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How poverty is measured impacts who gets classified as impoverished

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We test whether the classification of households into poverty categories is meaningfully influenced by the poverty measurement approach that is employed. These classification techniques are widely used by governments, non-profit organizations, and development agencies for policy design and implementation. Using primary data collected in Ethiopia, Ghana, and Uganda, we find almost no agreement in how four commonly used approaches rank 16,150 households in terms of poverty status. This result holds for each country, for urban and rural households, and across the entire socio-economic distribution. Households' poverty rankings differ by an entire quartile on average. Conclusions about progress toward poverty alleviation goals may depend in large part on how poverty is measured.

poverty | measurement | policy

Significance

A wide array of organizations measure poverty to inform their operations. They use a correspondingly diverse set of indicators to do so. In our study across three countries in sub-Saharan Africa, we find almost no agreement in how four commonly used measurement approaches rank 16,150 households in terms of poverty status. Our results suggest that conclusions drawn by an organization about progress toward their poverty alleviation objectives may in large part depend on how they choose to measure poverty.

Measuring poverty is critical to evaluating policy effectiveness, targeting programs successfully, and assessing the costs and benefits associated with new investments. Measuring poverty is also essential for monitoring progress toward poverty alleviation targets, such as those underpinning the Sustainable Development Goals (1–6). Choices about the approaches and metrics used to measure poverty thus require careful consideration because they have important implications for the types of policies and programs that are designed, funded, and implemented (7–10).

A wide array of public, private, non-profit, and international development organizations measure poverty to inform their operations (11). Governments measure poverty to inform the design and implementation of public policies. Philanthropic and non-profit organizations measure poverty to identify groups they want to target and to determine whether their programs are reaching the intended populations. Discussions about poverty measurement have also permeated the private sector, where entrepreneurs and investors increasingly seek to evaluate their social impact in addition to their financial returns on investments.

While the interest in measuring poverty is broadly shared, the approach to defining and measuring poverty is not (12, 13). A variety of metrics are used within the international development field alone. For example, the United Nations Development Programme considers a household to be impoverished if it lacks access to housing, basic infrastructure, or health and education services (14). By contrast, national governments classify households as living below the poverty line if their consumption expenditures are below the typical cost of consuming a minimum number of calories (15). In recent years, a new approach to measuring poverty has been gaining popularity: asking communities to collectively define what poverty means and looks like based on their lived experiences. The Uganda Participatory Poverty Assessment Project (led by Uganda's Ministry of Finance, Planning and Economic Development) has demonstrated that "insecurity, illness, isolation, and disempowerment are as important to the poor as low incomes" (16).

The use of diverse approaches is not necessarily a concern in itself, so long as an organization's ability to assess progress toward its poverty alleviation objectives is not meaningfully influenced by its choice of a measurement approach. Findings from our three-country study in sub-Saharan Africa, however, demonstrate that methodological choices do indeed lead to very different conclusions about who would qualify for programs and policies designed to target impoverished households.

We collected primary data from 16,150 households in Ethiopia, Ghana, and Uganda, and applied four different measurement approaches to determining household poverty status. We assessed agreement in how these different approaches classified households in our full sample, in each country, and in each urban and rural sub-sample at the district level.

The four poverty measurement approaches we compared are "regular" daily *per-capita* expenditure; the Demographic and Health Surveys' (DHS) wealth index (17); the Poverty Probability Index (PPI) (18); and Anirudh Krishna's Stages of Progress (19). These approaches reflect a variety of perspectives and relative prioritization of comprehensiveness

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versus implementation feasibility. The expenditure metric represents a household's reported spending on food, transport, and airtime in the two weeks prior to being interviewed. The DHS wealth index represents a household's reported ownership of assets (e.g., vehicles and appliances), access to services (e.g., electricity and water supply), and dwelling characteristics (e.g., floor and wall materials). The PPI is similarly based on a household's assets, housing stock, and service access, but uses only ten input variables (versus the 38 to 43 used for the DHS) to estimate the probability that a household is living below the international poverty line (IPL) of $1.90 *per capita* per day (20). Finally, the Stages of Progress approach applies a set of well-being milestones that communities themselves identify as hallmarks of having escaped poverty. For the countries in our sample, the milestones include having enough food for the household, having enough clothing for each household member, a tin roof on the dwelling, and being able to send all school-aged children to primary school (21).

Results

In our sample of 16,150 households, there is almost no agreement in how these four measurement approaches rank households in terms of poverty status. Pairwise comparisons of the approaches demonstrate weak correlations (i.e., $0 < |r_s| < 0.5$) for the full sample as well as for each country and district (22). When comparing the relationships between households' PPI scores, DHS scores, and regular expenditures *per capita*, correlation coefficients range between $r_s < 0.01$ and $|r_s| = 0.20$ for the full sample (Fig. 1).

Correlations are consistently weak even after controlling for geographic variability. Stratifying the analysis by country and district reveals negligible or weak correlations in 26 of the 30 strata (Fig. 1*A*). Stratifying the analysis by urban and rural sub-samples within each country reveals negligible or weak correlations in 20 of the 24 strata (Fig. 1*B* and see *SI Appendix*, Fig. S1 for sub-district analyses).

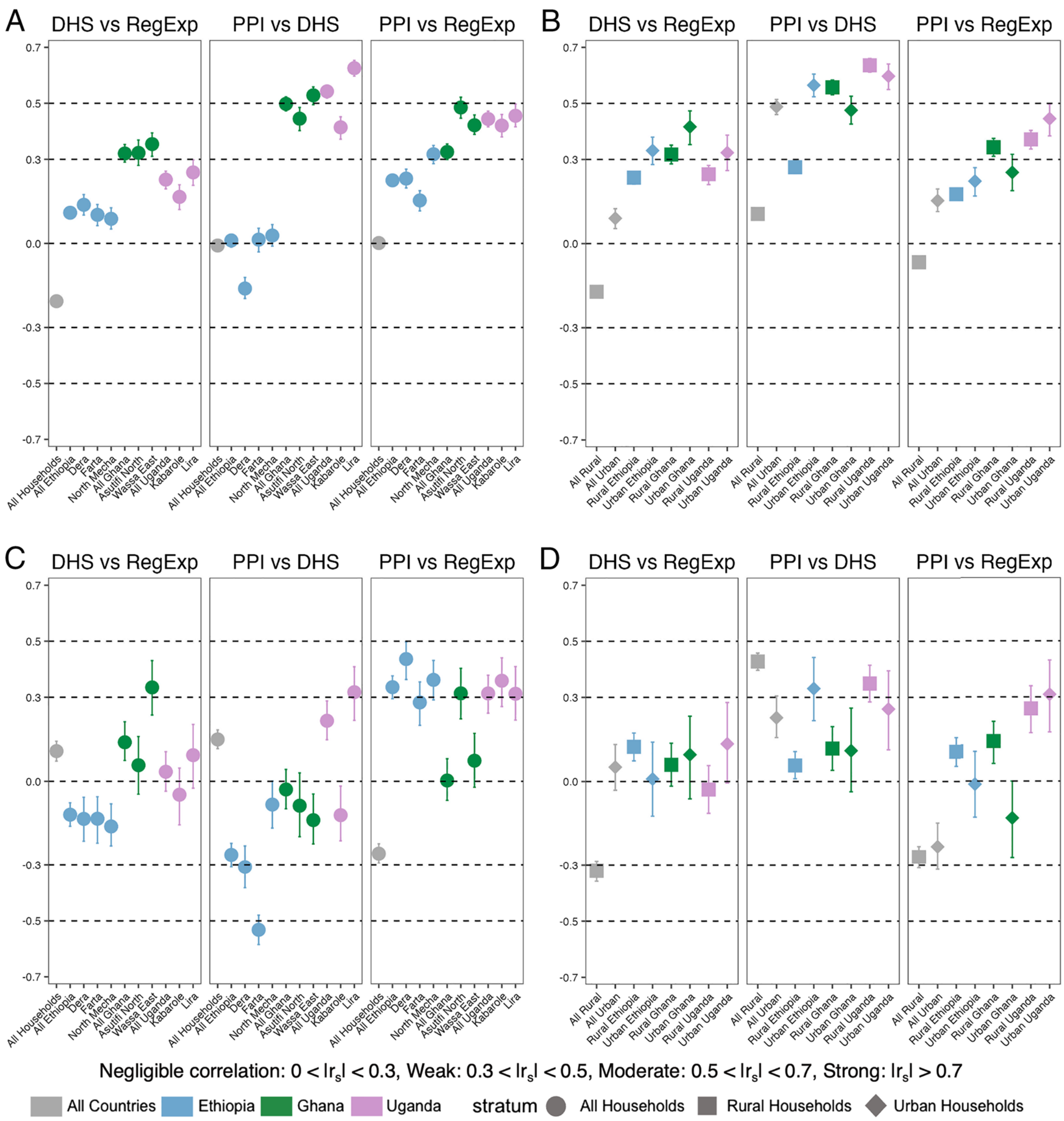

Fig. 1. There is almost no agreement in how 16,150 households are ranked based on their PPI scores, DHS scores, and regular expenditures per capita across three sub-Saharan African countries. Spearman's correlation coefficients with bootstrapped confidence intervals (n = 1,000 runs) are displayed for country and district strata in panel (*A*), for rural and urban sub-samples in panel (*B*), for country and district strata among the bottom quintile (based on households' DHS scores) in panel (*C*), and for rural and urban sub-samples among the bottom quintile (based on households' DHS scores) in panel (*D*). Sample sizes for the strata in panels (*A*) and (*B*) range from 872 to 16,150 households. Sample sizes for the strata in panels (*C*) and (*D*) range from 175 to 3,230 households. See *SI Appendix*, Supplementary Text for a complete breakdown of sample sizes by stratum. A factor of (−1) is applied to parameters related to the PPI to increase interpretability.

The lack of agreement persists among households ranked in the bottom quintile. Among the 57 "bottom quintile" strata displayed in Fig. 1 *C* and *D*, only one demonstrates a correlation greater than $|r_s| = 0.5$ ($r_s = -0.53$, 95% CI [−0.58, −0.48] in Farta district, Ethiopia). The remaining coefficients range from $r_s = 0$ to $|r_s| = 0.44$. This result is robust to different specifications of the bottom quintile (i.e., whether the bottom quintile is defined based on households' DHS scores, PPI scores, or regular expenditures *per capita*) (*SI Appendix*, Fig. S2).

Even at the "tails" of the distribution, there is little agreement in how the same household is ranked by the four measurement approaches. In theory, we would expect the household with the lowest DHS wealth index score to also have the smallest *per-capita* regular expenditure and the highest probability of living below the poverty line as measured by the PPI; we would expect this household to have met none of the Stages of Progress well-being milestones. This is not what we observe, however. When we compare households with the ten lowest rankings (i.e., "bottom 10" households) within each urban and rural sub-sample (n = 1,124 to 2,520 households per rural sub-sample and n = 209 to 640 households per urban sub-sample), we find that only one is consistently classified by all four approaches as a "bottom 10" household (Fig. 2 and *SI Appendix*, Fig. S3).

The observed inconsistencies are not simply the result of small differences in relative rankings. Households' poverty rankings differ by an entire quartile on average. The median difference in percentile rankings assigned to the same household by one approach versus another ranges from 13 to 29% for rural households and from 14 to 26% for urban households (Fig. 3 and *SI Appendix*, Fig. S4). Additional analyses yielded no systematic differences in demographic and livelihood characteristics between households whose percentile rankings (based on the DHS, PPI, and regular expenditure *per capita*) differed by 50 percentage points or more versus those with differences of 10 percentage points or less (*SI Appendix*, Table S2).

Discussion

Analyses from the sub-district to multi-country scale suggest that there is almost no agreement in how four commonly used poverty measurement approaches classify 16,150 households in Ethiopia, Ghana, and Uganda. Our results are robust across urban and rural sub-samples, and for each of the seven districts where data were collected. The consistency of our findings suggests that geography does not substantially affect how these measurement approaches rank households within this region.

There is limited agreement among the poverty measurement approaches even for households located in the bottom quintile. This finding is particularly salient because such approaches are often used to establish eligibility for assistance programs that target low-income households (23). The targeting strategy associated with the Government of Ghana's Livelihood Empowerment Against Poverty (LEAP) program is an illustrative example. When the LEAP program changed their process for determining household eligibility from a community-based participatory approach to using socioeconomic proxies (e.g., the marital status and age of household members), its inclusion errors (i.e., the proportion of program participants who were not in the target group) decreased from 62 to 36% (24).

Our results suggest that conclusions drawn by an organization about progress toward their poverty alleviation objectives may in large part depend on how they choose to measure poverty. Ideally, the choice of a measurement approach should be driven by a clearly articulated definition of poverty. Only with a well-defined construct can a potential indicator be evaluated for conceptual validity (the extent to which it embodies the idea of poverty conveyed in the definition), reliability (how consistently it performs in repeated applications), and feasibility (the effort and cost of using it).

Few organizations make the definition of poverty to which they subscribe explicit—including those with poverty alleviation as part of their central mission (25). The World Bank, for example, works to "end extreme poverty and promote shared prosperity in a sustainable way" (26). According to their website, people living in extreme poverty are "defined as those who live on less than \$2.15 per person per day" (this is the inflation-adjusted average of the national poverty lines associated with 15 countries deemed to be "poor" in 2008) (27, 28). The United Nations, sponsor of

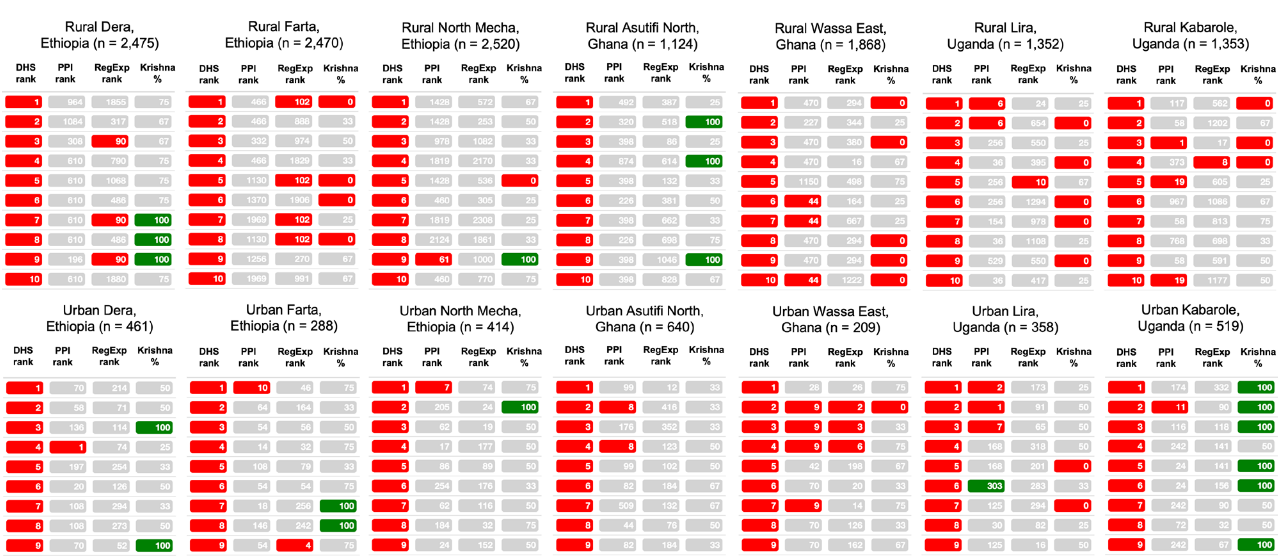

Fig. 2. Only one household is consistently classified by all four poverty measurement approaches as a "bottom 10" household across the urban and rural sub-samples in each district. Each table represents a different stratum, and every row represents a household in that stratum. In the first three columns of every table, the number in each cell represents the household's ranking within that stratum based on the specified poverty measurement approach; red cells indicate households with the ten lowest scores according to that approach (i.e., "bottom 10" households), green cells indicate households with the ten highest scores according to that approach (i.e., "top 10" households), and gray cells indicate households in between. In the last column of every table, the number in each cell represents the proportion of Krishna's Stages of Progress met by each household. Red cells in the last column indicate that the household achieved none of the stages whereas green cells indicate that the household achieved all four stages.

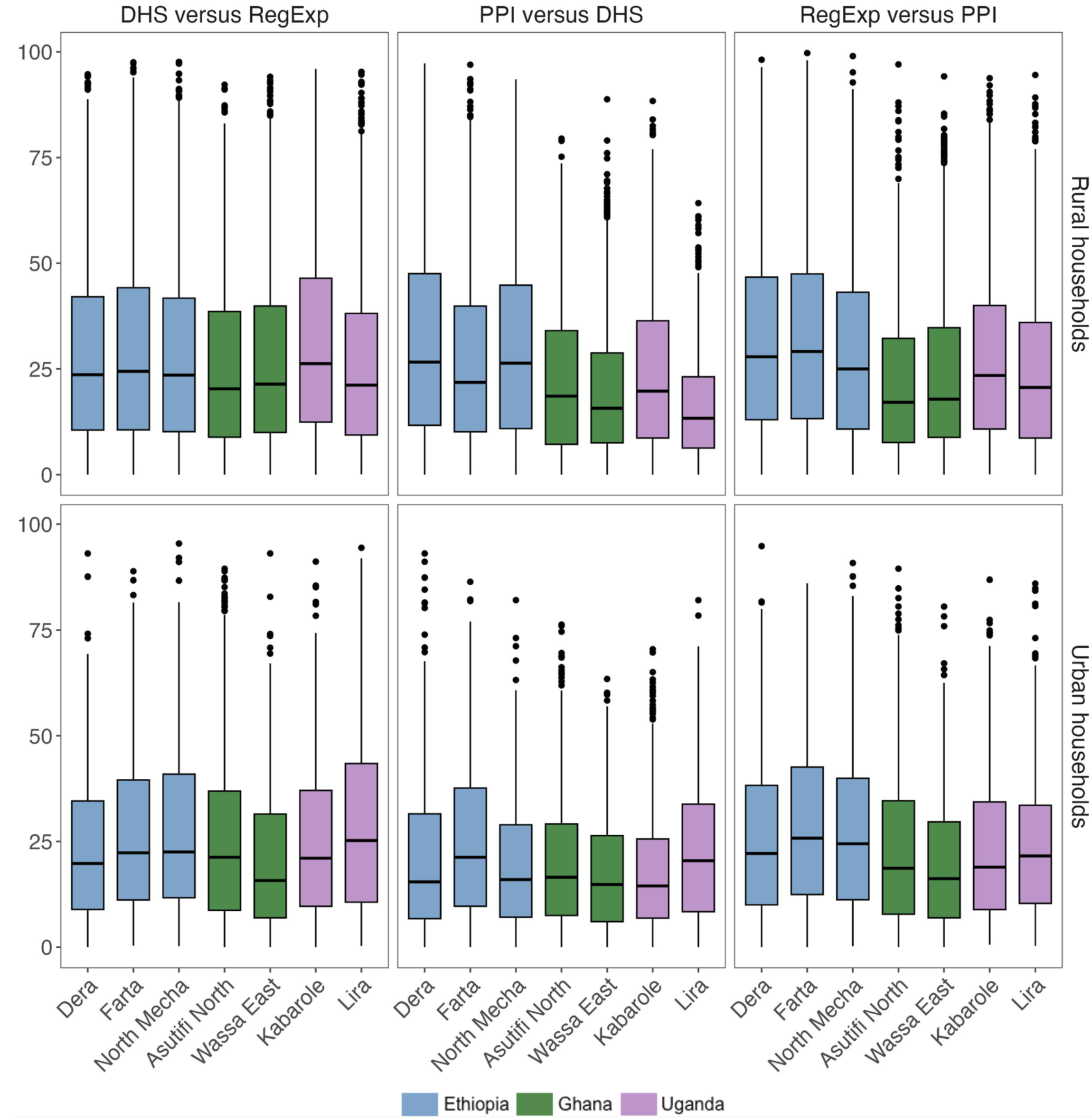

Fig. 3. Households' rankings, as determined by the four poverty measurement approaches, differ by an entire quartile on average. The distributions of the differences in household rankings are displayed for each pairwise comparison. The first row of graphs features comparisons made among rural households in each district: Dera (n = 2,477), Farta (n = 2,470), North Mecha (n = 2,520), Asutifi North (n = 1,146), Wassa East (n = 1,918), Kabarole (n = 1,353), and Lira (n = 1,354). The second row of graphs features comparisons made among urban households in each district: Dera (n = 461), Farta (n = 288), North Mecha (n = 414), Asutifi North (n = 655), Wassa East (n = 217), Kabarole (n = 519), and Lira (n = 358).

the Sustainable Development Goals, similarly reports that "[n]early half of the world's population currently lives in poverty, defined as income of less than US $2 per day" (29). These are not definitions of poverty, however. They are descriptions of the indicators that the World Bank, United Nations, and many other international development organizations use to classify households as living above or below the poverty line. Calling them definitions conflates the construct of poverty with the approach used to measure it. This is akin to saying the definition of intelligence is having an IQ test score of 115 or higher.

We did not find explicit definitions of poverty offered by the developers of the four poverty measurement approaches included in this study. Assuming that each approach comprises reasonably valid indicators of an underlying definition of poverty, a few observations can be made. First, all four approaches suggest a conception of poverty based largely on material wealth deficits. This stands in contrast to methodologies that center poverty within notions of limited opportunities or capabilities and thus give greater emphasis to measuring knowledge, skills, and social capital (30–32).

Second, despite their shared emphasis on material wealth, the approaches suggest slightly different underlying concepts of poverty. Ranking households based on how much they spend on everyday goods and services implies that poverty is not having enough money to engage meaningfully in the daily life of one's community. In a similar vein, the PPI implicitly defines poverty as the state in which a household is unable to secure the resources needed to feed itself adequately. This reference to securing some minimum number of calories underpins most "poverty line"-style indicators, including those used by the World Bank, United Nations, and national governments. Moving beyond calorific minimums, Krishna's Stages of Progress measures how close a household is to being free from experiencing "basic needs" poverty, where basic needs are defined by households themselves. The inferred definition of being *free* from poverty is the state in which a household is able to feed, clothe, house, and obtain basic education for its members.

In contrast to the other three approaches, the DHS wealth index was developed using data on households' assets, access to services at the community scale, and health outcomes and behaviors. As its name suggests, the DHS Program developed their wealth index primarily to identify correlates of health outcomes (17). This helps explain the seemingly counterintuitive treatment of some items included in the index. For example, while most rural development specialists would consider livestock ownership to be a sign of family wealth, it is assigned a negative weight when computing the DHS score for households in Ghana, Ethiopia, and Uganda (33). That is, every additional livestock unit a household owns *lowers* its wealth ranking, all else held constant. As an indicator of expected health status (rather than poverty), this is arguably valid, considering that livestock ownership is more widespread and access to health services more limited in rural communities compared to urban ones (34, 35).

Despite the fact that the DHS wealth index was not meant to be an indicator of overall socio-economic status, it is widely used in this manner today (36, 37). One particularly noteworthy example is its use in training machine-learning and remote-sensing algorithms to predict poverty (38). For example, Jean et al. use DHS wealth index data to train their deep learning model to predict households' long-term economic status. However, given that the DHS wealth index was constructed to identify disparities in health access rather than to represent household poverty, it is unclear whether the algorithm is suitable for predicting poverty. Novel machine-learning algorithms can increase the availability of predictions of household poverty, but they can only predict poverty *vis a vis* the existing definition associated with the input data (38–44). When these developers do not define the type of poverty they are trying to predict, the intellectual distance between what the algorithm is trying to do and the first-order questions about how poverty is being defined only compounds.

At a conceptual level, these measurement tools also differ in their focus on absolute versus relative poverty. The PPI is an example of an absolute poverty indicator; it compares a household's well-being against a fixed threshold to determine their poverty status. By contrast, the DHS wealth index and regular expenditures are indicators of relative deprivation; they measure the economic position of a household relative to their larger community.

The choice between absolute versus relative poverty matters (45). In fact, global poverty trends differ depending on whether absolute or relative poverty measures are used (46). For example, a household from a middle-income country might not be considered "poor" according to absolute international standards, but they still might experience significant relative deprivation such that they cannot participate in activities that are accepted as part of daily life in their communities. Measures of relative poverty explicitly acknowledge that living standards are socially determined; they more directly address the fact that culture and context shape the conception of poverty across different geographies (47).

The key insight that emerges both from our analysis and these examples from the world of practice is that it would be beneficial to use poverty measurement approaches that are fit for purpose. While it may be tempting to select a measurement approach based on expedience, with the belief that all poverty measurement approaches will yield somewhat equivalent results, our analyses make it clear that this is ill-advised. The best approach for measuring poverty depends on one's definition of poverty. Approaches like the PPI are likely most useful for identifying households that need assistance to meet their basic needs for food, clothing, medical supplies, and shelter (48). Approaches like the Stages of Progress, along with asset-based indices explicitly designed to reflect an underlying definition of poverty or wealth, could help identify households who have attained a measure of financial stability. Because these households can consistently meet basic needs, they are better able to avail of opportunities to build new capabilities (e.g., vocational training, microfinance services, or agricultural extension). At the same time, without initial subsidized supports, these households may not reach their full potential (49).

None of the poverty measurement approaches we compared appears well-positioned to identify households who fluctuate between barely surviving and stable enough to build new capabilities (50). Households in this intermediate group are often overlooked, despite presenting important implications for policy development. These households can meet their basic needs on some days, but small shocks (e.g., a sick family member or bad harvest) can easily trigger a descent back into survival mode.

Identifying households in this intermediate group requires measurement approaches that embrace the notion of poverty as a dynamic phenomenon (51, 52). Simply tracking the share of households that fall below a poverty line can obscure transitions that have important implications for public policy (53, 54). For example, one study in Uganda found that the share of households living below the poverty line fell by 9 percentage points over the 25-y period from 1980 to 2005. This statistic masks the fact that almost one in four (24%) households escaped poverty during this period, while another 15% of household fell into poverty (21). Having 39% of households experience a change in their poverty status suggests that people are simultaneously escaping from and falling into poverty at any given time. How one measures poverty, and therefore how one intervenes, must reflect this dynamic (55–57).

Our study demonstrates that the approach one takes to measure poverty meaningfully affects who gets classified as impoverished. Our work is unique compared to previous efforts in three ways. First, our study is based on primary data collected at the household level from more than 16,000 participants using an instrument that was deliberately designed to pursue these research questions. Prior research has largely relied on publicly available, secondary datasets that, due to aggregation, can only be analyzed at the regional or national level. Our approach allows us to fully capture the heterogeneity within a population instead of focusing on average values across administrative units. Second, our household-level focus generates additional insights through sub-sample analyses of households located in the tails of the socio-economic distribution. These households are frequently dropped as "outliers" in aggregate analyses, despite representing a key segment of the population that poverty metrics are trying to identify. Lastly, we know of no study that compares the classification of households into poverty categories across three countries in sub-Saharan Africa; existing studies tend to only focus on comparisons within one country (36).

To measure poverty accurately, one must be thoughtful about how it is defined to begin with. If an organization is interested in a particular dimension of poverty, its measurement approach should incorporate indicators that are valid and reliable with respect to that specific dimension. If an organization is interested in more than one dimension of poverty, then a measurement approach that integrates multiple indicators might be more appropriate. Organizations that adopt a measurement approach without reflecting on how it fits their conception of poverty are, at best, rolling the dice about creating classifications of households that work in alignment with their mission and objectives. At worst, these organizations are adopting methodologies that may be wholly inappropriate for their poverty alleviation goals.

Materials and Methods

Site Selection. This study took place in Ethiopia, Ghana, and Uganda. Our study sites included Dera, Farta, and North Mecha woredas in the Amhara Region of

Ethiopia; Asutifi North district (Ahafo Region) and Wassa East district (Western Region) in Ghana; and Kabarole district (Western Region) and Lira district (Northern Region) in Uganda. These districts were selected because they are priority geographies for one of the research funders, the Conrad N. Hilton Foundation, with whom we partnered on already planned data-collection activities.

Sample Frame. Within each district, we selected 24 enumeration areas (EA) using a stratified random sampling approach. The initial sample frame for each district included all EAs drawn by the Central Statistical Agency (CSA), Ghana Statistical Services, and Uganda Bureau of Statistics for the most recent population and housing census in each country (2019, 2021, and 2014 for Ethiopia, Ghana, and Uganda, respectively). We used the urban or rural classification that accompanied each EA to stratify the random sampling procedure. The number of urban and rural EAs included in the final study sample was determined based on the proportion of urban and rural EAs that constituted each district, respectively. We made one exception for Farta district in Ethiopia, where proportional sampling would have resulted in only one urban EA being selected. To facilitate the calculation of SE, we randomly selected a second urban EA for the final study sample.

Within each urban or rural stratum, the probability of selection of each EA was proportional to its size (proxied here by the number of households recorded in the most recent census). In Uganda and Ethiopia, we randomly selected 28 (instead of 24) EAs in each district; the four additional (rural) EAs served as potential replacements. EAs were only replaced (with randomly pre-selected replacements) when the data collection teams encountered logistical constraints (e.g., heavy rains) that prevented them from safely conducting the household surveys. No EAs were replaced in Ghana. One rural EA was replaced (by another rural EA) in each of the following districts: Kabarole (Uganda), North Mecha (Ethiopia), Dera (Ethiopia), and Farta (Ethiopia). The replacement EAs in Ethiopia were randomly selected by the CSA.

Household Selection. All households residing within the geographic boundaries of the selected EAs were surveyed. Consistent with the definitions used for each country's population and housing census, we defined a household as a group of individuals who lived together, pooled their money and resources, and shared at least one meal each day. We interviewed one respondent from each household. Respondents were eligible to be interviewed if they 1) reported being a household member, 2) reported being 18 y or older, 3) reported being able to answer questions about the household's water supply services, and 4) provided informed consent. We preferentially interviewed the head of household or spouse where possible. We surveyed a total of 16,150 households (see *SI Appendix*, Table S1 for sample sizes in each country and district).

Data Collection. Household surveys in Ethiopia, Ghana, and Uganda were conducted in local languages by trained enumerators recruited by the Ethiopian Public Health Association, the Kwame Nkrumah University of Science and Technology, and the International Growth Research and Evaluation Center, respectively. All enumerators completed at least 2 wk of training and participated in at least one full day of instrument piloting before the start of each round of data collection. Data collection took place from January to February 2022 in Ghana, from February to March 2022 in Uganda, and from June to July 2022 in Ethiopia.

Data collection instruments were standardized across Ethiopia, Ghana, and Uganda. Small modifications were made to the question wording and survey choices to contextualize the questionnaire for each country. This was done with the help of our local data collection partners. During the surveys, enumerators collected information about households' poverty status based on four poverty measurement approaches: the DHS wealth index, the PPI, regular expenditures *per capita*, and Krishna's Stages of Progress. Questions were borrowed directly from the country-specific DHS and PPI surveys, where applicable.

All data were collected on tablet computers using DigitalOcean (New York, USA), Ona Systems (Vermont, USA), and SurveyCTO (Dobility Inc., MA, USA) software in Ethiopia, Ghana, and Uganda, respectively. We followed up (via phone) with a subset of the households surveyed in Uganda (n = 1,566) within 4 wk of initially interviewing them in-person to collect information on a missing variable critical to the calculation of the PPI.

We reviewed the collected data in real time (daily, where possible) to identify data inconsistencies, unanticipated survey responses, and opportunities for re-training. Changes to the raw data were only made for confirmed data entry errors. Confirmation of these errors, and their corrected values, were obtained by reviewing enumerators' field notebooks and following up with enumerators and household respondents, where necessary.

Ethical Approvals. All study participants provided informed consent. The Stanford University Institutional Review Board (protocol 57868), Ethiopian Public Health Association (protocol EPHA/OG/736/22), Kwame Nkrumah University of Science and Technology's Committee on Human Research, Publications and Ethics (protocol CHRPE/AP/603/21), and MildMay (MUREC-2021-82) in Uganda approved the study.

Poverty Measurement Approaches. The PPI is a proxy means test developed by the Grameen Foundation and managed by Innovations for Poverty Action (18). The PPI produces country-specific 10-question surveys to estimate the probability that a household lives below a specific poverty line. We used the PPI to compare households against the IPL of $1.90 per capita per day (US 2011 PPP) because the IPL is the most widely used poverty line for temporal and spatial comparisons. The IPL is the inflation-adjusted average of the national poverty lines (i.e., the typical cost of consuming a minimum number of calories) associated with 15 countries deemed to be poor in 2008 (15, 28). Responses to the PPI survey questions are associated with specific scores. The total score, tallied across all ten questions, is associated with a specific probability of living below the poverty line. These probabilities are computed by the PPI using income and consumption expenditures data collected from national census surveys. For example, the probability of living below the IPL associated with each total score represents the share of households in the calibration sub-sample that had the same score and a *per-capita* consumption level below $1.90 per person per day (US 2011 PPP). We used the most recent PPI surveys available for each country at the time of data collection to assign each household a probability of living below the IPL. This included the 2020 version for Ethiopia, the 2019 version for Ghana, and the 2015 version for Uganda.

The DHS wealth index is a composite measure. Each asset, amenity, and service included in the DHS wealth index is associated with a specific coefficient weight. The items and coefficient weights are country-specific and determined using principal component analyses. We used the most recent DHS wealth index constructions available for each country at the time of data collection. This included the wealth index constructions derived from the 2019 Ethiopia Mini DHS, 2019 Ghana Malaria Indicator Survey, and 2018 to 2019 Uganda Malaria Indicator Survey for households interviewed in each respective country. Following the procedure stipulated by the DHS Program, we computed a wealth index score for each household based on their ownership of private assets (e.g., appliances, furniture, land, livestock) and access to (public) services (e.g., water, sanitation, energy) (33). We computed the wealth index scores for households living in urban EAs and rural EAs separately using urban-specific and rural-specific indices designed by the DHS Program, respectively.

Capturing the full extent of a household's consumption expenditures can be a time-consuming and cognitively difficult task for respondents. Surveys that accommodate these detailed modules are often unable to dedicate sufficient time to other variables of interest. Sensitive to this trade-off, we wanted to test the performance of a shorter set of expenditures-related questions. We asked households to report the total amount of money they spent in the 2 wk prior to being interviewed on "regular expenditures," which we defined as spending on food, airtime, and transportation. In Ghana, households were asked about regular expenditures over the 4 wk prior to being interviewed. We standardized these expenditure responses into *per-capita* quantities by dividing each household's response by its reported size.

The Stages of Progress methodology was developed by Anirudh Krishna, a professor of political science at Duke University (19). In this participatory approach, household representatives are gathered in village meetings and asked to identify the well-being milestones that poor households typically cross while making their way out of poverty. In Uganda, where Krishna conducted this exercise across 36 villages, the first four stages identified by every village were identical: 1) having enough food for the family, 2) having enough clothes for the family, 3) sending children to school, and 4) having a roof with iron sheets (21). Once a household had met all these milestones the community no longer considered the household poor. The unanimity about these four stages is meaningful because how people manage and respond to poverty depends on what they understand to be its defining features. Since its initial development, the Stages of Progress methodology has been conducted with more than 35,000 households across India, Peru, Kenya, and Uganda (19). The milestones leading up to the poverty line identified by almost all households were identical, regardless of country. Based on these four stages of progress, we assigned each household a binary poverty status. Households were categorized as living above the poverty line if they reported always having enough food to eat, always having enough clothing, sending their children to primary school, and having a roof with iron sheets (or an equivalently finished construction material). If a household did not report having children in the primary school age range, they were categorized as living above the poverty line if they met the three other stages of progress. Otherwise, households were categorized as living below the poverty line.

Data Analysis. Poverty status was assigned and analyzed at the household level. All households were eligible for inclusion, so long as they provided informed consent and complete answers to the questions required for the four poverty measurement approaches. No outliers were removed. Data were analyzed using R version 4.2.2 (Vienna, Austria) in RStudio (Boston, Massachusetts). Due to violations of the normality assumption, Spearman's rank correlation coefficients (r_s) were used to determine the strength of the relationships between continuous poverty measurement approaches (i.e., between the PPI, DHS wealth index, and regular expenditures). Correlations were considered to be weak if $0 < |r_s| < 0.5$; relationships were considered to be moderate if $0.5 \leq |r_s| < 0.7$; and relationships were considered to be strong if $0.7 \leq |r_s| < 1$ (22). Two-sided CI were bootstrapped using the RVAideMemoire package version 0.9-82-2 in R (1,000 runs, 95% CI).

Data, Materials, and Software Availability. Anonymized data have been deposited in Open Science Framework (58) (https://osf.io/h2swb/, DOI: 10.17605/OSF.IO/H2SWB). The code needed to replicate these results are available on GitHub (59) (https://github.com/cjpu/comparing_poverty_measurement_approaches).

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