition, Cambodia's official poverty line (called here "100% of the national line") was revised for the 2019/20 CSES to align with international practice in that it:

- Uses the cost-of-basic-needs approach[34]
- Uses a single consumption basket

The new scorecard here uses the new definition of *poverty.* Thus, its estimates are not comparable with estimates from old scorecards based old definitions of *poverty* used by the CSES in **2004**, **2011**, and **2017**. It is not possible to estimate changes in poverty with a baseline estimate from an old scorecard and a follow-up estimate from the new scorecard. To estimate changes, both baseline and follow-up must be from the new scorecard.

[33] **Ministry of Planning** (2021).
[34] **Ravallion**, 1998.

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

- 100% of national
- 150% of national
- 200% of national
- $6.85/day 2017 PPP
- $24.36/day 2017 PPP
- 10$^{th}$ percentile
- 20$^{th}$ percentile
- 30$^{th}$ percentile
- 40$^{th}$ percentile
- 50$^{th}$ percentile
- 60$^{th}$ percentile
- 70$^{th}$ percentile
- 80$^{th}$ percentile
- 90$^{th}$ percentile

## A2.1 Official poverty line

The new definition of Cambodia's official poverty line starts with the cost of a food basket with a minimum standard of 2,200 Calories per person per day. The 28 items in the basket, their shares, and their monetary values are based on data in the 2019/20 CSES for people in the 5$^{th}$ to 40$^{th}$ percentiles of total (food-plus-non-food) consumption expenditure. Prices are adjusted for differences across quarters during the 2019/20 CSES and across three geographic areas: Phnom Phen, other urban, and rural.

In average prices in Phnom Phen during the 2019/20 CSES fieldwork, the cost of the food standard is KHR5,276 per person per day.

The official line (called here "100% of the national line") is the cost of this food standard, plus the cost of a minimum standard for non-food expenditure, defined as the average of the average of non-food expenditure[35] across the two groups of households whose:

- *Food* expenditure is within ±10 percent of the food standard
- *Food-plus-non-food* expenditure is within ±10 percent of the food standard

The average of 100% of the national poverty line for Cambodia overall is KHR10,951 per person per day, giving a head-count poverty rate of 17.8 percent (**Figure 11**).[36]

150% of the national line and 200% of the national line are multiples of 100% of the national line.

## A2.2 International 2017 PPP poverty lines

The World Bank tracks world-wide poverty with four 2017 PPP poverty lines:[37]

- $2.15/day Low-income countries (the international "extreme poverty" line)
- $3.65/day Lower-middle-income countries
- $6.85/day Upper-middle-income countries
- $24.36/day High-income countries

Although the World Bank classifies Cambodia as a lower-middle-income country, the most relevant 2017 PPP line is $6.85/day, for which the head-count poverty rate is 17.0 percent (**Figure 11**). Almost no Cambodians are poor by $2.15/day (0.0 percent) or $3.65/day (1.0 percent).

The purpose of PPP lines is to adjust for differences in purchasing power across countries due to the fact that non-tradable goods and services are usually less costly in poorer countries while tradables are more costly. PPP adjustments improve the international comparability of poverty estimates.

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[35] **Ministry of Planning** (2021).

[36] This head-count poverty rate for Camboda overall for 100% of the national line matches that in **Ministry of Planning** (2021, p. 16), suggesting that the new scorecard uses the same data and calculations as did the NIS.

[37] **Jolliffe, *et al.***, 2022.

2017 PPP lines for Cambodia are derived from:

- 2017 PPP exchange rate for Cambodia for "individual consumption expenditure by households":[38] KHR1488.80 per $1.00
- Average all-Cambodia Consumer Price Index[39] (CPI):
  - Calendar-year 2017: 169.87
  - During the 2019/20 CSES: 179.86
- Person-weighted, all-Cambodia average of geographic price indexes: 0.8532
- Geographic price indexes for the 2019/20 CSES
  - Phnom Phen: 1.0000
  - Other urban: 0.8740
  - Rural: 0.8134

The $6.85/day 2017 PPP line for the example of rural Cambodia is then:

$$\$6.85 \cdot 2017\ \text{PPP} \cdot \frac{\text{CPI}_{\text{CSES}}}{\text{CPI}_{2017}} \cdot \frac{\text{CPI}_{\text{Area}}}{\text{CPI}_{\text{Ave.}}} = \$6.85 \cdot 1{,}488.80 \cdot \frac{179.86}{169.87} \cdot \frac{0.8134}{0.8532} = \text{KHR}10{,}295.$$

For Cambodia overall, the average $6.85/day line is KHR10,798, with a head-count poverty rate of 17.0 percent (**Figure 11**). As of this writing, the World Bank has not published 2017 PPP poverty lines nor rates for Cambodia.

The 2017 PPP line for $24.36/day is a multiple of the $6.85/day line.

[38] **World Bank**, 2020, Table 2.3, column 13, p. 32.
[39] Base = 100 in October, 2006, **link**.

## A2.3 Percentile-based poverty lines

The scorecard supports percentile-based poverty lines.[40] This facilitates a number of types of analyses. For example, the 40th-percentile line might be used to help track Cambodia'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.

More generally, the percentile lines can be analyzed together to look at the relationship of consumption expenditure with health outcomes (or anything else related with the distribution of consumption expenditure). The scorecard thus offers an alternative for health-equity analyses that typically have used an asset index (such as that supplied with public-use data from the Demographic and Health Surveys) to compare an estimate of socio-economic status with health outcomes.[41]

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

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

Unlike the scorecard, asset indexes only estimate relative wealth. Furthermore, the scorecard—unlike asset indexes—uses a straightforward, well-understood standard for socio-economic status whose definition is external to the tool itself (that is, consumption expenditure relative to a poverty line defined in monetary units).

In contrast, an asset index defines *poverty* in terms of its own questions and points, without calibration or 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*.

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[40] Percentiles are defined in terms of all people in Cambodia. For example, the head-count poverty rate for the 20th-percentile line is 20.0 percent (**Figure 11**).
[41] **Rutstein and Johnson**, 2004.

# Annex 3 Scorecard construction

For Cambodia, about 75 candidate questions are prepared:

- Household composition (such as the number of household members)
- Education (such as whether the female head—or the eldest wife of the male head—can read and write))
- Employment (such as the number of household members who work)
- Health (such as the recent consumption of specific food items)
- Housing (such as the main material of the floor)
- Ownership of consumer durables (such as motorcycles or cell phones)
- Agriculture (such as whether any household member farms)
- Location of residence (the province)

To facilitate the estimation of change over time, preference is given to questions with greater sensitivity to changes in poverty. For example, the ownership of a cell phone is probably more responsive to changes in poverty than is the age of the head of the household).

The scorecard itself is built using the 30$^{th}$-percentile 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 a 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.[42]

[42] **Ravallion**, 2009.

One of the one-question draft scorecards is then selected based on:[43]

- Improvement in accuracy
- Acceptability to users in terms of:
  - Simplicity
  - Cost of collection
  - Concordance with:
    - Experience
    - Theory
    - Common sense
- Sensitivity to changes in consumption expenditure
- Variety among types of questions
- Applicability across provinces
- Tendency to have a slow-changing relationship with poverty
- Relevance for distinguishing among people at the poorer end of the distribution of consumption expenditure
- 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 step. 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 ten 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 stepwise regression. It differs from naïve stepwise in that the selection of questions considers both statistical[44] and non-statistical criteria. The use of non-statistical criteria can improve robustness to violations in the scorecard's assumptions. It also helps to ensure that questions are straightforward, common-sense, inexpensive-to-collect, and acceptable to users.

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[43] **Schreiner *et al.***, 2014.

[44] The statistical criterion is not the *p* value of an estimated coefficient but rather a question's contribution to the ranking of households by poverty status in the context of a scorecard with nine other questions.

The single scorecard here applies to all of Cambodia. Customizing poverty-assessment tools by urban/rural does not improve targeting accuracy much.[45] Segment-specific tools may improve the accuracy of estimates of poverty rates,[46] but:

- They run a greater risk of overfitting[47]
- Most of their benefit can be had in a single scorecard that includes a question that identifies the specific segment of interest (such as, in the case of Cambodia, the province of residence)[48]

[45] **Brown, Ravallion, and van de Walle**, 2018; **World Bank**, 2012; **Sharif**, 2009; Schreiner, **2006** and **2005**; **Narayan and Yoshida**, 2005; and **Grosh and Baker**, 1995.
[46] **Diamond *et al.***, 2016; **Tarozzi and Deaton**, 2009.
[47] **Haslett**, 2012.
[48] **Schreiner**, 2016b.

# Annex 4 Estimates of poverty likelihoods and consumption expenditure

This annex tells how scores are converted into estimates of:

- Poverty likelihoods
- Daily per-capita household consumption expenditure

## A3.1 Scores

Scores are on an ordinal scale from 0 to 100. Higher scores signal less poverty, but not how much less. The ordered symbols that are used to represent scores are numbers, but those symbols do not stand for the usual 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 is it anything else).

## A3.2 Poverty likelihoods

To get cardinal units, a look-up table is used to convert scores to *poverty likelihoods*, that is, probabilities of having consumption expenditure below a poverty line.

For the example of 100% of the national line, scores of 30−31 correspond with a poverty likelihood of 19.1 percent, and scores of 32−33 correspond with a poverty likelihood of 13.7 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 19.1 percent for 100% of the national line but with a likelihood of 72.4 percent for the 150% of the national line.

## A3.3 Calibrating scores with poverty likelihoods

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

For the example of 100% of the national line and a score of 30–31 (**Figure 23** below), there are 5,398 (normalized) households in the construction sample. Of these, 1,032 (normalized) have consumption expenditure below the poverty line. The estimated poverty likelihood associated with a score of 30–31 is then 19.1 percent because 1,032 ÷ 5,398 ≈ 0.191 = 19.1 percent.

The same method is used to calibrate all scores with poverty likelihoods for all 14 supported poverty lines.[49]

[49] If needed to ensure that likelihoods never increase as scores increase, likelihoods across adjacent scores are averaged before grouping scores into ranges. This preserves unbiasedness while preventing higher scores from being associated with higher likelihoods.

## Figure 23: Estimation of poverty likelihoods (100% of the national line)

| Score | Households in range and < poverty line | | All households in range | | Poverty likelihood (%) |
|---|---|---|---|---|---|
| 0–17 | 2,657 | ÷ | 3,309 | = | 80.3 |
| 18–22 | 2,842 | ÷ | 4,905 | = | 57.9 |
| 23–25 | 1,675 | ÷ | 3,822 | = | 43.8 |
| 26–27 | 1,704 | ÷ | 4,309 | = | 39.5 |
| 28–29 | 1,170 | ÷ | 4,261 | = | 27.5 |
| 30–31 | 1,032 | ÷ | 5,398 | = | 19.1 |
| 32–33 | 737 | ÷ | 5,363 | = | 13.7 |
| 34–35 | 728 | ÷ | 6,227 | = | 11.7 |
| 36–37 | 672 | ÷ | 6,562 | = | 10.2 |
| 38–39 | 412 | ÷ | 6,344 | = | 6.5 |
| 40–41 | 197 | ÷ | 5,857 | = | 3.4 |
| 42–43 | 90 | ÷ | 6,143 | = | 1.5 |
| 44–45 | 74 | ÷ | 5,100 | = | 1.5 |
| 46–47 | 41 | ÷ | 4,939 | = | 0.8 |
| 48–50 | 0 | ÷ | 6,288 | = | 0.0 |
| 51–54 | 0 | ÷ | 5,633 | = | 0.0 |
| 55–60 | 0 | ÷ | 5,751 | = | 0.0 |
| 61–68 | 0 | ÷ | 4,571 | = | 0.0 |
| 69–100 | 0 | ÷ | 5,218 | = | 0.0 |

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

## A3.4 Calibrating scores with daily per-capita consumption expenditure

Scores are also calibrated with estimates of daily per-capita household consumption expenditure in KHR in average prices in Phnom Phen during the 2019/20 CSES.

The preliminary estimate for a given score is defined as the average of daily per-capita household consumption expenditure for households in the 2019/20 CSES who have the given score.

For example, there are 255 households in the 2019/20 CSES with a score of 31, and their average daily per-capita household consumption expenditure is KHR14,732. After applying a LOESS smoother[50] to the preliminary estimates for all scores to ensure that consumption never decreases as scores increase, a score of 31 is associated with a final estimate of KHR15,113.

**Figure 2** shows this final estimate of daily per-capita household consumption expenditure that corresponds with each possible score from 0 to 100. **Section 3.3** tells how to convert this per-capita estimate into a per-household figure as well as how to convert this daily estimate into a monthly or annual figure.

## A3.5 Objectivity of estimates of poverty likelihoods and consumption expenditure

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 expenditure.[51] The fact that some choices in scorecard construction are informed by judgment in no way impugns the objectivity of the estimated likelihoods, as that depends on using data (and nothing else) in score calibration, not on using data (and nothing else) in scorecard construction.

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[50] **Cleveland and Devlin**, 1988.

[51] The calibrated likelihoods are objective—even if scorecard construction does not use any data at all—as long as their calibration is based on data. In fact, objective scorecards of proven accuracy are often constructed using only expert judgment (**Caire**, 2004; **Schreiner *et al.***, 2014).

## A3.6 Why not use the Logit formula to find poverty likelihoods?

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 $2.718281828^{\beta X} \times (1 + 2.718281828^{\beta X})^{-1}$, where $\beta$ is a vector of the Logit coefficients and $X$ is a vector of a household's responses.

The scorecard uses the calibration approach is because the Logit formula is not understood by most people. In contrast, program managers can understand poverty likelihoods defined as the share of people with a given score in the construction sample from Cambodia's 2019/20 CSES who have consumption expenditure below a poverty line. A calibrated look-up table also allows analysts to convert scores to likelihoods without any math at all. This calibration approach can also improve accuracy, especially with large samples.

# Annex 5 Error and margins of error

This annex discusses the scorecard's estimation error for head-count poverty rates in a single time period, as well as margins of error for all estimates of poverty rates and numbers of poor people.

## 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 differ from the true value in the population.

For example, the estimation error of Cambodia's scorecard for estimates of head-count poverty rates in a single time period by 100% of the national poverty line is +1.7 percentage points (**Figure 3**).

An unadjusted estimate can usually be improved—that is, moved closer to the true value in the population—by subtracting off the known estimation error. For example, if the unadjusted estimate is 49.6 percent, and if the estimation error is +1.7 percentage points, then an improved estimate is 49.6 − (+1.7) = 47.9 percent.

### A5.1.2 What estimation errors are reported for the Cambodia scorecard?

Estimation errors are reported for estimates of head-count poverty rates in a single time period for each of the 14 supported poverty lines for Cambodia.

The estimation errors are derived *out-of-sample*. This means that the scorecard (made from the construction sample from the 2019/20 CSES, **Annex 1**), is tested with repeated sub-samples of households from the validation sample that were not used to construct the scorecard. The estimation error is the average of the differences between scorecard estimates and observed poverty rates across these repeated sub-samples.

There are no data now on poverty in the future, so it is impossible to report estimation errors for estimates of annual net changes in head-count poverty rates across two time periods. The scorecard cannot be tested *out-of-time* because it is both constructed and validated with data from a single time period (2019/20).

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 and consequences 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 estimation errors (and margins of error) reported here are the best available, and it makes sense to adjust 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 2019/20 CSES records actual (not estimated) consumption-expenditure-based poverty status for households in the validation sample. The observed (not estimated) poverty likelihood in the 2019/20 CSES is either 100 percent (for poor households) or 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 the observed poverty likelihoods.

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

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[52] Estimation errors due to being out-of-time can be measured with post-2019/20 data (say, from a future CSES). Of course, future CSES data are not yet available. When they are available, 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 estimates from repeated samples from the validation sample is an unbiased estimator of the true value in the population of Cambodia overall. The population's true value is taken as the value in the 2019/20 CSES (even though the CSES is itself only a sample).

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

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 Estimation errors for estimates of poverty rates in one time period

The first line in **Figure 3** ("Estimation error") presents estimation errors for estimates of poverty rates in one time period for Cambodia's 14 supported lines.

## 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 of scorecard estimates across many repeated samples is the same as the single true value in the population.

[54] Households in a sub-sample are drawn *with replacement*; each draw is from the full pool, including households that have already been drawn. Thus, a given household may appear in a given sub-sample once, more than once, or not at all.
[55] See **Schreiner** (2021) for details on the α factor and on the formulas for estimation errors and margins of error. See **Annex 5** and **Annex 6** for formulas for ideal sample sizes.

In any single sample, however, unusual luck may push that particular sample's estimate far from the true value in the population. Larger samples provide more chances for luck to even out, so large errors are less likely in larger samples.[56]

For a given estimate, sample size, and confidence level, the *margin of error* is the range of true population values that is (in some specified degree) consistent with the estimate.

A margin of error has two parts:

- The margin of error itself (such as ±2.0 percentage points). This range is centered on the estimate
- A confidence level (such as 90 percent) that the true population value falls within the margin of error

All else constant, narrower margins of error or higher confidence levels mean that it 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 47.9 percent and that the sample size is $n$ = 1,024. Given 90-percent confidence,[57] the margin of error is ±2.4 percentage points (**Figure 3**). 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 from 47.9 − 2.4 = 45.5 percent to 47.9 + 2.4 = 50.3 percent, with the most-likely true value being the center of the range (the 47.9-percent estimate).

Said another way: "With 90-percent confidence, the estimate has a margin of error from 45.5 to 50.3 percent." This means that the true population value has a:

- 5-percent chance of being less than 45.5 percent
- 90-percent chance of being in the range from 45.5 and 50.3 percent
- 5-percent chance of being greater than 50.3 percent

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[56] When flipping a fair (unbiased) coin, the true probability of "heads" is 50 percent. *Unbiasedness* means that the average of the share of "heads" across many samples will be close to 50 percent. In a single sample of 10 tosses, however, the chances of getting at least six "heads" (at least 60 percent of the 10 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 smaller (about 3 percent). Larger samples reduce the risk that estimates will be far from the true population value.
[57] Most real-world decisions are made with much less than 90-percent confidence.

### A5.2.2 Why do margins of error matter?

For a given confidence level, managers should put more weight on estimates with narrower margins of error.

As a hypothetical example, a pro-poor program in Cambodia probably is indeed pro-poor if the scorecard estimate of the head-count poverty rate for members in the households of in-coming participants by 100% of the national poverty line with 80-percent confidence is 25.0 percent with a margin of error of ±5.0 percentage points (that is, from 20.0 to 30.0 percent). This is because the estimate and its margin of error suggest that the true poverty rate for members in the households of in-coming participants is unlikely to be less than or about the same as the all-Cambodia poverty rate for this line of 17.8 percent (**Figure 11**).

If, however, the margin of error were ±10.0 percentage points (that is, from 15.0 to 35.0 percent), then there is a non-negligible chance that the poverty rate for members in the households in-coming participants is less than or about the same as that for Cambodia overall (17.8 percent). Thus, the program may very well not actually be pro-poor.

So far, almost all analyses of scorecard estimates have ignored margins of error. This deficient practice increases the risk of bad decisions. Do not make this mistake.

### A5.2.3 Margins of error for estimates of poverty rates in one time period

For sample sizes of $n$ = 1,024 and 90-percent confidence and across all supported poverty lines, the margins of error for estimates of head-count poverty rates in a single time period for the new Cambodia scorecard are ±2.7 percentage points or smaller (**Figure 3**). Given the scorecard's standard assumptions, this means that in 90 of 100 samples of this size, the true population value is within ±2.7 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. Alternatively, analysts can employ the formulas below.

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

All formulas for margins of error involve the following elements:

$\pm c$ is the 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 poverty rate as a proportion,

$\varphi$ 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.

Suppose that the following are given:

- A confidence level that corresponds with $z$
- A sample-based estimate $\hat{p}$
- A population size $N$
- A sample size $n$, and
- An adjustment factor α for a specific poverty line from **Figure 3**

Then the formula[58] for the margin of error $\pm c$ is $\pm z \cdot \alpha \cdot \sqrt{\frac{\hat{p} \cdot (1-\hat{p})}{n}} \cdot \sqrt{\frac{N-n}{N-1}}$.

To illustrate, Cambodia's 2019/20 CSES gives a direct-measure head-count poverty rate for 100% of the national line of $\hat{p}$ = 17.8 percent (**Figure 11**). The adjustment factor α is 1.00 by definition because $\hat{p}$ is a direct-measure estimate, not an indirect-scorecard estimate.[59] Cambodia in 2019/20 had a population of households (not people) of $N$ = 3,636,110, and the CSES sampled $n$ = 10,075 households. Assume that all households have the same number of members. Given a desired confidence level of 90 percent, $z$ is 1.64. The margin of error $\pm c$ is then about ±0.6 percentage points:

$$\pm z \cdot \alpha \cdot \sqrt{\frac{\hat{p} \cdot (1-\hat{p})}{n}} \cdot \sqrt{\frac{N-n}{N-1}} = \pm 1.64 \cdot 1.00 \cdot \sqrt{\frac{0.178 \cdot (1-0.178)}{10{,}075}} \cdot \sqrt{\frac{3{,}636{,}110-10{,}075}{3{,}636{,}110-1}}.$$

This implies a 90-percent chance that Cambodia's true head-count poverty rate for 100% of the national line in 2019/20 is in the range from 17.8 − 0.6 = 17.2 percent to 17.8 + 0.6 = 18.4 percent.

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[58] This formula ignores how sampling variability affects the derivation of the scorecard. It also ignores that household size varies and that larger households are more likely to have higher poverty likelihoods. This understates the margin of error.
[59] For scorecard estimates, α for a given poverty line is in **Figure 3**.

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

The lower (upper) limit of the margin of error for an 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 head-count poverty-rate estimate.

To illustrate, the baseline example in **Section 3** has an estimated poverty rate of 47.9 percent. With 70-percent confidence, the margin of error is about ±44.1 percentage points[60], or from 47.9 − 44.1 = 3.8 percent to 47.9 + 44.1 = 92.0 percent. The margin of error is huge because the sample size of $n = 2$ interviewed households is very small.[61]

The estimated number of people in participating households in the example in **Section 3.1.2** is 5,500,[62] so the lower limit of the 70-percent margin of error for the estimated number of poor people is 5,500 · 0.038 = 209. The upper limit is 5,500 · 0.920 = 5,060. Thus, the margin of error extends from "almost no one is poor" to "almost everyone is poor". This example estimate—based as it is on a sample of two households—should not be understood as "about half of all people in participating households are poor" (which is what the 47.9 percent estimated poverty rate, taken at face value, would seem to imply) but rather as "the sample-based estimate provides almost no information about how many people in participating households are poor".

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[60] The example in **Section 3.1.1** has an estimate of 47.9 percent with $N = 1{,}000$, $n = 2$, and $\alpha = 1.20$ (**Figure 3**). For 70-percent confidence, $z = 1.04$. The margin of error $\pm c$ for the head-count poverty-rate estimate is then

$$\pm 0.441 \approx \pm 1.04 \cdot 1.20 \cdot \sqrt{\frac{0.479 \cdot (1 - 0.479)}{2}} \cdot \sqrt{\frac{1{,}000 - 2}{1{,}000 - 1}}.$$

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

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

### 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 $\pm c$ is:

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

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

Illustrating with the earlier example of one sample scored twice (**Section 3.2.1**), $\hat{p}_{rise}$ is the share of household members estimated to rise above a poverty line from below. This is the absolute value of the sum of the estimated *negative* changes in the number of members in poor households (from rows 3 and 4 of column M in **Figure 12**), that is, | −0.918 + −0.664 | = +1.582), divided by the sum across all sampled households of each household's average household size across baseline and follow-up, that is, 6.5 + 5.5 = 12.0 (from rows 3 and 4, column G). Thus, $\hat{p}_{rise}$ = +1.582 ÷ 12.0 = 0.132.

In turn, $\hat{p}_{fall}$ is the share of household members estimated to fall below a poverty line from above. This is the sum of the estimated *positive* net changes in the number of members in poor households (from rows 3 and 4 of column M in **Figure 12)**. Given that the estimated poverty likelihood did not increase for any household, this is (+0.00) + (+0.00) = +0.000. Dividing this by the sum across all sampled households of each household's average household size across baseline and follow-up (6.5 + 5.5 = 12.0) gives $\hat{p}_{fall}$ = 0.000 ÷ 12.0 ≈ 0.000.[63]

The household-size-weighted average of the number of years between interviews $y$ is 3.04 (from row 9, column M in **Figure 12)**.

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[63] $\hat{p}_{fall} - \hat{p}_{rise}$ is the estimated net poverty-rate change. In this example, $\hat{p}_{fall}$ = 0.000 and $\hat{p}_{rise}$ = 0.132, so 0.000 − 0.132 = −0.132, which is the estimated (total, non-annual) −13.2 percentage-point decrease (improvement) in the poverty rate for 100% of the national line in 2019/20 (**Figure 12**).

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 (regardless of poverty line) of 1.14,[64] the margin of error ±$c$ is about ±0.093 ≈

$$\pm\frac{1.04\cdot 1.14}{3.04}\cdot\sqrt{\frac{0.132\cdot(1-0.132)+0.000\cdot(1-0.000)+2\cdot 0.132\cdot 0.000}{2}}\cdot\sqrt{\frac{1{,}000-2}{1{,}000-1}}.$$

The example's estimated net annual poverty-rate change is about −4.3 percentage points (**Figure 12**), so the 70-percent margin of error is from −4.3 − 9.3 = −13.6 to −4.3 + 9.3 = +5.0 percentage points. The margin of error shows that—due to the tiny sample of $n$ = 2—this estimate is uninformative; the true net change in the population could be strongly negative, close to zero, or strongly positive.

This example shows why margins of error are useful. Without them, program managers might believe that there was evidence that poverty rates decreased by about 4.3 percentage points per year even though the data in this sample is also consistent with widely different rates and directions of change.

### 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 in the households of on-going participants 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 head-count poverty rate.

To illustrate with the example in **Section 3.2.2** for one sample scored twice, the estimated annual net change in the poverty rate is about −4.3 percentage points. As just shown, the tiny sample size of $n$ = 2 means that the 70-percent margin of error runs from −13.6 to +5.0 percentage points.

[64] **Schreiner**, 2021.

The estimated average number of on-going participating people per year is 5,025 (**Figure 12**). Thus, the lower limit of the 70-percent margin of error for the estimated annual net change in the number of poor people is
5,025 · (−0.136) ≈ −683 (a net decrease in the number of poor people), and the upper limit is 5,025 · (+0.050) ≈ +251 (a net increase in poor people). The small sample leads to a large margin of error, so the estimate is not likely to be useful because it is consistent with a true reduction, a true increase, or a true change of zero.

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

with *z*, α, *y*, $\hat{p}$ and *N* defined as above. There are *n* households sampled and interviewed at baseline, and another *n* households sampled and interviewed at follow-up.

Illustrating with the example for two independent samples in **Section 3.2.4**:

- *z* = 1.04, given a desired confidence level of 70 percent
- α = 1.10, the adjustment factor (regardless of poverty line) for this estimator[65]
- *y* = 2.76, the years between the average interview at baseline and follow-up
- $\hat{p}$ = 0.496, the unadjusted) 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 in both baseline and follow-up

The margin of error ±*c* is ±0.207 ≈ $\pm\frac{1.04 \cdot 1.10}{2.76} \cdot \sqrt{\frac{2 \cdot 0.496 \cdot (1-0.496)}{2}} \cdot \sqrt{\frac{850-2}{850-1}}$.

The example's estimated net annual poverty-rate change is −8.4 percentage points (**Figure 13**). Thus, the 70-percent margin of error is
from −8.4 − 20.7 = −29.1 percentage points
to −8.4 + 20.7 = +12.3 percentage points. The tiny sample is consistent with a true value in the population that is strongly negative, close to zero, or strongly positive. This again shows why margins of error matter.

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[65] **Schreiner**, 2021.

### 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 in the households of on-going participants 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 head-count poverty rate.

To illustrate, the example in **Section 3.2.5** for two independent samples estimates the annual net change in the poverty rate as −8.4 percentage points. As just shown, the 70-percent margin of error runs from −29.1 to +12.3 percentage points.

The estimated average number of people in the households of on-going participants is 4,675 (**Figure 13**). 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 $4{,}675 \cdot (-0.291) \approx -1{,}360$ (a net decrease in the number of poor people), and the upper limit is $4{,}675 \cdot (+0.123) \approx +575$ (a net increase in poor people). The margin of error again shows that the estimate does not reveal much about the true value in the population.

# 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, and
- 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 sometimes 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. This is why programs must plan and budget for reporting and analysis. If the remaining budget (after planning for reporting and analysis) will not cover at least 1,000 interviews, then ignore the formulas below and do as many interviews as the budget allows.

Second, both statistical sample size and psychological 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[66]
- Plans to report and analyze margins of error (as already mentioned)

If margins of error are not understood, or if margins of error 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 may be less costly if all in-coming participants are scored as a routine step of the in-take process rather than repeatedly deciding in real time whether to score a given enrollee.

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[66] Academic conventions for levels of confidence, when applied to business, are often too demanding and thus may imply unnecessarily large samples.

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

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

Otherwise:

- If checking fulfillment of 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 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 $n = N \cdot \left( \dfrac{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p})}{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p}) + c^2 \cdot (N-1)} \right)$,

where $n$, $c$, $z$, $\alpha$, and $N$ are defined as in **Annex 5**, and $\tilde{p}$ is a before-estimation guess for the poverty rate to be estimated.[67]

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 $\alpha$ = 1.20 (**Figure 3**)
- The pre-estimation expected poverty rate is the all-Cambodia rate for 100% of the national line in 2019/20, so $\tilde{p}$ = 17.8 percent = 0.178 (**Figure 11**)
- The desired margin of error ±$c$ = ±3.0 percentage points = ±0.030

Given these hypothetical values,

$$n = 10{,}000 \cdot \left( \frac{1.28^2 \cdot 1.20^2 \cdot 0.178 \cdot (1-0.178)}{1.28^2 \cdot 1.20^2 \cdot 0.178 \cdot (1-0.178) + 0.03^2 \cdot (10{,}000-1)} \right) \approx 370.$$

## A6.2 Sample-size formula for estimates of annual net changes in head-count-poverty rates across two time periods with one sample scored twice

In this case, $n$ households are interviewed at baseline, and those same $n$ households are interviewed again at follow-up. The formula for $n$ is:

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

where $n$, $\alpha$, $z$, $c$, 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.

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

The illustration below for this formula uses the following values:

- The poverty line is 100% of the national line
- The desired confidence level for the margin of error is 80 percent, so $z$ = 1.28
- α = 1.14 (regardless of the scorecard or poverty line)
- 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-Cambodia rate for 100% of the national line in 2019/20: $p_{\text{pre-baseline}}$ = 17.8 percent = 0.178 (**Figure 11**)
- The population of participating households is $N$ = 10,000

Assuming $N$ is large relative to $n$ so that $\sqrt{\frac{N-n}{N-1}} \approx 1$, then the baseline sample size $n$ is $2 \cdot \left(\frac{1.28 \cdot 1.14}{0.03}\right)^2 \cdot [-0.01 + 0.016 \cdot 3 + 0.56 \cdot 0.178 \cdot (1 - 0.178)] \cdot 1 \approx 568$.

The follow-up sample size is also 568.

## A6.3 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 an estimate at a point in time. If $n$ and $\tilde{p}$ are the same at both baseline and follow-up, then $n = 2 \cdot N \cdot \left(\frac{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p})}{z^2 \cdot \alpha^2 \cdot \tilde{p} \cdot (1-\tilde{p}) + c^2 \cdot (N-1)}\right)$.[68]

There are $n$ interviews at baseline, and another $n$ interviews at follow-up. For this estimator and regardless of the scorecard or poverty line, α = 1.10.

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

$$2 \cdot 10{,}000 \cdot \left(\frac{1.28^2 \cdot 1.10^2 \cdot 0.178 \cdot (1-0.178)}{1.28^2 \cdot 1.10^2 \cdot 0.178 \cdot (1-0.178) + 0.03^2 \cdot (10{,}000-1)}\right) \approx 625.$$

The sample size at follow-up is also $n$ = 625.

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

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