IARIW 2022

IARIW 2022

11 Friday - 13 Sunday November

A New, Nuanced Narrative of Poverty in Sub-Saharan Africa with the 2017 PPPs

Samuel Kofi Tetteh Baah
(World Bank)
stettehbaah@worldbank.org

Christopher Lakner
(World Bank)

Paper prepared for the IARIW-TNBS Conference on "Measuring Income, Wealth and Well-being in Africa", Arusha, Tanzania November 11-13, 2022

Session 3: National and Household Income

Time: Friday, November 11, 2022 [1:15 PM - 2:45 PM]

A new, nuanced narrative of poverty in Sub-Saharan Africa with the 2017 PPPs

Samuel Kofi Tetteh Baah and Christoph Lakner

Abstract

Substantial progress against poverty is required in Sub-Saharan Africa for the world to achieve the first Sustainable Development Goal (SDG) of eradicating extreme poverty by 2030. This study estimates extreme poverty in Sub-Saharan Africa in a global context using the new 2017 purchasing power parity exchange rates (PPPs). Extreme poverty is estimated to decrease by 3 percentage points to 38% in Sub-Saharan Africa in 2017 when moving from the 2011 PPPs to the 2017 PPPs, while it is estimated to increase slightly by up to 1.5 percentage points in all other regions. The estimated reduction in extreme poverty in Sub-Saharan Africa appears substantial and seems to be driven by improvements in statistical capacity and improved quality of price data in the region. However, when one accounts for differential poverty levels across the regions of the world, the change in estimated poverty in Sub-Saharan Africa is small and is driven by a few populous countries, such as Nigeria and the Democratic Republic of Congo. Overall, the new PPPs do not change the perception of high levels of extreme poverty in Sub-Saharan Africa.

JEL code: I32 - Measurement and Analysis of Poverty

Keywords: Sub-Saharan Africa, PPPs, extreme poverty

1. Introduction

Sub-Saharan Africa is estimated to be the poorest region in the world. For the world to achieve the first Sustainable Development Goal (SDG) of eradicating extreme poverty by 2030, there should be substantial progress in Sub-Saharan Africa (World Bank 2018). More research on the measurement of poverty in the region is therefore needed to monitor progress and inform policy.

Researchers and policymakers usually agree that extreme poverty in the world and Sub-Saharan Africa has been falling over the years, but the level of poverty is a subject of considerable debate (Deaton 2010; Reddy and Pogge 2010; Ravallion 2014; Allen 2017; Deaton and Aten 2017). As a result, more emphasis has been placed on poverty trends in policy work (World Bank 2017). However, it is equally policy-relevant to have more reliable estimates of poverty levels (World Bank 2017). High levels of extreme poverty in Sub-Saharan Africa, for instance, would imply that it would be less likely to achieve SDG 1 by 2030.

In 2022, the World Bank adopted new purchasing power parities exchange rates (PPPs) for monitoring global poverty. These new PPPs are based on the most recent price data collected in 2017 across 176 countries. The adoption of the new 2017 PPPs reveals interesting patterns in the regional distribution of extreme poverty in the world. In 2017, extreme poverty in Sub-Saharan Africa is estimated to *decrease* from 41% to 38% when moving from the previously used 2011 PPPs to the 2017 PPPs (i.e., 3 percentage points). By contrast, extreme poverty is estimated to *increase* slightly by up to 1.5 percentage points in all other regions in the world (Jolliffe et al. 2022). Quite intriguing, these findings inspire this follow-up study.

The main objective of this study is to shed light on the magnitude and direction of the change in extreme poverty estimates for Sub-Saharan Africa and note that the perception of high levels of extreme poverty in the region remains virtually unchanged. In what follows, this study argues that extreme poverty in Sub-Saharan Africa is not systematically lower than previously thought based on the new PPPs.

Sub-Saharan Africa has a greater room for changes in its poverty estimates than the other regions of the world, due to its high levels of poverty. When one accounts for differential levels of poverty across regions, a change of 3 percentage points in extreme poverty in Sub-Saharan Africa is not substantial. Sub-Saharan Africa has the largest absolute change in extreme poverty, but the magnitude of relative change in extreme poverty in the region is comparable to that of other regions.

The apparently large change in extreme poverty in Sub-Saharan Africa is driven by a few populous countries, such as Nigeria and the Democratic Republic of Congo, where the new PPPs suggest lower living costs relative to the rest of the world. In nearly half of the countries in Sub-Saharan Africa with survey data, extreme poverty estimates increase or decrease with the 2017 PPPs. However, due to population weighting, the change in the few populous countries drives the magnitude and direction of the estimated change in extreme poverty for the whole region.

In fact, the study shows that poverty estimates with the 2011 and 2017 PPPs are broadly similar, using cross-country variation in related indicators of well-being, such as age dependency ratio and multi-dimensional poverty (Vijayakumar 2013; Evans, Nogales, and Robson 2020). In other words, poverty estimates with the 2011 PPPs generally correlate with age dependency ratio and multi-dimensional poverty, just as much as poverty estimates with the 2017 PPPs. Thus, the new PPPs do not change the perception of extreme poverty in Sub-Saharan Africa.

However, there are a few exceptional cases where there are large changes in poverty estimates when moving from the 2011 PPPs to the 2017 PPPs and countries get re-ranked drastically. In 2017, extreme poverty in Angola is estimated to decrease from 45% to 27%, while in Ghana it increases from 12% to 25%. As a result, the poverty ranking of Angola improves from 33rd to 17th in Sub-Saharan Africa and Ghana worsens in rank from 8th to 15th.

A possible explanation for some of the large absolute changes in poverty estimates in Sub-Saharan Africa is the improvement in statistical capacity in the region coupled with improved quality of price data (World Bank 2020). For example, in Angola, the underlying price data for estimating PPPs got improved from an urban coverage in the 2011 ICP cycle to a national coverage in the 2017 cycle, and prices were collected on more items in the 2017 ICP cycle. This might explain the estimated large reduction in extreme poverty in Angola when moving to the 2017 PPPs. The results of this study suggest that this anecdotal evidence from Angola can be generalized for the whole region.

The rest of the study proceeds as follows. Section 2 describes the data. Section 3 discusses the methods used to achieve the study objective. Section 4 presents the results and Section 5 concludes.

2. Data

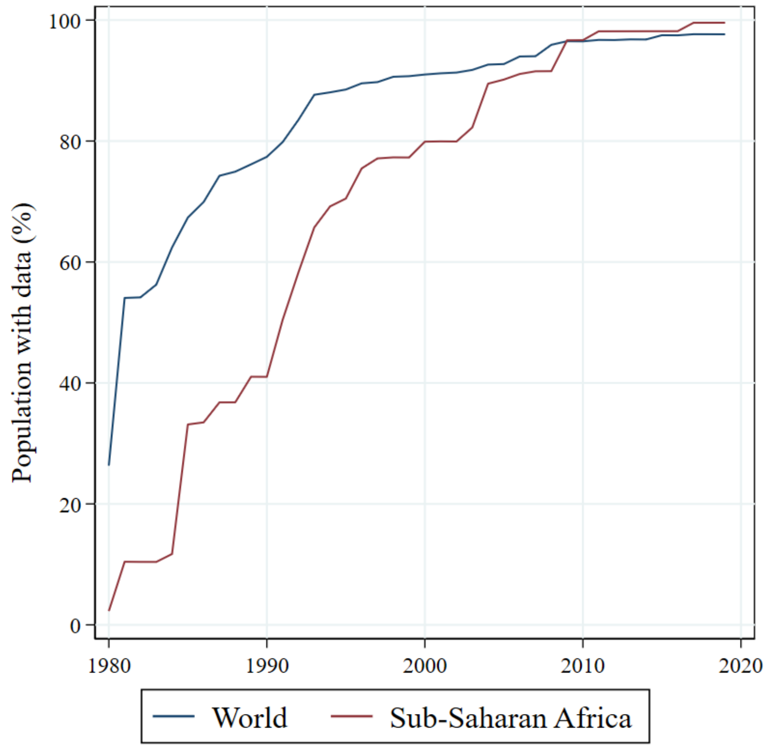
This study uses data from the following sources. First, the study primarily uses nationally representative income and consumption survey data collected from 168 countries since 1990. These data can be found in PovcalNet, the World Bank's database and online portal for monitoring global poverty.[1] The countries covered in the database account for 97% of the world's population. The frequency of survey data differs by country. The average number of surveys conducted for a country is 11 and the median survey year is 2008. For Sub-Saharan Africa, 46 countries have data with an average of 4 surveys and a median survey year of 2005.

However, Sub-Saharan Africa is not the region that has the least data coverage. Starting far back from 1980, the population share with data coverage has increased a lot in Sub-Saharan Africa relative to the world. Figure 1 shows the paucity of survey data from Sub-Saharan Africa in the 1980s and the drastic improvement in the 1990s and 2000s. In more recent years, Sub-Saharan Africa outperforms the world in data coverage. The progress with data availability in Sub-Saharan

[1] PovcalNet has been replaced by the Poverty and Inequality Platform (PIP) in April 2022. The survey data discussed here are from the last vintage of PovcalNet. These are the same survey data used in Jolliffe et al. (2022), the study which inspires this one. PIP has new data from Nigeria, India and other countries that have not been included here.

Africa reflects improvements in statistical capacity in the region as well as huge investments by the World Bank toward data collection and capacity building in the region.

Figure 1: Share of population with survey data coverage



Second, the study uses purchasing power parity (PPP) data to obtain poverty estimates that are comparable across countries. In estimating global poverty, PPPs are used to convert consumption or income data collected in surveys, expressed in local currency units, into a common, comparable currency unit. PPPs are price indices that measure the cost of a basket of goods and services in a country relative to a reference country, typically the United States. Market exchange rates are expected to equilibrate the prices of tradable goods across countries, while PPPs are expected to equilibrate the prices of both goods and services across countries. PPPs are preferred to market exchange rates when estimating global poverty, because the former account for the Balassa-Samuelson-Penn effect—the empirical fact that services of the same quality are cheaper in developing countries than industrialized countries.

The study estimates poverty with the most recent vintages of PPPs published by the International Comparison Program (ICP), namely (revised) 2011 PPPs and 2017 PPPs. The ICP has the mandate to collect detailed price data across countries in the world and estimate purchasing power parities often used in policy and research work. It is headquartered at the World Bank and has regional offices across the globe. The 2011 PPPs were originally published in 2014 and revised in 2020 when the 2017 PPPs were also published (World Bank 2014; 2020). Without changing the underlying price data, the revisions to the 2011 PPPs were mainly driven by revisions to national accounts expenditures, which are used as weights when aggregating price data in the estimation of

PPPs (World Bank 2020; Tetteh-Baah et al. 2020). The same index-number methodology was used in estimating PPPs in the 2011 and 2017 ICP cycles, suggesting that the changes in the PPPs largely reflect new price information (World Bank 2020; Deaton and Schreyer 2022; Jolliffe et al. 2022).

This study uses the PPPs the World Bank uses in estimating global poverty, including the PPPs the ICP officially published and special PPPs derived by the Bank for a few exceptional countries. There were issues with the underlying price data of the PPPs of a few countries in the 2011 ICP cycle, thus casting doubts on their reliability for measuring global poverty. Special, imputed 2011 PPPs were therefore derived for six countries, including Egypt, Jordan, Iraq, Myanmar, Laos, and Yemen, none of which is in Sub-Saharan Africa (Ferreira et al. 2016; Atamanov et al. 2018; 2020). In the 2017 cycle, the PPPs have been assessed again for their reliability for poverty measurement. Special 2017 PPPs, derived as the geometric average of official and imputed PPPs, are used for eight countries whose official PPPs were deemed to be problematic for poverty measurement (Jolliffe et al. 2022). Four of these countries—Guinea, Nigeria, Sao Tome and Principe, and Sudan—are in Sub-Saharan Africa.

Next, the study uses consumer price indices (CPIs) to convert consumption or income data from surveys into the prices of the ICP reference year when estimating poverty. The standard source of CPI data is the International Financial Studies (IFS) from the International Monetary Fund (IMF), which is the same source of CPI data for the World Bank's global poverty estimates (Lakner et al. 2018). In five countries (Bangladesh, Ghana, Laos, Malawi, and Tajikistan), survey-based CPI series are used instead of the IFS CPIs for the Bank's global poverty estimates. The survey-based CPIs are used for these countries because they better reflect prices faced by the poor (Lakner et al. 2018; Ferreira et al. 2016). For comparability of poverty estimates, this study uses the CPIs series the World Bank uses for measuring global poverty.

Further, national accounts data are used in this study to estimate poverty for years without survey data. National account data on Gross Domestic Product (GDP) per capita and household final consumption expenditure (HFCE) per capita from the World Development Indicators (WDI), January 2022 vintage are used for the analysis. These data are used to extrapolate and interpolate annual poverty estimates from less frequent survey estimates.

The study uses two series of statistical capacity created by the World Bank to evaluate and monitor the ability of national statistical systems to collect, process, and use high-quality data on a wide range of social and economic indicators. These include the Statistical Capacity Index (SCI) (World Bank 2022a) and Statistical Performance Index (SPI) (Dang et al. 2021). The SCI has more historic data, dating back to 2004, whereas the SPI starts from 2016. Building upon the SCI, the SPI goes beyond monitoring the data infrastructure that makes for the production of high-quality data, and includes several other pillars of data systems, such as data use, data services, data products, and data sources. The SPI also uses improved weighting methodology to aggregate the sub-components of the index. Both indices lie between 0 and 100 and are quite correlated (Figure A1).

Lastly, the study uses data on age dependency ratio (World Bank 2022b) and Multi-dimensional Poverty Index (MPI) (Alkire, Kanagaratnam, and Suppa 2021) to achieve its objective.

3. Methodology

3.1. Estimating country-level poverty and aggregating poverty at the regional and global levels

The country-level, regional, and global poverty estimates are primarily based on consumption and incomes survey data. These surveys are typically conducted annually in high-income countries and once in every few years in developing countries. When there are no poverty estimates for a given year, poverty is extrapolated or interpolated from the nearest survey estimates using growth rates from GDP per capita and household final consumption expenditure (HFCE) per capita, which are more readily available on an annual basis. Country-level poverty estimates are aggregated to produce global and regional poverty estimates. Countries without survey data take the poverty rate of the region to which they belong. The regional and global poverty estimates are population-weighted averages of the country-level poverty estimates.

More details on the methodology used in estimating country-level, regional, and global poverty can be found in the Poverty and Inequality Platform (PIP) Methodology Handbook (World Bank 2022c).

3.2. Assessing the possible role of statistical capacity in large differences in poverty estimates

The idea here is to investigate if and how statistical capacity might predict differences in poverty estimates particularly for countries in Sub-Saharan Africa. As statistical capacity improves, revisions to price and national accounts data are more likely, and such revisions can potentially impact on PPP estimates. Thus, differences in poverty estimated with the 2011 and 2017 PPPs might correlate with statistical capacity.

Equation 1 specifies the relationship between differences in poverty estimates and changes in statistical capacity over time.

$$D_i = \beta_0 + \beta_1 SCI_i + \beta_2 GDP_i + \sum_{k=1}^{K} \gamma_k v_k + \alpha_K * SCI_i * v_K + e_i \qquad (1)$$

where:

D_i is the absolute OR relative change in poverty rate in 2017,
SCI_i is the annualized change in Statistical Capacity Index (SCI) for country i over time,
GDP_i is GDP per capita in 2017 in current US dollars,
v_k are dummy variables for K regions with region K being Sub-Saharan Africa,
e_i is an error term.

Equation 1 regresses country-level change in 2017 poverty estimates on annualized change in statistical capacity, GDP per capita, regional dummies, and interaction between Sub-Saharan Africa and statistical capacity. The study investigates both absolute and relative changes in poverty estimates when moving from the 2011 PPPs to 2017 PPPs. The parameter of interest in Equation 1 is α_K, which shows whether there is a relationship between improvements in statistical capacity and changes in poverty estimates in Sub-Saharan Africa. Improvement in statistical capacity is a phenomenon that may be best captured over a considerably long period of time (i.e., beyond the 2011 and 2017 benchmark years). Both a short-run period (2011-2017) and long-run period (2005-2020) are used for the analysis, but the latter is preferred.

Equation 2 investigates the relationship between differences in poverty estimates and cross-country variation in the *level* of statistical capacity.

$$D_i = \beta_0 + \beta_1 SPI_i + \beta_2 (SPI_i)^2 + \beta_3 GDP_i + \sum_{k=1}^{K} \gamma_k v_k + \alpha_K * SCI_i * v_K + e_i \qquad (2)$$

where:

D_i is the absolute OR relative change in poverty rate in 2017,
SPI_i is the Statistical Performance Index (SPI) for country i in 2017,
GDP_i is GDP per capita in 2017 in current US dollars,
v_k are dummy variables for K regions with region K being Sub-Saharan Africa,
e_i is an error term.

Equation 2 follows a similar structure as Equation 1. However, the Statistical Capacity Index is replaced with the Statistical Performance Index (SPI).[2] Equation 2 also investigates if there is a non-linear relationship between observed differences in poverty estimates and the level of statistical capacity across countries. The data used to estimate Equation 2 are all for 2017.

3.3. Assessing poverty estimates with related indicators of well-being

A seemingly unrelated regressions (SUR) model is used to assess whether there are significant differences in poverty estimated with the 2011 PPPs and 2017 PPPs. This analysis exploits variation in related indicators of well-being, such as age dependency ratio (ADR) and Multi-dimensional Poverty Index (MPI). With a vector of related indicators, X = (ADR, MPI), the following equations are estimated separately.

$$P_{1i} = \alpha_1 + \beta_1 X_i + e_{1i} \qquad (3)$$

$$P_{2i} = \alpha_2 + \beta_2 X_i + e_{2i} \qquad (4)$$

Equation 3 specifies the relationship between poverty estimated with the 2011 PPP, denoted P_{1i}, and a related indicator of well-being for country i in a given year. Equation 4 specifies the

[2] The Statistical Capacity Index (SCI) has more historic data (2004-2020) and is used as an indicator for the trend in statistical capacity. The Statistical Performance Index (SPI) starts from 2016 and is to capture cross-country variation in the level of statistical capacity. This paper uses both indices as similar indicators of statistical capacity.

relationship between poverty estimated with the 2017 PPP, denoted P_{2i}, and a related indicator of well-being for country i in a given year. A SUR model is used for this analysis under the assumption that the error terms are correlated across the two equations. Formally, $E[e_{1i}, e_{2i}] \neq 0$. The study investigates whether $\beta_1 = \beta_2$ to suggest that there are no significant differences in poverty estimated with the 2011 PPPs and 2017 PPPs. For example, one can say that the association between poverty estimates with the 2011 PPPs and age dependency ratio in a given year is not any different from the association between poverty estimates with the 2017 PPPs and age dependency ratio in the year in question.

Annual data are available for ADR, but not MPI. A more complete annual series of MPI is imputed from less frequent survey estimates in two steps. First, a weighted average of the two nearest survey estimates is taken. Second, the series is extended forward and backward using average yearly growth rate of all observations imputed between the survey estimates. Figure A2 has more details.

4. Results

4.1. Extreme poverty in Sub-Saharan Africa in a global context

Table 1 presents extreme poverty estimates for Sub-Saharan Africa in 2017 in comparison with other regions of the world. Extreme poverty estimates increase slightly with the 2017 PPPs in all regions except Sub-Saharan Africa, where a substantial reduction of 3.2 percentage points drives down the global poverty rate. Some 34 million fewer people would be considered extreme poor in Sub-Saharan Africa with the 2017 PPPs. That is about twice the magnitude of change in millions of poor at the global level.

Table 1: Changes in poverty at the regional and global levels in 2017

Region	*Headcount, % (2011 PPP)*	*Headcount, % (2017 PPP)*	*Absolute change in poverty, pp*	*Relative change in poverty, %*	*Chane in millions of poor*
Sub-Saharan Africa	**41.2**	**37.9**	**-3.2**	**-7.9**	**-34**
South Asia	9.7	9.7	0.1	0.6	1
World	9.3	9.1	-0.2	-2.3	-16
Middle East & North Africa	6.3	6.4	0.0	0.4	0
Latin America & Caribbean	3.8	4.1	0.3	8.1	2
Europe & Central Asia	1.3	2.8	1.5	113.9	7
East Asia & Pacific	1.4	1.8	0.4	26.7	8
Other High Income	0.7	0.7	0.0	0.1	0

Note: Extreme poverty is estimated with the 2011 PPPs using the international poverty line of \$1.90 and is estimated with the 2017 PPPs using the international poverty line of \$2.15. Other High Income (OHI) refers to high-income countries across different geographical regions (e.g., Germany, Switzerland, United Arab Emirates, France, and United States) that are not considered to be a part of the developing world.

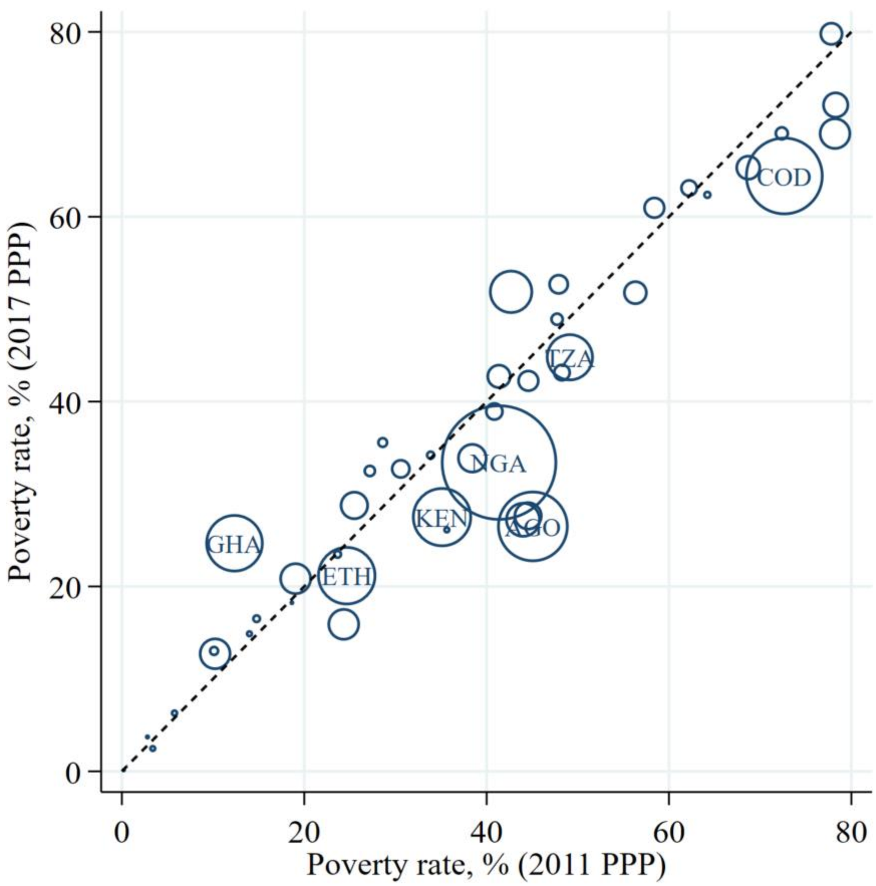
It makes a difference whether one considers absolute or relative changes in extreme poverty. While Sub-Saharan Africa has the largest absolute change in extreme poverty, it has a small relative change in extreme poverty that is lower in magnitude than the relative changes observed in Latin America and the Caribbean, Europe and Central Asia, and East Asia and the Pacific (see Table 1).

4.2. Poverty (re-ranking) within Sub-Saharan Africa

The top drivers of the change in estimated poverty in Sub-Saharan Africa in 2017 are Nigeria, the Democratic Republic of Congo, Angola, Ethiopia, Kenya, and Tanzania (see Table A1). Nigeria alone accounts for about a half of the change in millions of extreme poor in Sub-Saharan Africa.

Poverty in Sub-Saharan Africa decreases with the 2017 PPPs, but this result hides the fact that in some countries, estimated poverty increases and in other countries estimated poverty decreases. In 21 of 46 countries in the region with data—about a half—extreme poverty estimates have increased with the 2017 PPPs. Extreme poverty is estimated to decrease overall largely because extreme poverty estimates decrease in the most populous countries, including Nigeria, the Democratic Republic of Congo, Kenya, and Ethiopia (Figure 2).

Figure 2: Changes in extreme poverty in Sub-Saharan Africa, 2017



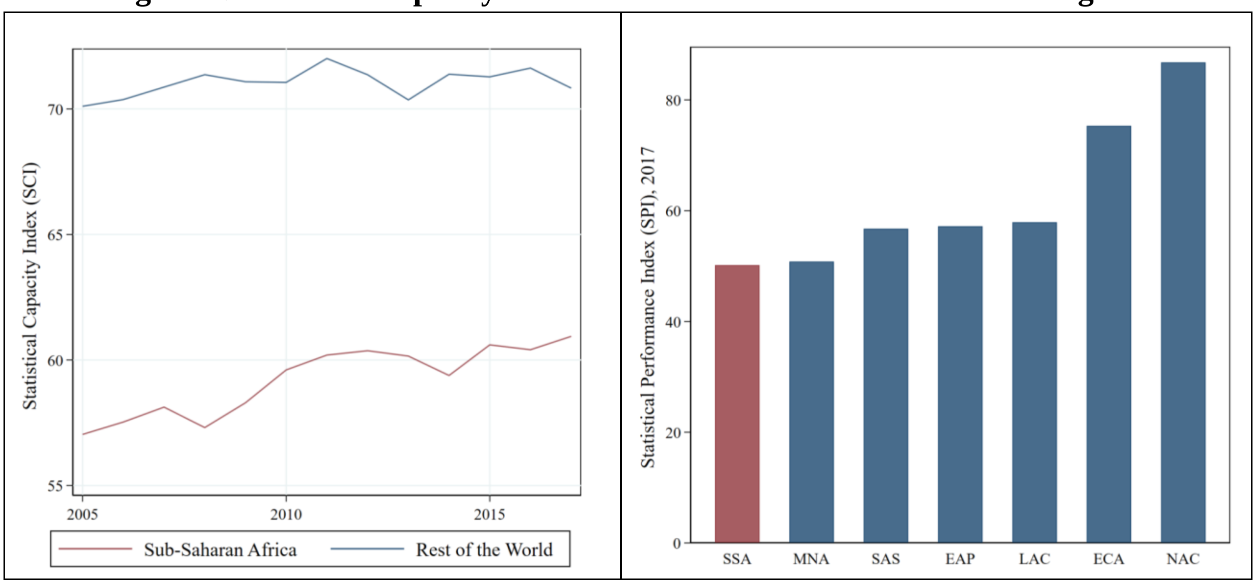
Notes: This chart shows estimates of extreme poverty in 2017 for countries in Sub-Saharan Africa. For countries, without a survey in 2017, the estimates are based on extrapolations or interpolations from recent surveys. Extreme poverty is measured using the international poverty line of $1.90 (2011 PPP) or $2.15 (2017 PPP). Marker size is proportional to absolute change in millions of poor. The dotted line is a 45-degree line.

In general, there are limited changes in the relative rankings of countries. The countries with the lowest levels of poverty in the region with the 2011 PPPs are often also the ones with the lowest levels of poverty with the 2017 PPPs (e.g., Mauritius, Seychelles, Cabo Verde, and Gabon). The countries with the highest levels of poverty in the region with the 2011 PPPs are often also the ones with the highest levels of poverty with the 2017 PPPs (e.g., Burundi, South Sudan, Madagascar, and the Democratic Republic of Congo). Yet, there are also cases with striking re-ranking of countries with the 2017 PPPs. For example, Ghana ranks 8th with the 2011 PPPs and worsens in rank to 15th, and Angola ranks 33rd with the 2011 PPPs and improves in rank to 17th. Figure A3 indicates the changes in the rankings of countries with the 2017 PPPs, and Figure A4 indicates the changes in poverty estimates with the 2017 PPPs.

4.3. The possible role of statistical capacity in explaining large differences in poverty estimates

Figure 3 illustrates that statistical capacity has been quite low in Sub-Saharan Africa. There has been remarkable improvement since 2005 compared to the rest of the world (Figure 3, left panel). However, the region still lags behind all regions of the world in statistical capacity based on data from 2017 (Figure 3, right panel).[3]

Figure 3: Statistical capacity in Sub-Saharan Africa relative to other regions



Note: The regions in the world are Sub-Saharan Africa (SSA), Middle East & North Africa (MNA), South Asia (SAS), East Asia & Pacific (EAP), Latin America & Caribbean (LAC), Europe & Central Asia (ECA), and North America (NAC). The Statistical Capacity Index (SCI) and Statistical Performance Index (SPI) are based on different methodologies and are therefore not comparable in levels.

[3] Figure 3 uses different sources of data. Statistical Capacity Index (SCI) has more historical data, while the Statistical Performance Index (SPI) is a more recent database constructed to replace the Statistical Capacity Index (SCI). The indices differ by methodology but are conceptually similar. For simplicity, this study refers to both indices as measures of statistical capacity.

Table 2 presents results of the observed relationship between differences in poverty estimates and changes in statistical capacity over time. Changes in Statistical Capacity Index (SCI) over a long time period is likely to capture systematic improvements in statistical capacity of time. Thus, the entire period [2005-2020] of the series of the Statistical Capacity Index (SCI) is selected for this analysis. Two dependent variables are selected for the analysis, namely absolute change in poverty in percentage points and relative change in poverty in percentages.

Since improvements in statistical capacity can lead to revisions in PPP or national accounts data in either direction, and consequently increase or decrease poverty estimates, the data on the dependent variables enter into the regressions **as absolute values**. Thus, the magnitude of change in poverty estimates is what matters here, rather than the direction of change. For example, estimated poverty increases in Ghana by 12 percentage points (pp) with the 2017 PPPs and decreases in Angola by 19 percentage points (pp) with the 2017 PPPs.[4] Thus, a change of 12 for Ghana and 19 for Angola enter into the regressions whose results are shown in columns 1 and 2. The corresponding data that enter into the regressions whose results are shown in column 3 and 4 are 100 percent (%) for Ghana and 41 percent (%) for Angola, also as absolute values.

Table 2: Relationship between differences in poverty estimates and changes in statistical capacity

	Absolute change in poverty, pp		**Relative change in poverty, %**	
	(1)	*(2)*	*(3)*	*(4)*
% Change in SCI – 2005-20	0.60**	0.16	2.86**	2.37
	(0.25)	(0.21)	(1.15)	(1.64)
GDP per capita	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Europe & Central Asia	0.70	0.37	1.28	0.92
	(1.20)	(1.18)	(11.25)	(11.31)
Latin America & Caribbean	1.41**	0.63	-5.65	-6.51
	(0.69)	(0.54)	(5.94)	(6.10)
Middle East & North Africa	0.19	-0.48	10.32	9.58
	(0.84)	(0.51)	(9.93)	(10.08)
South Asia	0.07	-0.59	-1.37	-2.10
	(0.68)	(0.55)	(8.50)	(8.62)
Sub-Saharan Africa (SSA)	3.11***	2.21***	-11.49**	-12.49**
	(0.89)	(0.72)	(5.33)	(5.12)
% Change in SCI * SSA		**1.28*** **		1.42
		(0.34)		(2.11)
Observations	129	129	129	129
Adjusted R-Squared	0.281	0.354	0.056	0.050

Note: The first regressor is annualized change the Statistical Capacity Index (SCI) between 2005 and 2020. This same variable is used in the interaction term with Sub-Saharan Africa. East Asia and the Pacific is the comparison region for the regional dummies, hence it is dropped from the regression results. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[4] In 2017, extreme poverty in Ghana is estimated to increase from 12.3% to 24.7% with the 2017 PPPs, while in Angola it is estimated to decrease from 45% to 26.5% with the 2017 PPPs.

The results in Table 2 suggest that improvements in statistical capacity correlate with large changes in estimated poverty in either direction. When one considers absolute changes in poverty in percentage points, Sub-Saharan Africa has the largest changes and drives the relationship between large differences in poverty estimates and improvements in statistical capacity. In column 1, the coefficient on change in statistical capacity is positive and significant. However, in column 2 when the change in statistical capacity is interacted with a Sub-Saharan Africa dummy, the relationship between statistical capacity and differences in poverty becomes insignificant. If the Statistical Capacity Index increases by 1% a year, poverty is estimated to increase or decrease significantly for a Sub-Saharan African country by 1.28 percentage points on average, relative to countries in other regions.

Relative changes in poverty estimates in Sub-Saharan Africa are even lower than other regions (see column 3) and Sub-Saharan Africa does not explain the positive relationship between improvements in statistical capacity and differences in poverty estimates (see column 4). Similar results are obtained when an indicator variable for a positive annualized change in statistical capacity between 2005 and 2020 is used instead of annualized change in statistical capacity between 2005 and 2020. The analysis is also repeated for a short time horizon spanning 2011-2017 and the results are generally weak. This finding is expected, as a short time horizon will not effectively capture systematic improvements in statistical capacity over time (see Table A2-A4).

Table 3: Relationship between differences in poverty estimates and the <u>level</u> of statistical capacity

	Absolute change in poverty, pp		**Relative change in poverty, %**	
	(1)	*(2)*	*(3)*	*(4)*
SPI	0.06	0.06	2.03***	2.03***
	(0.07)	(0.06)	(0.58)	(0.58)
SPI^2	-0.00	-0.00	-0.02***	-0.02***
	(0.00)	(0.00)	(0.01)	(0.01)
GDP per capita	-0.00**	-0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Europe & Central Asia	0.42	0.41	0.74	0.70
	(1.34)	(1.40)	(11.16)	(11.56)
Latin America & Caribbean	-0.51	-0.52	-9.76**	-9.78**
	(0.79)	(0.79)	(4.70)	(4.78)
Middle East & North Africa	-1.08	-1.08	8.39	8.40
	(0.83)	(0.84)	(9.41)	(9.42)
Other High Income	1.50	1.48	-8.84	-8.89
	(1.35)	(1.41)	(10.72)	(11.21)
South Asia	-0.74	-0.75	-6.20	-6.23
	(0.86)	(0.85)	(8.94)	(8.99)
Sub-Saharan Africa (SSA)	2.74**	3.03	-13.04**	-12.34
	(1.06)	(3.33)	(5.01)	(18.04)
SPI * SSA		-0.01		-0.01
		(0.05)		(0.35)
Observations	158	158	158	158
Adjusted R-Squared	0.244	0.239	0.142	0.136

Note: The first regressor is the Statistical Performance Index (SPI) for 2017. This same variable is used in the interaction term with Sub-Saharan Africa. East Asia and the Pacific is the comparison region for the regional dummies, hence it is dropped from the regression results. Other High Income refers to high-income countries across different geographical regions (e.g., Germany, Switzerland, United Arab Emirates, France, and United States) that are not considered to be a part of the developing world. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Absolute changes in poverty estimates correlate with improvements in statistical capacity over time (see Table 2, columns 1 and 2) and not cross-country variation in the level of statistical capacity (see Table 3, columns 1 and 2). Instead, relative changes in poverty seem to be positively related to cross-country variation in statistical capacity, and there is a concave, non-linear relationship. Both coefficients on the SPI and squared SPI are significant (see Table 3, columns 1 and 2), suggesting that relative changes in poverty estimates are lower for countries with quite low or high levels of statistical capacity and higher for countries with average levels of statistical capacity. Figure A5 illustrates this relationship graphically. Sub-Saharan Africa is not different from any other region when it comes to the relationship between changes in poverty and the level of statistical capacity. Overall, the changes in poverty estimates in Sub-Saharan Africa are likely to be driven by improvements in statistical capacity rather than the low levels of statistical capacity relative to other regions.

4.4. Relationship between poverty estimates in Sub-Saharan Africa and related indicators

In Section 4.2, the study shows how countries get re-ranked in Sub-Saharan Africa by poverty status. In this section, the study uses cross-country variation in age dependency ratio and multi-dimensional poverty to assess whether poverty estimated with the 2011 PPPs is broadly similar or dissimilar to poverty estimated with the 2017 PPPs. Overall, it turns out that one set of PPPs is not systematically different from the other (see Table 4).

Table 4: Results of significance tests from SUR regressions: p-values

Year	Age dependency ratio		Multi-dimensional poverty	
	Population weighted (1)	Equally weighted (2)	Population weighted (3)	Equally weighted (4)
2010	0.11	0.07	0.73	0.26
2011	0.14	0.09	0.75	0.31
2012	0.12	0.08	0.68	0.30
2013	0.11	0.07	0.67	0.32
2014	0.10	0.08	0.73	0.34
2015	0.12	0.10	0.83	0.37
2016	0.16	0.14	0.90	0.43
2017	0.18	0.16	0.96	0.49

Notes: This table shows the p-values from chi-square tests under the null hypotheses that a related indicator of well-being is similarly correlated with different poverty series. The first entry 0.11 for 2010 can be interpreted as follows: the correlation between age dependency ratio and poverty estimated with the 2011 PPPs is not statistically different from the correlation between age dependency ratio and poverty estimated with the 2017 PPPs. In columns 1 and 3, the country-level observations that enter into Equations 3 and 4 in the main text are population weighted. In columns 2 and 4, the country-level observations that enter into Equations 3 and 4 in the main text are equally weighted.

In other words, the poverty series with the 2011 PPPs generally aligns with age dependency ratio and multi-dimensional poverty for any given year between 2010 and 2017, just as much as the poverty series with the 2017 PPPs. This confirms that only a few countries are re-ranked by poverty status in a systematic way, such as Angola and Ghana. It also suggests that the perception of poverty in Sub-Saharan Africa as a whole is generally unchanged with the new PPPs.

Some caveats are worth noting. First, it is not clear whether the true, unknown variation in extreme poverty can be sufficiently assessed with data on age dependency and multi-dimensional poverty. Several other variables can be correlated with poverty but are not used in this study. Second, the test results from the SUR regressions do not say anything about the accurateness of any of the poverty series, rather the possible accurateness of one series relative to others. All poverty estimates with the 2011 PPPs and 2017 PPPs can be scaled up or down by some scaling factor, and the results of the SUR regressions will remain the same.

5. Conclusion

New purchasing power parity exchange rates (PPPs) based on the latest price data collected across 176 countries in the world in 2017 by the International Comparison Program (ICP) were published in 2020 and have been adopted for the measurement of global poverty in 2022. These new PPP data make almost no difference to extreme poverty estimates for the world but make a relatively substantial difference for extreme poverty in Sub-Saharan Africa (Jolliffe et al. 2022). In 2017, extreme poverty in the world reduces from 9.3% to 9.1% and in Sub-Saharan Africa from 41% to 38% when moving from the 2011 PPPs to the 2017 PPPs—i.e., 0.2 and 3.2 percentage points, respectively. Extreme poverty estimates increase slightly by up to 1.5 percentage points in all other regions. Thus, the change in Sub-Saharan Africa alone is large enough to determine the direction of change for the whole world. This finding is intriguing and hence a motivation for this study.

The goal of this study is to look into these results for Sub-Saharan Africa with additional data. The results generally discourage poverty analysts and policymakers from updating their perceptions about poverty in Sub-Saharan Africa and the relative rankings of countries in Sub-Saharan Africa solely on the basis of the new PPPs. The large changes observed in extreme poverty in a number of countries in Sub-Saharan Africa seem to be correlated with improvements in statistical capacity over time, for example, in the collection and coverage of price data. Further, the data suggest that the substantial reduction in extreme in Sub-Saharan Africa is driven by a few populous countries, including Nigeria and the Democratic Republic of Congo. When assessed with variation in related indicators of well-being, such as age dependency ratio and multi-dimensional poverty, the 2011 and 2017 PPPs do not differ systematically in ranking countries.

Beyond this study, there is a strand of literature that suggests that extreme poverty in Sub-Saharan Africa might be actually lower than is usually estimated (Beegle et al. 2016; Dabalen et al. 2016;

Dabalen, Gaddis, and Nguyen 2020). These authors argue that extreme poverty in the region might be lower when one accounts for underreporting of consumption, corrects for CPI bias, and adjusts for spatial price differences within countries, among several ways of improving the data and methods used in poverty estimation. New survey data collected in Western and Central Africa not included in this study suggest that extreme poverty in the sub-region falls from 36.7% to 33.2% in 2017 (Castaneda et al. 2022). Again, when household economies of scale are accounted for in the estimation of global poverty, extreme poverty is estimated to decrease slightly by 2 percentage points in Sub-Saharan Africa where household size is relatively large (Jolliffe and Tetteh-Baah 2022).

There is still scope for building more statistical capacity in Sub-Saharan Africa, particularly in standardizing the collection and processing of the data used for poverty estimation. These include survey data, CPI and PPP data, national accounts data, and population data. More studies are needed to improve the reliability of poverty estimates in Sub-Saharan Africa until 2030, the target year of the SDGs.

6. References

Alkire, S., U. Kanagaratnam, and N. Suppa. 2021. "The Global Multidimensional Poverty Index (MPI) 2021." 51. OPHI MPI Methodological Notes. Oxford.

Allen, Robert C. 2017. "Absolute Poverty: When Necessity Displaces Desire." *American Economic Review* 107 (12): 3690–3721. https://doi.org/10.1257/aer.20161080.

Atamanov, Aziz, Dean Jolliffe, Christoph Lakner, and Espen Beer Prydz. 2018. "Purchasing Power Parities Used in Global Poverty Measurement." *Global Poverty Monitoring Technical Note* 5 (September).

Atamanov, Aziz, Christoph Lakner, Daniel Gerszon Mahler, Samuel Kofi Tetteh-Baah, and Judy Yang. 2020. "The Effect of New PPP Estimates on Global Poverty: A First Look," no. May.

Beegle, Kathleen, Luc Christiaensen, Andrew Dabalen, and Isis Gaddis. 2016. "Poverty in a Rising Africa." Washington, DC.

Castaneda, R Andres Aguilar, Reno Dewina, Carolina Diaz-bonilla, Ifeanyi N Edochie, Tony H M J Fujs, Dean Jolliffe, Jonathan Lain, et al. 2022. "April 2022 Update to the Poverty and Inequality Platform (PIP) What's New." Global Poverty Monitoring Technical Note 20.

Dabalen, Andrew, Alvin Etang, Rose Mungai, Ayago Wambile, and Waly Wane. 2016. "Is Poverty in Africa Overestimated Because of Poor Data?" In *Contemporary Issues in Development Economics*, edited by Timothy Besley. London: Palgrave Macmillan. https://doi.org/10.1177/146499340200200309.

Dabalen, Andrew, Isis Gaddis, and Nga Thi Viet Nguyen. 2020. "CPI Bias and Its Implications for Poverty Reduction in Africa." *Journal of Economic Inequality* 18 (1): 13–44. https://doi.org/10.1007/s10888-019-09429-3.

Dang, Hai-Anh H., John Pullinger, Umar Serajuddin, and Brian Stacy. 2021. "Statistical Performance Indicators and Index: A New Tool to Measure Country Statistical Capacity." 9570. Policy Research Working Paper. Washington, DC.

Deaton, Angus. 2010. "Price Indexes, Inequality, and the Measurement of World Poverty." *American Economic*, 5–34. https://doi.org/10.1257/aer.100.1.5.

Deaton, Angus, and Bettina Aten. 2017. "Trying to Understand the PPPs in ICP 2011: Why Are the Results so Different." *American Economic Journal: Macroeconomics* 9 (1): 243–64. https://doi.org/10.1257/mac.20150153.

Deaton, Angus, and Paul Schreyer. 2022. "GDP, Wellbeing, and Health: Thoughts on the 2017 Round of the International Comparison Program." *Review of Income and Wealth* 68 (1): 1–15. https://doi.org/10.1111/roiw.12520.

Evans, Martin, Ricardo Nogales, and Matthew Robson. 2020. "Monetary and Multidimensional Poverty: Correlations, Mismatches and Joint Distributions Martin." 133. OPHI Working Paper. Oxford.

Ferreira, Francisco H.G., Shaohua Chen, Andrew Dabalen, Yuri Dikhanov, Nada Hamadeh, Dean Jolliffe, Ambar Narayan, et al. 2016. "A Global Count of the Extreme Poor in 2012: Data Issues, Methodology and Initial Results." *Journal of Economic Inequality* 14 (2): 141–72. https://doi.org/10.1007/s10888-016-9326-6.

Jolliffe, Dean, Daniel Gerszon Mahler, Christoph Lakner, Aziz Atamanov, and Samuel Kofi Tetteh-Baah. 2022. "Assessing the Impact of the 2017 PPPs on the International Poverty Line and Global Poverty." 9941. Policy Research Working Paper. https://documents1.worldbank.org/curated/en/353811645450974574/pdf/Assessing-the-Impact-of-the-2017-PPPs-on-the-International-Poverty-Line-and-Global-Poverty.pdf.

Jolliffe, Dean, and Samuel Kofi Tetteh-Baah. 2022. "Changing Profiles of Extreme Poverty – Accounting for Household-Level Economies of Scale in the Global Profile of Poverty."

Lakner, Christoph, Daniel Gerszon Mahler, Minh C Nguyen, Joao Pedro Azevedo, Shaohua Chen, and Dean Jolliffe. 2018. "Consumer Price Indices Used in Global Poverty Measurement." *Global Poverty Monitoring Technical Note* 8 (September).

Ravallion, Martin. 2014. "An Exploration of the International Comparison Program's New Global Economic Landscape." *National Bureau of Economic Research*. https://doi.org/10.3386/w20338.

Reddy, Sanjay G., and Thomas Pogge. 2010. "How Not to Count the Poor." In *Debates on the Measurement of Global Poverty*, edited by Sudhir Anand, Paul Segal, and Joseph E. Stiglitz. https://doi.org/10.1093/acprof:oso/9780199558032.001.0001.

Tetteh-Baah, Samuel Kofi, Aziz Atamanov, Christoph Lakner, Daniel Gerszon Mahler, Marko Rissanen, William Vigil-Oliver, Mizuki Yamanaka, and Judy Yang. 2020. "Why Have the 2011 PPPs Been Revised and What Does It Mean for Estimates of Poverty?" *World Bank Data Blog*, 2020. https://blogs.worldbank.org/opendata/why-have-2011-ppps-been-revised-and-what-does-it-mean-estimates-poverty.

Vijayakumar, Sinnathurai. 2013. "An Empirical Study on the Nexus of Poverty, GDP Growth, Dependency Ratio and Employment in Developing Countries." *Journal of Competitiveness* 5 (2): 67–82. https://doi.org/10.7441/joc.2013.02.05.

World Bank. 2014. "Purchasing Power Parities and Real Expenditures of World Economies Summary of Results and Findings of the 2011 International Comparison Program," 104.

———. 2017. *Monitoring Global Poverty: Report of the Commission on Global Poverty*. Washington, DC: World Bank.

———. 2018. *Piecing Together the Poverty Puzzle*. *Poverty and Shared Prosperity Report 2018*. Washington, DC: World Bank Publications.

———. 2020. *Purchasing Power Parities and the Size of World Economies: Results from the 2017 International Comparison Program*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1530-0.

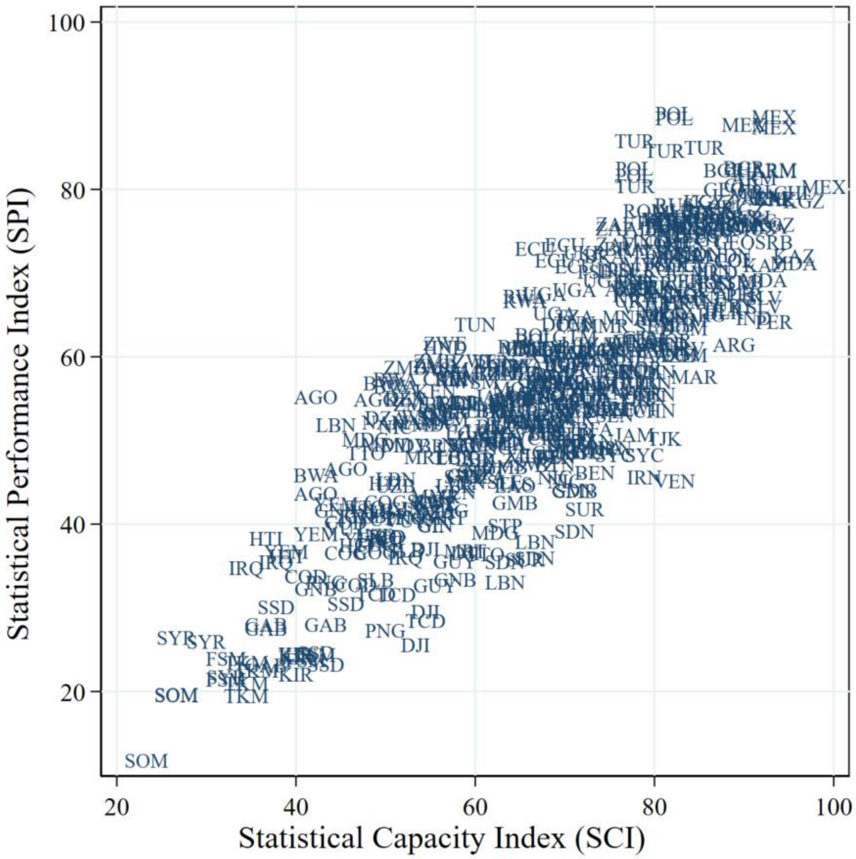
———. 2022a. "Data on Statistical Capacity." 2022. https://datatopics.worldbank.org/statisticalcapacity/.

———. 2022b. "DataBank: World Development Indicators (WDI)." 2022. https://databank.worldbank.org/source/world-development-indicators.

———. 2022c. "Poverty and Inequality Platform (PIP) Methodology Handbook." 2022. https://worldbank.github.io/PIP-Methodology/.

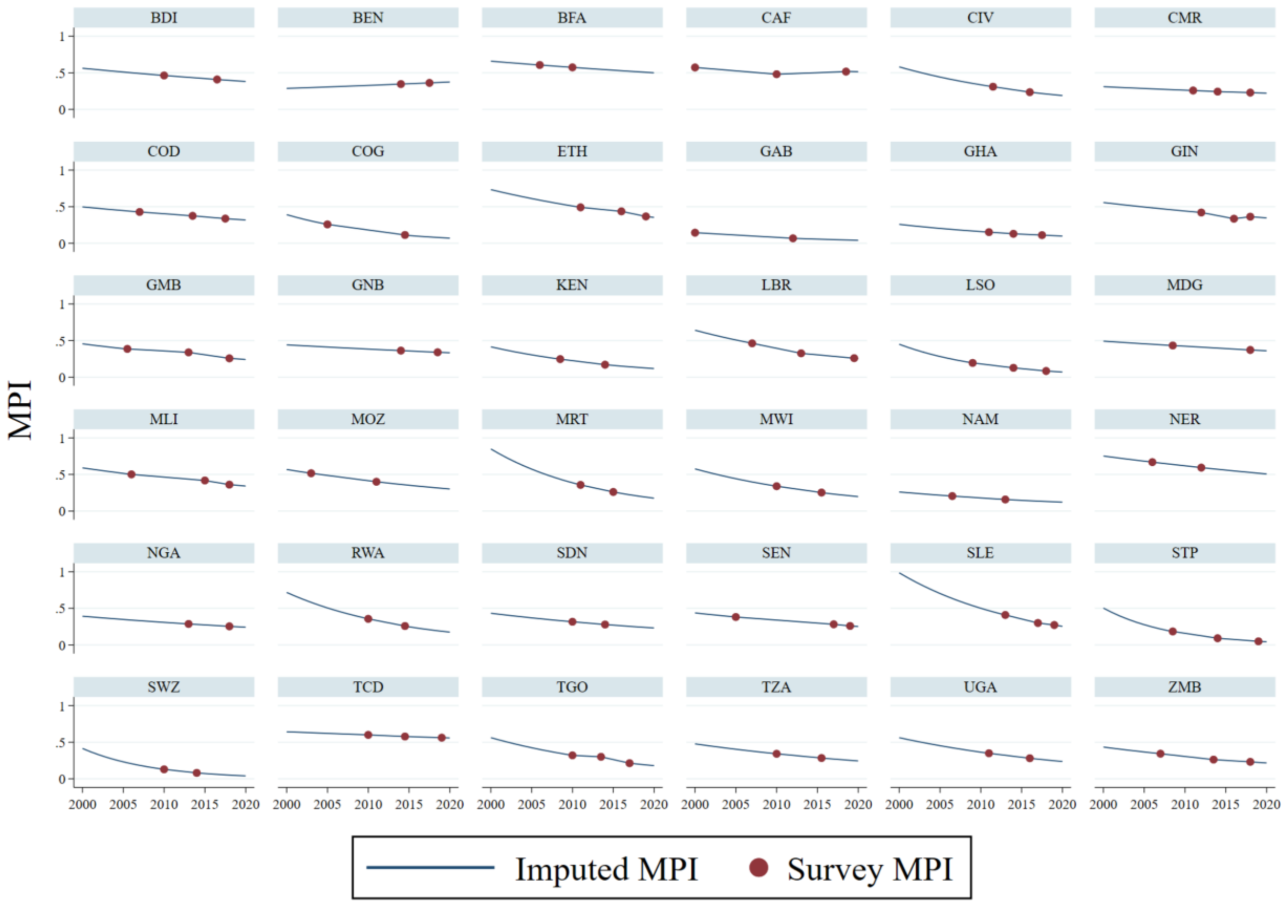
Appendix

Figure A1: Statistical Capacity Index (SCI) vs. Statistical Performance Index (SPI)



Note: Spearman's rank correlation coefficient between the Statistical Capacity Index (SCI) and Statistical Performance Index (SPI) is 0.84 and Pearson's correlation coefficient between the two variables is 0.85. All matching country-year observations are shown in this chart.

Figure A2: Complete MPI series by country



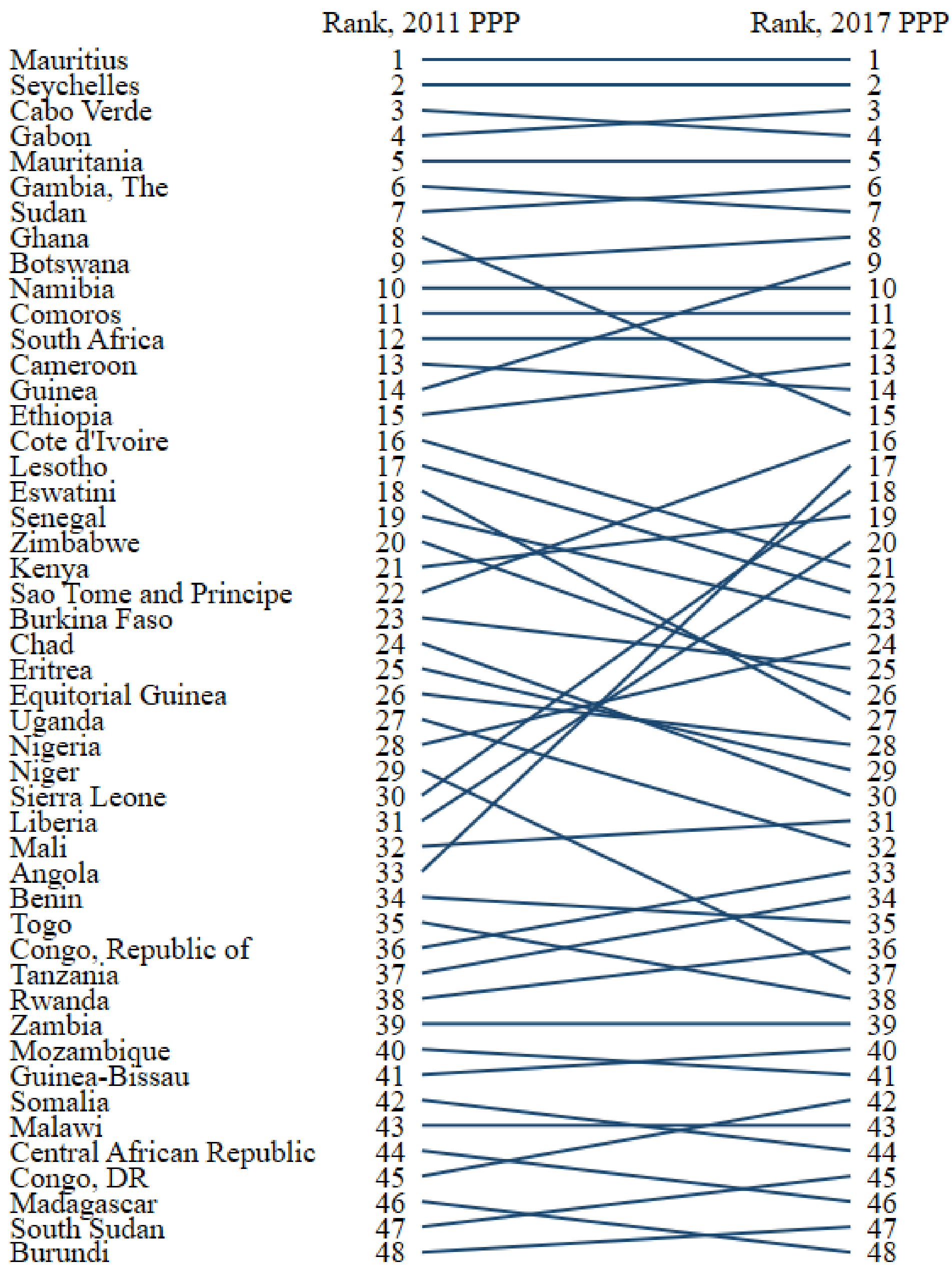
Notes: The Oxford Poverty and Human Development Initiative (OPHI) is the source of the survey estimates of MPI. The MPI data are taken from Alkire, Kanagaratnam, and Suppa (2021), Table 6.1 Harmonised MPI results by country and survey period, sheet(6.1 Harmonised MPI). A more complete annual series is imputed from the survey estimates in two steps. First, a weighted average of the two nearest survey estimates is taken. The respective weights are the inverse of the relative distances from the two survey years. Second, the series is extended forward and backward using average annual growth rate of all observations imputed between the survey estimates. Comparing countries having two survey estimates with those with three estimates reveals that the imputation of annual MPI series is far from perfect. Imputed MPI data might introduce some measurement errors that could potentially bias the results of this study. Other indicators of well-being considered in this study, such as age dependency ratio and child mortality, do not have this drawback.

Table A1: Top drivers of changes in poverty in Sub-Saharan Africa, 2017 - $2.15

Country	Headcount, % (2011 PPP)	Headcount, % (2017 PPP)	Absolute change in poverty, pp	Relative change in poverty, %	Change in millions of poor
Nigeria	41.4	33.4	-8.0	-19.2	-15.2
Congo, DR	72.7	64.4	-8.2	-11.3	-6.7
Angola	45.1	26.5	-18.6	-41.2	-5.5
Kenya	35.1	27.5	-7.6	-21.7	-3.8
Ethiopia	24.7	21.2	-3.5	-14.2	-3.7
Ghana	12.3	24.7	12.3	99.9	3.6
Tanzania	49.1	44.8	-4.3	-8.8	-2.4
Niger	42.7	51.9	9.2	21.6	2.0
Sierra Leone	44.0	27.2	-16.8	-38.1	-1.3
South Africa	19.1	20.8	1.8	9.4	1.0

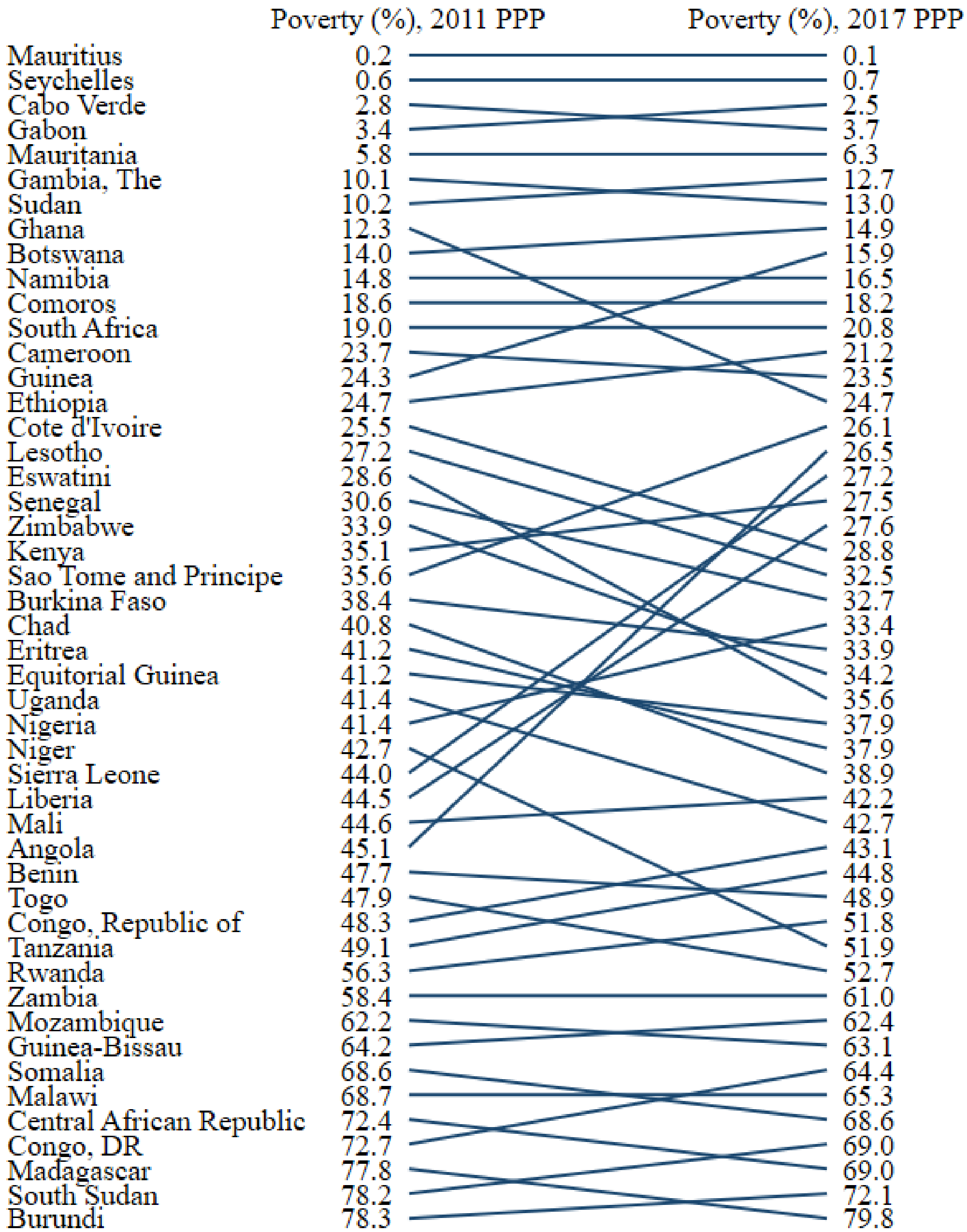
Note: Extreme poverty is estimated with the 2011 PPPs using the international poverty line of $1.90 and is estimated with the 2017 PPPs using the international poverty line of $2.15.

Figure A3: Poverty re-ranking in Sub-Saharan Africa in 2017



Note: The relationship between poverty estimates with the 2011 PPPs and 2017 PPPs has a Spearman's rank correlation coefficient of 0.94.

Figure A4: Poverty re-ranking (or estimates) in Sub-Saharan Africa in 2017



<u>Note</u>: The relationship between poverty estimates with the 2011 PPPs and 2017 PPPs has a Pearson's correlation coefficient of 0.96.

Table A2: Relationship between differences in poverty estimates and changes in statistical capacity

	Poverty change, pp		Poverty change, %	
	(1)	*(2)*	*(3)*	*(4)*
Positive change in SCI – 2005-20	1.22**	0.03	9.15**	9.45
	(0.56)	(0.45)	(4.42)	(6.54)
GDP per capita	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Europe & Central Asia	0.52	0.29	1.09	1.14
	(1.26)	(1.27)	(11.47)	(11.65)
Latin America & Caribbean	0.99	0.43	-6.01	-5.86
	(0.82)	(0.77)	(6.95)	(7.53)
Middle East & North Africa	-0.42	-0.73	8.34	8.42
	(0.75)	(0.70)	(10.30)	(10.48)
South Asia	-0.33	-0.84	-1.84	-1.71
	(0.80)	(0.75)	(8.23)	(8.39)
Sub-Saharan Africa (SSA)	2.92***	0.88	-11.27*	-10.74
	(1.03)	(0.86)	(6.11)	(7.61)
% Change in SCI * SSA		3.04**		-0.78
		(1.30)		(8.28)
Observations	129	129	129	129
Adjusted R-Squared	0.227	0.255	0.046	0.038

Note: The first regressor is based on annualized change the Statistical Capacity Index (SCI) between 2005 and 2020. This same variable is used in the interaction term with Sub-Saharan Africa.

Table A3: Relationship between differences in poverty estimates and changes in statistical capacity

	Poverty change, pp		Poverty change, %	
	(1)	*(2)*	*(3)*	*(4)*
% Change in SCI – 2011-17	0.10	-0.17	1.36	1.35
	(0.15)	(0.16)	(0.90)	(1.63)
GDP per capita	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Europe & Central Asia	0.44	0.09	1.42	1.40
	(1.14)	(1.01)	(10.84)	(10.55)
Latin America & Caribbean	0.64	0.14	-7.34	-7.37
	(0.70)	(0.64)	(5.55)	(5.61)
Middle East & North Africa	-0.53	-1.11	8.86	8.82
	(0.73)	(0.76)	(10.34)	(10.92)
South Asia	-0.69	-1.15	-3.46	-3.49
	(0.78)	(0.79)	(8.94)	(9.23)
Sub-Saharan Africa (SSA)	2.68***	2.10**	-12.16**	-12.20**
	(1.01)	(0.98)	(5.74)	(6.12)
% Change in SCI * SSA		0.59*		0.04
		(0.30)		(1.80)
Observations	129	129	129	129
Adjusted R-Squared	0.209	0.240	0.037	0.029

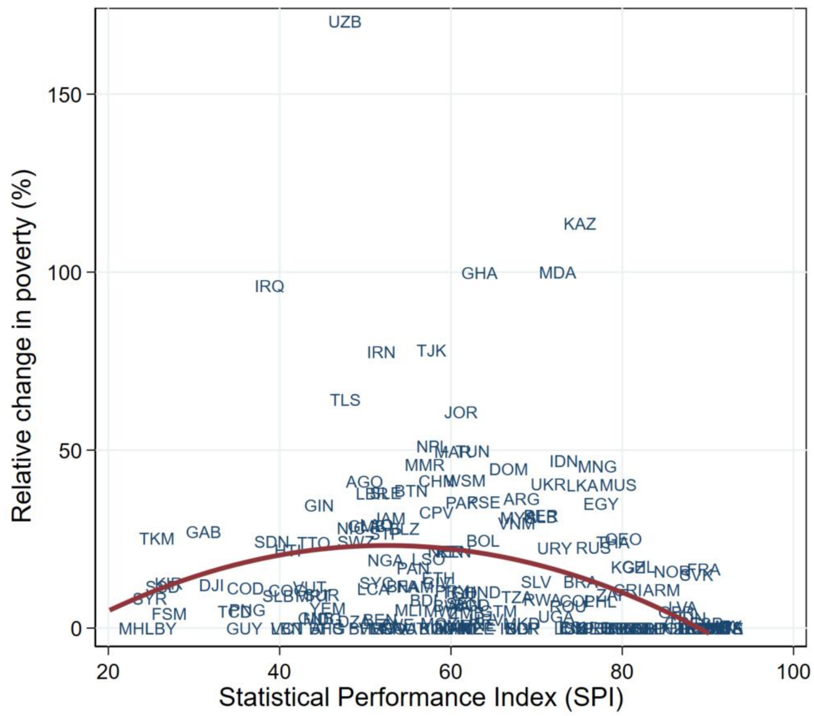
Note: The first regressor is annualized change the Statistical Capacity Index (SCI) between 2011 and 2017. This same variable is used in the interaction term with Sub-Saharan Africa.

Table A4: Relationship between differences in poverty estimates and changes in statistical capacity

	Poverty change, pp		Poverty change, %	
	(1)	*(2)*	*(3)*	*(4)*
Positive change in SCI – 2011-17	0.14	-0.61	8.20	10.70
	(0.66)	(0.67)	(4.98)	(7.16)
GDP per capita	-0.00***	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Europe & Central Asia	0.33	0.14	1.40	2.02
	(1.15)	(1.08)	(11.12)	(11.11)
Latin America & Caribbean	0.48	0.17	-6.85	-5.80
	(0.70)	(0.66)	(5.86)	(5.91)
Middle East & North Africa	-0.71	-0.87	7.64	8.16
	(0.70)	(0.72)	(10.05)	(10.06)
South Asia	-0.84	-0.90	-5.08	-4.88
	(0.76)	(0.77)	(8.99)	(9.03)
Sub-Saharan Africa (SSA)	2.57**	1.39	-11.42*	-7.49
	(1.01)	(1.21)	(6.17)	(8.00)
% Change in SCI * SSA		2.03		-6.72
		(1.55)		(9.20)
Observations	129	129	129	129
Adjusted R-Squared	0.205	0.214	0.042	0.038

Note: The first regressor is based on annualized change the Statistical Capacity Index (SCI) between 2005 and 2020. This same variable is used in the interaction term with Sub-Saharan Africa.

Figure A5: Differences in poverty estimates and statistical performance in 2017



<u>Note</u>: The red line is a bivariate, quadratic fit.