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Trends in Female Education in Low- and Middle-Income Countries: Coherence across Data Sources

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Abstract: Educational expansion and the closing of gender gaps in education are key objectives in national and international policy agendas. Monitoring progress towards these goals requires comparable data across countries and over time. The availability of international census and survey microdata allows for cross-national comparisons of education participation and completion. However, we lack systematic analyses of how trends vary across data sources and of the extent to which these data sources offer a consistent account of progress in education. In this paper, we examine coherence in estimates of educational attainment among women aged 25 to 29 in 75 countries across the three main repositories of international population microdata: IPUMS International, the Demographic and Health Surveys (DHS) and the Multiple Indicator Cluster Surveys (MICS). Coherence analysis of 535 census and survey observations from 1960 to 2017 shows high levels of consistency overall but also identifies observations misaligned with trends. Results provide practical information to the research community about the validity of comparative investigations using three important data sources for demographic studies. The data also serve as benchmarks for assessing the quality of education information obtained in data sources not included in our analysis and the trend alignment of future estimates.

Keywords: Educational expansion · Census microdata · DHS · MICS · Data coherence

1 Introduction

Education is widely recognised as a vehicle for individual agency, social change and economic growth. It is also considered an important policy instrument for development in many low- and middle-income countries (LMICs), where enrolment in primary and secondary schooling is not universal and gender disparities in education remain. As a result, national and international policy agendas include as

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key objectives expanded access to schooling and the closing of the gender gaps in education (see *United Nations* 2013; *UNICEF* 2019; *UNESCO* 2016, 2018). Monitoring progress towards these goals requires comparable data across countries and over time. The availability of international census and survey microdata allows for cross-national comparative assessments of education participation and completion. However, we lack systematic analyses of how trends in education vary across these data sources and of the extent to which these trends offer a consistent account of progress in education in recent decades. Do the multiple rounds of census and survey microdata available for LMICs provide a coherent picture of trends in educational expansion? Are there systematic differences across data sources? Which specific censuses or surveys stand apart from the trend presented by other census and survey observations in the country?

To answer these questions, we pooled individual-level data from 535 censuses and surveys from 75 low- and middle-income countries to monitor trends in educational attainment and examine coherence across data sources. The data cover 1960 to 2017 and come from three sources: population censuses from the IPUMS database, the Demographic and Health Surveys (DHS) and the Multiple Indicator Cluster Surveys (MICS).[1] All censuses available from IPUMS as well as all DHS and MICS surveys collect information on school attendance and educational attainment. We examine trends in educational attainment among females aged 25 to 29. While gender gaps in education have reversed in most high- and middle-income countries, women trail men in school enrolment and completion in many developing countries, particularly in sub-Saharan Africa and South Asia (*Ilie/Rose* 2016; *Kebede et al.* 2019). Accordingly, international policy agendas include specific targets to address gender disparities in education. We find strong coherence across data sources overall with heterogeneity by data source and region. Our results provide practical information to the research community about the validity of comparative investigations using the data sources we examine. Our analysis focuses on young women, but sensitivity analyses examining trends in male educational attainment yield similar results and conclusions.

2 Background

The contribution of basic education to economic growth is widely recognised (*Schultz* 1961; *Becker* 1994; *Barro/Lee* 1994; *Cohen/Soto* 2007). Its importance is not, however, confined to economic progress. Education has intrinsic positive effects for people and societies. Education imparts knowledge and skills that provide access to better paying jobs, alleviating poverty and increasing the availability of cultural and economic resources for households (*Becker* 1994). Highly educated

[1] To access international census data from IPUMS, visit international.ipums.org. DHS data are available for download from the DHS Program, dhsprogram.com, and IPUMS-DHS, idhsdata.org. MICS data are available for download at mics.unicef.org.

individuals tend to have better health and live longer lives (*Hannum/Buchmann* 2005; *Kc/Lentzner* 2010; *Lutz et al*. 2014; *Masquelier/Garbero* 2016). The children of highly educated parents are also more likely to have better health and cognitive outcomes (*Caldwell* 1981; *Cochrane et al.* 1982; *Lutz et al.* 2014; *Bicego/Boerma* 1993; *Rosenzweig/Wolpin* 1994; *Mellington/Cameron* 1999; *Wang* 2003; *Schady* 2011; *Abuya et al.* 2011; *Vikram et al.* 2012; *Grépin/Bharadwaj* 2015). Due to the link between female education and demographic outcomes, educational expansion has the potential to significantly influence population growth (*Lutz/Skirbekk* 2014). Based on this evidence, policymakers and development practitioners view access to and completion of education as key policy instruments for development in low- and middle-income countries. The United Nations 2030 Agenda for Sustainable Development includes educational expansion and gender parity in schooling as primary goals, challenging LMICs to ensure universal and equal access at all levels of education. Many of these countries trail high-income countries in quantitative and qualitative progress in education. Enrolment in primary and secondary education is far from universal and college graduates represent less than five percent of the population in much of sub-Saharan Africa (*UNESCO Institute for Statistics* 2019). Moreover, the expansion of primary, secondary and tertiary education has not been gender-neutral (*Grant/Behrman* 2010; *Dorius/Firebaugh* 2010; *Dorius* 2013; *UNESCO* 2019).

During the Millennium Development Goals (MDGs) era, countries with better performance monitoring made better progress towards targets (*Jacob* 2017). To track progress towards new education targets, accurate measures of school participation and completion are fundamental. Policymakers and researchers worldwide have traditionally relied on official reports and statistics from international agencies and some scholarly databases (*Barro/Lee* 2013, for example) to obtain macro level indicators on educational attainment. These statistics were compiled from censuses and surveys, resources for which microdata were rarely available to researchers. Only recently have researchers gained access to census and survey microdata from LMICs upon which to build new and large comparative analysis. These microdata come from three main sources: the IPUMS International database for population censuses and household surveys (*Minnesota Population Center* 2019), the Demographic Health Surveys Program (*ICF* 2004-2017) and the Multiple Indicators Cluster Surveys (*UNICEF* 2020).

Among these sources, censuses have served as the underlying source for global databases on educational attainment like those maintained by the United Nations. They also provide the benchmark observations for modelled estimates and projections of educational attainment produced and used by the scholarly community (*Barro/Lee* 2013; *Bauer et al.* 2012; *Cohen/Soto* 2007; *Kc et al.* 2010; *Lutz et al.* 2014; *De la Fuente/Doménech* 2012; *Jordá/Alonso* 2017). For many countries, especially LMICs, population censuses represent the only available source for educational data. Compared to surveys, censuses offer some advantages – most importantly universal coverage of the population – which contribute to reliable and consistent trends over time. However, in the best of cases, censuses are conducted every ten years. In low-resource and/or conflict settings, more than ten years may

elapse between censuses. Furthermore, access to census microdata has been limited until recent years. The IPUMS International project has simplified access to census microdata by collaborating with National Statistical Offices to compile, integrate and harmonise representative samples of census microdata from around the world. At the time of writing, harmonised microdata from more than 500 censuses and surveys and more than 100 countries were available to researchers free of charge through IPUMS International. Nearly every country in South and Central America disseminates microdata through IPUMS. Twenty-seven of 54 African countries disseminate data through IPUMS. Twenty-three of 60 low- and middle-income countries in Asia, the Middle East and the Pacific disseminate through IPUMS.

Prior to the publication of international census microdata through IPUMS international, cross-national research on the expansion and implications of education in LMICs mostly relied on surveys. Compared to censuses, surveys provide more timely data and cover a broader range of topics in greater depth. Data from two global survey programs are most frequently used to monitor development progress in LMICs: the Demographic and Health Surveys (DHS) and the Multiple Indicator Cluster Surveys (MICS). The Demographic and Health Surveys are nationally representative household surveys that collect data on a number of topics related to population, health and nutrition (*ICF* 2019). DHS surveys are conducted about every 5 years. Since 1984, more than 400 DHS surveys have been completed in over 90 countries in Africa, Latin America, Asia, Oceania and Eastern Europe. Data on literacy, school attendance and educational attainment are collected for all household members in every DHS survey. DHS surveys primarily target women in reproductive years and they have been the main source for large cross-national studies in trends in women's education and their influence on family transitions and health (e.g. *Castro Martín* 1995; *Lloyd* 2005; *Grant/Behrman* 2010).

A complement to DHS, the UNICEF MICS Surveys provide data on the wellbeing of women and children in LMICs. More than 300 surveys have been fielded in 116 countries covering the period 1993 to the present (*UNICEF* 2020). Most MICS surveys are also nationally representative and collect education information similar to that collected in DHS surveys. DHS and MICS are important sources for measuring progress towards the Sustainable Development Goals (SDGs). Likewise, the data are used extensively by social scientists and policy and health researchers to study a wide range of topics related to child health and wellbeing and human development (e.g. *Pace et al.* 2019; *Kang et al.* 2018; *Jeong et al.* 2018). DHS and MICS surveys use similar multi-stage cluster sampling strategies. Primary sampling units (PSU) typically correspond to census enumeration areas and are stratified by administrative regions and urban and rural areas before selection. A complete household listing is conducted in each selected PSU and households are selected for the survey by equal probability systematic sampling (*ICF International* 2012). This type of probability sampling relies on updated and reliable sampling frames. Censuses are considered the most suitable sampling frames for DHS and MICS surveys. For this reason, we expect strong coherence between census-based estimates and survey-based estimates. When a census has not been conducted recently, alternative sampling frames such as electoral rosters are used.

Used together, IPUMS, DHS and MICS constitute a vast repository of individual-level data for cross-national research on population dynamics, development and health in LMICs. Despite the nearly limitless potential of these data, cross-national studies combining census, DHS and MICS microdata are still rare because microdata for a critical mass of countries only became available in the last decade. This paper – a first attempt in this direction – examines the feasibility of combining these sources to examine trends in and implications of educational expansion. While the topical coverage and policy purposes of these data collection instruments differ, censuses and DHS and MICS surveys share basic features that make them suitable for large comparative studies. The collection of information on basic educational attainment is one of these common features. In theory, comparing educational attainment across countries and data sources should be straightforward. Most education systems are organised around three distinct levels: primary, secondary and tertiary. Systems within regions and among countries with shared colonial histories are usually quite similar. Moreover, the International Standard Classification of Education (ISCED) provides clear guidelines for measuring educational attainment in censuses, surveys and population registers. In practice, accurate comparisons across countries are difficult because the definition of educational levels varies significantly across countries.

Scholars considering education at the global level have grappled with comparability across data sources. In their work to produce population projections disaggregated by level of education, researchers at the Wittgenstein Centre for Demography and Global Human Capital have relied on microdata from censuses, DHS, MICS and other household surveys to construct global datasets on educational attainment (*Bauer et al.* 2012; *Goujon et al.* 2016; *Lutz et al*. 2014, 2018; *Speringer et al.* 2019). *Bauer et al.* (2012) and *Speringer* and *colleagues* (2019) document the comparability issues and harmonisation challenges encountered in the construction of the base-year datasets used across these education and population projections, including discrepancies between national education systems and ISCED categories, changes over time in national education systems, inconsistencies across data sources in the treatment of complete versus incomplete levels, age-heaping in survey data and a lack of detail at the lowest and highest levels of education in developed and developing countries, respectively. Results of validation exercises confirm that different data sources lead to different educational compositions and that census or register data are generally the most reliable. The few examples provided of discrepancies between DHS surveys and censuses and intra-country inconsistencies across DHS surveys support the need for further investigation of coherence across these important sources of population data.

This paper seeks to fill this gap by providing a systematic evaluation of trends in educational attainment across the three primary sources of demographic data in low- and middle-income countries: population censuses, Demographic and Health Surveys (DHS) and UNICEF Multiple Cluster Indicator Surveys (MICS). We aim to identify coherence and inconsistencies in the empirical measurement of education within and across data sources and to contribute to a better understanding of the validity of a critical independent variable in development research.

3 Data and Methodology

We use individual-level data from 210 IPUMS census samples,[2] 219 DHS surveys and 106 MICS surveys to assess coherence in the measurement of education across data sources in 75 low- and middle-income countries. For a robust picture of trends over time, we include in the analysis all countries with four or more censuses and/or surveys across two or more data sources. The data were collected during the period 1960 to 2017 and cover more than half of the 138 countries designated as low or middle income by the World Bank. A plurality of countries studied are represented in all three data sources: IPUMS, DHS and MICS (Table 1).

IPUMS census samples vary in size but typically include 10 percent of the population. Sample sizes for DHS and MICS surveys typically cover 20,000 to 50,000 households. See Table A1 in the appendix for analysis sample sizes. DHS and MICS data used in the analysis were collected in household questionnaires and come from corresponding household-member microdata files. DHS and MICS surveys collect basic demographic information on all usual residents and visitors in surveyed households via the household questionnaire. From these census and survey samples, we select women aged 25 to 29. In many low- and middle-income countries, women trail men in access to and completion of secondary education. Development agendas focus on confronting barriers to girls' schooling and require accurate information on female educational attainment. Women in this age range represent the population that recently completed formal education, more accurately reflecting the educational context in the country at the time of the survey compared to older cohorts. Coherence analysis based on men yield similar results.

Most IPUMS census samples and DHS and MICS surveys include retrospective questions on years of schooling and highest level of education attended and/or completed. Our analysis focuses on the population completing secondary and higher education. Existing literature suggests secondary education is an important threshold for individual outcomes and development (*Caldwell/McDonald* 1982; *Ainsworth et al.* 1996; *Desai/Alva* 1998; *Abuya et al.* 2012; *Makoka/Masibo* 2015).

Tab. 1: Number of analysis countries by data source and world region

	Africa	Asia	Europe	Latin Americ /Caribbean	Total
DHS, MICS, IPUMS	17	5	1	3	26
IPUMS, DHS	7	8	–	7	22
IPUMS, MICS	2	4	1	9	16
DHS, MICS	8	2	–	1	11
Total	34	19	2	20	75

Source: own design

[2] Certain microdata samples disseminated by IPUMS come from large-scale household surveys rather than censuses. See appendix for more information.

We generate a dichotomous educational attainment variable that distinguishes women who have completed secondary education or higher from those who have not. For census samples, we recode the IPUMS EDATTAIN variable. DHS survey data were accessed directly from the DHS Program and from IPUMS DHS. For DHS surveys, we use the educational attainment summary variable constructed by the DHS Program during data processing (hv109 or EDSUMM in IPUMS). The MICS datasets do not include a summary educational attainment variable. We construct a summary measure of educational attainment for MICS samples according to each country's educational system using variables indicating the highest education level attended and highest grade completed at level.

We calculate the percentage of women aged 25 to 29 who have completed secondary education for each census or survey, yielding 535 country-year observations in total. The mean number of census and survey observations among countries examined is 7.7. We use polynomial regression to fit trends over time in educational attainment within each country. More specifically, we have specified a second-degree polynomial (quadratic) regression model to account for the curvilinear nature of the relationship between female educational attainment and time. Previous studies of global educational expansion during the time period of interest identified a sigmoidal pattern in most countries, with initially slow growth, a phase of rapid expansion and then a slow approach towards universal participation (*Barakat/Durham* 2014). We explored both quadratic and cubic specifications, but found the quadratic model to provide the most parsimonious fit to the data for the developing countries included in our analysis, many of which have not yet reached the final phase of educational expansion.

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 Year^2 + \beta_2 Year + \varepsilon$$

In the model specified above, P is the proportion of women aged 25-29 completing secondary or higher education. Each observation of P is weighted by sample size. By doing this, we give more importance to census observation over DHS and MICS. Census microdata samples are usually drawn from complete-count census databases. Results derived from census samples are therefore extremely close to those derived from complete-count databases. We use the parameters estimated by the model to generate predicted values of P. We then compare observed and predicted values, calculating and summarising absolute differences between the two and classifying observations based on absolute deviance from the predicted trend. We disregarded the use of confidence intervals as samples vary greatly in size and large samples usually yield very narrow confidence intervals such that even a tiny deviation from that value represents an outlier. On the contrary, small sample sizes generate wider confidence intervals and relatively large deviations may fall within the interval.

4 Results

4.1 Observed trends in educational attainment

Figure 1 presents, by country and world region, estimates of the percent of women aged 25 to 29 completing upper secondary education or higher for the 75 countries included in our analysis (see also Table A1 in the appendix). Each line represents a country, showing change over time based on multiple data sources. The colour and shape of the symbol marking each point estimate indicates the data source: Census, DHS or MICS. This figure corroborates trends well-known to researchers and policymakers. Over the last several decades, there has been a general upward trend in all world regions in the proportion of young women completing at least secondary education in LMICs. The percentage of women aged 25 to 29 completing secondary education or higher has increased between the earliest census or survey observation and the most recent in nearly every country examined.

However, levels of secondary or higher completion vary widely across countries and regions. Educational attainment is lowest in Africa. Less than 10 percent of women aged 25 to 29 had completed secondary education according to the most recent census or survey in Burkina Faso, Burundi, Benin, Central African Republic, Chad, Ethiopia, Mali, Mozambique, Niger, Senegal and Togo. Levels of secondary completion are much higher in Latin America. Since 2010, in two-thirds of the Latin American countries studied, more than 50 percent of women complete secondary or higher. Levels of completion were highest in Cuba (2014) and Trinidad and Tobago (2011), where more than 80 percent of young women complete secondary or higher, and lowest in Haiti (2016) and Guatemala (2014), where less than 25 percent of young women complete secondary or higher. Recent levels of secondary completion vary within Asia, where the most heterogeneity is observed. Female educational attainment remains low in several of the Southern and Southeast Asian countries studied according to recent surveys. Less than 30 percent of women aged 25 to 29 had completed secondary or higher in Cambodia (2014), Bangladesh (2014), Laos (2017), India (2015) and Pakistan (2012). In contrast, educational attainment is high in Central Asia and Eastern Europe: more than 95 percent of women aged 25 to 29 complete secondary education or higher in Armenia, Belarus, Kazakhstan, Kyrgyz Republic and Ukraine according to recent surveys.

The rate of increase in secondary completion in LMICs during the last several decades also varies across countries and regions, as reflected in the variation in the slope of country trend lines in Figure 1. Change has been slowest in Africa, where the median annual increase in the percentage of women aged 25 to 29 completing secondary or higher among the countries examined is 0.43 percentage points. By comparison, the median annual increase in the percentage of women aged 25 to 29 completing secondary or higher is 0.66 percentage points among Asian countries examined is 1.1 percentage points among Latin American countries studied.

The dominant trend of increasing female educational attainment over time and the relative levels of educational attainment we observe in recent censuses and surveys reflect what we understand about access to education across and

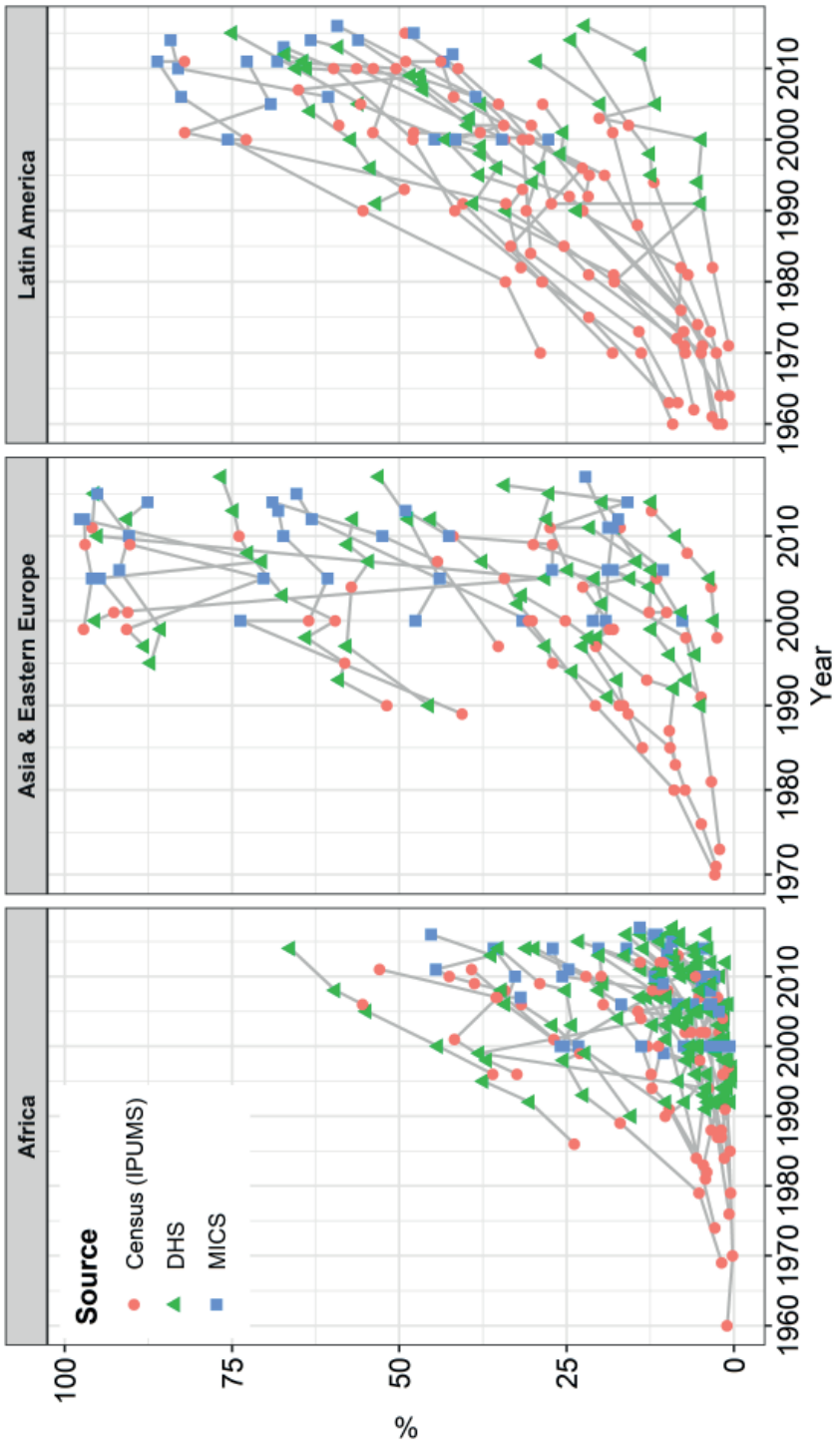


Fig. 1: Percent of women aged 25-29 completing secondary education or higher by year, country, data source and world region

Source: own design

within world regions. A closer look at country-specific patterns, however, reveals inconsistencies within and across data sources, even among observations that are only a few years apart. We do not expect that educational expansion is linear in all countries. This expectation is reflected in the data. In some countries, secondary or higher completion has expanded more rapidly in recent decades and we see this trend reflect in a J-shaped curve for many countries. In other countries, educational attainment increased rapidly during the MDG era but has slowed in recent years as countries approach universal secondary participation. This trend is reflected in an inverse J-shaped curve. We do, however, expect that in most countries educational attainment among young women will always be non-decreasing. As clearly visible in Figure 1, this is not the case. In 49 of 75 countries examined, at least one point estimate of secondary completion among women aged 25 to 29 is lower than the previous point estimate. In 11 countries, we observe a decline of 10 percentage points or more between adjacent point estimates.

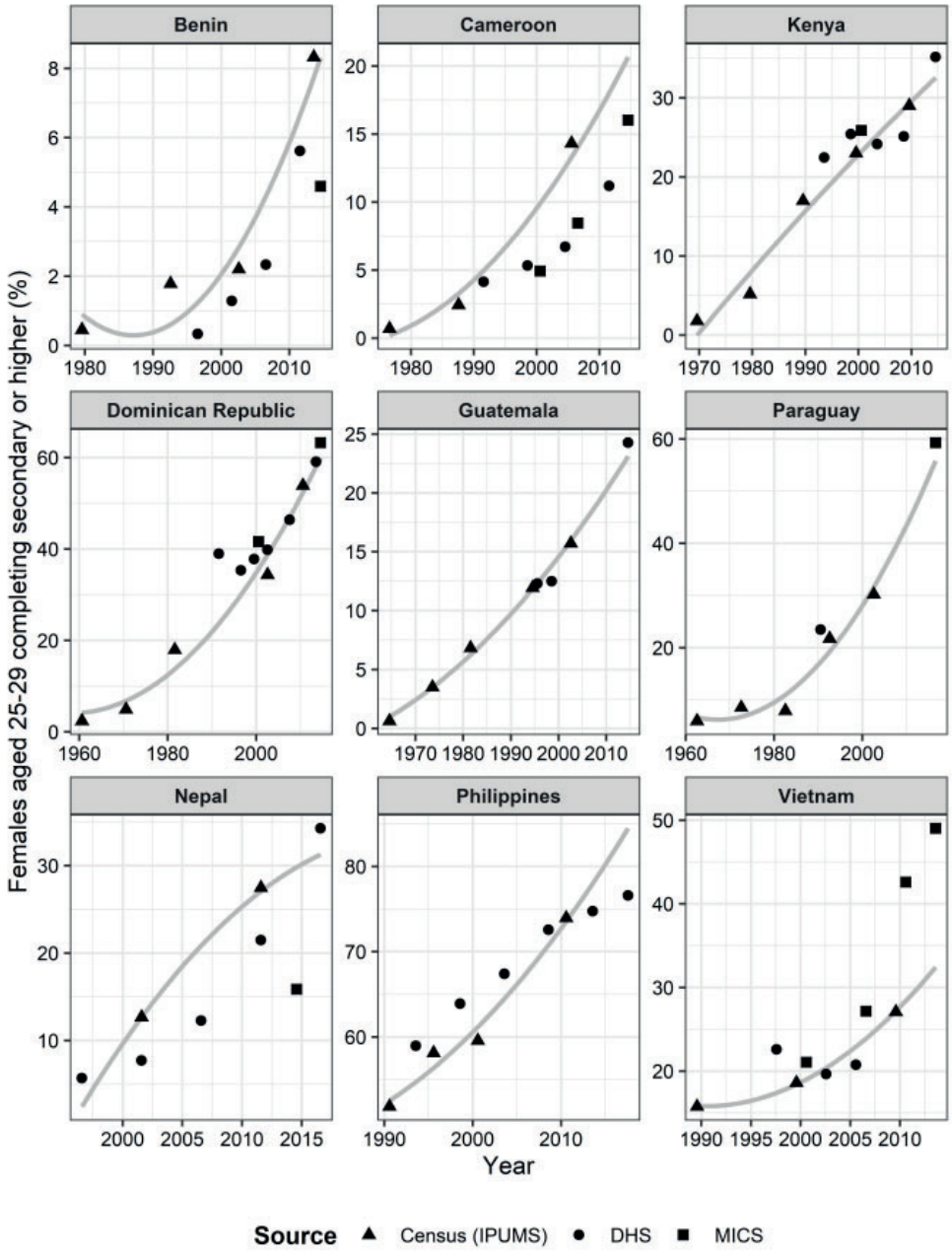
4.2 Generating new trends: country examples

To address incoherent trends over time, we calculate adjusted estimates of female educational attainment. Providing adjusted estimates poses some challenges. The application of inferential models to correct biases due to poor data quality and to fill in missing values are commonplace in international research databases (*Bauer et al.* 2012; *Barro/Lee* 2013; *Cohen/Soto* 2007; *Kc et al.* 2010; *De la Fuente/Doménech* 2012; *Jordá/Alonso* 2017) and not only for data on education but also for databases measuring mortality, fertility and various economic indicators. The variety of methods used to carry out these estimations makes it difficult to pool or compare data across sources. A parsimonious yet efficient approach is to infer trends from as many observations as possible within a country. Thanks to the availability of international census and survey microdata, we can now perform such an analysis. In our analysis, we use weighted regression to infer trends in educational expansion based on observations from the same country.

Figure 2 presents observed point estimates of educational attainment among young females for nine illustrative countries. For each of these countries, at least 8 observations from censuses, DHS surveys and/or MICS surveys are available. All nine countries experienced an increase in the proportion of females aged 25 to 29 completing secondary education or higher between the earliest and most recent census or survey observations, but no country experienced a monotonic increase during the observed period. In Benin, for example, 1.8 percent of females aged 25 to 29 had completed secondary or higher according to the 1992 census but only 0.3 percent of females aged 25 to 29 had completed secondary or higher according to the 1996 DHS survey. In Nepal, 27.5 percent of females aged 25 to 29 had completed secondary or higher according to the 2011 census, but only 15.9 percent in 2014 according to that year's MICS survey.

To identify which and to what extent observations diverge from overall country-level trends, we specify polynomial regression models for each country that estimate the best-fitting trend line according to the survey and census observations, weighted

Fig. 2: Percent of women aged 25-29 completing secondary education or higher in nine countries



Source: own design

by sample size. As the dependent variable, we use the logit of the proportion of women aged 25 to 29 with secondary or more education (ln(P/1-P)) to account for non-linearity in educational expansion. The grey regression line in each country graph depicts the fitted relationship between time and the percent of females aged 25 to 29 completing secondary or higher. By design, regression lines favour census observations, which are based on sample sizes much larger than those provided by DHS and MICS surveys. We use regression parameters to produce predicted values of the percentage of females aged 25 to 29 completing secondary education or higher that align with expected trends (results in Appendix 1).

4.3 Adjusted trends

Figure 3 plots predicted values of educational attainment among young females for all countries studied. Adjusted data show a monotonically increasing pattern of educational expansion in nearly every country. The few exceptions might reflect actual population trends or lack of observations, in particular from censuses. To assess coherence in the measurement of female educational attainment across censuses, DHS surveys and MICS surveys, we produced Figure 4 and Table 2. Figure 4 plots observed and predicted values of the percentage of women aged 25 to 29 completing secondary education or higher for all countries studied. Table 2 summarises the absolute difference between observed and predicted values by data source, region and time period. Overall, coherence across data sources is strong: the mean absolute difference between observed and predicted values is 2.2 percentage points. Of 535 census and survey observations, two-thirds deviate from expected trends by less than two percentage points. Only 11 percent of observations deviate from expected trends by five or more percentage points. The difference between observed and predicted values is 10 or more in 19 of 535 observations (labelled in Fig. 4). As expected, census-based estimates deviate least from expected trends. At the global level, predicted values for DHS-based estimates deviate from observed values by 2.7 percentage points on average compared to 3.2 percentage points for MICS-based estimates. MICS and DHS are similar in terms of the number of observations diverging from predicted estimates by 0 to 2 percentage points, but the plurality of observations with large deviations – 10 percentage points or more – are derived from MICS data. In relative terms, the percent of observations deviating more than 10 percentage points from predicted values for MICS is more than twice (8.5 percent) the number than for DHS (3.2 percent).

In terms of regional differences, Africa, Asia and Eastern Europe show the highest levels of conformity between observed and expected patterns and across data sources. In Africa, nearly 80 percent of observed point estimates deviate from predicted values by less than 2 percentage points. The share of African observations that diverge 10 or more percentage points is 2 percent or less for all data sources. Compared to MICS-based observations in other regions, MICS surveys in Africa are more in line with expected country trends. In Asia, 70 percent of observations fall within the minimum deviation category (0 to 2 percentage points). MICS surveys in Asia show higher levels of deviation than DHS surveys

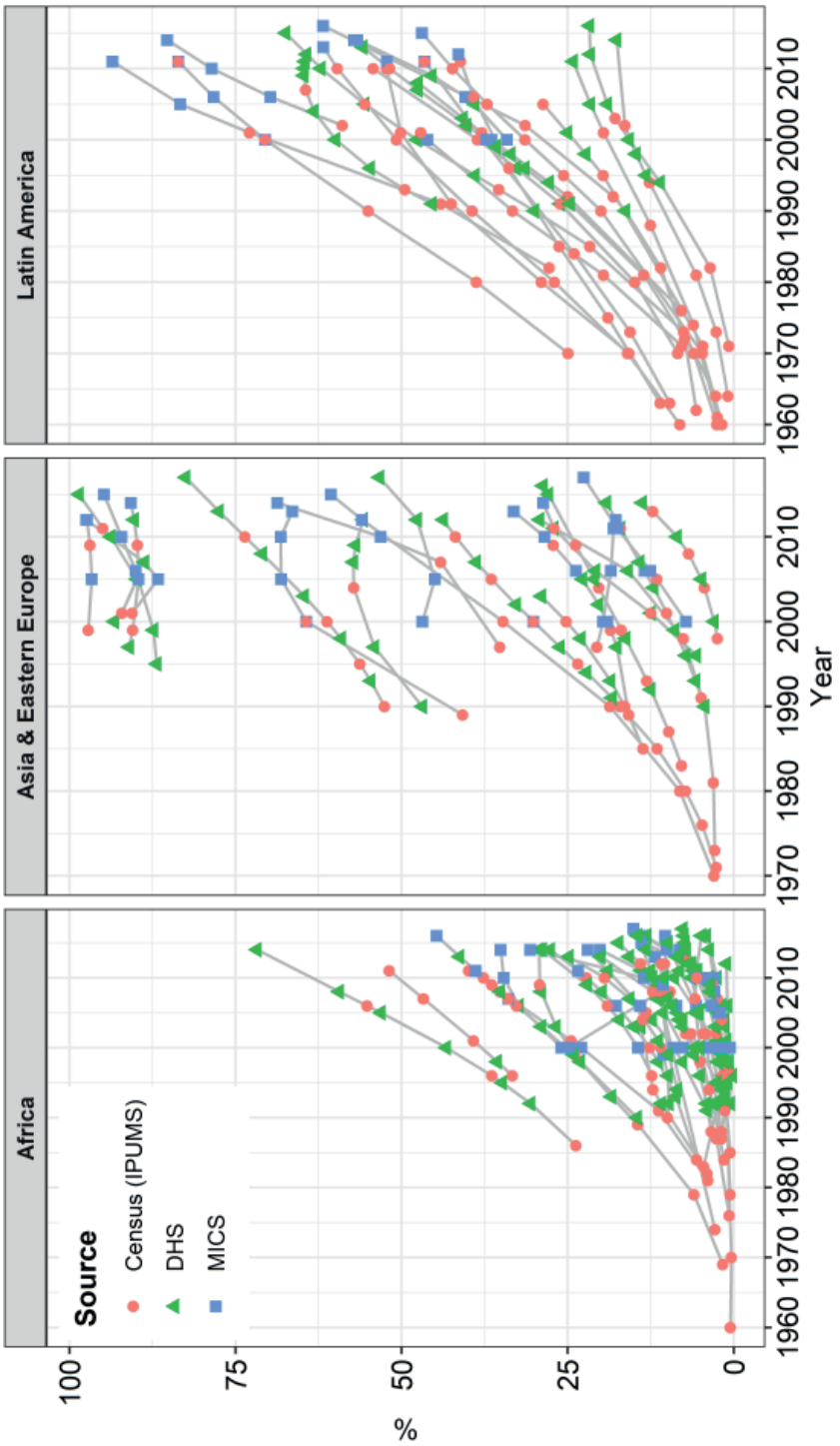
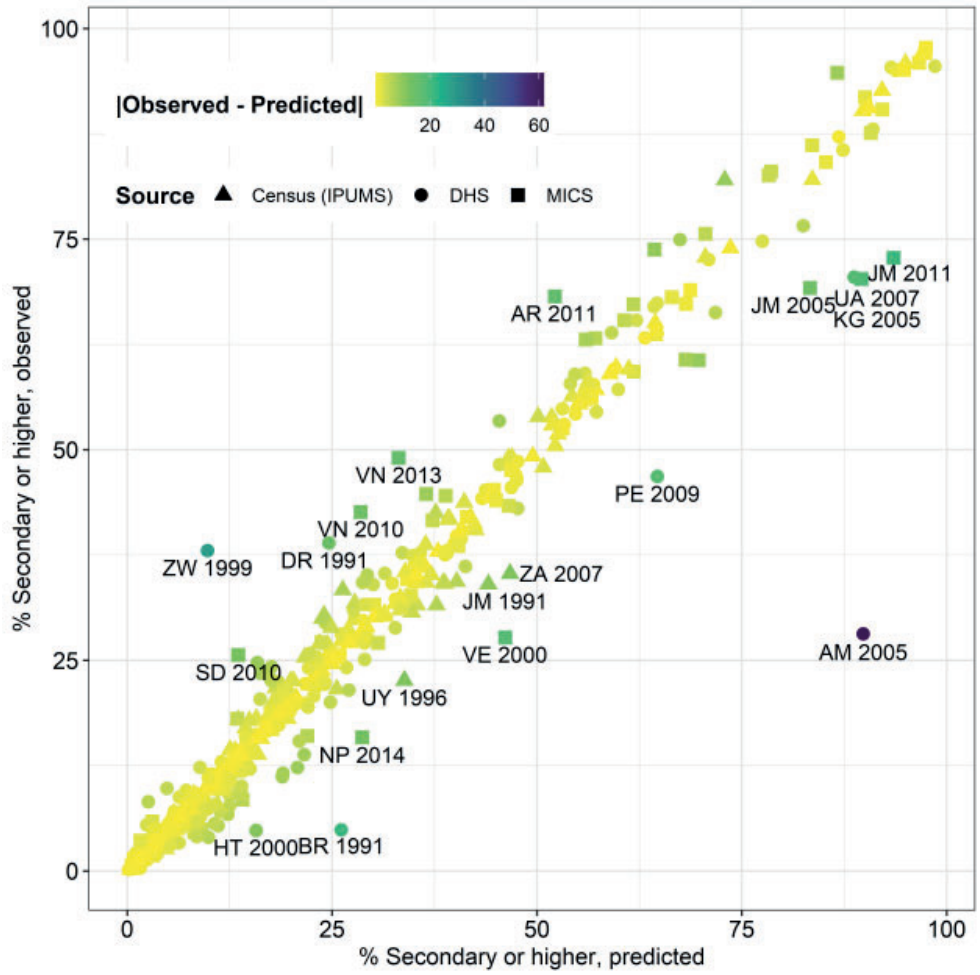


Fig. 3: Predicted percent of women aged 25-29 completing secondary education or higher by year, country, data source and world region

Source: own design

Fig. 4: Percent of women aged 25 to 29 completing secondary or higher, observed versus predicted values



Source: own design

in the region. Finally, coherence across data sources in Latin America are lowest than in other regions. More than half of all survey and census observations from the region deviate from predicted values by 2 or more percentage points. Results for Latin America are influenced by the predominance of census samples for the region compared to surveys. There are three times as many census samples as DHS surveys and four times as many census samples than MICS surveys available for Latin America. The relative quantity of large census samples means the model demands higher precision from both census and survey observations for most Latin American countries. Accordingly, survey observations perform particularly poorly

Tab. 2: Distribution of samples based on the gap between the observed and predicted percentages of women aged 25-29 with secondary or more

	Gap between observed and predicted values				
	0-1.9	2-4.9	5-9.9	10+	N
All Countries	67.9	20.7	7.9	3.6	535
Census (IPUMS)	76.2	19.5	2.9	1.4	210
DHS	61.6	24.2	11.0	3.2	219
MICS	64.2	16.0	11.3	8.5	106
Africa	79.1	14.8	4.9	1.2	244
Census (IPUMS)	91.7	6.9	0.0	1.4	72
DHS	71.9	19.8	7.4	1	121
MICS	78.4	13.7	5.9	2.0	51
Asia & Eastern Europe	69.9	17.8	8.2	4.1	146
Census (IPUMS)	87.3	10.9	1.8	0.0	55
DHS	56.1	28.1	12.3	3.5	57
MICS	64.7	11.8	11.8	11.8	34
Latin America	46.9	33.8	12.4	6.9	145
Census (IPUMS)	55.4	36.1	6.0	2.4	83
DHS	39.0	31.7	19.5	9.8	41
MICS	28.6	28.6	23.8	19.0	21
2000 or earlier	68.3	23.8	5.0	2.9	240
Census (IPUMS)	75.4	20.8	2.3	1.5	130
DHS	54.9	32.9	7.3	4.9	82
MICS	75	10.7	10.7	3.6	28
2001 or later	67.5	18.3	10.2	4.1	295
Census (IPUMS)	77.5	17.5	3.8	1.3	80
DHS	65.7	19	13.1	2.2	137
MICS	60.3	17.9	11.5	10.3	78

Samples are classified by data source, region, and time period.

Source: own design

in the region. Thirty percent of DHS observations and more than 40 percent of MICS observations deviate from predicted values by 5 percentage points or more.

Our results do not reveal significant differences in the coherence of observations from the year 2000 or earlier compared to observations after 2000. We also considered the temporal proximity of surveys to censuses. There is no discernible relationship between the number of years elapsed since the previous census and the magnitude of the difference between observed and predicted values for survey observations (Pearson correlation coefficient = -0.06).

5 Conclusion and Discussion

Improved access to census and survey microdata for LMICs has opened new opportunities for large-scale comparative investigations based on multiple sources of data. Used together, these data sources provide more comprehensive temporal and geographic coverage than any single source used in isolation. Yet this type of comparative work is still rare in socio-demographic analysis. Researchers tend to work with a single data source, shying away from the challenges of harmonisation and coherence across sources. In this paper, we challenge perceived limitations of cross-national research to examine the measurement of educational expansion across data sources. Literature from a variety of disciplines documents the role of education in personal and social development. Many studies considering this relationship use data from a single country; those studies that do offer a cross-national perspective typically use only one of the three data sources utilised in this paper: censuses, DHS or MICS. As a result, our understanding of the links between education and individual, household and societal outcomes has been informed by studies using different datasets. Whether these datasets yield similar results was previously unknown. To address this gap, we carried out a simple coherence exercise to measure the consistency of trends in female educational expansion across data sources. We focus on women aged 25 to 29 completing secondary education because gender gaps persist in post-primary education in many LMICs. Analyses of men and other categories of educational attainment produced similar results.

We pooled nearly 20 million individual-level observations from 535 censuses and surveys and 75 countries from IPUMS, DHS and MICS. To maximise comparability across data sources, we use a dichotomous measure of education to identify females completing upper secondary education or higher. These data confirm previously observed patterns of educational expansion: Access to education is increasing in all regions, but levels of educational attainment among young women remain low in the majority of LMICs. Less than half of women aged 25 to 29 had completed secondary education or higher in the most recent survey or census available in 51 of 75 countries studied. Our coherence analysis, however, shows that the general upward trend in educational attainment among young females conceals erratic trajectories in the majority of countries studied. Our model smooths these trajectories. To assess the accuracy of each point estimate, we compared observed estimates to predicted values. Overall, coherence across data sources is high. Two-thirds of observed point estimates differ from predicted point estimates by two or fewer percentage points. Still, thirty percent of observed point estimates diverge from predicted values by two or more percentage points. Censuses perform better than DHS and MICS. Coherence across data sources is strongest in Africa. Coherence across data sources is lowest in Latin America, where nearly 20 percent of observed point estimates deviate from predicted values by 5 or more percentage points.

Discrepancies across data sources may originate during survey design, data collection and/or data processing. While DHS and MICS use similar sampling

strategies and typically rely on recent censuses as sampling frames, practices vary across countries to adapt to national circumstances. In cases where surveys are fielded soon after the most recent national census, an updated census-based sampling frame may not yet be available, producing discrepancies between data sources even when collected during the same year. For example, in Nepal, the 2001 DHS survey uses the 1991 census as its sampling frame and 2011 DHS survey uses the 2001 census (though there was a census fielded in 2011). This may explain gaps between DHS- and census-based estimates for these years in Nepal (see Fig. 2). Non-response and other non-sampling errors occur in both censuses and surveys, but there may be systematic differences by data source. For example, refusal to participate may contribute more to non-response for surveys than for censuses, which are obligatory or well-promoted in many countries. Likewise, depending on the cultural context, the reporting of educational attainment among female household members might vary depending on the characteristics of interviewers and perceived use of collected information, which is likely to differ by data source. As indicated in previous studies (*Bauer et al.* 2012; *Speringer et al.* 2019), discrepancies related to data processing are particularly likely with education data due to varied treatment of complete versus incomplete levels of education. In countries where secondary completion rates are still low, the distinction between secondary attendance and completion may not be reported or recorded consistently across sources. Our results identify the countries for which further investigation of these sources of discrepancies may be required for analyses that combine census and survey data.

Results presented here have other practical applications. Adjusted estimates of the percent of women aged 25 to 29 completing at least secondary education can be used in a variety of demographic and economic investigations. The data also serve as benchmarks for assessing the accuracy of estimates reported in international databases, the trend alignment of future DHS, MICS and census-based estimates and the quality of education information obtained in other sources not included in our analysis such as household surveys with small sample sizes. In future research, we will evaluate consistency across data sources based on other dimensions captured in censuses and household surveys such as demographic composition of the population, family structure and living arrangements. When data are scarce, as is the case for many LMICs, pooling data resources can be a useful strategy. Still, in the interest of reliable empirical evidence for policymaking, we should not take the coherence of data within and across sources for granted. Our analysis provides empirical validity for most analyses that combine census, DHS and MICS and identifies survey and census samples that should be used with caution.

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Appendix

Tab. A1: Percent of women aged 25-29 completing secondary education or higher (P) by country, year and data source: observed and predicted values

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Argentina					
1970	Census (IPUMS)	18.10	15.76	2.34	17162
1980	Census (IPUMS)	28.58	28.94	0.36	100336
1991	Census (IPUMS)	40.47	42.52	2.05	153473
2001	Census (IPUMS)	53.92	50.14	3.78	136778
2010	Census (IPUMS)	50.47	52.24	1.77	156901
2011	MICS	68.20	52.20	16.00	3317
Armenia					
2000	DHS	95.39	93.24	2.15	849
2001	Census (IPUMS)	92.63	92.10	0.53	11471
2005	DHS	28.13	89.83	61.70	953
2010	DHS	95.02	93.79	1.23	943
2011	Census (IPUMS)	95.87	94.98	0.89	13888
2015	DHS	95.51	98.57	3.06	1111
Bangladesh					
1991	Census (IPUMS)	4.89	4.89	0	471616
1993	DHS	7.08	5.75	1.33	2208
1996	DHS	9.56	7.22	2.34	2166
1999	DHS	12.28	8.89	3.39	2371
2001	Census (IPUMS)	10.03	10.10	0.07	602539
2004	DHS	12.55	12.06	0.49	2303
2006	MICS	18.06	13.44	4.62	12378
2007	DHS	14.49	14.14	0.35	2252
2011	DHS	17.67	17.01	0.66	3851
2011	Census (IPUMS)	16.96	17.01	0.05	362601
2012	MICS	17.27	17.74	0.47	10765
2014	DHS	19.57	19.16	0.41	3771
Belarus					
1999	Census (IPUMS)	97.16	97.16	0	34310
2005	MICS	95.93	96.64	0.71	1252
2009	Census (IPUMS)	96.94	96.91	0.03	36923
2012	MICS	97.08	97.38	0.30	1358

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Benin					
1979	Census (IPUMS)	0.45	0.52	0.07	15000
1992	Census (IPUMS)	1.78	1.18	0.60	21115
1996	DHS	0.33	1.59	1.26	1092
2001	DHS	1.28	2.41	1.13	1314
2002	Census (IPUMS)	2.20	2.63	0.43	29520
2006	DHS	2.33	3.77	1.44	4079
2011	DHS	5.61	6.08	0.47	3417
2013	Census (IPUMS)	8.32	7.42	0.90	42883
2014	MICS	4.59	8.20	3.61	2859
Bolivia					
1976	Census (IPUMS)	7.91	7.88	0.03	17702
1992	Census (IPUMS)	24.56	24.98	0.42	24420
1994	DHS	29.98	27.79	2.19	1496
1998	DHS	37.75	33.57	4.18	1834
2000	MICS	44.74	36.48	8.26	771
2001	Census (IPUMS)	37.91	37.92	0.01	31187
2003	DHS	39.42	40.77	1.35	2877
2008	DHS	46.69	47.52	0.83	2928
Botswana					
1981	Census (IPUMS)	4.21	3.88	0.33	3696
1991	Census (IPUMS)	9.67	11.30	1.63	5470
2000	MICS	23.22	22.96	0.26	1188
2001	Census (IPUMS)	26.86	24.47	2.39	7424
2011	Census (IPUMS)	39.18	39.90	0.72	10408
Brazil					
1970	Census (IPUMS)	7.25	8.43	1.18	175630
1980	Census (IPUMS)	17.83	14.89	2.94	242723
1991	DHS	4.87	26.12	21.25	1108
1991	Census (IPUMS)	27.25	26.12	1.13	362413
1996	DHS	28.84	32.73	3.89	2291
2000	Census (IPUMS)	34.21	38.57	4.36	407987
2010	Census (IPUMS)	56.35	54.27	2.08	416354

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Burkina Faso					
1985	Census (IPUMS)	0.54	0.53	0.01	33016
1993	DHS	1.25	1.28	0.03	1296
1996	Census (IPUMS)	1.62	1.67	0.05	38956
1998	DHS	1.41	1.95	0.54	1171
2003	DHS	2.23	2.71	0.48	2145
2006	MICS	1.81	3.16	1.35	1451
2006	Census (IPUMS)	3.40	3.16	0.24	56225
2010	DHS	2.01	3.68	1.67	3064
Burundi					
2000	MICS	3.63	3.16	0.47	721
2005	MICS	1.96	2.38	0.42	1501
2010	DHS	2.94	2.51	0.43	1689
2016	DHS	4.02	4.12	0.10	3023
Cambodia					
1998	Census (IPUMS)	2.48	2.46	0.02	45814
2000	DHS	2.98	2.96	0.02	2193
2004	Survey[3] (IPUMS)	3.37	4.40	1.03	2990
2005	DHS	3.58	4.89	1.31	2320
2008	Survey[3] (IPUMS)	6.96	6.80	0.16	62643
2010	DHS	8.60	8.56	0.04	3396
2013	Census (IPUMS)	12.29	12.21	0.08	6015
2014	DHS	12.28	13.77	1.49	3111
Cameroon					
1976	Census (IPUMS)	0.69	0.66	0.03	27308
1987	Census (IPUMS)	2.43	2.60	0.17	34447
1991	DHS	4.14	3.99	0.15	754
1998	DHS	5.33	7.71	2.38	1033
2000	MICS	4.92	9.10	4.18	975
2004	DHS	6.70	12.29	5.59	1933
2005	Census (IPUMS)	14.31	13.17	1.14	72900
2006	MICS	8.45	14.08	5.63	1595
2011	DHS	11.18	18.94	7.76	2859
2014	MICS	16.02	22.00	5.98	1854

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Central African Rep.					
1994	DHS	1.72	1.77	0.05	1098
2000	MICS	2.39	2.32	0.07	3255
2006	MICS	3.16	3.34	0.18	2257
2010	MICS	4.62	4.51	0.11	2290
Chad					
1996	DHS	0.17	0.18	0.01	1480
2000	MICS	0.62	0.56	0.06	1130
2004	DHS	1.34	1.33	0.01	1179
2010	MICS	2.88	2.99	0.11	3305
2014	DHS	3.76	3.69	0.07	3579
Colombia					
1964	Census (IPUMS)	2.05	2.72	0.67	12319
1973	Census (IPUMS)	7.48	7.55	0.07	70229
1985	Census (IPUMS)	25.36	21.66	3.70	122574
1990	DHS	33.99	30.00	3.99	1786
1993	Census (IPUMS)	31.57	35.35	3.78	152653
1995	DHS	37.99	38.94	0.95	2045
2000	DHS	43.02	47.67	4.65	1919
2005	DHS	56.03	55.52	0.51	6363
2005	Census (IPUMS)	55.75	55.52	0.23	153211
2010	DHS	65.37	62.15	3.22	8165
2015	DHS	74.93	67.46	7.47	6322
Congo					
2005	DHS	8.47	8.49	0.02	1399
2009	DHS	11.55	11.36	0.19	1237
2011	DHS	13.80	13.94	0.14	2101
2014	MICS	20.20	20.14	0.06	1926
Congo DR					
2000	MICS	7.53	7.64	0.11	2188
2007	DHS	12.96	11.50	1.46	1782
2010	MICS	11.86	13.50	1.64	2299
2013	DHS	16.20	15.71	0.49	3590

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Costa Rica					
1963	Census (IPUMS)	8.34	9.65	1.31	2641
1973	Census (IPUMS)	14.16	15.60	1.44	6271
1984	Census (IPUMS)	30.36	24.00	6.36	10629
2000	Census (IPUMS)	31.57	37.75	6.18	15029
2011	MICS	43.35	46.54	3.19	985
2011	Census (IPUMS)	49.01	46.54	2.47	19652
Cote d'Ivoire					
1994	DHS	0.86	1.37	0.51	1534
1998	DHS	5.46	2.40	3.06	569
2000	MICS	5.87	3.07	2.80	1926
2005	DHS	3.63	5.18	1.55	1067
2006	MICS	3.83	5.66	1.83	2268
2011	DHS	8.12	8.15	0.03	2123
2016	MICS	11.46	10.34	1.12	2325
Cuba					
2002	Census (IPUMS)	59.00	58.91	0.09	43868
2006	MICS	60.62	69.74	9.12	1274
2010	MICS	83.03	78.59	4.44	1791
2014	MICS	84.15	85.28	1.13	1961
Dominican Republic					
1960	Census (IPUMS)	2.37	2.55	0.18	7222
1970	Census (IPUMS)	4.88	6.01	1.13	9222
1981	Census (IPUMS)	17.92	13.53	4.39	17021
1991	DHS	38.93	24.62	14.31	1424
1996	DHS	35.32	31.44	3.88	1564
1999	DHS	37.75	35.78	1.97	224
2000	MICS	41.60	37.25	4.35	653
2002	Census (IPUMS)	34.35	40.21	5.86	35614
2002	DHS	39.78	40.21	0.43	3894
2007	DHS	46.35	47.54	1.19	4434
2010	Census (IPUMS)	53.86	51.79	2.07	38209
2013	DHS	59.06	55.85	3.21	1474
2014	MICS	63.22	57.15	6.07	5545

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Egypt					
1986	Census (IPUMS)	23.83	23.76	0.07	261427
1992	DHS	30.48	30.58	0.10	2419
1995	DHS	37.42	34.85	2.57	3293
1996	Census (IPUMS)	36.03	36.41	0.38	226212
2000	DHS	44.21	43.29	0.92	3424
2005	DHS	54.86	53.11	1.75	4658
2006	Census (IPUMS)	55.44	55.19	0.25	323772
2008	DHS	59.54	59.39	0.15	4029
2014	DHS	66.28	71.79	5.51	5593
Eswatini					
2000	MICS	25.62	25.94	0.32	882
2006	DHS	34.12	32.33	1.79	809
2010	MICS	32.68	34.63	1.95	897
2014	MICS	35.91	35.11	0.80	803
Ethiopia					
1984	Census (IPUMS)	1.41	1.44	0.03	117671
1994	Census (IPUMS)	3.81	3.70	0.11	192189
2000	DHS	5.21	5.08	0.13	2907
2005	DHS	5.94	5.74	0.20	2791
2007	Census (IPUMS)	5.20	5.82	0.62	55486
2011	DHS	6.59	5.65	0.94	3490
2016	DHS	9.79	4.86	4.93	3185
Ghana					
1984	Census (IPUMS)	5.60	5.58	0.02	54221
1993	DHS	4.43	8.72	4.29	903
1998	DHS	7.03	11.38	4.35	940
2000	Census (IPUMS)	12.92	12.69	0.23	78720
2003	DHS	12.09	14.99	2.90	1058
2006	MICS	16.81	17.73	0.92	1019
2008	DHS	20.18	19.83	0.35	1968
2010	Census (IPUMS)	22.06	22.17	0.11	110632
2011	MICS	24.68	23.44	1.24	1701
2014	DHS	30.98	27.64	3.34	1678

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Guatemala					
1964	Census (IPUMS)	0.63	0.88	0.25	7460
1973	Census (IPUMS)	3.50	2.64	0.86	10147
1981	Census (IPUMS)	6.83	5.65	1.18	11083
1994	Census (IPUMS)	11.94	12.69	0.75	29376
1995	DHS	12.30	13.22	0.92	1947
1998	DHS	12.49	14.72	2.23	1026
2002	Census (IPUMS)	15.70	16.35	0.65	41847
2014	DHS	24.25	17.61	6.64	4206
Guinea					
1983	Census (IPUMS)	4.53	4.52	0.01	20630
1996	Census (IPUMS)	1.52	1.54	0.02	31379
1999	DHS	2.44	1.60	0.84	1383
2005	DHS	1.75	2.38	0.63	1332
2012	DHS	8.77	6.37	2.40	1677
2016	MICS	11.94	13.79	1.85	1964
Guyana					
2000	MICS	34.65	34.16	0.49	814
2005	DHS	37.73	39.02	1.29	418
2006	MICS	38.59	40.41	1.82	769
2009	DHS	48.24	45.46	2.78	763
2014	MICS	56.12	56.66	0.54	976
Haiti					
1971	Census (IPUMS)	0.76	0.74	0.02	16771
1982	Census (IPUMS)	3.17	3.56	0.39	6648
1994	DHS	5.37	11.10	5.73	902
2000	DHS	4.80	15.73	10.93	1589
2003	Census (IPUMS)	20.08	17.81	2.27	36205
2005	DHS	11.59	19.02	7.43	1769
2012	DHS	13.80	21.60	7.80	2403
2016	DHS	22.22	21.72	0.50	2256

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Honduras					
1961	Census (IPUMS)	3.21	2.44	0.77	700
1974	Census (IPUMS)	5.40	6.08	0.68	9166
1988	Census (IPUMS)	14.39	12.54	1.85	15661
2001	Census (IPUMS)	18.07	19.58	1.51	22690
2005	DHS	19.91	21.58	1.67	3566
2011	DHS	29.42	24.17	5.25	3981
India					
1983	Survey[4] (IPUMS)	8.72	7.86	0.86	24520
1987	Survey[4] (IPUMS)	9.64	9.77	0.13	27059
1992	DHS	8.92	12.51	3.59	22344
1993	Survey[4] (IPUMS)	13.01	13.10	0.09	23612
1998	DHS	20.38	16.24	4.14	22949
1999	Survey[4] (IPUMS)	17.98	16.90	1.08	24926
2004	Survey[4] (IPUMS)	22.54	20.30	2.24	24527
2005	DHS	15.39	20.99	5.60	23759
2009	Survey[4] (IPUMS)	29.96	23.78	6.18	19333
2015	DHS	27.50	27.88	0.38	124239
Indonesia					
1971	Census (IPUMS)	2.65	2.62	0.03	26274
1976	Survey[5] (IPUMS)	4.86	4.74	0.12	9953
1980	Census (IPUMS)	7.28	7.25	0.03	283374
1985	Survey[5] (IPUMS)	9.51	11.54	2.03	26639
1990	Census (IPUMS)	17.10	17.07	0.03	41494
1991	DHS	18.78	18.29	0.49	5832
1994	DHS	24.07	22.14	1.93	6739
1995	Survey[5] (IPUMS)	27.03	23.47	3.56	31556
1997	DHS	28.12	26.15	1.97	6860
2000	MICS	31.59	30.15	1.44	1834
2000	Census (IPUMS)	30.13	30.15	0.02	951041
2002	DHS	32.27	32.76	0.49	6744
2005	Survey[5] (IPUMS)	34.27	36.47	2.20	48676
2007	DHS	37.52	38.77	1.25	7956
2010	Census (IPUMS)	41.94	41.90	0.04	1059239
2012	DHS	45.21	43.74	1.47	7682

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Iraq					
1997	Census (IPUMS)	20.61	20.60	0.01	79448
2000	MICS	19.12	19.68	0.56	3759
2006	MICS	18.82	18.49	0.33	4452
2011	MICS	18.04	18.10	0.06	9025
Jamaica					
1982	Census (IPUMS)	31.80	27.76	4.04	8181
1991	Census (IPUMS)	34.04	44.08	10.04	10401
2001	Census (IPUMS)	82.02	72.92	9.10	8461
2005	MICS	69.20	83.32	14.12	492
2011	MICS	72.77	93.53	20.76	736
Jordan					
1990	DHS	45.51	46.88	1.37	2089
1997	DHS	57.83	54.09	3.74	1971
2004	Census (IPUMS)	57.12	57.18	0.06	21753
2007	DHS	54.49	57.27	2.78	3167
2009	DHS	57.72	56.92	0.80	2874
2012	DHS	56.84	55.77	1.07	3145
Kazakhstan					
1995	DHS	87.13	86.84	0.29	592
1999	DHS	85.58	87.36	1.78	734
2006	MICS	91.83	90.05	1.78	1943
2010	MICS	90.39	92.17	1.78	2059
2015	MICS	95.10	94.81	0.29	2215
Kenya					
1969	Census (IPUMS)	1.79	1.66	0.13	26558
1979	Census (IPUMS)	5.18	5.98	0.80	45921
1989	Census (IPUMS)	16.97	14.43	2.54	42454
1993	DHS	22.44	18.41	4.03	1338
1998	DHS	25.40	23.09	2.31	1412
1999	Census (IPUMS)	22.99	23.92	0.93	60253
2000	MICS	25.87	24.72	1.15	1853
2003	DHS	24.13	26.78	2.65	1539
2008	DHS	25.09	28.98	3.89	1497
2009	Census (IPUMS)	28.99	29.22	0.23	167262
2014	DHS	35.13	29.30	5.83	6334

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Kyrgyz Republic					
1997	DHS	88.07	91.01	2.94	598
1999	Census (IPUMS)	90.72	90.46	0.26	18992
2005	MICS	70.27	89.60	19.33	1019
2009	Census (IPUMS)	90.24	89.76	0.48	23637
2012	DHS	90.65	90.26	0.39	1331
2014	MICS	87.59	90.75	3.16	1191
Laos					
2000	MICS	7.70	7.20	0.50	1488
2005	Census (IPUMS)	11.54	11.59	0.05	21626
2006	MICS	10.57	12.56	1.99	1157
2011	MICS	18.75	17.50	1.25	3884
2017	MICS	22.18	22.58	0.40	4260
Lesotho					
1996	Census (IPUMS)	12.34	12.34	0	6976
2000	MICS	13.82	14.42	0.60	1102
2004	DHS	17.21	17.22	0.01	1456
2006	Census (IPUMS)	19.49	18.96	0.53	8026
2009	DHS	19.44	22.07	2.63	1789
2014	DHS	29.72	28.82	0.90	1572
Liberia					
1974	Census (IPUMS)	2.83	2.83	0	6725
2007	DHS	11.24	11.10	0.14	1296
2008	Census (IPUMS)	12.18	12.20	0.02	15151
2013	DHS	20.04	20.01	0.03	1718
Malawi					
1987	Census (IPUMS)	1.85	1.85	0	30849
1992	DHS	2.76	3.06	0.30	887
1998	Census (IPUMS)	5.09	5.10	0.01	39520
2000	DHS	6.52	5.92	0.60	2479
2004	DHS	8.62	7.69	0.93	2301
2006	MICS	6.07	8.63	2.56	5007
2008	Census (IPUMS)	9.87	9.58	0.29	57404
2010	DHS	10.94	10.52	0.42	4538
2013	MICS	9.97	11.87	1.90	4502
2016	DHS	13.84	13.11	0.73	4225

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Mali					
1987	Census (IPUMS)	1.98	1.89	0.09	30491
1995	DHS	0.27	0.90	0.63	1903
1998	Census (IPUMS)	0.84	0.89	0.05	35398
2001	DHS	2.10	1.04	1.06	2492
2006	DHS	1.26	1.86	0.60	2774
2009	MICS	4.83	3.21	1.62	4935
2009	Census (IPUMS)	3.42	3.21	0.21	54723
2012	DHS	3.32	6.34	3.02	2335
2015	MICS	9.24	13.88	4.64	3523
Mexico					
1960	Census (IPUMS)	1.70	1.77	0.07	18860
1970	Census (IPUMS)	2.61	4.71	2.10	17035
1990	Census (IPUMS)	22.55	19.96	2.59	337284
1995	Census (IPUMS)	21.58	25.58	4.00	13721
2000	Census (IPUMS)	30.57	31.41	0.84	430071
2005	Census (IPUMS)	35.15	37.10	1.95	440673
2010	Census (IPUMS)	41.19	42.35	1.16	458103
2015	Survey[6] (IPUMS)	49.08	46.94	2.14	440085
2015	MICS	47.80	46.94	0.86	2290
Mongolia					
1989	Census (IPUMS)	40.60	40.81	0.21	8623
2000	MICS	73.75	64.35	9.40	1863
2000	Census (IPUMS)	63.52	64.35	0.83	10967
2005	MICS	60.68	68.14	7.46	1387
2010	MICS	67.31	68.19	0.88	1489
2013	MICS	68.10	66.46	1.64	2103
Morocco					
1982	Census (IPUMS)	4.01	4.01	0	38493
1992	DHS	10.10	10.92	0.82	1562
1994	Census (IPUMS)	12.22	12.16	0.06	53354
2003	DHS	10.06	13.97	3.91	2852
2004	Census (IPUMS)	13.88	13.71	0.17	64611

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Mozambique					
1997	DHS	0.25	0.76	0.51	1887
1997	Census (IPUMS)	0.78	0.76	0.02	65059
2003	DHS	1.47	1.32	0.15	2542
2007	Census (IPUMS)	2.42	2.44	0.02	83801
2008	MICS	3.50	2.93	0.57	2882
2009	DHS	3.30	3.56	0.26	1076
2011	DHS	5.52	5.41	0.11	2424
Nepal					
1996	DHS	5.69	5.64	0.05	1838
2001	DHS	7.72	12.49	4.77	1863
2001	Census (IPUMS)	12.66	12.49	0.17	82787
2006	DHS	12.27	20.78	8.51	1841
2011	DHS	21.47	27.05	5.58	2219
2011	Census (IPUMS)	27.45	27.05	0.40	142388
2014	MICS	15.86	28.69	12.83	2461
2016	DHS	34.24	28.73	5.51	2210
Nicaragua					
1971	Census (IPUMS)	4.68	4.67	0.01	6485
1995	Census (IPUMS)	19.29	19.64	0.35	17001
1998	DHS	25.82	22.29	3.53	2367
2001	DHS	25.41	25.01	0.40	2245
2005	Census (IPUMS)	28.55	28.68	0.13	21272
Niger					
1992	DHS	0.45	0.49	0.04	1443
1998	DHS	0.79	0.69	0.10	1388
2000	MICS	0.97	0.76	0.21	996
2006	DHS	0.74	0.95	0.21	1847
2012	DHS	1.17	1.09	0.08	2432
Nigeria					
1990	DHS	15.29	14.55	0.74	1836
1999	DHS	22.16	24.11	1.95	1637
2003	DHS	27.06	28.95	1.89	1471
2006	Survey[7] (IPUMS)	31.73	32.68	0.95	3674
2007	MICS	31.87	33.93	2.06	5394
2007	Survey[7] (IPUMS)	35.49	33.93	1.56	3679

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
2008	Survey[7] (IPUMS)	34.19	35.17	0.98	4748
2008	DHS	34.67	35.17	0.50	6815
2009	Survey[7] (IPUMS)	38.74	36.41	2.33	3385
2010	Survey[7] (IPUMS)	42.51	37.64	4.87	3121
2011	MICS	44.54	38.87	5.67	6342
2013	DHS	36.15	41.27	5.12	7381
2016	MICS	45.24	44.75	0.49	6201
Pakistan					
1973	Census (IPUMS)	2.10	2.87	0.77	49036
1981	Census (IPUMS)	3.34	3.06	0.28	340212
1990	DHS	4.92	4.37	0.55	1974
1998	Census (IPUMS)	7.15	7.60	0.45	469545
2006	DHS	24.72	15.88	8.84	29428
2012	DHS	27.87	29.24	1.37	3982
Palestine					
1997	Census (IPUMS)	35.19	35.20	0.01	9101
2007	Census (IPUMS)	44.28	44.12	0.16	8145
2010	MICS	52.50	53.14	0.64	2743
2014	MICS	68.96	68.72	0.24	2065
Panama					
1960	Census (IPUMS)	9.12	8.11	1.01	1926
1970	Census (IPUMS)	13.81	15.97	2.16	5335
1980	Census (IPUMS)	28.66	26.98	1.68	7740
1990	Census (IPUMS)	41.70	39.37	2.33	10055
2000	Census (IPUMS)	47.93	50.77	2.84	12097
2010	Census (IPUMS)	59.78	59.67	0.11	13446
2013	MICS	67.27	61.78	5.49	1497
Paraguay					
1962	Census (IPUMS)	5.95	5.65	0.30	2896
1972	Census (IPUMS)	8.53	7.40	1.13	7511
1982	Census (IPUMS)	7.89	11.00	3.11	11577
1990	DHS	23.46	16.28	7.18	1054
1992	Census (IPUMS)	21.74	18.11	3.63	15747
2002	Census (IPUMS)	30.22	31.40	1.18	18117
2016	MICS	59.26	61.82	2.56	1372

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Peru					
1991	DHS	53.41	45.41	8.00	2848
1993	Census (IPUMS)	49.22	49.49	0.27	92731
1996	DHS	54.24	54.72	0.48	5309
2000	DHS	57.16	59.94	2.78	4644
2004	DHS	63.28	63.19	0.09	6546
2007	Census (IPUMS)	65.06	64.43	0.63	116384
2009	DHS	46.83	64.70	17.87	3792
2010	DHS	63.75	64.68	0.93	3576
2011	DHS	64.27	64.55	0.28	3502
2012	DHS	67.00	64.30	2.70	3650
Philippines					
1990	Census (IPUMS)	51.82	52.56	0.74	249175
1993	DHS	58.95	54.64	4.31	2614
1995	Census (IPUMS)	58.12	56.28	1.84	286916
1998	DHS	63.88	59.11	4.77	2420
2000	Census (IPUMS)	59.56	61.22	1.66	292832
2003	DHS	67.38	64.67	2.71	2221
2008	DHS	72.56	70.98	1.58	2279
2010	Census (IPUMS)	73.94	73.60	0.34	375739
2013	DHS	74.74	77.52	2.78	2461
2017	DHS	76.59	82.51	5.92	4133
Rwanda					
1992	DHS	1.56	1.71	0.15	1131
2000	DHS	4.14	3.47	0.67	1647
2000	MICS	2.88	3.47	0.59	739
2002	Census (IPUMS)	4.21	4.17	0.04	30290
2005	DHS	5.28	5.54	0.26	1820
2010	DHS	6.48	8.96	2.48	2567
2012	Census (IPUMS)	11.01	10.88	0.13	46952
2014	DHS	13.47	13.21	0.26	2352
Senegal					
1988	Census (IPUMS)	1.85	1.87	0.02	28965
1992	DHS	3.09	2.52	0.57	1181
2000	MICS	3.31	4.13	0.82	2434
2002	Census (IPUMS)	4.87	4.58	0.29	38821
2005	DHS	3.06	5.26	2.20	2646

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
2010	DHS	5.59	6.37	0.78	2974
2012	DHS	5.30	6.77	1.47	1648
2014	DHS	5.99	7.15	1.16	1624
2015	DHS	7.98	7.33	0.65	1713
2016	DHS	8.00	7.49	0.51	1657
2017	DHS	9.06	7.65	1.41	3016
Sierra Leone					
2000	MICS	1.41	0.82	0.59	980
2004	Census (IPUMS)	1.63	1.73	0.10	22401
2005	MICS	2.22	2.08	0.14	2070
2008	DHS	5.04	3.55	1.49	1811
2010	MICS	5.01	5.01	0	2679
2013	DHS	9.04	8.21	0.83	2891
2017	MICS	14.05	15.09	1.04	3103
South Africa					
1996	Census (IPUMS)	32.41	33.31	0.90	158301
1998	DHS	36.84	35.61	1.23	1907
2001	Census (IPUMS)	41.74	39.19	2.55	166246
2007	Survey[8] (IPUMS)	35.31	46.71	11.40	42443
2011	Census (IPUMS)	52.91	51.86	1.05	209390
Sudan					
2000	MICS	25.35	24.83	0.52	6951
2008	Census (IPUMS)	10.95	11.05	0.10	212414
2010	MICS	25.62	13.55	12.07	3444
2014	MICS	27.07	30.63	3.56	3718
Tajikistan					
2000	MICS	47.57	46.88	0.69	936
2005	MICS	43.98	45.02	1.04	1503
2012	DHS	48.61	47.67	0.94	1676
2017	DHS	53.00	53.33	0.33	1938
Tanzania					
1988	Census (IPUMS)	3.36	3.36	0	98157
1992	DHS	3.85	4.09	0.24	1737
1996	DHS	5.65	5.07	0.58	1554
1999	DHS	6.59	6.03	0.56	818
2002	Census (IPUMS)	7.24	7.23	0.01	165233
2003	DHS	7.4	7.7	0.30	1365

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
2004	DHS	9.3	8.21	1.09	2009
2007	DHS	10.02	9.99	0.03	1697
2010	DHS	11.18	12.23	1.05	1774
2012	Census (IPUMS)	13.97	114.04	0.07	183634
2015	DHS	23.1	17.32	5.78	2307
Thailand					
1970	Census (IPUMS)	2.83	2.97	0.14	27739
1980	Census (IPUMS)	8.92	8.12	0.80	15679
1990	Census (IPUMS)	20.67	18.62	2.05	24278
2000	Census (IPUMS)	30.70	34.73	4.03	27316
2012	MICS	63.07	55.96	7.11	3072
2015	MICS	65.36	60.65	4.71	3625
Togo					
1960	Census (IPUMS)	0.99	0.49	0.50	805
1970	Census (IPUMS)	0.17	0.37	0.20	1181
1998	DHS	1.19	1.31	0.12	1751
2000	MICS	3.60	1.61	1.99	960
2006	MICS	3.36	3.27	0.09	1275
2010	MICS	4.85	5.60	0.75	1242
2010	Census (IPUMS)	5.73	5.60	0.13	26741
2013	DHS	5.71	8.60	2.89	1768
Trinidad and Tobago					
1970	Census (IPUMS)	28.90	24.92	3.98	2115
1980	Census (IPUMS)	34.12	38.76	4.64	4336
1990	Census (IPUMS)	55.40	55.02	0.38	5262
2000	MICS	75.63	70.56	5.07	527
2000	Census (IPUMS)	72.84	70.56	2.28	4263
2006	MICS	82.56	78.31	4.25	666
2011	MICS	86.14	83.60	2.54	756
2011	Census (IPUMS)	82.07	83.60	1.53	5449
Türkiye					
1985	Census (IPUMS)	13.64	13.66	0.02	98502
1990	Census (IPUMS)	16.46	16.40	0.06	118632
1993	DHS	17.32	18.52	1.20	1577
1998	DHS	21.70	23.01	1.31	1587
2000	Census (IPUMS)	25.16	25.20	0.04	146356
2003	DHS	31.63	28.96	2.67	2043

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
Uganda					
1991	Census (IPUMS)	1.28	1.30	0.02	63199
1995	DHS	8.21	2.58	5.63	1462
2000	DHS	5.69	5.14	0.55	1494
2002	Census (IPUMS)	6.40	6.43	0.03	94313
2006	DHS	7.20	9.25	2.05	1649
2011	DHS	10.63	12.52	1.89	1792
2016	DHS	15.98	14.47	1.51	3392
Ukraine					
2001	Census (IPUMS)	90.55	90.56	0.01	170044
2005	MICS	94.75	86.67	8.08	1358
2007	DHS	70.48	88.71	18.23	1087
2012	MICS	97.72	97.48	0.24	1985
Uruguay					
1963	Census (IPUMS)	9.68	11.07	1.39	9449
1975	Census (IPUMS)	21.63	18.93	2.70	9735
1985	Census (IPUMS)	33.35	26.29	7.06	10917
1996	Census (IPUMS)	22.62	33.83	11.21	10898
2006	Survey[9] (IPUMS)	41.85	39.18	2.67	8300
2011	Census (IPUMS)	43.76	41.13	2.63	11590
2012	MICS	42.03	41.45	0.58	478
Venezuela					
1971	Census (IPUMS)	7.38	7.82	0.44	39993
1981	Census (IPUMS)	21.66	19.57	2.09	62069
1990	Census (IPUMS)	30.99	33.28	2.29	71554
2000	MICS	27.70	46.14	18.44	745
2001	Census (IPUMS)	47.81	47.11	0.70	96038
Vietnam					
1989	Census (IPUMS)	15.75	15.79	0.04	125526
1997	DHS	22.58	17.58	5.00	1336
1999	Census (IPUMS)	18.59	18.50	0.09	102748
2000	MICS	21.05	19.05	2.00	1336
2002	DHS	19.65	20.33	0.68	1256
2005	DHS	20.75	22.77	2.02	992
2006	MICS	27.15	23.74	3.41	1245
2009	Census (IPUMS)	27.07	27.16	0.09	621601

Tab. A1: Continuation

Country/Year	Data Source	Observed P	Predicted P	Difference[1]	Sample size[2]
2010	MICS	42.60	28.50	14.10	1853
2013	MICS	49.02	33.13	15.89	1423
Zambia					
1990	Census (IPUMS)	10.24	9.99	0.25	29844
1992	DHS	7.31	9.77	2.46	1285
1996	DHS	3.98	9.92	5.94	1427
1999	MICS	10.51	10.60	0.09	1780
2000	Census (IPUMS)	11.22	10.95	0.27	37791
2001	DHS	10.08	11.36	1.28	1465
2007	DHS	13.96	15.65	1.69	1479
2010	Census (IPUMS)	19.77	19.42	0.35	54052
2013	DHS	20.01	24.80	4.79	3049
Zimbabwe					
1994	DHS	4.07	8.50	4.43	1026
1999	DHS	38.01	9.81	28.20	1088
2005	DHS	5.61	10.66	5.05	1664
2009	MICS	10.57	10.68	0.11	2238
2010	DHS	7.85	10.62	2.77	1858
2012	Census (IPUMS)	10.58	10.41	0.17	30674
2014	MICS	9.96	10.10	0.14	2519
2015	DHS	11.04	9.91	1.13	1800

[1] Absolute value of observed value less predicted value
[2] Number of females aged 25 to 29 (unweighted)
[3] Cambodia Intercensal Population Survey
[4] National Sample Survey Organisation Socio-Economic Survey of India
[5] Indonesia Intercensal Population Survey
[6] Intercensal Survey
[7] Nigeria: National Bureau of Statistics General Household Survey
[8] South Africa Community Survey
[9] Uruguay Extended National Survey of Homes 2006
Source: own design

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