EDUCATION EQUITY RESEARCH INITIATIVE

# PRACTICAL RECOMMENDATIONS FOR EQUITY ANALYSIS IN EDUCATION

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***The Education Equity Research Initiative is a collaborative partnership formed by organizations and individuals committed to improving data and evidence around equity in education. It is led by FHI 360 and Save the Children.***

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## Acronyms

| | |
|---|---|
| ASER | Annual Status of Education Report |
| DFID | United Kingdom Department for International Development |
| EFA | Education for All |
| EGRA | Early Grade Reading Assessment |
| IDMC | International Displacement Monitoring Centre |
| MICS | Multiple Indicator Cluster Survey |
| ORF | Oral Reading Fluency |
| PIRLS | Progress in International Reading Literacy Study |
| SCORE | Sustainable Comprehensive Responses for Vulnerable Children and their Families |
| SES | Socio-economic status |
| TIMSS | Trends in International Mathematics and Science Study |
| UN | United Nations |
| UNESCO | United Nations Educational, Scientific and Cultural Organization |
| UNICEF | United Nations Children's Fund |
| USAID | United States Agency for International Development |

## Introduction

The Education Equity Research Initiative (henceforth referred to as the Equity Initiative) is a collaborative partnership of international development and research organizations committed to strengthening the global evidence base around education equity. One of the key objectives of this partnership is to improve the availability, quality, and consistency of data on equity in education. We seek to move away from a "one size fits all" approach in educational development towards a better, more in-depth understanding of how various policy and program interventions affect the learning trajectories and outcomes of all children and youth.

In the spirit of this collaboration, the following recommendations are put forward as a means to consolidate current best practices in data collection in education and to chart a way forward together. They serve as a sounding board for future data collection and analysis as well as a starting point for honing our practice in areas not yet well measured. As these recommendations are integrated, we will make further refinements based on experience and will revisit our progress together annually. Our hope is that through more consistent metrics and analysis we can further both evidence and dialogue in pursuit of educational equity.

## Strengthening Comparability of Common Dimensions of Equity

We begin by reviewing the importance of consistency in capturing and measuring dimensions of populations that have conventionally been the focus of equity (analysis): poverty, socio-economic status (SES), gender, age, ethnicity, and language. As our Measuring Equity in Education landscape analysis [1] shows, measures of these dimensions are often present in surveys and studies, but are not always standardized or applied consistently, limiting one's ability to compare equity assessment across studies and programs. In these recommendations, we draw on the instruments and tools reviewed and presented in Appendix A of the landscape analysis to come up with best practices that will help researchers and program implementers ensure that key dimensions are captured, and to the extent possible, consistent across studies. In addition, we offer guidance on expanding the spectrum of equity analysis to include dimensions not currently collected, such as disability and residence or displacement status.

### Recommendations for collecting data on poverty, gender, age, language and residence status

For educational studies, especially those of learning, we recommend capturing at least two of three elements of SES: economic wealth, socio-cultural assets, and home learning environment.

**Relative economic wealth** is estimated by asking adults, children, and youth about ownership of context-specific assets in the household. The responses are combined to create an index of relative wealth. This index then allows researchers to rank-order the respondents by wealth and to create wealth quartiles or quintiles. The array of assets may vary by context, as the items selected should signal a family of higher/lower wealth in the area being surveyed. Common items, for example, are questions regarding ownership or availability of: electricity, water, a cook stove, a toilet, roofing material, a mobile phone, a refrigerator, a television, a motorbike, a radio, a bicycle and, in more affluent contexts, a computer. An

[1] FHI 360 and Save the Children. (2016). *Measuring equity in education: Review of the global and programmatic data landscape*. Washington, D.C.: Education Equity Research Initiative. Available at http://www.educationequity2030.org/resources-2/2016/12/14/measuring-equity-in-education-landscape-review

initial list can be generated by sourcing items from national DHS, MICS or LSMS surveys or checking the Equity Tool (http://www.equitytool.org/the-equity-tool-2/).

**Socio-cultural assets.** Social and cultural assets include resources related to social integration and the value placed on education in the home. They do not always overlap with economic disparity but tend to shape educational opportunities and outcomes. Questions about socio-cultural assets are most reliable when asked of youth and adults, as children do not always know their parents' education or last year of school. Such questions are present in Annual Status of Education Reports (ASER) surveys[2] in which parents' educational participation and last grade of completion are asked. ASER has further found that, due to the combined realities of joint households and cases in which neither parent has been to school, broader questions about household members are useful, such as: Is there a person in the household who has completed [a particular level of education]? Or: Is there a person in the household who knows how to use a computer? Finally, Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS) ask students if parents attended school, as do many Early Grade Reading Assessment (EGRA) implementations.

**Home learning environment.** Home learning environment data includes questions about activities of children and parents like reading together, homework support, whether reading is modeled and valued, and telling stories in the home. It also includes the variety of reading materials – age appropriate and otherwise – in the home and the number of family members who have engaged with the child in the above activities in the past week (see Annex 1). TIMSS and PIRLS, which also ask students if parents read and if their parents read to them. This last question is an element of the home learning environment.

**Sex**. Whether working with adults, youth, or children, is most often a binary indicator marked off by the assessor or interviewer in a learning study and not posed as an interview question.

**Age**. Getting reliable data on the age of respondents has proven to be challenging in past data collections, especially in the international development context. Frequently respondents, whether adults or children, do not know their exact birth date. While analysts prefer age in months, age in years is most realistic when asking children. Parents, in some cases, can offer exact dates. To enable optimal data collection, train assessors and configure survey questions to collect the most data possible and to ensure that these questions are not skipped if only years of age is known. For example, have assessors ask for year, month and date of birth as well as age in years.

**Language.** As the Measuring Equity in Education landscape analysis report[3] indicates, language is often used as a proxy for ethnicity, which can be a key predictor of inequity in several contexts. Respondents are normally able to respond to questions about the language(s) they speak at home, are taught in school, read, etc. We recommend a combination of a fairly comprehensive list of common languages as response options along with a blank space to capture "other" less common languages. In localities where many languages and multilingual homes are common, the questions can elicit the primary language and then ask about additional languages spoken at home. For example, in Guatemala, a learning study uncovered

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[2] For an example of ASER tools, see: ASER. (2014). Survey booklet. India: Pratham. Available at http://img.asercentre.org/docs/Aser%20survey/Survey%20Process/surveybooklet_english_aser2014.pdf.
[3] FHI 360 and Save the Children: *Measuring equity in education*.

a difference between the skill profiles of children who spoke only an indigenous language at home and those who reported speaking some Spanish at home.

**Ethnicity**. We recommend that language of the respondent be collected at a minimum, both as a predictor on its own, as well as a proxy of ethnicity as an equity dimension. However, it cannot always be assumed that different ethnicities speak different languages at home. Therefore, we recommend that, where it is deemed appropriate and safe to ask, youth and adults be asked questions about ethnic or racial group membership alongside questions on language. As with language, questions on ethnicity may be open-ended or pre-set options. We recommend a combination of pre-set responses and write-in fields. Among adults and children, questions about group membership should be given consideration for contextual appropriateness as well as whether pre-set or open ended strategies better fit the data collection situation.

## Expanding the Scope: Additional Dimensions of Equity

Our review of equity measures in learning studies found three dimensions of equity less often or never measured: disability, orphanhood/living circumstances, and displacement/mobility. While it is plausible that one or two of these are not relevant in some learning settings, we can move our understanding of these dimensions and their relationship to learning outcomes forward simply by raising the issues at the design stage of every study. Additionally, where applicable, it is useful to collect information on the prevalence of such dimensions in learning study samples. This section presents best practices from which to build on in measuring disability, orphanhood/living circumstances, and displacement/mobility.

**Disability** data are sparse in research focused on learning outcomes and even estimates of prevalence are few among school-based surveys as disabled children are often not in school to be sampled. The Washington Group on Disability Statistics has established long and short lists of questions on disability for use in conjunction with other surveys.[4] The United Kingdom's Department for International Development (DFID) Disability Framework[5] uses the short list of six questions and four answer options (see Annex 1). The Disability Framework has detailed guidance for adaptation and use. We recommend that these questions are included in every background survey for respondents ages 6 and above and propose a 2018 check-in among organizations who do so to review the experience using the items with young children.

The United Nations Children's Fund (UNICEF) Multiple Indicator Cluster Surveys (MICS) uses the longer list alongside the same four categories of response. This broader range of questions includes: seeing, hearing, mobility, self-care, fine motor, communication/cognition, learning, remembering, emotions: anxiety and depression, controlling behavior, focusing attention and concentrating, coping with change, relationships, and playing. In the recently released UNICEF MICS Child Functioning Modules[6], developed with the

[4] The Washington Group on Disability Statistics makes the short and extended sets of questions on disability available at http://www.washingtongroup-disability.com/.
[5] DFID. (2015). Disability framework – one year on: Leaving no one behind. London: DFID. Available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/554802/DFID-Disability-Framework-2015.pdf
[6] The Child Functioning Modules, with separate modules for children ages 2-4 and those ages 5-7, are available at http://www.washingtongroup-disability.com/washington-group-question-sets/child-disability/.

Washington Group on Disability Statistics, questions are asked of the caregiver, while the DFID phrasing is written for a child to answer.

Across six pilot sites, UNICEF reported bias in parent-reported measures depending on parent's knowledge of "what is normal" for children of the same age. The questions are phrased as comparisons to other children of their age, which can generate bias as a result of the relationship between the parent and child, or the parental level of frustration with the child. On the other hand, caregivers not involved closely with the child's day to day care may underreport compared to those working with them daily, while those frustrated with the child might over-report. While some participating organizations have taken other approaches, e.g., asking second and third grade students whether they can see the blackboard in their classroom or ever have trouble hearing the teacher, documenting how well children ages 7-15 can answer even the short list of questions would add to our understanding of how to collect information on disability effectively.

In research on learning, the disability dimension of equity has both a data and a measurement gap, so ensuring that more researchers use and reflect on these questions – whether asked of students themselves or their caregivers – can propel the conversation forward.

**Orphanhood and living circumstances** data collected by colleagues working in child protection programs and systems are routinely gathered via two sets of questions to caregivers – the first relating to whether parents are alive and the second relating to parental presence. Initially, one or two questions can be used to create a binary "orphan" variable in cases where the child has no parent alive as well as binaries to represent maternal or paternal orphans. These questions can similarly be used to create binary variables to signal whether one or both parents are absent for use testing the influence of orphanhood and living circumstances on learning. In the United States Agency for International Development- (USAID)-supported Sustainable Comprehensive Responses for Vulnerable Children and their Families[7] (SCORE) instruments focused on assessing child vulnerability, these same parenthood items are scored in a gendered way, attaching the notion of increased risk as the score increases if mother is absent/dead as compared to the father (See Annex 1).

For younger respondents in learning assessment settings, asking whether parents are alive is often not culturally acceptable and students are asked who they are living with, who the head of the household is, and, if not living with parents, then whether they are living with a relative. This last question can capture child fostering practice, allowing a view into its prevalence and where feasible a test of its impact on learning. Note also that if the home learning environment matrix in Annex 1 is used for collecting home learning environment data, then that data shows whether the mother and/or father are listed as living in the home. As such, items about whether the parents are living in the home could proxy for the child's family structure. Increasing the use of these categories in ongoing learning research can facilitate better understanding of how both orphanhood and living circumstances affect learning for all.

**Displacement and mobility**, where it varies as in conflict settings or large urban areas, can affect learning and is an important equity factor to collect. An initial contextual scan can inform both relevance as well as groups for consideration, e.g., refugees, international migrants, national migrants, immigrants, and

[7] For more information on SCORE tools and resources, see http://www.avsi-usa.org/score.html and http://score.or.ug/.

internally displaced persons. Where such populations exist, attention should be paid to how the sampling frame for the study captures – or fails to capture – these groups and to the development of remedies that will ensure their inclusion. Often these questions ask for the time lived in an area or even in the same home. Children could be asked, for example: Have you always lived in the same home? Or: Have you always lived in the same village? Of course, these questions would be inappropriate for some settings, such as refugee camps, where they could be adapted to ask about the number of homes prior to coming to the camp. Group membership in the categories above are most effectively answered by youth and adults.

## Technical Implications for Sampling and Design

An important challenge facing organizations interested in equity-focused analyses is determining an adequate sample size, one that allows for disaggregation of data without substantial loss of statistical power. Within the context of most program-level research and evaluation, the desire to have an informative sample that allows for meaningful analysis must be balanced with a realistic budget and a feasible time frame for collection and analysis.

Many texts offer general parameters for determining appropriate sample size, depending on the researcher's assumptions and starting conditions, such as the desired level of precision for the sample estimate, confidence level for the estimate, intra-class correlation (for clustered samples), and the magnitude of difference between a given sample estimate and a known population value. In evaluation settings, the latter parameter is replaced by the magnitude of expected differences between the treatment and comparison conditions (see Hedges and Rhoads, 2010; Gellman & Hill, 2011). The EGRA Toolkit[8] provides a useful breakdown of these considerations for studies involving the administration of EGRAs.

Each of these parameters carries implications for the size and, consequently, the cost of a given data collection effort. Analyzing data with an eye towards equity heightens the challenge, especially when increasing the number of dimensions across which meaningful conclusions are to be drawn, as this raises the requirements for the number of observations per dimension and, therefore, for the entire sample needed to maintain a reasonable level of reliability and precision. Indeed, desired levels of precision for a given estimate are what largely drives the sample size and cost: reducing the standard error for a given population-based estimate by *half* may require *quadrupling* of the sample size (UN Department of Economic and Social Affairs Statistics Division, 2005, p. 38). This is an increase most development organizations are not at liberty to make. The recommendations presented here are intended to help researchers and practitioners with an interest in equity-oriented analysis in making decisions regarding sampling for impact analyses.

The following are the general steps we have outlined to guide the decision process and sample size determination for equity analysis. Note that the objective is to obtain a sufficient sample to reliably estimate parameters of interest (e.g. treatment effects) for a given subgroup/equity dimension.

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[8] RTI International. (2015). Early Grade Reading Assessment (EGRA) Toolkit (2nd edition). Washington, D.C.: USAID. Available at [https://globalreadingnetwork.net/resources/early-grade-reading-assessment-egra-toolkit-second-edition](https://globalreadingnetwork.net/resources/early-grade-reading-assessment-egra-toolkit-second-edition). See Annexes B-D for sampling recommendations.

1. **Determine which dimensions will act as *domains* in your analysis.** Household surveys distinguish between *domains* and *tabulation categories* for subpopulation analysis. Domains represent critical subpopulations for the study in question, important enough to justify substantial cost increases required to reach sufficient sample sizes within each domain. By contrast, tabulation categories are informative but do not require the same degree of precision of group-level estimates, and therefore, are not factored into the sample size estimation (Ibid., p. 40).

2. **Determine whether certain intersections of equity dimensions should be treated as domains.** With multiple dimensions of equity present in a dataset, choices may have to be made as to which intersections of characteristics will require a closer examination as *domains* of analysis. Intersections combine multiple dimensions in a single category, such as the intersection of gender and poverty, for example. Naturally, an intersection of dimensions creates a smaller cell size within a dataset, therefore requiring higher power – and in most cases, a higher overall sample size – to generate reliable estimates (Table 1).

3. **Obtain an estimated proportion of each domain or dimension in the population.** While it is not always possible to know how many observations for a given domain one can expect to obtain in a sample, existing household surveys and censuses often provide a general gauge of how large a given disadvantaged group is within a general population. One can expect, for example, to find roughly 50% females in a simple random sample of households, and administrative data from a school census will indicate what proportion of girls can be expected to be present in a given school sample. Similarly, rough proportions may be obtained from prior sources on the presence of ethnic or linguistic minorities and persons with certain types of disabilities. While the actual proportion in a given sample may vary, prior information provides a useful starting point for subsequent decision making around sampling and design. When no such information is available, assumptions will have to be made up front, and samples will need to be adjusted once initial data become available.

   Table 1 below provides an illustration of the ways in which intersections of dimensions reduce the effective cell size and, as a result, decrease the ability of a researcher to reliably estimate a parameter. As the table shows, we may start with an overall expectation of 50% girls, of which 30% may be categorized as poor, and 25% from a minority ethnic group. However, if our equity analysis is focusing on poor girls, or girls of the particular ethnic minority group, we must account for the fact that this subgroup will be only 15% or 10% of our sample. If either of these intersections is a *domain* for our analysis, the sample size calculation should be run with the smallest domain in mind.

*Table 1. Expected domain size across two equity dimensions of different proportions.*

| | Population Proportion | Dimension 1: Girls | Dimension 2: Poor | Dimension 3: Minority |
|---|---|---|---|---|
| | | 50% | 30% | 20% |
| Dimension 1: Girls | 50% | | | |
| Dimension 2: Poor | 30% | 15% | | |
| Dimension 3: Minority | 20% | 10% | 6% | |

4. **Determine whether a domain can be purposefully oversampled to gather a sufficient number of observations.** Since the sample size determination is largely driven by the smallest domain of interest, it is important to consider whether purposeful oversampling is generally feasible to ensure a sufficient number of observations within a cell. The question of whether a group can be identified a priori and targeted for additional sampling can be context-driven – as, for example, may be the case with ethnic minorities. In other cases, this may not be feasible, as with many types of disability or displacement, which leads one to determine if obtaining a sufficient number of observations for that group requires overall inflation of the sample. It is important to note that in case groups are oversampled, unweighted analyses of the data will not be representative of the larger population. As such, appropriate weighting of the observations would be necessary to ensure representativeness.

5. **Determine acceptable cluster size.** Another decision point in determining the sample size, and the overall cost of a given data collection effort is the acceptable cluster size. In many cases, data for education research and monitoring purposes are clustered at the school level, with the school serving as the primary sampling unit. Determining a realistic number of observations that can be gathered on students within a school may provide a useful approach to increasing the sample size and, consequently, the number of observations on a given equity dimension, without dramatically increasing the cost of the study, which is largely driven by the number of clusters to be visited during data collection. It is helpful to determine the maximum cluster size that allows for the optimal number of schools visited within a day and compare the resulting number with the number of days and sites allowed within the budget.

6. **In evaluation settings: determine the acceptable minimum group-level effect size.** As referenced above, a key ingredient in the decision making process for impact evaluation data collection is magnitude of change in the outcome that is attributable to the treatment or intervention in question (Hedges and Rhoads, 2010). As many texts on evaluation methodology indicate, the researcher's task is to determine what magnitude of change is worth searching for, as smaller changes in outcomes are generally more difficult to detect, and therefore require larger samples.

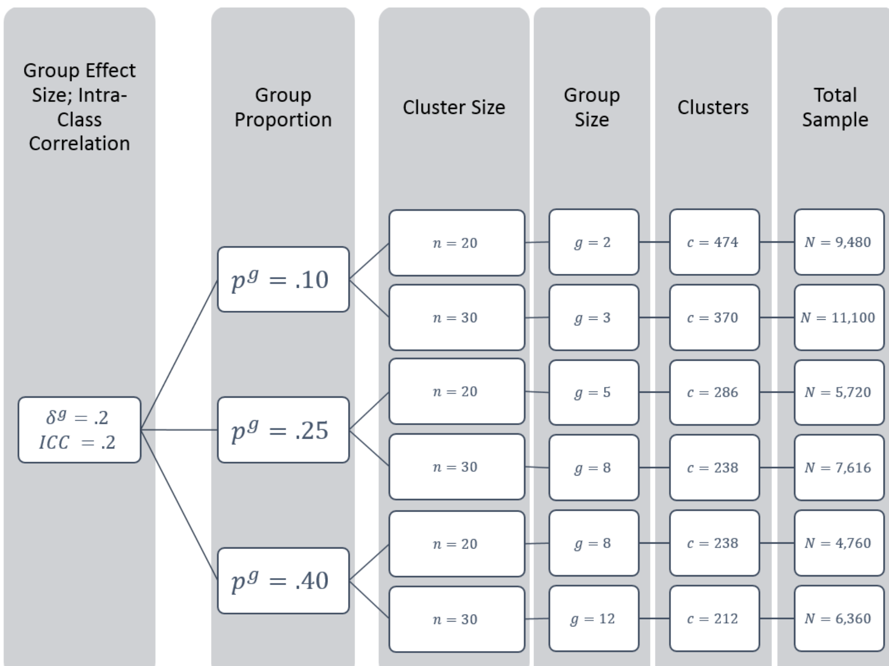
In the context of the Equity Initiative, we are concerned not just with change across the entire population, but change for a given equity dimension or, as we referenced above, a domain, which can be an intersection of dimensions (e.g., minority girls). There may be reasons to assume that a program may have affected the subgroup in question in more or less substantive ways than the overall population. For example, if a particular intervention was used that specifically focuses on girls, the program effect on girls may be larger than the effect across the board.

The decision making around how to factor the magnitude of group-level change into the sampling strategy is not very different from a process that would be required to determine a sample size across the board. As with any other instance of sampling calculation, we would examine the distribution of the outcome variable, obtain a general expectation of program effect, gauge the level of intra-class correlation present in our data (Hedges and Rhoads, 2010), and take into account the possible attrition or measurement error. The only difference would be the locus of decisions, where the smallest domain determines the key assumptions for sample size calculation.

Figure 1 illustrates the decision making process to identify the optimal sample size that makes it possible to identify the anticipated group-level effect size, while taking into account the proportion of that group in the target population (group proportion), the possible number of students to be sampled at each school (cluster size) and, hence, the resulting number of schools (clusters) to be sampled. The figure assumes proportional increase of the sample; however, in some cases a deliberate oversampling may present a more efficient approach to meeting the sample size requirements at the group level (e.g., oversampling students from language minority concentrated in some communities/schools).

As an illustration, if the true group proportion is 0.1 and 20 children per cluster (school/village) are being sampled, then the number of children of that group that we can reasonably expect to find in each cluster sample would be 2. In order to detect a minimum effect size of 0.2 standard deviations, with an intra-cluster correlation of 0.2, a sample size of 474 clusters would be required. This would translate into a total sample size of 9,480 children (= 20 x 474).

*Figure 1. Decision tree determining optimal sample size and number of clusters based on group proportion and cluster size. Effect size assumed at 0.2 standard deviations and intra-class correlation at 0.2.*




**General recommendation: focus on generating comparable data.** While these recommendations provide some tips for strengthening reliability in equity analysis, it is useful to remember that lack of precision is not the greatest hurdle in education data analysis at this time; rather, it is the simple availability of data on key dimensions. Therefore, we encourage organizations working in education to include these parameters in their data collection and analysis to the extent possible even if the size and power of a given sample does not always allow for reliable equity analysis across multiple categories. The Equity Initiative builds on the idea that the use of a common, harmonized framework would increase opportunities for meaningful learning to take place across multiple dimensions of equity. When data are harmonized – with comparable definitions and target populations – that presents opportunities for increasing the power of the equity analysis, drawing on a much larger scale.

## School-based or household-based?

Most research as well as monitoring efforts in international education and development use schools as sampling units. Since schools are often the targets of program interventions, data collection at the school-level allows for direct assessment of program impact on students enrolled and regularly attending. However, this approach has implications for one's understanding of equity and disadvantage in education, as it assumes that all intended beneficiaries are equally likely to be captured within a study frame. In contexts where large proportions of students are out-of-school or attending irregularly, school-based studies may suffer from selection bias, as those present at school on the day of data collection will tend to be systematically better off than the overall population of that age. In such cases, household-based data collection presents a strong alternative.

Other situations where one may opt for household-based, rather than school-based, studies include contexts where there is a large non-formal schooling sector, such that the known school sampling frame does not include community-based, unregistered private or religious schools. Collecting data from households ensures that all children, regardless of the type of school they attend, are represented in the study sample.

Finally, household-based studies are useful where access to schools is restricted. Schools may not always grant permission to conduct studies on their premises, particularly in situations where the data collection is not tied to a program. In these cases, household-based data collection provides a more reliable, comprehensive approach to capturing equity in student outcomes. However, it is likely that household-based data collections are more costly and require a more intricate sampling framework and process.

## The use of longitudinal studies when focusing on equity

Historically, it has been increasingly understood (and argued) that equity in education goes beyond equality (i.e., it is more than equal treatment) to also include the redress of past or current inequalities (Unterhalter, 2009; Nordstrum, 2011). In addition to this, the notion of equity has generally been expanded over time so as to be more inclusive for more individuals and population groups (UNESCO, 2010). With equity conceptualized as redress for prior or current inequalities, longitudinal studies, as compared to cross-sectional data, are appealing as they may more accurately depict improvements in equity. For example, with longitudinal data we can measure performance gain or loss over time in specific children identified as being part of an underserved population and gain an understanding about what factors (background, experience at school, etc.) are related to this change. With this data we can also gain insights about how certain characteristics at the household and individual level (e.g., household composition, income, socioeconomic status) evolve over time and relate to equity concerns. However, logistically tracking students is challenging in the international context because students do not typically have unique identifiers. Thus, tracking them requires storing personally identifiable information, which then requires additional measures to safeguard participant confidentiality. Locating students for follow-up visits can also be difficult, this is particularly true for marginalized populations. At baseline, we recommend collecting student names, other readily available identifiable information (sex, age, parent names, etc.) addresses and parent cell phone numbers to help track students in future rounds of data collection. With school-based studies, we suggest enlisting teachers and school administrators to help gather contact information for the children. Prior parental consent will be needed to collect this information.

Attrition is also an issue to consider. While it is natural to focus on the loss in sample size and statistical power, the main challenge of attrition is non-response bias. That is, the children lost to the study often have different demographic characteristics from those who remain. The result may be a sample that is not representative of the population and bias estimates. The issue of attrition is particularly relevant for equity studies because disadvantaged students may be more likely to dropout or to migrate.

Therefore, when evaluating longitudinal data, researchers should check the data for attrition bias. One way to check for attrition bias is by running a logistic regression model. This analysis allows you to determine if any baseline child or home-environment characteristics are predictive of study dropout and which population sub-groups (e.g. girls, lower SES) were lost over time in the study (Jukes et al., 2016).

In cases where attrition is prevalent, the researcher should then test whether the composition of the remaining sample has significantly shifted, which in turn can bias resulting impact estimates. This is measured by comparing mean outcome scores among students who have left to those of the students who remained at baseline. You should also compare basic demographic information of these students to better understand the types of students who have left. Guidelines suggest that potential bias from attrition should not exceed an effect size of 0.05 standard deviations in student scores (Institute of Educational Sciences, 2014). If attrition bias is above this level, weights adjustment or other techniques must be used to account for non-response bias. This weighting procedure, however, increases standard errors and potential bias from an increased unequal weighting effect. You could also utilize other statistical techniques to account for attrition, including but not limited to imputation of missing subjects or weight adjustment using baseline subject characteristics.

If too many children from any sub-group are lost through attrition, you may not be able to report on that sub-population. For this reason, when logistically and financially possible, we would recommend making the extra effort to reach the children who have dropped out of the study; in particular children from sub-populations with a greater probably of drop-out. As noted above, supplemental contact and location data can be used for follow-up data collections. When conducting school-based surveys, this contact information can help you locate children who may no longer be attending schools. Similarly, having family cell numbers may help you find families participating in household based surveys who have moved away. Cell numbers and information from former neighbors can help locate family so that assessors can contact parents to determine whether or not the child is still attending the same school, and if not, their new location.

If the challenges (logistical and cost) of conducting a longitudinal study are too great, depending upon the research question to be answered, you may want to consider conducting a repeated cross sectional study instead. Repeated cross sectional studies follow a cohort of children (and not individual children) as they progress through school and these studies can also provide insight into the changes in equity over time. Cross-sectional studies can be significantly cheaper and easier to organize. It's worth noting, however, that there are several things to consider. Differential attrition also biases results from repeated cross-sectional surveys. If disadvantaged children dropout of school or migrate out of the region, they will not be present in follow-up surveys. Longitudinal designs do have the advantage that the extent of differential attrition can be assessed and subsequently accounted for in analyses and interpretation. However, one key drawback of a repeated cross-sectional design is that you cannot draw the same conclusions or make the same claims on individual student performance as with a longitudinal study, because you lose the ability to better understand the "why" behind an intervention. The research question being asked as well as funding limitations should drive the decision between these two tools, along with other contributing factors.

## Reaching the "difficult to reach": ensure a sufficient size sample

Researchers may face many challenges when trying to survey hard-to-reach or "invisible" populations. For example:

- **Barriers to access may exist.** Individuals may be hard to physically locate or reach, such as with nomadic, migrant fishermen, or homeless populations (UNESCO, 2010). Other barriers may be less tangible, such as differences in language, culture, or even the assumptions about how a group of people will interpret an interview question or will act in given situations.
- **Potential for resistance to being surveyed.** This could be due to general fear, anticipated stigma, fear of being included in government systems (such as for taxation purposes), or for other cultural reasons that must be explored and addressed.
- **Lack of formal record keeping** on information such as birth dates, family members, years of schooling, etc. This can make both estimating the full population for the sampling frame and gathering any type of demographic information for your survey extremely difficult.
- **Lack of resources.** Depending upon these and other challenges, the cost and resources required to gather data from these populations may be too high relative to the value of the potential data gathered.
- **Conflict.** Many marginalized regions are often defined by social or military conflict, which inherently renders data collection dangerous and difficult. Conflict can also lead to geographical displacement, exacerbating barriers to access discussed previously (Internal Displacement Monitoring Center, 2009)

Sampling methodologies such as snowball sampling or respondent-driven sampling are recommended when surveying hard-to-reach populations because researchers must rely on non-traditional methods to obtain a large enough sample. Both methods rely on referrals to gain more input from within a group. Given the costs of data collection and to maximize the benefit gained from the data, it is important to rigorously pilot questions and data collection methodologies and evaluate their efficacy.

It is also the case that layers of marginalization act in concert with one another: characteristics that define marginalization (e.g., sex, socioeconomic status, disability, ethnicity, geography, and language) do not operate in isolation (UNESCO, 2010). Methods of measurement therefore must be able to describe such interactions and take the overlap into account.

## Choice of education equity metrics

The following section details common metrics used in equity-focused analyses, including visual representation of overall indicators of dispersion, disparities between student groups, and measurement of achievement gaps/ratios. The choice of education equity metrics would depend on the research question that the researcher is addressing and the educational outcomes that are of interest to the study. As such, the discussion will be organized into the different equity metrics that are appropriate for impact evaluations and/or general quantitative research using microdata for continuous (e.g., test scores, years of schooling and number of absences) and binary outcomes (e.g., grade progression, completion and proficiency status) of interest.[9] Table 2, below, highlights common statistical indicators of educational outcomes at the micro- and macro- level and the corresponding equity metric applicable.

*Table 2*. Mapping of common education indicators and applicable equity metrics

| Indicator | Observation | Applicable Equity Metric | | | |
|---|---|---|---|---|---|
| | | *Difference* | *Ratio* | *Variance* | *Gini/Theil* |
| **Gross/net enrollment rate** | Macro | X | X | | |
| **Years of schooling** | Micro/Macro | X | X | X | X |
| **Pupil teacher ratio** | Macro | X | X | | |
| **Dropout rate** | Macro | X | X | | |
| **Survival rate** | Macro | X | X | | |
| **Attendance/absence** | Micro/Macro | X | X | X | X |
| **% at performance benchmark** | Macro | X | X | | |
| **Average assessment score** | Micro/Macro | X* | X* | X | X* |

Note: Micro and Macro designations refer to the most common method of reporting the indicator, as all data are collected in its raw form at the micro level, then aggregated. As a result, indicators reported at the macro level as rates are binary variables collected at the individual level. The asterisk (*) denotes that the scale of the assessment score needs to be on a linear scale for differences and ratios to be applicable.

### Visual representation of overall dispersion

A recommended first step involving equity analysis is to provide an overall summary or snapshot of the educational outcomes of interest to the study. This can be achieved in a straightforward manner by coupling a visual representation of the educational outcome with basic summary statistics (one of which will introduce the first equity metric). With continuous outcomes collected at the individual level, we introduce the use of distributional plots such as histograms and density functions and summary statistics that reflect the overall level of dispersion along that outcome such as variance/standard deviation and coefficient of variation. A histogram provides the researcher with a visual representation of the overall distribution of correct words read per minute, for instance, across all students in the sample and helps identify clustering patterns and outliers. This mode of analysis provides the researcher with a gauge on within-group inequality of outcomes (the degree of dispersion among the members of the same group) and on the between-group inequality/disparity in outcomes (this is achieved by comparing the distance between the central tendencies from each equity group). This can be applied by overlaying distribution plots from various groups onto the same two-dimensional plane.

*Figure 2. Distribution of ORF performance for males and females*

[9] It is important to note in equity-focused research that the equity dimensions need to first be identified and summarized prior to delving into inequality measurement and analysis.

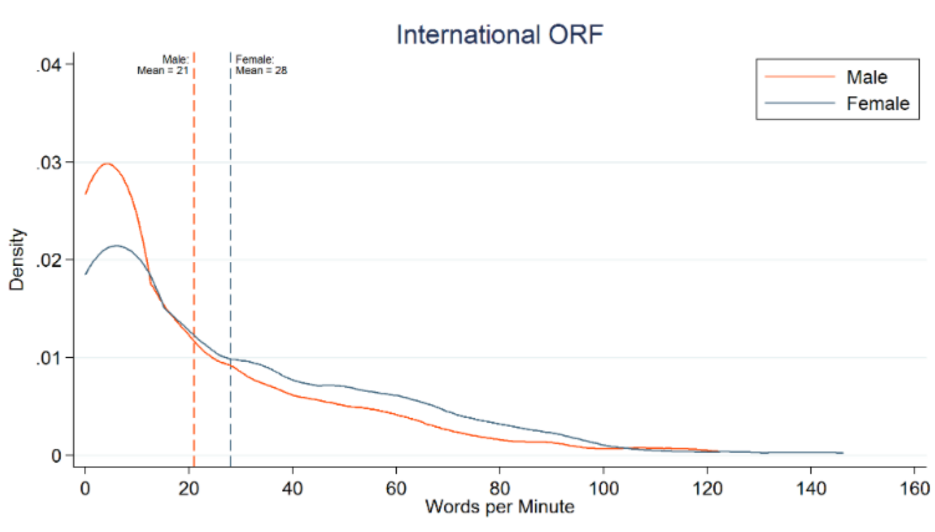



Figure 2 informs the researcher on two equity-focused characteristics regarding oral reading fluency (ORF) performance by gender. First, the plot shows that females in the sample exhibit a higher mean ORF score (correct words read per minute), and, second, that the within-gender inequality appears to be higher among males since their distribution exhibits a higher rate of clustering relative to females. We can see that a single distributional graphic can provide several pieces of information with equity implications. However, the clear drawback of relying on distributional plots lies in their inability to provide the researcher with a summary statistic, a single number, that describes the degree of inequality that exists along the educational outcome.

**Difference in Means**

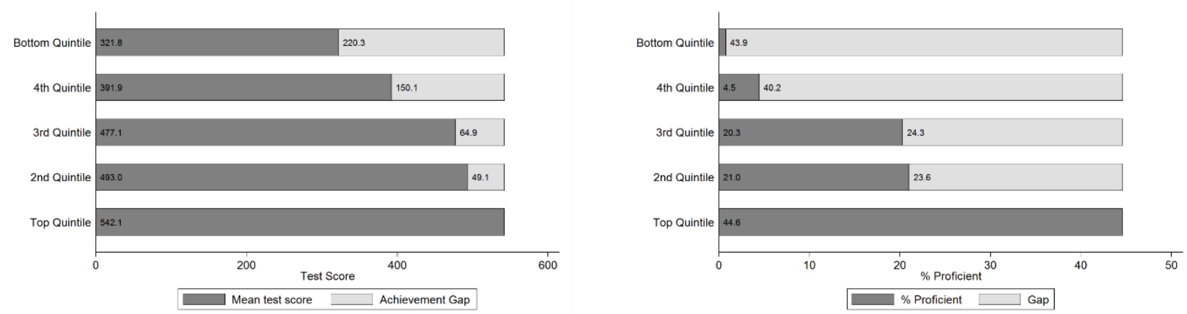
The logical next step in assessing the degree of inequality between groups is measuring disparities in educational outcomes using a simple difference in means. This metric is versatile in its use as it can be useful regardless of the type of outcome variable being used, be it continuous or binary (macro or micro). The researcher would only need to compare the mean educational outcome between the different groups and measure the straight-line distance between the two means. This approach provides an additional advantage in that the difference in means is a testable hypothesis. However, the drawback is that this method can only be computed for two groups at a time. Differences in means are therefore representative of the disparity between two groups only, and not necessarily of inequality, as a whole. In a sense, this allows the researcher to take a deeper dive into the data to dissect the disparities at a more granular level. Figure 3 plots two graphs to illustrate achievement gaps, the first depicts means from simulated test scores for students in each wealth quintile, and the second shows the proportion of students attaining proficiency on the same test.[10]

*Figure 3*. Disparities in Learning Outcomes, using Continuous and Binary Outcomes

Disparities in assessment scores between wealth quintiles

Disparities in proficiency (% of students) between wealth quintiles

[10] Data represented in Figure 5 are based on an assumed data generating process and not empirical data points.




Note that the magnitude of the differences should be interpreted with caution when the group means are unknown. A best practice for reporting mean differences is to show both the mean outcome for each group and the calculated group difference. It is important to note that educational outcomes that are measured on a non-linear scale, such as scaled assessment scores, may not produce an interpretable measurement of the straight line difference. Lastly, differences in means always reflect the absolute difference between groups and not the relative difference, i.e., the magnitude of the disparity does not reflect the starting point for the comparison.

**Parity Ratios**

A parity ratio is operationally similar to an achievement gap as it is a metric that requires inputs from only two groups at a time, but measures the disparity in relative terms. This metric is appropriate when the relative size of the magnitude is important to the researcher and the scale of the original educational outcome is linear. Moreover, parity ratios are not appropriate to represent disparities in continuous variables, such as scaled learning outcomes. However, the application of ratios provides a clear advantage when investigating binary outcomes, that are represented as proportions when aggregated, since increments in proportions are linear in nature. As shown in Table 2, parity ratios can be applied to almost any indicator of educational outcomes. Most popular is the gender parity index, popularized by the Education for All Global Monitoring Report, that measures the ratio of gross enrollment rates of girls to that of boys. The gender parity index is a typical application of parity ratios as enrollment rates are measured on a linear scale and the relative difference is of importance. Lastly, it is worth noting that the relative magnitude of parity ratios can be highly inflated in cases where the denominator is near-zero.

**Variance-Based Measures**

A popular method in statistics to summarize inequality across the sample is the **variance** or **standard deviation**. The variance is defined as the average of the squared distance between each student's learning outcome and the sample mean. The variance measure is useful in summarizing the overall level of disparity that exists between students in a given sample. The standard deviation provides an intuitive interpretation of the variance as the unit of measurement of the learning outcome is preserved. Another advantage of the variance/standard deviation measure is that it utilizes all the information available in summarizing the degree of disparity within the sample. A major advantage of variance based measures is that they are decomposable into a between-group and within-group level variances using standard ANOVA methods. This enables the researcher to determine along which equity dimension inequality is most systematic.

The variance and standard deviation, however, are not immune to variable transformations. In other words, if students from a given sample were to double their performance over time, the variance and standard deviation would quadruple and double, respectively. Out of context, this could lead the researcher to conclude that inequality has increased, when in fact the learning outcome distribution has been preserved. The **coefficient of variation** helps to circumvent this issue while still providing the researcher with an overall gauge of the student-level disparity. The coefficient of variation is an elegant solution to the mentioned drawbacks of the variance and standard deviation, whereby the standard deviation is normalized by the sample mean, i.e., dividing the standard deviation by the sample mean. This metric rescales the standard deviation to be measured as a factor of the sample mean and is comparable across populations. Additionally, this normalization process is not sensitive to variable transformations or distributional shifts, as the numerator and denominator undergo the same transformation.

**Gini and Theil Indices**

The final metrics summarizing inequality of educational outcomes are the Gini and Theil indices. Both are useful and most common in quantifying inequality using micro-level and continuous outcomes, such as years of schooling. The Gini coefficient is a measure that relies on information from cumulative distribution function of years of schooling of a particular population to show how evenly/unevenly the stock of education is distributed across all individuals. The Theil index, on the other hand, is a measure of entropy which quantifies the amount of information redundancy found in a given distribution – more redundancy equates to more equality. Another advantage the Gini and Theil metrics share with the variance-based metrics is that they are decomposable into within- and between-group inequalities. Again, this enables the researcher to determine the proportion of the total inequality that is explained by certain equity groupings. Note that with the Gini index, the decomposition is not as straightforward as in the case of the Theil index or the variance because the Gini decomposition generates a residual term to ensure unity.

## Analyzing equity in education: a structured approach

In the final section of this document, we outline a general sequence of equity focused analyses that can be applied across multiple research modalities en route to identification of program and policy impacts. As such, the following sequence exemplifies a typical analytic sequence with a relevant equity perspective to finally assess the degree of heterogeneity in potential program impacts. Broadly, the process entails a description of the overall analytic sample and identification of the relevant equity subgroups; analysis of the distribution of outcomes, overall, and by equity group; construction of statistical profiles for groups relevant to the study based on the observable characteristics of the sample; aggregation of the outcome statistics at a higher level in the data hierarchy (e.g., if the data are collected at the student level, then aggregate to the school level); comparison of unconditional mean outcomes between treatment and control groups within each equity grouping; and, lastly, estimate program impact (relying on the appropriate research design for identification of the impact) for the overall sample and for each equity group. The remainder of the discussion provides additional details and motivation for each step in the sequence.

1. **Describe the sample and identify equity groups.** As the first step in any research effort, describe the overall analytic sample and summarize the overall observable characteristics of the sample. In addition, identify the relevant equity groups of interest to the study and highlight the sample proportions in each respective equity group. This step enables the researcher to validate the overall sample and confirm its level of representativeness for the purposes of generalization of any inferences made during the analysis. Identifying the equity groups and summarizing the size of each subsample

also doubles as a test for the representativeness of each of the groups from the larger population as well as provides the researcher with a statistical basis for determining whether program impacts are feasibly identifiable – this is relevant when certain subgroups are relatively small in size. Lastly, in case of a traditional impact evaluation, the analysis described earlier can be replicated by stratifying the entire sample into treatment and control groups and repeating the same steps. Stratifying the sample by treatment and control status will enable the researcher to test for sample balance between the two groups to ensure adequate identification of the program impact.

2. **Analyze the distribution of outcomes, overall and disaggregated.** For this step, the researcher may rely on a visual representation of the distribution of outcomes that are of interest to the study using a kernel density estimate or a histogram. Analyzing the overall distribution of educational outcomes provides the researcher with a gauge of the overall level of inequality in student performance across the entire sample by supplying both a measure of central tendency in the data as well as a measure of the overall level of dispersion in the outcomes. The natural evolution of this analysis is to stratify the outcome distributions by equity groups that will show the central tendency of each, thus informing the researcher on the between-group inequality in outcomes. Analyzing the stratified distributions will also inform the research about the extent of the within-group disparity in outcomes.

3. **Build a profile of students at the bottom of distribution.** This type of analysis can be augmented by dividing the overall outcome distributions into student performance categories (e.g., in an EGRA, students can be divided into fluent, non-fluent, and non-reader categories). Once outcomes are grouped into performance categories, the researcher can construct statistical profiles that highlight the mean observable characteristics of the students who fall into each category. This type of analysis mimics a student early-warning system to identify the characteristics most associated with poor student performers, or vice versa. The additional advantage of this analysis is that it identifies whether the equity groups are disproportionately distributed across the different performance levels.

4. **Analyze school-level outcome distributions: are lower-performing students clustered within a few schools?** In this step, the researcher generates aggregate outcomes-based statistics to either show mean outcomes, or student proportions over or under a certain performance threshold, at the school level. This analysis provides an overall snapshot at an aggregate level that informs programming of the number of schools with high proportions of underperforming students, or vice versa. In addition, this type of analysis will identify such schools, providing stakeholders with information on the relative performance at the school and enabling targeted adjustments to any existing interventions. From a numerical perspective, this exercise is irrelevant as means or proportions will be the same as those reported from the student level descriptive analyses. However, by providing a visual representation of such a school-level distribution, one can easily identify deviations from the ideal or targeted distribution.

5. **Estimate program impacts, overall and by equity group.** The final step in the proposed analytic sequence may vary depending on the research design implemented to identify the program impacts. In case of a randomized experiment, it may be sufficient to report differences in unconditional means between treatment and control groups to estimate the program effects. Similar to the previous set of analyses, this can be enhanced by interacting treatment status with equity group membership for each observation in the sample and then reporting differences in unconditional means between treatment and control groups within each equity group. This allows the researcher to determine

whether the program effects were in fact different for the different groups, i.e., to test whether each group is affected by the program in the same way.

Finally, using a regression analysis framework, the researcher can incorporate heterogeneity of the program impact by running the appropriate regression specification of the educational outcome of interest on treatment status and observable controls, while interacting the treatment effect parameter with the equity group indicators. This specification will disaggregate the treatment effect for each equity group included in the regression equation and provides an estimate of a program's effect on students from each group separately. The obvious advantage of using a regression-based framework is the calculation of the appropriate standard errors for each estimated treatment effect that makes statistical testing more straightforward. Further, with any typical statistical software the standard errors can be adjusted for the sampling structure, e.g., a clustered random sampling framework can be incorporated into the standard error computations by weighting the variance-covariance matrix with the individual-level contribution from each cluster into the maximum likelihood first order conditions.

## Bibliography

Castelli, L., Ragazzi, S., and Crescentini, A. (2012). Equity in education: A general overview. *Procedia – Social and Behavioral Sciences*, 69, 2243-2250.

Fiske, E.B. and Ladd, H.F. (2004). *Elusive equity: Education reform in post-apartheid South Africa*. Washington D.C.: Brookings Institution Press.

Gelman, A., and Hill, J. (2007). *Data analysis using regression and multilevel hierarchical models*. Vol. 1. New York, NY, USA: Cambridge University Press.

Hedges, L.V., and Rhoads, C. (2010*). Statistical Power Analysis in Education Research*. NCSER 2010-3006. National Center for Special Education Research.

Institute of Educational Sciences, U.S. Department of Education. (2014). *What Works Clearinghouse: Procedures and Standards Handbook, 3.0*. Washington, D.C.: Institute of Education Sciences.

Internal Displacement Monitoring Center. (2009). *Internal displacement global overview of trends and developments in 2008*. Geneva, Switzerland: IDMC/Norwegian Refugee Council.

Jukes, M.C., Turner, E.L., Dubeck, M.M., Halliday, K.E., Inyega, H.N., Wolf, S., Zuilkowski, S.S. and Brooker, S.J. (2016). Improving literacy instruction in Kenya through teacher professional development and text messages support: A cluster randomized trial. *Journal of Research on Educational Effectiveness* [published online].

Nordstrum, L.E. (2006). Insisting on equity: A redistributional approach to education. *International Education Journal, 7*(5), 721-730.

UNESCO. (2010). *Reaching the marginalized*. EFA Global Monitoring Report 2010. Paris: UNESCO.

UNESCO. (2014). *Teacher and learning: Achieving quality for all*. EFA Global Monitoring Report 2013/14. Paris: UNESCO.

UN Department of Economic and Social Affairs Statistics Division. (2005). *Designing household survey samples: Practical guidelines*. New York, NY: United Nations.

Unterhalter, E. (2009). What is equity in education? Reflections from the capability approach. *Studies in Philosophy and Education, 28*(5), 415-424.

Waage, J. et al. (2010). The Millennium Development Goals: A cross-sectoral analysis and principles for goal setting after 2015. *The Lancet, 376*(9745), 991-1023.

## Annex 1: Sample instrument for collecting equity-relevant data

For ease of uptake, the recommendations made by the Equity Initiative are transformed below into questions that an assessor might ask a student in the second or third grade, additional questions more appropriate for youth or adult respondents are in blue.

### Wealth and Socio-cultural assets

| | | | |
|---|---|---|---|
| ASK OF THE CHILD | | | |
| **1.** Does your home have: | | | |
| | a) Electricity | ☐ NO | ☐ YES |
| | b) Roof made of tin | ☐ NO | ☐ YES |
| | c) Mobile phone | ☐ NO | ☐ YES |
| | d) Refrigerator | ☐ NO | ☐ YES |
| | e) TV | ☐ NO | ☐ YES |
| | f) Motorbike | ☐ NO | ☐ YES |
| | g) Radio | ☐ NO | ☐ YES |
| | h) Bike | ☐ NO | ☐ YES |
| | i) Toilet | ☐ NO | ☐ YES |
| | j) Computer | ☐ NO | ☐ YES |
| ASK OF AN ADULT | | | |
| **2.** Has the child's father ever attended school? | | ☐ NO | ☐ YES |
| | a) If yes, what grade did he complete? | ___ grade | |
| **3.** Has the child's mother ever attended school? | | ☐ NO | ☐ YES |
| | a) If yes, what grade did she complete? | ___ grade | |
| **4.** Is there a person in the household who has completed (a particular level of education)? | | ☐ NO | ☐ YES |
| **5.** Is there a person in the household who know how to use the computer? | | ☐ NO | ☐ YES |

### Home learning environment

Ask the child: *Who do you live with?* As s/he responds, fill in the boxes below. For each person the child names, ask the child if s/he saw the person reading during the last week, etc. (enter 1 for yes, and 0 for no).

| Name/ Initials | Relationship 1=Mom, 2=Dad, 3=Sister, 4=Brother, 5=Grandma, 6=Grandpa, 7=Other Female, 8=Other Male | In the past week, did… | | | |
|---|---|---|---|---|---|
| | | you see them reading? 1=YES, 0=NO | he/she tell or help you to study? 1=YES, 0=NO | he/she read to you? 1=YES, 0=NO | he/she tell you a story? 1=YES, 0=NO |
| | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| | | | | | |
| **1.** In the last week, did you use your reading skills outside of school? | | | | ☐ NO | ☐ YES |
| a) If yes, where? ________________________________ | | | | | |
| **2.** In the last week, have you helped anyone using your reading skills? | | | | ☐ NO | ☐ YES |
| **3.** Other than at school, did you read alone last week? | | | | ☐ NO | ☐ YES |

| | | | |
|---|---|---|---|
| **4.** | Other than at school, did you read or share books with anyone in the last week? | ☐ NO | ☐ YES |
| **5.** | Other than at school or at home, did anyone in your community read to you last week? | ☐ NO | ☐ YES |
| **6.** | Does your home have: | | |
| | a) Newspaper | ☐ NO | ☐ YES |
| | b) Magazine | ☐ NO | ☐ YES |
| | c) Textbook | ☐ NO | ☐ YES |
| | d) Story books | ☐ NO | ☐ YES |
| | e) Comic books | ☐ NO | ☐ YES |
| | f) Religious books | ☐ NO | ☐ YES |
| | g) Coloring books | ☐ NO | ☐ YES |

## Age

| | | | | |
|---|---|---|---|---|
| **1.** | When were you born? | Year______ | Month_____ | Day_____ |
| **2.** | How old are you? | Years_____ | Months____ | |

## Language

| | | | |
|---|---|---|---|
| What language do you speak at home?[11] | | | |
| | a) Language option 1 | ☐ NO | ☐ YES |
| | b) Language option 2 | ☐ NO | ☐ YES |
| | c) Language option 3 | ☐ NO | ☐ YES |
| | d) Language option 4 | ☐ NO | ☐ YES |
| | e) Other | _______________ | |

## Ethnicity

| | | | |
|---|---|---|---|
| What is your ethnicity? | | | |
| | a) Ethnicity option 1 | ☐ NO | ☐ YES |
| | b) Ethnicity option 2 | ☐ NO | ☐ YES |
| | c) Ethnicity option 3 | ☐ NO | ☐ YES |
| | d) Ethnicity option 4 | ☐ NO | ☐ YES |
| | e) Other | _______________ | |

## Disability: Ask the child

| | No: no difficulty | Yes: some difficulty | Yes: a lot of difficulty | Cannot do at all |
|---|---|---|---|---|
| **1.** Do you have difficulty seeing, even if wearing glasses? | | | | |
| **2.** Do you have difficulty hearing, even if using a hearing aid? | | | | |
| **3.** Do you have difficulty walking or climbing steps? | | | | |
| **4.** Do you have difficulty remembering or concentrating? | | | | |

[11] In multilingual contexts, first ask: what language do you speak most at home? Then ask: what other language do you speak? The answer options are the same for both.

| | | | | |
|---|---|---|---|---|
| **5.** Do you have difficulty (with self-care such as) washing all over or dressing? | | | | |
| **6.** Using your usual language, do you have difficulty communicating, for example understanding or being understood? | | | | |

Note that this is the DFID short form. UNICEF's MICS includes caregiver questions about: seeing, hearing, mobility, self-care, fine motor, communication/cognition, learning, remembering, emotions: anxiety and depression, controlling behavior, focusing attention and concentrating, coping with change, relationships, and playing.

## Orphanhood and living circumstances

| ASK OF THE CHILD | | |
|---|---|---|
| **1.** Do you live with your mother? | ☐ NO | ☐ YES |
| **2.** Do you live with your father? | ☐ NO | ☐ YES |
| a) If 23 and 24 no: do you live with a relative? | ☐ NO | ☐ YES |
| ASK OF AN ADULT | | |
| **3.** Is the child's mother alive? | ☐ NO | ☐ YES |
| **4.** Is the child's father alive? | ☐ NO | ☐ YES |
| **5.** Does child live with his/her mother? | ☐ NO | ☐ YES |
| **6.** Does child live with his/her father? | ☐ NO | ☐ YES |

## Displacement and mobility

| ASK OF THE CHILD | | |
|---|---|---|
| **1.** Have you always lived in your current house? | ☐ NO | ☐ YES |
| a) If no, how many houses have you lived in before this one? | ___ houses | |
| ASK OF AN ADULT | | |
| **2.** Is the child a refugee? | ☐ NO | ☐ YES |
| **3.** Is the child an international migrant? | ☐ NO | ☐ YES |
| **4.** Is the child a national migrant? | ☐ NO | ☐ YES |
| **5.** Is the child an immigrant? | ☐ NO | ☐ YES |
| **6.** Is the child an internally displaced person? | ☐ NO | ☐ YES |