**METHODS**

**Data sources:** The data used in this visualization come from multiple sources. Most of these sources are publicly available. For sources that are not (yet) publicly available, we share the (aggregate) age distribution obtained from the survey or census data in \*.csv format, so that interested researchers can replicate our visualization.

*Household surveys:*

Data from household surveys come cross-national programs implemented by national statistical offices in partnership with international organizations. These programs have different focus, for example the Demographic and Health Surveys are traditionally focused on fertility, as well as maternal and child health (Corsi et al. 2012); the Living Standards Measurement Study is focused on poverty and household livelihood (Grosh and Glewwe 1998), whereas the Population-based HIV Impact Assessments are focused on progress towards HIV control milestones (Sachathep et al. 2021). For each of the countries included in this visualization, the data can be found at the following links (registration required):

* Demographic and Health Surveys (DHS): <https://dhsprogram.com/data/available-datasets.cfm>
* Living Standards Measurement Study (LSMS): <https://microdata.worldbank.org/index.php/catalog/lsms>
* Multiple Indicator Cluster Survey (MICS): <https://mics.unicef.org/surveys>
* Population-Based HIV Impact Assessment (PHIA): <https://phia-data.icap.columbia.edu/datasets>
* Performance, Monitoring and Accountability (PMA): <https://datalab.pmadata.org/>
* World Health Survey (WHS): <https://apps.who.int/healthinfo/systems/surveydata/index.php/catalog/whs>

In each of these surveys, we used datasets that documented the age of household members. These data were reported by a household informant (usually the head of household) for each member of the household. Specifically, the household informant was first asked to provide of all the usual members of the household; then he/she was asked a series of questions about each person listed, including their age in completed years. In the DHS, for example, the results from this interview with the household informant are stored in a dataset called the “household member recode”, and age data are stored in variable hv105.

*Household censuses:*

Household censuses are complete enumerations of a population, usually conducted every 10 years in most countries. They generate data on the age of every household member, by asking a household informant to provide this information. This follows a methodology that is largely similar to the methodology described above for household surveys.

Data from household censuses were predominantly downloaded from the international database of IPUMS (registration required): <https://international.ipums.org/international/>

Exceptions include:

* The 2021 Ghana census, for which the age distribution in single years was extracted from the volume 3B of the general report (table 5.1), available at: <https://census2021.statsghana.gov.gh/>
* The 2018 Malawi census, for which the age distribution in single years was extracted from table A5 in series A (Population tables), available at: <http://www.nsomalawi.mw/images/stories/data_on_line/demography/census_2018/2018%20MPHC%20Published%20Tables/Series%20A.%20Population%20Tables.xlsx>
* The 2019 Burkina-Faso census, for which the age distribution was available from the final report available at: <http://www.insd.bf/index.php/rgph-5>
* The 1998 Cote d’Ivoire census, for which the age distribution was obtained from table 3 on page 102 of volume IV, tome 1 of the general census report.

Data from the 2014 Cote d’Ivoire census could not be located, and are thus missing from the visualization. Age-disaggregated data from the 2021 Cote d’Ivoire census have not yet been released (raw population counts are available at: <https://www.ins.ci/>).

*Mobile phone surveys:*

MPS data analyzed in this visualization came from a variety of sources. In particular, we used data from two cross-country programs, the RECOVR program implemented by Innovations for Poverty Action (<https://www.poverty-action.org/recovr/recovr-survey>) and the Rapid Mortality Mobile Phone Surveys (RaMMPS) implemented by the London School of Hygiene and Tropical Medicine and a consortium of in-country partners (<https://www.lshtm.ac.uk/research/centres-projects-groups/rapid-mortality-mobile-phone-survey>).

We only included national mobile phone surveys, to ensure comparability with household surveys and censuses listed above. We also focused on mobile phone surveys that were constituted using random digit dialing (Glasser and Metzger 1972), i.e., a procedure to generate a random sample of mobile phone numbers in use in a country. Other MPS have been conducted that relied on existing lists of phone numbers generated during prior rounds of a longitudinal study (e.g., Banda et al. 2021; Quaife et al. 2020), or compiled by various organizations and administrations (Bamezai et al. 2021). In such MPS, age data might not have been ascertained remotely and thus would not reflect the impact of administering interviews by mobile phone on data quality.

Below, we list each data source and how to access it, by country:

* Burkina-Faso:
  + The 2018 MPS was part of the PMA program and study results are available elsewhere (Greenleaf et al. 2020). The dataset is available at: <https://datalab.pmadata.org/dataset/doi%3A1034976mcfq-rk60>
  + The 2020 MPS was part of the RECOVR program. Links to data description and data access are at:
    - Study description: <https://www.poverty-action.org/recovr-study/recovr-burkina-faso-tracking-effects-covid-19-pandemic>
    - Data download: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/BGHJYK>
  + The 2021 MPS was part of the RAMMPS project. The age distribution obtained in this survey was shared by study investigators and is included in the repository.
* Côte d’Ivoire:
  + The 2013 MPS was of a survey of mobile phone users focused on HIV knowledge. Methods and results of this survey have been published elsewhere (Larmarange et al. 2016). The age distribution obtained in this survey was shared by the study authors and is included in the repository.
  + The 2020 MPS was part of the RECOVR program. Links to data description and data access are at:
    - Study description: <https://www.poverty-action.org/recovr-study/recovr-c%C3%B4te-divoire-tracking-effects-covid-19-pandemic>
    - Data download: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/UJQPGD>

* Ghana:
  + The 2020 MPS was part of the RECOVR program. Links to data description and data access are at:
    - Study description: <https://www.poverty-action.org/recovr-study/recovr-ghana-tracking-effects-covid-19-pandemic>
    - Data download: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/QWLV0M>
* Malawi: in Malawi, all 3 MPS come from the RAMMPS program. Access to age data collected during these surveys was provided by RAMMPS investigators. Aggregate age distributions from each MPS are included in the repository.
  + The 2021-22 MPS comes from a randomized trial of the feasibility of mortality-related MPS (Chasukwa et al. 2022).
  + The first 2021 MPS comes from the RAMMPS implementation study.
  + The second 2021 MPS comes from a randomized trial of the impact of interview duration on study participation and data quality.
* Rwanda:
  + The 2015 MPS was a survey of phone users aimed at measuring poverty. Full results have been published elsewhere (Blumenstock, Cadamuro, and On 2015). The age distribution obtained in this survey was shared by study investigators and is included in the repository.
  + The 2020 MPS was part of the RECOVR program. Links to data description and data access are at:
    - Study description: <https://www.poverty-action.org/recovr-study/recovr-rwanda-tracking-effects-covid-19-pandemic>
    - Data download: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910/DVN/RTMVNO>
* Senegal:
  + The 2020 MPS was a study conducted by the Centre de Recherche pour le Développement Economique et Social (CRDES) and the Center for Global Development (CGDEV). Links to data description and data access are at:
    - Study description: <https://www.cgdev.org/blog/five-findings-new-phone-survey-senegal>
    - Data download: <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/9XE95F>

RAMMPS data in Burkina-Faso and Malawi are still being collected, so we used the subset of interviews conducted during the first 2 trimesters of the project in each country.

**Data analysis**

In each of the datasets listed above (i.e., household surveys, household censuses, and mobile phone surveys), we first computed the age distribution in single years. To do so, in household surveys, we applied sampling weights provided by survey programs. In census extracts obtained from the IPUMS international database (10% sample), we also applied similar weights. In census data obtained directly from national reports, we used the full count distribution without weights.

In MPS, survey data are often re-weighted using post-stratification techniques to match the distribution of several key variables observed in the census or other nationally-representative dataset. Such weights were not available for all MPS included in this study, so we used the unweighted data. For the datasets that included post-stratification weights, weighted and unweighted computations of the Whipple index yielded similar results, so we report estimates from the unweighted distribution.

We computed Whipple’s index as follow in each dataset:

where is the number of individuals at age (Ewbank 1981; Spoorenberg 2007)*.*

In the household surveys and censuses, the age distribution included all household members. This information was reported by a household informant, often the head of household, as described above. In MPS, on the other hand, the age distribution only included the information respondents provided about themselves (self-reports). All else being equal, we would thus expect age reports to be more precise in MPS since respondents are likely to be better informed about their own age than about the age of their household members.

We used the R software for all statistical analyses. To calculate Whipple’s index, we used the DemoTools package developed by Tim Riffe (<https://github.com/timriffe/DemoTools>). In particular, we used the check\_heaping\_whipple() function. Additional analyses that used the Myers blended index of age heaping yielded similar results.

**Data visualization**

We assembled a dataset that contained estimates of the Whipple index for household surveys and censuses, and MPS, in each country, along with the date of data collection. We then plotted the time-series of Whipple estimates for household surveys and censuses in each country. The shape of each data point was determined according to the program of data collection (e.g., DHS vs MICS vs Census).

We then estimated the conditional average of the Whipple index in household surveys and censuses for a specific year between 1990 and 2022, using local regression methods (Loess). In some countries, Loess estimates are not available for subsets of years at the beginning or end of this interval, e.g., if the first survey or census only occurred a few years after 1990 or before 2022 (e.g., Senegal). We did not attempt to extrapolate the trends in age heaping to these years without data. We also calculated the 95% confidence intervals associated with Loess estimates.

Finally, we added Whipple estimates from each MPS to that visualization, thus allowing an assessment of the differences in heaping levels between MPS and household surveys and censuses. To aid interpretations of age data quality, we divided the surface of the graph in different areas colored in shades of orange along values of the y-axis. These areas match a classification of Whipple estimates used by the United Nations and other researchers to evaluate and compare the accuracy of age data in different datasets (Pardeshi 2010):

* Accurate age data: Whipple < 110
* Approximate age data: Whipple in [110; 125[
* Rough age data: Whipple in [125; 175[
* Very rough age data: Whipple 175.

The data visualization was constructed using ggplot2 tools. In particular, we used the geom\_smooth() function to calculate and display Loess estimates. We used default span values (0.8) but similar results were obtained with larger (span = 1) or smaller (span = 0.6) values. We provide the dataset that contains all Whipple estimates, along with an R script that allows replicating the visualization.

**Limitations**

Our analyses have several limitations. First, they focus on a small number of LMICs, for which recent MPS data were available to the study team. The impact of mobile data collection on the accuracy of age data might be different in other settings. Second, our analyses compared age data about all household members collected from informants during household surveys and censuses to data self-reported data by survey respondents during MPS. Our comparison is thus biased in favor of MPS: since respondents should have better information about their own age, than about the age of their household members, we should expect lower levels of age heaping in self-reported data collected in MPS. Yet, we observe *more* heaping in MPS than in household surveys and censuses. The impact of this new mode of data collection on data quality might thus be larger than shown here. Third, our analyses of household surveys and censuses include the entire population, whereas MPS are limited to mobile phone users. This might also confound our comparison of heaping patterns, if these patterns are different in individuals who do not have access to mobile phone. However, the extent of age heaping might be higher in individuals who do not have access to mobile phones, for example, because they are often less educated. As a result, our comparison of heaping in household surveys and censuses vs. MPS is again biased in favor of MPS, and we should expect lower levels of heaping in MPS. Yet, our analyses documented the opposite pattern. Finally, our analyses only included MPS that were administered by interviewers; they did not include other forms of MPS, e.g., those administered by SMS or by interactive voice recording systems (Feng, Grépin, and Chunara 2018; Greenleaf et al. 2017). Such MPS are less common; they also often ascertain age only in broad age groups, e.g., younger than 18 vs. 18 years and older.

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