IARIW 2022

Monday 22 - Friday 26 August

Identifying the Poor – Accounting for Household Economies of Scale in Global Poverty Estimates

Dean Jolliffe
(World Bank)
djolliffe@worldbank.org

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

Paper prepared for the 37th IARIW General Conference

August 22-26, 2022

Session 6B-1, New Developments in Poverty Measurement with a Focus on National Statistical Office Efforts III

Time: Friday, August 26, 2022 [9:00-10:30 CEST]

Identifying the Poor –
Accounting for Household Economies of Scale in Global Poverty Estimates

Dean Jolliffe and Samuel Kofi Tetteh-Baah*
July 29, 2022

Abstract: Estimates of the number of people living in extreme poverty, as reported by the World Bank and used by many international organizations, figure prominently in international development dialogue. An assumption underpinning these global poverty counts is that there are no economies of scale in household size – a family of six needs three times as much as a family of two. This paper examines the sensitivity of global estimates of extreme poverty to relaxing this assumption. This analysis is based on national representative household survey from 162 countries providing inferences to nearly 5.9 billion people, more than three-fourths of the world's population, and 98 percent of the people estimated to be in extreme poverty in 2017. The analysis compares current-method estimates with new estimates based on a commonly used, single parameter, constant-elasticity scale adjustment that divides total household consumption or income not by household size but by the square root of household size. The analysis first demonstrates that while the regional profile of extreme poverty is robust to this change, the determination of who is poor changes substantially – the poverty status of 270 million people changes from being poor to not poor, or *vice versa*. The analysis then shows that the measure which accounts for economies of scale is substantially more strongly correlated with a series of presumed covariates of poverty (i.e., years of schooling, literacy, asset index, working in agriculture, access to electricity, piped drinking water, improved sanitation).

JEL codes: I32, O10, O20
Keywords: global poverty, ending poverty, household economies of scale, sustainable development goals

***** Jolliffe, the corresponding author (djolliffe@worldbank.org) is a lead economist at the World Bank. He also holds positions as an adjunct lecturer at the Johns Hopkins University School of Advanced International Studies (SAIS), Research Fellow with the Institute for the Study of Labor (IZA) in Bonn, and as a Fellow of the Global Labor Organization (GLO). Tetteh-Baah (stettehbaah@worldbank.org) is an economist in the Global Poverty and Inequality Data Team of the World Bank. The authors wish to thank Daniel Mahler, members of the Global Poverty and Inequality (GPI) Data Team for feedback on initial drafts of this work. The authors gratefully acknowledge financial support from the Knowledge for Change program and from the UK government through the Data and Evidence for Tackling Extreme Poverty (DEEP) Research Programme.

1. Introduction

Eradicating extreme poverty is the first target of the Sustainable Development Goals (SDGs) and ending extreme poverty by reducing the global share of people living on less than the international poverty line (IPL) to under 3 percent by 2030 is the first of the World Bank's twin goals.[1] These goals are foundational to international economic development. Over the last 30 years, there has been massive progress in reducing extreme poverty from 37 percent in 1989 to 8 percent in 2019 (World Bank, forthcoming). In 2015, extreme poverty as measured by living on less than $1.90 per day was less than 3 percent in more than half the countries of the world (Jolliffe and Prydz, 2021). Progress in reducing extreme poverty has slowed dramatically (World Bank, 2018; 2020a) and it's been clear for several years that the broad-spectrum effects of economic growth alone will not be enough to reach the 3-percent goal by 2030 (Jolliffe et al., 2014; World Bank, 2018; 2020a). Better identification and targeting of the poor through pro-poor policies are needed in combination with economic growth to reach the goal.

Better identification of the poor is inherently a measurement issue. One central challenge in identifying who is poor is linked to the problem that the measures of consumption and income (referred to more generally in this paper as household resources) used to assess extreme poverty are typically measured at the level of the household while poverty is typically considered to be an attribute of the individual. Most of the world's poor live in rural areas and many derive their income from farming (Desiere and Jolliffe, 2018) and nonfarm enterprises (Haggblade et al., 2010), both of which tend to be household-level activities. Consumption is similarly measured

[1] Extreme poverty as reported by the World Bank is defined as living on less than the daily value of the international poverty line (IPL). The value of the IPL is updated at irregular intervals but typically follows the release of updates to the purchasing power parity exchange rates (PPPs). The current value of the IPL is 1.90 per person per day in 2011 PPP US dollars, and it will be soon updated to $2.15 in 2017 PPPs.

primarily at the household level – this is typically true for consumption of food and also nonfood items such as housing and other durable goods.

The mismatch between measuring consumption and income at the household level and the interest in identifying poor individuals means that household resources (i.e., consumption and income) need to be allocated to the individual. The methodological approach followed by the World Bank for the monitoring of the Sustainable Development Goal (SDG), target 1.1 (i.e., eradicate extreme poverty by 2030) is to divide total household resources by household size, thereby converting household consumption into a per capita measure.[2] This approach essentially assumes that there are no economies of scale in the use of household resources, and similarly assumes that consumption needs are the same across men, women, boys, girls and infants.

Ferreira et al. (2017, p. 149, fn. 14), referring to the World Bank methodology, state that the "adoption of a per capita scale imposes cross-country comparability and is easy to explain." The Global Consumption and Income Project (GCIP) database[3] also uses per capita measures of wellbeing, and Lahoti et al. (2016, p.7) similarly argue that "…per capita surveys are easier to understand" and assert that "…limiting our focus to per capita surveys greatly aids comparability…" Both papers make the case for per capita allocation based on arguments of simplicity, transparency, and enhanced comparability. Decades ago, when the decision to use per capita allocation of household resources was made, Deaton and Zaida (2002, p.47) argued that "deflation to a per capita basis has become the standard procedure, and although its deficiencies are widely understood, none of the alternatives discussed have been able to command universal assent." They also assert that "years of experience with per capita expenditure has given analysts

[2] https://worldbank.github.io/PIP-Methodology/welfareaggregate.html#equivalence-scale
[3] http://gcip.info/

a good working understanding of its strengths and weaknesses, when it is sound (in most cases), and when it is likely to be misleading…"

The assertions of simplicity and transparency are difficult to argue against. In contrast though, the claim of improved comparability is problematic. Under the very restrictive assumption that all goods consumed by people in the household are private (i.e., none is shared), and strictly in the money metric, per capita allocation may indeed be comparable across countries and people. But once we acknowledge that there may be economies of scale in household consumption, emanating for several reasons including the existence of within-household public consumption goods (such as shelter and other shareable goods like light, radios, televisions, and many durable goods), a per capita allocation of household consumption or income will neither be comparable across households nor countries. Similarly, if we consider measuring wellbeing in the metric of meeting needs (i.e., proportion of basic needs met with the money allocated), and acknowledge that men, women and children have differing biological needs, the per capita metric will not be comparable across households or countries as long as household demographic composition differs. These issues are noted by Lahoti et al. (2016, p.7) in discussing the per capita allocation in the context of the GCIP, "…differences in the real value of resources arising from variations in household size and composition are not taken [into account]."

Both of these issues – economies of scale in household consumption and adjusting for differences in needs based upon age – will matter for cross-country comparisons if there is variation in average household demographic attributes across countries. Two coarse indicators, average age and household size, reveal significant variation across countries (Figure 1) and regions (Table 1). In terms of average household size, the data used in our analysis indicate that average household size within regions ranges from 2.4 people in high-income countries to 5 in Sub-Saharan

Africa and 5.1 in the Middle East and North Africa.[4] Across countries, average household size ranges from 2 in many high-income countries to above 9 in Senegal and Mali (based on the data used in this paper). In terms of variation in age, 20 percent of the population in upper-middle-income countries was 14 years of age or less in 2021; this proportion doubles (41%) when considering low-income countries.[5] Given that this age category on average needs fewer calories to meet basic needs, the per capita assignment differentially treats countries in a manner that is systematically correlated with income level.

[INSERT FIGURE 1 APPROXIMATELY HERE]

[INSERT TABLE 1 APPROXIMATELY HERE]

The aim of this paper is to understand the implications of relaxing the per-capita allocation assumption for the profile of global poverty and the identification of poor people by contrasting it with an alternative allocation rule (i.e., dividing household resources by the square root of household size). We show that the regional profile of extreme poverty is relatively insensitive to changing the household-resource-allocation rule, but the within country identification of who is poor is highly sensitive to the change (reclassifying the poverty status of 270 million people across the world). We also provide evidence that the probability of being poor as identified by the square-root allocation is more strongly negatively correlated (compared to being poor as identified by the per-capita allocation) with indicators presumed to be related to poverty status (i.e., years of

[4] Other data sources indicate even greater dispersion in household size. UN-DESA (2019a) estimate that countries range from slightly more than 2 people to slightly more than 8 people. These differences have clear geographic patterns with the average person living in a household with 6.9 people in Sub-Saharan Africa, compared to 3.1 in Europe (Kramer, 2020). For detailed breakdown by age, see UN-DESA (2019b).
[5] The proportion of the population 0-14 years in a country is monotonically decreasing in income classification (i.e., low-income, lower middle-income, upper middle-income, high-income). World Development Indicators, https://data.worldbank.org/indicator/SP.POP.0014.TO.ZS?most_recent_value_desc=false [Last accessed July 23, 2022.]

schooling, literacy, asset index, working in agriculture, access to electricity, piped drinking water, improved sanitation). In the next section, we further discuss the literature around allocation of household resources and the data used in the analysis. In section 3, we first examine the sensitivity of the regional profile of poverty and the identification of who is poor. We then examine the conditional correlation analysis between the competing measures of poverty and the indicators of wellbeing. Section 4 provides a brief conclusion.

2. Data and Methods

2a. Adjusting the allocation of household resources to account for household size

In arguing against a per capita allocation of household resources, Smeeding (2016, p. 31) states that "…except for the World Bank, everyone agrees that a household-size adjustment is needed." Whether everyone agrees on this or not, the more general point is that there is an extensive literature that considers other methods for allocating household resources. A common framework for allocating resources is to assume that the needs of a household comprised of A adults and C children can be described by $(A + pC)^h$ where p adjusts for differences in needs between adults and children (or in other words, converts children into adult equivalents) and h adjusts for economies of scale in household size. If h=0, then the marginal cost of an additional person in the household is zero, and total value of household resources are allocated to each individual in the household. The per capita allocation sets p=1 and h=1, and household needs are equal to household size. Smeeding (2016) notes that setting p=1 and h to some value less than one (i.e., a single parameter, constant-elasticity scale adjustment), is the most common approach particularly for international comparisons (Rainwater and Smeeding, 2005). Lanjouw and Ravallion (1995) also demonstrate how changing the value of h alters commonly held views of larger households being poorer on average.

For the analysis in this paper, where we aim to understand how the allocation of resources affects the global profile of poverty, we only have data on household size and not the age composition of each household. The implication of this is that we can only consider changing the single parameter, h, which describes the elasticity of needs to household size. The per-capita allocation sets h=1 which would be defensible if households only consumed nonshareable goods, such as food. When the initial "dollar-a-day" IPL was set (World Bank, 1990), and the decision to use per capita consumption as the measure of wellbeing was made, food budget shares were very high in most poor countries. Over time though, as the world has grown richer (and as our instruments better measure complete consumption), food budget shares have steadily declined and setting h=1 is less tenable. As related evidence, the share of food and nonalcoholic beverages in gross domestic product (GDP) has dropped from 49 to 37 percent between 2005 (Muhammad et al., 2011, Table 2) and 2017 (World Bank, 2020b, Figure 1.4). While there is variation in values used for h, Johnson and Torrey (2004) note that adjusting needs by the square root of household size (i.e., p=1, h=0.5) is becoming common in international poverty comparisons.[6] Buhmann et al. (1988), Ruggles (1990) and Vleminckx and Smeeding (2001) provide examples of this, and Dudel et al. (2021) suggest that the square-root adjustment performs well, particularly for larger households.

[6] The square-root adjustment is often applied in research work (Johnson et al., 2005; Ravallion, 2016; Smeeding, 2016; Taylor et al., 2011), policy work (OECD, 2015; US Congressional Budget Office, 2018), and international comparison of poverty and inequality, as done with the Luxembourg Income Study (LIS) (Buhmann et al., 1988).

2b. Data for Regional Profiles and Correlation Analysis

We draw heavily on the same data the World Bank uses in estimating global poverty both to enhance comparability of our analysis with the measures used by many international development agencies (e.g., United Nations, USAID, UK FCDO) and also to maximize country coverage and ensure that our primary findings are valid for the world. The main source of data is the Global Monitoring Database (GMD), an internal World Bank archive of harmonized micro-level income and consumption survey data from 154 countries. (For details, see World Bank, 2020a, Appendix 1A.) In addition, we supplement the GMD survey data with household survey data from the Luxembourg Income Study (LIS) for 8 countries.[7] These are the same data ingested into the Poverty and Inequality Platform (PIP), an interactive online computational tool for the Bank's poverty and inequality estimates.

In total, our global analysis is based on nationally representative income and consumption survey data from 162 countries. These data are a subset of the 168 countries used for the March 2021 update to the World Bank's global poverty estimates as described in Arayavechkit et al. (2021). These are the same data that are used to monitor SDG 1.1. We are unable to include six countries primarily because the data for these countries are reported in aggregate form (grouped data) and not available at the unit-record level.[8] The global poverty estimate we report in this paper, based on the per-capita allocation of household resources from the 162 countries in our analysis, is higher than the reported poverty estimate of 9.2 percent in 2017 based on the 168 countries (Arayavechkit et al., 2021). The primary reason the global estimate reported in this paper is higher

[7] These eight countries are: Australia, Canada, Germany, Israel, Japan, Republic of Korea, Taiwan-China, and the United States.

[8] The six countries for which we cannot re-estimate individual-level wellbeing based on adjusting resources by the square root of household size are: Algeria, China, Trinidad and Tobago, St. Lucia, United Arab Emirates and Venezuela.

is due to the exclusion of China, which has both a large population and low rate of extreme poverty. Nonetheless, the data in our analysis is representative of nearly 5.9 billion people or more than 3/4th of the world's population.

For each country, the surveys have been conducted in different years and the data are reported in local currency units in current prices. Following the methodology used to report on SDG 1.1, we convert all income and consumption data into 2011 constant local prices using Consumer Price Indices from each country, and then convert the resulting vector into an internationally comparable US dollars using 2011 purchasing power parity exchange rates (PPPs).[9] The CPIs are used to estimate real changes in income and consumption over time, while the PPPs account for relative price differences across countries. In addition to using the same CPI and PPP data as used by the World Bank for global poverty monitoring, we also use the same population and national accounts data. For more details on how the World Bank estimates poverty, see World Bank (2020a).

In the second part of the analysis, we use covariates of poverty status to investigate the reliability of the square-root allocation rule of household consumption in identifying the poor, relative to the per-capita allocation rule. For this analysis, we use detailed micro-level data from the latest surveys of a subsample of eight countries, namely Nigeria, Mali, India, Pakistan, Colombia, Tajikistan, Indonesia, and Yemen.[10] We wanted this analysis to have at least one country per region with two countries each from Sub-Saharan Africa and South Asia—the two

[9] For more details on the CPI series, see: https://worldbank.github.io/PIP-Methodology/convert.html#CPIs. For more details on the PPPs, see: https://worldbank.github.io/PIP-Methodology/convert.html#PPPs . [Both last accessed on July 23, 2022.]

[10] The latest survey year varies across these countries. The surveys years are 2018.75 for Nigeria, 2009.89 for Mali, 2011.5 for India, 2018.5 for Pakistan, 2015 for Tajikistan, 2017 for Indonesia, Yemen for 2014, and 2017 for Colombia. By convention, the decimal indicates the share of the survey conducted in the second year. For example, 75% of the Nigeria survey was conducted in 2019.

regions where the prevalence of extreme poverty is the highest in the world. Our choice of countries was also constrained by our interest in having data on important co-variates of poverty, including completed years of schooling, asset ownership, literacy, access to electricity, agriculture as source of income, piped drinking water and improved sanitation. Table 2 shows the dispersion in these selected co-variates of poverty with Colombia, Indonesia, and Nigeria have relatively high levels of education (at least an average of 7 years of schooling for the head of households) while India and Pakistan have relatively low levels of education (an average of about 5.5 years of schooling).[11] We have no data on years of schooling for Mali and Tajikistan. The downside of limited data for some covariates in some countries is offset by the fact that we analyze pooled data from eight different countries that are carefully selected.

[INSERT TABLE 2 APPROXIMATELY HERE]

In addition to select nonmonetary co-variates of poverty, we also use principal components analysis (PCA) to compute an asset index in each country to proxy wealth. The asset information that is available for each country varies, but our interest in examining the poverty covariates is to assess whether within each country the covariates are more strongly correlated with poverty as measured by the per-capita or square-root allocations. PCA extracts a latent, underlying variable which in our case, we interpret as a proxy for wealth, from a set of related indicators. (For examples and details of this, see Pritchett and Filmer, 2001; Vyas and Kumaranayake, 2006; Filmer and Scott, 2012; Harttgen and Vollmer, 2013). The idea is to exploit variation in a range of related variables and estimate the principal components or factors that are orthogonal to each other. In this case, we have data on the ownership of different household assets for each country, such as having

[11] These figures are to be interpreted with caution due the highly varied survey years. The data for India is much older than the data for the other countries.

good floor material, having good roofing material, or owning a bicycle, computer, stove, television, washing machine, fan, refrigerator, car, and land. (For a complete list of assets used in each country, see Table 3.) PCA relies on the information from the covariance structure of these assets and the hypothesized latent variable that maximizes the explained variance in the set of assets. Table 3 shows the loadings for the first principal component which are treated as the relative weights assigned to each asset to construct the proxy for wealth, or the asset index. For example, in Nigeria, owning television is a strong positive contributor to household wealth (first factor loading of 0.82), while owning a bicycle is a negative contributor to household wealth (first factor loading of -0.02). For Mali, Pakistan, and Colombia, we have data on the ownership of only three assets, namely computer, cell phone, and landline. In these cases, *asset ownership* variable is instead created as a binary/indicator variable of owning at least a computer or landline phone. The ownership of cell phone has quite limited variation across households, hence it has a low weight in the asset index, while owing a computer or landline has greater variation across households and is more likely to indicate household wealth.

[INSERT TABLE 3 APPROXIMATELY HERE]

3. Results

3a. Regional profiles and Reclassification of Poverty Status

By using the same data from 162 countries on household resources as used for the per-capita poverty estimates, we examine how poverty profiles would change under the assumption of household economies of scale, as reflected by allocating household resources based on the square root of household size. Our focus is on how changing the allocation rule changes the composition of who is poor and not on the level of poverty. The IPL of $1.90 (in 2011 PPP US dollars) reflects typical values of national poverty lines expressed in per capita terms from some of the poorest countries in the world (Ferreira et al., 2016). Since the national poverty lines used to estimate the IPL are all in per capita terms (Jolliffe and Prydz, 2016), we have no ability to directly estimate the equivalent IPL in square-root of household size terms.

The approach we follow instead, is to solve for the value of the IPL based on the square-root allocation of household resources that keeps the overall headcount unchanged (from the per-capita allocation). More specifically, let the global poverty rate in a reference year (in our analysis, this is 2017) be given as:

$$F(z) = \int_0^z f(y(pc))\, dy = P^* \qquad (1)$$

where z is the value of the IPL in per-capita, per-day terms (expressed in 2011 PPP US dollars).[12] P^* is the global poverty rate obtained from a global welfare probability density function, $f(y(.))$ of daily consumption per capita, *y(pc)*, in revised 2011 PPPs. For our sample of 162 countries, P^* is equal to 11.6 percent (Table 4). We then find the value of $\hat{z}$ on the density function of consumption that has been allocated to the individual based on the square root of household size, $f(y(rn))$:

$$F(\hat{z}) = \int_0^{\hat{z}} f(y(rn))\, dy = P^* \qquad (2)$$

Thus, the equivalent "square-root" poverty line ($\hat{z}$) keeps the global poverty rate fixed at P^*. The value of z that equates the square-root poverty line with the per-capita poverty line for the 162 countries in our analysis is $4.47 in 2011 PPPs (Table 4).[13]

[12] We first examine the IPL value of $1.90 (2011 PPPs) and then also consider the reported higher values lines of $3.20 and $5.50 (World Bank, 2018; Jolliffe and Prydz, 2016).
[13] When we carry out this analysis at higher-value lines, we repeat this method and solve for the values of the square-root poverty line that keep the poverty rate the same as when evaluated at the higher-value, per capita lines (i.e., $3.20 and $5.50).

This substantial increase in the value of the square-root poverty line, relative to the per-capita poverty line, is expected. Recall that the per-capita allocation rule divides total household resources by household size and assigns this ratio to each individual in the household. The square-root allocation rule divides resources by the square root of household size and assigns this to each individual in the household. The assumption of household-level economies of scale means that the sum of each individual's allocation is greater than total household resources. For all individuals who live in households with more than one person, this change assigns a greater measure of consumption or income to each individual relative to the per-capita allocation. For example, for all individuals in households with four people, the level of resources assigned to each individual with the square-root allocation is doubled relative to the per capita allocation.[14] Table 1 indicates that the average values of household size in those regions that have the most people living in extreme poverty (i.e., Sub-Saharan Africa and South Asia) are close to 5 – the square root of which is reasonably close to the ratio of the square-root and per-capita poverty lines.

Table 4 presents the first set of findings by comparing the regional profile of global poverty based on the current per-capita, \$1.90 poverty line and the square-root, \$4.47 poverty lines. By design, both lines produce poverty rates of 11.6 percent, or 682 million people living in extreme poverty. In terms of percentage point change in regional poverty rates, the largest change occurs in Sub-Saharan Africa which declines from 41.3 percent under the per capita line to 39 percent under the square-root line. The change of 2.3 percent points represents 24.2 million fewer people living in poverty in Sub-Saharan Africa than are measured with per-capita allocation of resources. The change in the Middle East and North Africa region, as well as East Asia and Pacific region, is

[14] The increase in assigned value to each individual is equal to the square root of the size of their household.

between 1 and 2 percentage points, while the change is less than a percentage points in all other regions.

Despite the significant variation in household size across regions, the overall profile of poverty is not so sharply changed. The ranking of the top three regions with the highest prevalence of extreme poverty in unchanged when switching from the per-capita to the square-root allocation of household resources. Sub-Saharan Africa and South Asia having significantly greater poverty rates than the other regions under both allocations, followed by the Middle East and North Africa. The ranking of regions, and largely the regional profile of extreme poverty is fairly insensitive to changing assumptions about household economies of scale.

A simple comparison of changes in regional poverty rates though misses important parts to the story. Column 7, Table 4 counts the net change in the number of people who are poor in each region. By design, the sum of these net changes is zero, but the sum of the absolute value of the net changes across the regions reveals a change in the regional profiles of 60.5 million people when switching from the per-capita to the square-root allocation. These changes at the regional level reflect net shifts of about nine percent of the total population of poor people (60.5 million out of the estimated 682 million poor people).

[INSERT TABLE 4 APPROXIMATELY HERE]

If only concerned about regional patterns of poverty, this estimate of nine percent is a reasonable indicator of the sensitivity of the global poverty estimates to assuming household economies of scale. The work to eradicate extreme poverty though, largely is undertaken at the country level and not at the regional level. Poverty reduction policies are programs are typically national or subnational programs. An examination of net changes at the regional level hides important information about changes taking place at the country level. We consider two ways of thinking about these changes. One is to examine the global sum of absolute net changes at the country level, and the other estimate is the global sum of the number of people who are reclassified as poor or not poor (or vice versa) from switching to a square-root allocation of household resources.

To better understand these two approaches, consider first some country in a region that has a net increase of six million people while another country in that same region had a net decline of four million people. The net change in that region is two million people, but if we are interested in changes at the country level, the sum of the absolute value of changes for these two countries is more informative of how much the countries profile change from the per-capita allocation. In this hypothetical example, the sum of absolute value of the change registered for the two countries is ten million people, or five-folder greater than the net regional effect.

The data reveal that in South Asia, the net change for the region is an increase in the number of people living in extreme poverty of 16.6 million people when switching from the per-capita to the square-root allocation. If the focus shifts from the region to the country, the data indicate that the sum of the absolute value of the increase or decrease in the number of poor people in each country within South Asia, is 27 million people. Overall regions, the sum of the absolute value of the change in the number of poor people in each country is 86 million people, or about 13 percent of the total number of poor people. The inference that the regional profile is reasonably robust to changing the assumption about household economies of scale only holds when examining net changes at the regional level. When we shift to examining the net change in the number of poor people in each country, we observe a sizeable change in the distribution of poverty.

Just as looking at net changes to regional average poverty rates hides net changes at the country level, it is also the case that looking at the net change in the count of poor people within a country masks significant reclassification of who is poor. Consider a country where eleven million people are reclassified from being poor under the per-capita allocation to not poor when switching to the square-root allocation. Further, assume that nine million people are reclassified from being not poor to poor when this switch is made. The net change for that country is a decline of 2 million people who are identified as poor in the country but the total number whose poverty status changes from this switch is 20 million people (ten-fold larger).

To understand the distinctions in these measures, consider Sub-Saharan Africa. We noted that Table 4 indicates that on net there are 24 million fewer poor people (Table 4, column 7) there if poverty is estimated with the square-root allocation as compared to the per-capita measure. The sum of the absolute value of all net changes at the country level within Sub-Saharan Africa is much larger though, 35 million people (Table 4, column 8). For each country though, policy makers typically need to know who is being identified as poor to better improve the targeting of their policies and programs. Table 5 provides relevant information to address this need. While the net change at the regional level for Sub-Saharan Africa is 24 million, and the sum of absolute value of net country changes is 35 million people, Table 5 (column 3) indicates that 68 million people are reclassified from poor to not-poor status when switching from per-capita to square-root measures, and 44 million people have the opposite occur. The total number of people within Sub-Saharan Africa whose poverty status changes is 112 million people – nearly five times greater than what would imagine if only examining the net change for Sub-Saharan Africa. Overall all 162 countries in our analysis, the poverty status of 270 million people changes when switching from the per-capita to square-root allocation of resources. This is equal to 40 percent of the total population of poor people as estimated by both either of these rules.

[INSERT TABLE 5 APPROXIMATELY HERE]

3b. Correlation between competing poverty measures and wellbeing

The primary objective of this paper is to examine the sensitivity of the identification of who is poor to changing the assumption about the economies of scale to household size. The motivation for this analysis makes the case that when food shares were very high and the focus of the estimates of extreme poverty were in relatively lower income countries, assuming no economies to household scale (i.e., allocating household resources on a per-capita basis) may have been reasonable. Now that the focus of estimating extreme poverty has shifted to a global exercise (Jolliffe et al., 2014) including rich countries in the counts of people in extreme poverty, and now that food shares have declined and the consumption of within-household public goods has increased, the assumption may no longer be tenable.

The analysis above makes the case that identifying who is poor is highly sensitive to assumptions made on the extent of household economies of scale. Nothing in the analysis suggests though that allocating resources by the square root of household size identifies who is poor as effectively as the currently used per-capita measure. The objective of this section is to compare the two measures of extreme poverty – the per-capita and square-root measures – with presumed covariates of poverty. The covariates examined are the years of schooling of the head of household, a proxy for household wealth (i.e., an asset index), and a series of indicator variables for asset ownership, literacy, whether agriculture is the source of income, access to electricity, access to piped drinking water, and access to improved sanitation.

Many of these covariates are correlated with household size and regressing the covariates on the two different measures of poverty would provide estimates that confound both the effect of switching from the per-capita to square-root measure as well as the effect of household size on the covariate. To better understand the correlation between the two measures of poverty and each of the covariates – independent of the effect that household size has on both, we first condition out the effect of household size from each of the covariates. More specifically, first consider:

$$P_{h,c}^{a} = \partial_0 + \partial_1 Y_{h,c} + \vartheta_{h,c} \qquad (3)$$

where P is an indicator for being poor, h subscripts the household, c subscripts the country and the superscript a indicates whether household resources are allocated based on a per-capita or square-root allocation. Y is variously one of the poverty covariates (e.g., years of schooling of the household head). In this specification, ∂_1 will estimate the correlation between the poverty covariate (e.g., schooling) and the measure of poverty. A potential problem though is that household size is correlated by definition with the per-capita and square-root (of household size) allocation used for the two poverty measures, and household size is correlated with most of the poverty covariates. In this case, the E(Y| $\vartheta_{i,c}$) is not zero and ∂_1 will be biased. To address this source of bias, we estimate the following specification:

$$P_{h,c}^{a} = \beta_0 + \beta_1 (Y_{h,c}|N_{h,c}) + \varepsilon_{h,c} \qquad (4)$$

where N is household size and $(Y_{h,c}|N_{h,c})$ are the poverty covariates conditioned on household size. To estimate the conditional poverty covariates, we first regress each of the covariates on household size and then use the residuals as the regressor which are by construction, orthogonal to household size, but positively correlated with the covariates.

The eight countries examined in this part of the analysis countries are from Sub-Saharan Africa (Nigeria, Mali), South Asia (Pakistan, India), East Asia and the Pacific (Indonesia), Middle East and North Africa (Yemen), Latin America (Columbia) and Europe and Central Asia

(Tajikistan). These countries were purposely selected to ensure regional coverage, because they have large populations of people living in extreme poverty within each region and, just as importantly, they are countries for which we had access to unit-record data with the identified poverty co-variates.[15] While the countries are purposefully selected, and not randomly, there's no statistical basis for us to suggest the findings hold external to the populations they reflect, but these 8 countries do represent 417 million people living in extreme poverty or two-thirds of the total poverty population in this analysis.

In estimating equation (4), we make inferences from the comparison of the size and significance of the estimated β_1 parameter. To enhance comparability, each comparison presented is based on identical samples and specifications, except for switching the allocation rule from per-capita to square-root in $P_{i,c}^{a}$ across the models. To further enhance comparability of the comparisons, we ensure that the relative size of the estimated poverty population is the same in each country whether estimated by the per-capita or square-root measure. This means that the square-root poverty line will vary in value across countries. To find the values of the poverty lines for each country, we solve equations (1) and (2) to derive the value of the square-root allocation poverty lines that produces the same poverty rate as with the $1.90 IPL for each country (Table 6). We repeat this for the higher-valued poverty line of $3.20 (Table 7).

[INSERT TABLE 6 APPROXIMATELY HERE]

[INSERT TABLE 7 APPROXIMATELY HERE]

[15] The countries selected are from Sub-Saharan Africa (Nigeria, Mali), South Asia (Pakistan, India), East Asia and the Pacific (Indonesia), Middle East and North Africa (Yemen), Latin America (Columbia) and Europe and Central Asia (Tajikistan).

Except for years of schooling and the asset index, all of the other the poverty covariates examined in Table 8 are binary variables. The advantage of binary indicators as opposed to continuous variables is that the units are comparable across countries. The value of 1 for the binary indicator of literacy has the same meaning across countries, and the distance between 0 and 1 for this indicator are comparable across countries as well. This is not necessarily true of the two continuous variables, years of schooling and the asset index. A one year increase in years of schooling is unlikely to have comparable interpretations across countries – heterogeneity in things like school quality will harm cross-country comparability. To address this concern, we sort the continuous variables and use their rank rather than level in the regression analysis. The interpretation of a one-unit change is then a one-step increase in the ranking – not solving the comparability concerns but improving cross-country comparability.

Tables 8 and 9 provide estimates of β_1 from 32 separate regressions – eight different poverty covariates and 4 different dependent variables. All of the regressions are the same in each table, as well as the pooled sample of data from the eight countries. The only difference is that in Table 8 the estimates are weighted to treat each country as the unit of observation (i.e., the sampling weights are normalized such that the sum of weights for all observations within a country sums to one). In Table 9, poor people are the units of observation (i.e., the sampling weights are rescaled so that the sum of weights for all observations within a country sums to the estimated number of poor people in that country as estimated by the per-capita measure of poverty). The objective of this weighting scheme is to give greater importance to countries that have more people living in extreme poverty.

The parameter estimates in the first column report on the correlation between each of the poverty covariates and a binary indicator that takes the value of one for all individuals who are classified as poor *only* with the per-capita allocation (and the $1.90 poverty line). All nonpoor individuals are zero, and all individuals who are identified as poor under both allocations are zero. The second column repeats this but the binary indicator identifies those individuals who are classified as poor *only* with the square-root allocation. By construction, there is no overlap of the identified poor people from these two indicators. Column (5) report the parameter estimates for the same regressions except the binary indicator identifies all people who are classified as poor under the per-capita allocation (including those who are classified as poor under both classifications). Similarly, column (6) repeats this except for all people classified as poor under the square-root allocation.

Across the 64 parameter estimates in the two tables, the correlation is negative as expected (the indicators are constructed to take the value of one for the outcome assumed to be associated with improved economic wellbeing). Within each country, as the rankings of years of schooling and the asset index increase, the likelihood of being classified as poor under either allocation is negative. The same expected relationship holds for the indicator variables (e.g., households that have electricity, or have a head that is literate, are less likely to be poor under either allocation). All estimates are statistically significantly different from zero – all are significant at $\alpha = 0.01$ except for one. The variance estimates underpinning the significance measures account for the complex designs of each of the country random samples. The metadata on the primary sampling units (PSUs) are used to correct for within-PSU correlation (i.e., violations of the independent and identically distributed assumption), and leveraging the fact that each country survey is an independent operation, each country in our pooled sample is treated as a stratum. It is expected that most of the correlations take the expected sign. That all are negative and statistically significant is somewhat surprising (these are sample data and presumably also contain measurement error concerns) but certainly aligns with the view that both the per-capita and square-root allocation of household resources produce a classification of poverty that contains useful signal.

Furthermore, we carry out 32 tests of equality between the pairs of estimated β_1 coefficients. The differences between the estimated coefficients from the per-capita and square-root regressions are statistically significant for all 32 comparisons (all comparisons in Tables 8 and 9). The p-value is less than 0.01 for all comparisons except two (which have p-values less than 0.02).[16] The tests are meant to inform on whether each poverty covariate (e.g., literacy, wealth) is more negatively correlated with either the per-capita or square-root poverty measure. The idea is to assess whether one of these two measures consistently outperforms the other in terms of being more strongly correlated with presumed attributes of people living in poverty. Over all 32 tests, the absolute value of the magnitude of the estimated β_1 coefficients are greater for the indicator that classifies people as poor under the square-root allocation.

[INSERT TABLE 8 APPROXIMATELY HERE]

[INSERT TABLE 9 APPROXIMATELY HERE]

Columns (5) in both tables provide the estimated coefficients from regressing the indicator variable which identifies all individuals who are classified as per-capita poor on each of the poverty covariates. Column (6) repeats this for the indicator which identifies all individuals who are classified as poor under the square-root measure. Despite there being significant overlap between these two samples (the majority of people who are classified as poor under one measure are also poor under the other), the correlation is more strongly negative for all of the regressions based on

[16] Each of the p-values in columns (4) and (7) of Tables 8, 9, 10, and 11 report on tests of whether the estimated coefficients from the regression of the poverty indicators (whether for the per-capita or square-root indicators) are equal.

the square-root measure. Column (7) reports the p-values from each test and indicates that no p-value is greater than 0.02.

Because the statistical support for the estimates in columns (5) and (6) is coming substantially from the overlap in the samples, columns (2), (3), and (4) repeat this exercise but eliminate the overlap. As noted above, columns (2) and (3) identify those individuals who are classified as poor only under one measure (either the per-capita or square-root allocation). All others are zeros. It continues to be the case that the square-root classification of poverty is more negatively correlated with the presumed covariates of poverty, but the differences when the overlap in the samples is eliminated are substantial. For example, the estimated coefficient on the indicator for the ranked years of schooling is nineteen times greater in magnitude than the correlation with the per-capita indicator. The correlation between the square-root indicator and the literacy indicator is 6.5 times larger in magnitude than the estimated correlation between literacy and the per-capita indicator. The weakest difference between the two indicators is the evidence indicating that access to piped drinking water is more negatively correlated with the square-root poverty measure than with the per-capita measure. In this case though, the square-root measure is still more than 3 times greater in terms of the negative correlation with access to piped drinking water (with a p-value of 0.017).

The finding that the square-root allocation is more strongly correlated with a series of independent poverty covariates is robust to several factors. First, Tables 8 and 9 demonstrate that this finding is robust to a wide array of alternative poverty covariates. The relationship appears to hold in the space of public health investments (i.e., access to piped water an improved sanitation), education outcomes (i.e., literacy and years of schooling), and wealth (i.e., the asset index). The findings are also robust to the expected concern that the measures are highly correlated. The tables examine the subset of people who are identified as poor only under one rule and not the other. Further on this same point, the estimation approach used treats the pair of regressions (i.e., per-capita, square-root indicators) as seemingly unrelated regressions to estimate and adjust the tests for the expected positive covariance of the residuals across the two regression (particular for the comparisons where the per-capita and square-root samples have substantial overlap, column 7). Tables 10 and 11 also explore the sensitivity of the finding to the value of the IPL of $1.90 by replicating the test of equality but with the poverty line set at the higher value of $3.20. The findings from these tables suggest there is some sensitivity to increasing the value of the IPL. Whereas all 32 differences were statistically significant when the IPL is $1.90, at $3.20, 25 of the 32 differences are statistically significant (p-values < 0.01) and indicate stronger correlation with the square-root measure.[17]

[INSERT TABLE 10 APPROXIMATELY HERE]

[INSERT TABLE 11 APPROXIMATELY HERE]

4. Conclusion

Eradicating extreme poverty figures prominently is international development dialogue and is ultimately the goal of many economic development organizations and institutions. The World Bank's monitoring and reporting on progress in ending extreme poverty is widely accepted and directly informs the status of target 1.1 of the United Nation's Sustainable Development Goal, to eradicate extreme poverty for all people everywhere. Measuring progress in ending poverty is a difficult measurement challenge that rests upon many assumptions. The analysis in this paper examines how our understanding of who is poor and where they live is affected by changing one

[17] One test suggests greater correlation with the per-capita measure (Table 11, column (7) for the asset index) and 6 differences are not statistically significant.

of these assumptions. The methodology used by the World Bank divides total household consumption or income (depending on the welfare metric used for measuring poverty in a particular country) and divides this by the number of people in the household. This method allocates household resources on a per-capita basis and assumes that there are no household economies of scale. This is to say it assumes that a household of six people needs three times as many resources as a household of three people to attain the same standard of living. Decades ago, when food budget shares were much higher and prior to the World Bank's focus on measuring global poverty (previously rich countries were not part of the poverty estimates), this assumption may be tenable. But in a world that has grown richer with declining food shares, increasing budget shares for shelter, and with an expanded objective of measuring global poverty, it is important to assess the sensitivity of our understanding of global poverty to the assumption of zero household economies of scale.

To address this issue, this paper considers a commonly used, single a single parameter, constant-elasticity scale adjustment that divides total household consumption of income not by household size but by the square root of household size. The analysis first examines how the global profile of poverty changes and also how many people have their poverty status reclassified when using the square-root adjustment. This analysis is based on national representative household survey from 162 countries covering nearly 5.9 billion people or more than 3/4th of the world's population, and 98 percent of the estimated population of people living in extreme poverty.

To focus on whether changing from per-capita to a square-root allocation of household resources changes the profile of who is poor, the analysis takes parametrically the level of extreme poverty as currently estimated and solves for the square-root allocation poverty line that maintains the same global poverty headcount. While the value of this line more than doubles, the net change to the regional profile of poverty is remarkably stable. By construction, the sum of the change in the estimated number of poor people in each region is zero. But in terms of the sum of the absolute value of regional net changes, 60.5 million people (or nine percent of the total population of poor people) moved in the regional profile of poverty.

The analysis shows though that net changes at the regional level mask significant variation at the country level. Figure 2 reveals that there are expected, systematic patterns from switching from per-capita to square-root measures of poverty. In particular, in low income countries which tend to have larger households, country-level poverty rates drop when using the square-root measure. The opposite happens for high-income countries. In considering the sum of net changes across countries (not regions), the profile of country poverty rates changes by 13 percent (on net, across countries, the poverty status of 86 million people changes).

[INSERT FIGURE 2 APPROXIMATELY HERE]

Ultimately though, designing policies and programs to reach the goal of ending extreme poverty requires more than just knowing the level of poverty in a region or a country, it requires correctly identifying who is poor. On this point, the analysis indicate that switching from the current allocation of household resources on a per-capita basis (i.e., assuming that there are no economies of scale in household size) to dividing total resources by the square root of household size (i.e., assuming household economies of scale) results in a substantial level of reclassification of poverty status. Overall, the findings indicate that 270 million people either change from being poor to not poor, or vice versa, when switching from the per-capita to the square-root measure of poverty. This is equal to 40 percent of the total population of people estimated to be in extreme poverty.

The second part of the analysis examines if there is any evidence that one of these two measures of poverty is more strongly correlated with other measures that are presumed to be indicators of poverty status. In particular, the analysis considers attributes like years of schooling, literacy, asset index, working in agriculture, access to electricity, piped drinking water, improved sanitation. When comparing the performance of the square-root measure against the per-capita, $1.90 poverty line, the square root measure of poverty was much more highly correlated with each of the poverty covariates. Our interpretation of these findings is that the decision to allocate household consumption on a per-capita basis is an assumption that is difficult to justify and has significant implications for identifying who is living in extreme poverty.

References

Arayavechkit, Tanida, Atamanov, Aziz, Herrera, Karen Y. Barreto, Belghith, Nadia Belhaj Hassine, Aguilar, R. Andres Castaneda, Fujs, Tony H. M. J., Dewina, Reno, Diaz-Bonilla, Carolina, Edochie, Ifeanyi N., Jolliffe, Dean M., Lakner, Christoph, Mahler, Daniel Gerszon, Montes, Jose, Herrera, Laura Liliana Moreno, Mungai, Rose, Newhouse, David Locke, Nguyen, Minh C., Castro, Diana M. Sanchez, Schoch, Marta, Sharma, Dhiraj, Simler, Kenneth, Swinkel, Rob, Takamatsu, Shinya, Uochi, Ikuko, Mendoza, Martha C. Viveros, Yonzan, Nishant, Yoshida, Nobuo, and Wu, Haoyu. 2021. "March 2021 PovcalNet Update: What's New," *Global Poverty Monitoring Technical Note Series*, no. 15, Global Poverty Monitoring Technical Note Series, Washington, D.C.: The World Bank. http://hdl.handle.net/10986/35340

Buhmann, Brigitte, Rainwater, Lee, Schmaus, Gunther, and Tim Smeeding. 1988. "Equivalence Scales, Well-Being, Inequality, and Poverty: Sensitivity Estimates Across Ten Countries Using the Luxembourg Income Study (lis) Database." *Review of Income and Wealth*, *34*(2), 115–142. https://doi.org/10.1111/j.1475-4991.1988.tb00564.x

Deaton, Angus and Salman Zaidi. 2002. *Guidelines for Constructing Consumption Aggregates for Welfare Analysis.* Washington, DC: World Bank. https://openknowledge.worldbank.org/handle/10986/14101

Desiere, Sam and Dean Jolliffe. 2018. "Land Productivity and Plot Size: Is Measurement Error Driving the Inverse Relationship?" *Journal of Development Economics* 130 (January): 84–98. https://doi.org/10.1016/j.jdeveco.2017.10.002.

Dudel, Christian, Garbuszus, Jan Marvin, and Julian Schmied. 2021. "Assessing differences in household needs: a comparison of approaches for the estimation of equivalence scales using German expenditure data." *Empirical Economics*, 60 (4), 1629–1659. https://doi.org/10.1007/s00181-020-01822-6.

Haggblade, Steven, Peter Hazell, and Thomas Reardon. 2010. "The Rural Non-Farm Economy: Prospects for Growth and Poverty Reduction." *World Development* 38 (10): 1429–41.

Ferreira, Francisco, 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." *The Journal of Economic Inequality* 14 (2): 141–72.

Filmer, Deon and Lant Pritchett. 2001. "Estimating Wealth Effects without Expenditure Data-or Tears: An Application to Educational Enrollments in States of India". *Demography* 38(1): 115–132. https://doi.org/10.2307/3088292

Filmer, Deon, and Kinnon Scott. 2008. "Assessing Asset Indices". Policy Research Working Papers, no. 4605. Washington, D.C.: The World Bank. doi:10.1596/1813-9450-4605.

Harttgen, Kenneth, and Sebastian Vollmer. 2013. "Using an Asset Index to Simulate Household Income." *Economics Letters* 121(2): 257–262. doi:10.1016/j.econlet.2013.08.014.

Johnson, David, Smeeding, Tim and Barbara Boyle Torrey. 2005. "Economic Inequality through the Prisms of Income and Consumption." *Monthly Labor Review* 128 (4): 11–24.

Johnson, David and Barbara Torrey. 2004. "Child Poverty in Wealthy Countries." *Review of Income and Wealth* 50(1):125-34. https://doi.org/10.1111/j.0034-6586.2004.00115.x

Jolliffe, D., Lanjouw, P., Chen, S., Kraay, A., Meyer, C., Negre, M., Prydz, E., Vakis, R., Wethli, R., 2014. *A Measured Approach to Ending Poverty and Boosting Shared Prosperity: Concepts, Data, and the Twin Goals*. Washington, D.C.: The World Bank. https://openknowledge.worldbank.org/handle/10986/20384

Jolliffe, Dean and Espen Beer Prydz. 2016. Estimating international poverty lines from comparable national thresholds. *Journal of Economic Inequality* 14(2), 185–198. https://doi.org/10.1007/s10888-016-9327-5

———. 2021. "Societal Poverty: A Relative and Relevant Measure." *The World Bank Economic Review* 35(1): 180–206. https://doi.org/10.1093/wber/lhz018.

Kramer, Steven. 2020. "With Billions Confined to Their Homes Worldwide, Which Living Arrangements Are Most Common?" *Pew Research Center, FACTANK* (blog). March 31, 2020. https://www.pewresearch.org/fact-tank/2020/03/31/with-billions-confined-to-their-homes-worldwide-which-living-arrangements-are-most-common/.

Lahoti, Rahul, Arjun Jayadev, and Sanjay G. Reddy. 2016. "The Global Consumption and Income Project (GCIP): An Overview." SSRN Scholarly Paper ID 2480636. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.2480636.

Lanjouw, Peter and Martin Ravallion. 1995. "Poverty and Household Size." *The Economic Journal* 105(433): 1415–1434. https://doi.org/10.2307/2235108

Muhammad, Andrew, Seale Jr, James, Meade, Birgit and Anita Regmi. 2011. *International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data.* USDA-ERS Technical Bulletin, no. 1929. Washington, DC: U.S. Department of Agriculture, Economic Research Service. https://doi.org/10.2139/ssrn.2114337

OECD. 2015. "In It Together: Why Less Inequality Benefits All." Paris: OECD Publishing. https://doi.org/10.1787/9789264235120-en.

Rainwater, Lee and Tim Smeeding. 2005. Poor Kids in a Rich Country: America's Children in Comparative Perspective, New York, NY: Russell Sage Foundation.

Ravallion, Martin. 2016. *The Economics of Poverty: History, Measurement, and Policy*. New York.

Ruggles, Patricia. 1990. *Drawing the line: Alternative poverty measures and their implications for public policy*. Washington, DC: Urban Institute Press.

Smeeding, Tim. 2016. Chapter 2: Poverty Measurement. In *The Oxford Handbook of the Social Science of Poverty*, (eds. Brady, David and Linda Burton). Oxford University Press.

Taylor, Paul, Rakesh Kochhar, D'Vera Cohn, Jeffrey S. Passel, Gabriel Velasco, Seth Motel, and Eileen Patten. 2011. "Fighting Poverty in a Bad Economy, Americans Move in with Relatives." *Pew Research Center's Social & Demographic Trends Project* (202).

United Nations - Department of Economic and Social Affairs (UN-DESA), Population Division. 2019a. *Database on Household Size and Composition 2019.* https://population.un.org/Household/index.html

———. 2019b. *Database on Median age by region, subregion and country, 1950-2100 (years).* https://population.un.org/wpp/Download/Standard/Population/

US Congressional Budget Office. 2018. "The Distribution of Household Income, 2014." Washington, DC: Congressional Budget Office. https://www.cbo.gov/publication/53597

Vyas, Seema, and Lilani Kumaranayake. 2006. "Constructing Socio-Economic Status Indices: How to Use Principal Components Analysis." *Health Policy and Planning* 21(6): 459–468. doi:10.1093/heapol/czl029.

World Bank, 1990. *World Development Report 1990: Poverty*. Washington, DC: World Bank. https://doi.org/10.1596/0-1952-0851-X

———. 2018. *Poverty and Shared Prosperity 2018: Piecing Together the Poverty Puzzle*. Washington, DC: The World Bank. http://www.worldbank.org/en/publication/poverty-and-shared-prosperity.

———. 2020a. *Poverty and Shared Prosperity 2020: Reversals of Fortune*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1602-4

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

———. Forthcoming. *Poverty and Shared Prosperity 2022: Toward an Inclusive Recovery*. Washington, DC: World Bank.

Vleminckx, Koen, and Tim Smeeding. 2001. *Child Well-Being, Child Poverty and Child Policy in Modern Nations: What Do We Know?* 1st edition. Bristol, UK: Policy Press.

TABLES & FIGURES

Table 1: Household size by region

Regions (1)	**Household size** (2)	**Year** (3)	**Households (in millions)** (4)	**Countries** (5)
Sub-Saharan Africa	4.7	2014.7	207	46
Middle East & North Africa	4.4	2013.5	71	11
South Asia	4.5	2014.8	366	7
East Asia & Pacific	3.8	2013.9	169	19
World	**3.6**	**2014.8**	**1578**	**162**
Latin America & Caribbean	3.3	2013.4	176	22
Europe & Central Asia	2.8	2015.2	171	30
Other High Income	2.4	2016.6	418	27

Source: Authors' calculations from the Global Monitoring Database (GMD) and Luxembourg Income Study (LIS)
Notes: The table shows the distribution of average household size by region. Column (3) represents the year of the surveys on average. The table is arranged in descending order of average household size in column (2).

Table 2: Summary statistics on covariates of poverty

Category	**Nigeria** 2018	**Mali** 2009	**India** 2011	**Pakistan** 2018	**Tajikistan** 2015	**Indonesia** 2017	**Yemen** 2014	**Colombia** 2017
Years of schooling	7.0		5.5	5.4		8.21	6.12	8.22
Asset index	2.51		2.12		1.77	2.21	2.68	
Asset ownership: computer or landline		0.04		0.14				0.43
Literacy	0.72	0.35	0.68	0.58		0.96	0.71	0.93
Not employed in the agricultural sector	0.92			0.70		0.65		0.80
Access to electricity	0.64	0.22	0.80	0.91	0.98	0.98	0.65	0.98
Piped drinking water	0.03	0.64		0.93	0.46	0.11	0.48	0.98
Improved sanitation	0.58	0.22		0.70	0.96	0.76	0.59	0.90

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: These statistics are computed on a subsample of household heads only. The first two covariates of poverty, mean years of schooling and average asset index, are continuous variables. The remaining covariates are binary indicators. For example, 4% of household heads in Mali (2009) own at least a computer or landline. The asset index is not comparable across countries but is added to the table for completeness. Mali, Pakistan, and Colombia have data on only three assets. In these cases, *asset ownership* variable is instead created as a binary variable of owning at least a computer or landline phone. Empty cells indicate missing data, or cases that are not applicable (i.e., asset index and asset ownership which are mutually exclusive). The survey period spans two consecutive calendar years in Nigeria (2018.75), Mali (2009.89), India (2011.5), and Pakistan (2018.5). By convention, the decimal indicates the share of the survey conducted in the second year. For example, 75% of the Nigeria survey was conducted in 2019. The floor of the survey period is indicated in the table.

Table 3: Principal components analysis (PCA)

1st factor loadings of household assets

Asset	**Nigeria** 2018	**Mali** 2009	**India** 2011	**Pakistan** 2018	**Tajikistan** 2015	**Indonesia** 2017	**Yemen** 2014	**Colombia** 2017
Has access to electricity	0.77		0.76		0.19	0.36		
Has good floor material	0.53				0.31	0.47	0.60	
Owns air conditional	0.42		0.50		0.50	0.62		
Owns bicycle	-0.02						0.23	
Owns car	0.51				0.49	0.65	0.44	
Owns computer	0.45	0.77	0.38	0.80	0.59	0.68	0.56	0.84
Owns cell phone	0.42	0.41	0.54	0.21	0.22		0.40	0.40
Owns radio	0.20		0.01		0.04		0.09	
Owns sewing machine	0.20				0.46			
Owns stove	0.65		0.71		0.46		0.47	
Owns television	0.82				0.27		0.63	
Owns washing machine	0.38						0.79	
Owns fan	0.81		0.82				0.47	
Owns refrigerator	0.66				0.67	0.66	0.80	
Owns boat						-0.16	0.03	
Owns landline		0.78		0.76	0.24		0.61	0.81
Owns motorcycle					0.02	0.47	0.10	
Has flushed toilet							0.48	
Owns land						0.18		
Has good roofing material						0.31	0.49	
Owns electric water pump							0.54	

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: This table shows the first factor loadings from principal components analysis (PCA) done with different assets and household infrastructure and amenities. These factor loadings are the weights used in creating an *asset index* variable for each country. Empty cells indicate missing data. Mali, Pakistan, and Colombia have data on only three assets. In these cases, *asset ownership* variable is instead created as a binary variable of owning at least a computer or landline phone. The survey period spans two consecutive calendar years in Nigeria (2018.75), Mali (2009.89), India (2011.5), and Pakistan (2018.5). By convention, the decimal indicates the share of the survey conducted in the second year. For example, 75% of the Nigeria survey was conducted in 2019. The floor of the survey period is indicated in the table.

Table 4: Distributional changes in global poverty profiles with square-root allocation rule

Region (1)	Per capita poverty rate (%) at $1.90 (2)	Square-root poverty rate (%) at $4.47 (3)	Change in poverty (pp) (4)	Per-capita poor (millions) (5)	Square-root poor (millions) (6)	Change in millions of poor (7)	Absolute deviations in millions of poor (8)
Sub-Saharan Africa	41.3	39.0	-2.3	432	407	-24.2	35
Middle East & North Africa	7.1	5.3	-1.8	23	17	-5.9	6
Europe and Central Asia	1.3	1.3	0.0	6	6	-0.2	1
World	**11.6**	**11.6**	**0.0**	**682**	**682**	**0.0**	**86**
Other High Income	0.7	0.8	0.1	7	8	1.0	1
Latin America & Caribbean	3.8	4.4	0.6	22	26	3.7	5
South Asia	9.6	10.6	0.9	169	186	16.6	27
East Asia & Pacific	3.6	5.0	1.4	23	32	8.9	11

Source: Authors' calculations from the Global Monitoring Database (GMD) and Luxembourg Income Study (LIS)
Notes: This table reports poverty estimates for the 2017 reference year. For countries with no surveys conducted exactly in 2017, the poverty estimates are extrapolated from the latest survey if conducted before 2017, otherwise extrapolated or interpolated from the closest surveys before and after 2017. The extrapolation and interpolation rules applied are the same ones the World Bank applies when "lining-up" global poverty estimates for every year (see the Poverty and Inequality Platform (PIP) Methodological Handbook via https://worldbank.github.io/PIP-Methodology/lineupestimates.html). The table is arranged in ascending order of change in poverty (column 4). These results are based on the full sample of 162 countries covered in the paper.

Table 5: Population (in millions) reclassified moving from per capita to root N rule - $1.90

Region (1)	Not poor under both rules (2)	Poor by pc rule, RECLASSIFIED as not poor (3)	Not poor by pc rule, RECLASSIFIED as poor (4)	Poor under both rules (5)	Population (6)
Sub-Saharan Africa	570	68	44	364	1045
Middle East & North Africa	304	8	2	16	329
Europe and Central Asia	483	1	1	5	491
World	**5048**	**135**	**135**	**547**	**5865**
Other High Income	1012	0	1	7	1020
Latin America & Caribbean	555	2	6	20	583
South Asia	1521	50	66	119	1757
East Asia & Pacific	602	6	15	17	640

Source: Authors' calculations from the Global Monitoring Database (GMD) and Luxembourg Income Study (LIS)

Notes: This table is an extension of Table 4 above, so these estimates are also for the 2017 reference year. These results are based on the full sample of 162 countries covered in the paper.

Table 6: Country-level poverty status at $1.90 PPP

Country (1)	Survey year (2)	Poverty rate (%), per capita (3)	Poverty rate (%), square root (4)	Millions of poor, per capita (5)	Millions of poor, square root (6)	Square-root equivalent poverty line (2011 USD PPP) (7)
Nigeria	2018.75	39.1	39.1	78.0	78.1	4.871
Mali	2009.89	50.3	50.3	7.5	7.5	6.713
India	2011.5	22.5	22.5	282.9	282.9	4.343
Pakistan	2018.5	4.4	4.4	9.5	9.5	5.202
Tajikistan	2015	4.1	4.1	0.3	0.3	5.46
Indonesia	2017	4.5	4.5	11.8	11.8	3.958
Yemen	2014	18.3	18.3	4.7	4.7	5.473
Colombia	2017	4.0	4.0	2	2	3.942

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: The survey years with decimals are the cases where the survey spans two consecutive calendar years. By convention, the decimal indicates the share of the survey conducted in the second year. For example, 75% of the Nigeria survey was conducted in 2019.

Table 7: Country-level poverty status at $3.20 PPP

Country (1)	Survey year (2)	Poverty rate (%), per capita (3)	Poverty rate (%), square root (4)	Millions of poor, per capita (5)	Millions of poor, square root (6)	Square-root equivalent poverty line (2011 USD PPP) (7)
Nigeria	2018.75	71.0	71.0	141.8	141.8	7.602
Mali	2009.89	79.8	79.8	12	12	11.236
India	2011.5	61.7	61.7	775.9	775.9	7.193
Pakistan	2018.5	35.7	35.7	76.6	76.6	8.682
Tajikistan	2015	17.8	17.8	1.5	1.5	8.795
Indonesia	2017	24.6	24.6	65.2	65.2	6.721
Yemen	2014	51.2	51.2	13.2	13.2	9.155
Colombia	2017	11.1	11.1	5.4	5.4	6.713

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: The survey years with decimals are the cases where the survey spans two consecutive calendar years. By convention, the decimal indicates the share of the survey conducted in the second year. For example, 75% of the Nigeria survey was conducted in 2019.

Table 8: Identifying the $1.90 poor based on covariates of poverty

(Pooled data across countries with equal weights for each country)

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)	Obs (8)
Years of schooling	-0.007***	-0.133***	0	-0.158***	-0.284***	0	683,533
Asset index	-0.041***	-0.139***	0	-0.380***	-0.478***	0	431,436
Asset ownership	-0.007***	-0.033***	0	-0.095***	-0.121***	0	264,680
Literacy	-0.010***	-0.065***	0	-0.136***	-0.191***	0	694,463
Not employed in the agricultural sector	-0.009***	-0.031***	0	-0.052***	-0.074***	0	450,521
Access to electricity	-0.017***	-0.093***	0	-0.263***	-0.339***	0	697,574
Piped drinking water	-0.006***	-0.020***	0.0174	-0.095***	-0.108***	0.0174	595,934
Improved sanitation	-0.011***	-0.049***	0	-0.134***	-0.172***	0	592,937

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: This table shows the results of regressing an indicator variable of being poor on (ranked) residuals of covariates of poverty (see Section 3b in the paper for more details). The residuals are determined by conditioning out household size from the covariates of poverty, including years of schooling, asset ownership/index, literacy, access to electricity, etc. Ranked residuals are used for only the first two covariates, years of schooling and asset index, which are continuous variables by construction. The remaining covariates are binary variables (e.g., literacy, ownership of a computer, etc.). With limited asset categories (e.g., only three assets for Colombia, Mali, and Pakistan), it makes more sense to create a binary variable than an asset index. The regressions are based on all countries with data for each covariate of poverty, with each country having a weight of 1. Table 2 above has summary statistics on the various covariates of poverty, thus providing information on the availability of data from the different countries pooled together in these regressions. The per capita poor are defined using the $1.90 line for all countries, and the root N poor are defined using the root N-equivalent poverty line, which is country-specific (see Table 4). The per capita poor only are those individuals who are only poor by the per capita allocation rule but not the root N allocation rule. The regressions run on a subsample of household heads only. Column 4 indicates the results of a test of equality between the coefficients reported in columns 2 and 3 under the assumptions of seemingly unrelated regressions. Column 7 indicates the results of a test of equality between the coefficients reported in columns 5 and 6 under the assumptions of seemingly unrelated regressions.

Table 9: Identifying the $1.90 poor based on covariates of poverty

(Pooled data across countries with each country weighted by millions of poor)

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)	Obs (8)
Years of schooling	-0.007***	-0.216***	0	-0.257***	-0.465***	0	683,533
Asset index	-0.052***	-0.185***	0	-0.529***	-0.661***	0	431,436
Asset ownership	-0.010***	-0.053***	0	-0.154***	-0.197***	0	264,680
Literacy	-0.012***	-0.085***	0	-0.155***	-0.227***	0	694,463
Not employed in the agricultural sector	-0.009*	-0.079***	0	-0.130***	-0.199***	0	450,521
Access to electricity	-0.015***	-0.082***	0	-0.262***	-0.329***	0	697,574
Piped drinking water	-0.011***	-0.033***	0.0007	-0.143***	-0.164***	0.0007	595,934
Improved sanitation	-0.008***	-0.058***	0	-0.182***	-0.232***	0	592,937

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: This table shows the results of regressing an indicator variable of being poor on (ranked) residuals of covariates of poverty (see Section 3b in the paper for more details). The residuals are determined by conditioning out household size from the covariates of poverty, including years of schooling, asset ownership/index, literacy, access to electricity, etc. Ranked residuals are used for only the first two covariates, years of schooling and asset index, which are continuous variables by construction. The remaining covariates are binary variables (e.g., literacy, ownership of a computer, etc.). With limited asset categories (e.g., only three assets for Colombia, Mali, and Pakistan), it makes more sense to create a binary variable than an asset index. The regressions are based on all countries with data for each covariate of poverty, with each country having a weight of 1. Table 2 above has summary statistics on the various covariates of poverty, thus providing information on the availability of data from the different countries pooled together in these regressions. The per capita poor are defined using the $1.90 line for all countries, and the root N poor are defined using the root N-equivalent poverty line, which is country-specific (see Table 6). The per capita poor only are those individuals who are only poor by the per capita allocation rule but not the root N allocation rule. The regressions run on a subsample of household heads only. Each country has a weight equal to millions of poor. The per capita millions of poor and root N millions of poor are the same, due to the use of a root N equivalent poverty line that yields the same poverty rate as the rate obtained when the per capita allocation rule is used (see Table 6). Column 4 indicates the results of a test of equality between the coefficients reported in columns 2 and 3 under the assumptions of seemingly unrelated regressions. Column 7 indicates the results of a test of equality between the coefficients reported in columns 5 and 6 under the assumptions of seemingly unrelated regressions.

Table 10: Identifying the $3.20 poor based on covariates of poverty

(Pooled data across countries with equal weights for each country)

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)	Obs (8)
Years of schooling	0.013***	-0.112***	0	-0.324***	-0.449***	0	683,533
Asset index	-0.020***	-0.044***	0.0008	-0.667***	-0.691***	0.0008	431,436
Asset ownership	-0.010***	-0.026***	0	-0.187***	-0.204***	0	264,680
Literacy	0.001	-0.012***	0.0006	-0.220***	-0.233***	0.0006	694,463
Not employed in the agricultural sector	-0.008***	-0.038***	0	-0.141***	-0.171***	0	450,521
Access to electricity	0.015***	0.021***	0.3081	-0.351***	-0.346***	0.3081	697,574
Piped drinking water	0.000	0.023***	0.0002	-0.140***	-0.117***	0.0002	595,934
Improved sanitation	0.000	-0.017***	0	-0.224***	-0.241***	0	592,937

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: This table shows the results of regressing an indicator variable of being poor on (ranked) residuals of covariates of poverty (see Section 3b in the paper for more details). The residuals are determined by conditioning out household size from the covariates of poverty, including years of schooling, asset ownership/index, literacy, access to electricity, etc. Ranked residuals are used for only the first two covariates, years of schooling and asset index, which are continuous variables by construction. The remaining covariates are binary variables (e.g., literacy, ownership of a computer, etc.). With limited asset categories (e.g., only three assets for Colombia, Mali, and Pakistan), it makes more sense to create a binary variable than an asset index. The regressions are based on all countries with data for each covariate of poverty, with each country having a weight of 1. Table 2 above has summary statistics on the various covariates of poverty, thus providing information on the availability of data from the different countries pooled together in these regressions. The per capita poor are defined using the $3.20 line for all countries, and the root N poor are defined using the root N-equivalent poverty line, which is country-specific (see Table 7). The per capita poor only are those individuals who are only poor by the per capita allocation rule but not the root N allocation rule. The regressions run on a subsample of household heads only. Column 4 indicates the results of a test of equality between the coefficients reported in columns 2 and 3 under the assumptions of seemingly unrelated regressions. Column 7 indicates the results of a test of equality between the coefficients reported in columns 5 and 6 under the assumptions of seemingly unrelated regressions.

Table 11: Identifying the $3.20 poor based on covariates of poverty

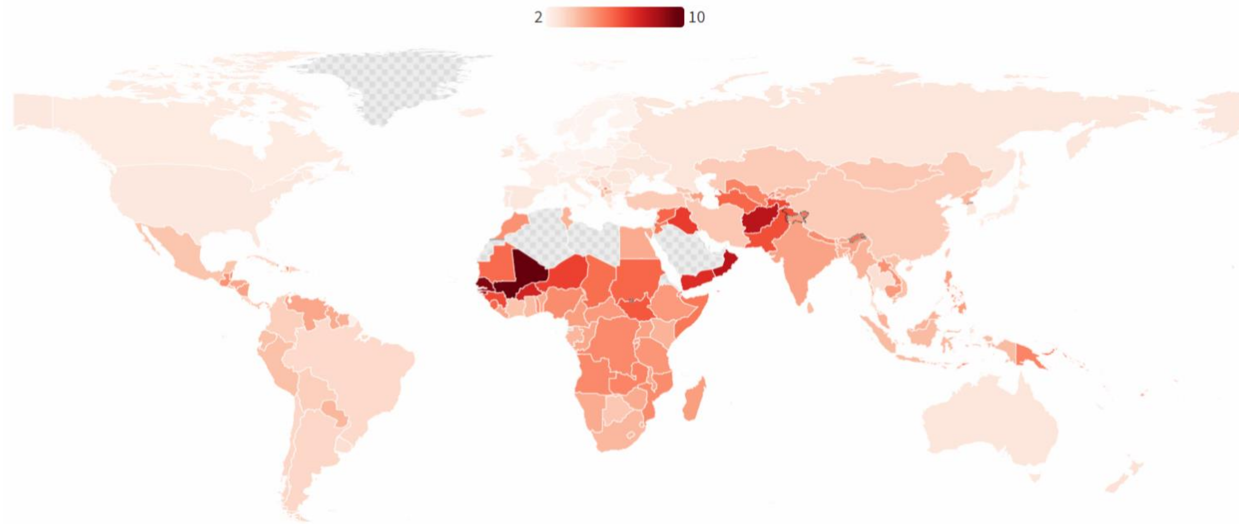
(Pooled data across countries with each country weighted by millions of poor)

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)	Obs (8)
Years of schooling	0.021***	-0.088***	0	-0.462***	-0.571***	0	683,533
Asset index	-0.005*	0.038***	0	-0.802***	-0.759***	0	431,436
Asset ownership	-0.021***	-0.085***	0	-0.284***	-0.347***	0	264,680
Literacy	0.003	-0.011***	0.0014	-0.238***	-0.252***	0.0014	694,463
Not employed in the agricultural sector	-0.004	-0.040***	0.0002	-0.158***	-0.194***	0.0002	450,521
Access to electricity	0.017***	0.021***	0.4559	-0.316***	-0.311***	0.4559	697,574
Piped drinking water	0.002	0.013**	0.0929	-0.132***	-0.122***	0.0929	595,934
Improved sanitation	0.003	-0.022***	0	-0.220***	-0.245***	0	592,937

Source: Authors' calculations from the Global Monitoring Database (GMD)

Notes: This table shows the results of regressing an indicator variable of being poor on (ranked) residuals of covariates of poverty (see Section 3b in the paper for more details). The residuals are determined by conditioning out household size from the covariates of poverty, including years of schooling, asset ownership/index, literacy, access to electricity, etc. Ranked residuals are used for only the first two covariates, years of schooling and asset index, which are continuous variables by construction. The remaining covariates are binary variables (e.g., literacy, ownership of a computer, etc.). With limited asset categories (e.g., only three assets for Colombia, Mali, and Pakistan), it makes more sense to create a binary variable than an asset index. The regressions are based on all countries with data for each covariate of poverty, with each country having a weight of 1. Table 2 above has summary statistics on the various covariates of poverty, thus providing information on the availability of data from the different countries pooled together in these regressions. The per capita poor are defined using the $3.20 line for all countries, and the root N poor are defined using the root N-equivalent poverty line, which is country-specific (see Table 7). The per capita poor only are those individuals who are only poor by the per capita allocation rule but not the root N allocation rule. The regressions run on a subsample of household heads only. Each country has a weight equal to millions of poor. The per capita millions of poor and root N millions of poor are the same, due to the use of a root N equivalent poverty line that yields the same poverty rate as the rate obtained when the per capita allocation rule is used (see Table 7). Column 4 indicates the results of a test of equality between the coefficients reported in columns 2 and 3 under the assumptions of seemingly unrelated regressions. Column 7 indicates the results of a test of equality between the coefficients reported in columns 5 and 6 under the assumptions of seemingly unrelated regressions.

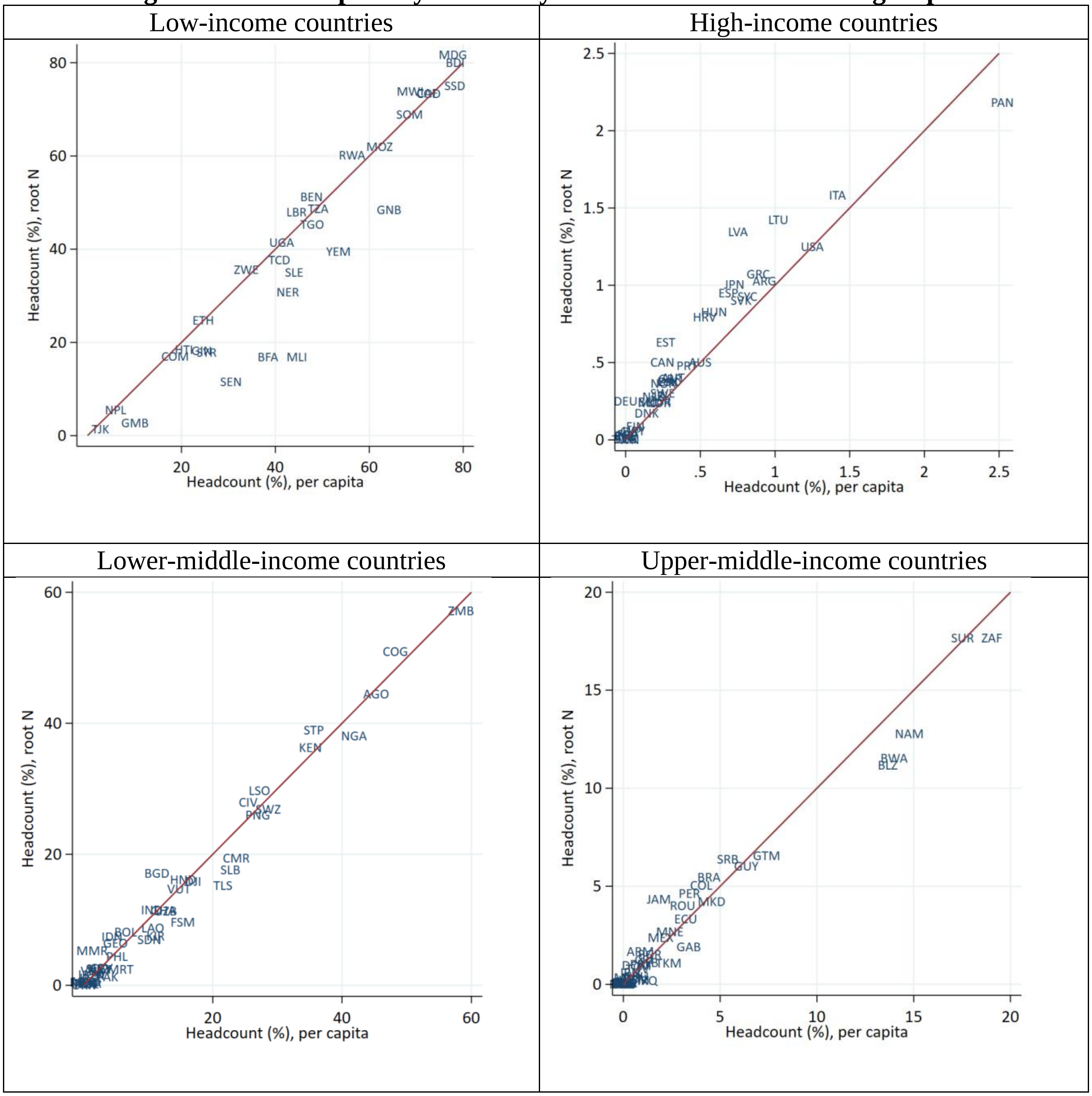
Figure 1: Average household size across countries



Sources: Global Monitoring Data (GMD), Luxembourg Income Study (LIS), United Nations Department of Economic and Social Affairs (DESA)

Notes: An interactive version of the map may be accessed here: https://public.flourish.studio/visualisation/7486748/. The GMD and LIS are the main data sources, and supplementary data from DESA for 21 countries have been added to improve data coverage.

Figure 2: Extreme poverty in 2017 by allocation rule and income group



APPENDIX TABLES & FIGURES

Table A1: Distributional changes in global poverty profiles with root N allocation rule

Region (1)	Per capita poverty rate (%) at **$3.20** (2)	Root N poverty rate (%) at **$7.36** (3)	Change in poverty (pp) (4)	Millions of per capita poor (5)	Millions of root N poor (6)	Change in millions of poor (7)	Absolute deviations in millions of poor (8)
Middle East & North Africa	20.1	18.3	-1.8	66	60	-6.0	9
Sub-Saharan Africa	67.4	65.7	-1.7	705	687	-17.7	31
South Asia	43.4	43.1	-0.2	762	758	-4.2	54
World	**29.6**	**29.6**	**0.0**	**1736**	**1736**	**0.0**	**129**
Europe and Central Asia	4.6	4.7	0.1	23	23	0.5	4
Other High Income	0.9	1.1	0.3	9	12	2.7	3
Latin America & Caribbean	9.3	10.5	1.2	54	62	7.1	8
East Asia & Pacific	18.3	21.1	2.8	117	135	17.7	19

Note: Table is arranged in ascending order of ascending order of change in poverty (column 4).

Table A2: Population (in millions) reclassified moving from per capita to root N rule -$3.20

Region	Not poor under both rules	Poor by pc rule, RECLASSIFIED as not poor	Not poor by pc rule, RECLASSIFIED as poor	Poor under both rules	Population
(1)	(2)	(3)	(4)	(5)	(6)
Middle East & North Africa	255	14	8	52	329
Sub-Saharan Africa	294	65	47	640	1045
South Asia	878	121	116	641	1757
World	**3905**	**225**	**225**	**1511**	**5865**
Europe and Central Asia	463	4	5	18	491
Other High Income	1008	0	3	9	1020
Latin America & Caribbean	516	5	13	49	583
East Asia & Pacific	490	16	34	101	640

Figure A1: Poverty at $3.20 in 2017 by allocation rule and income group

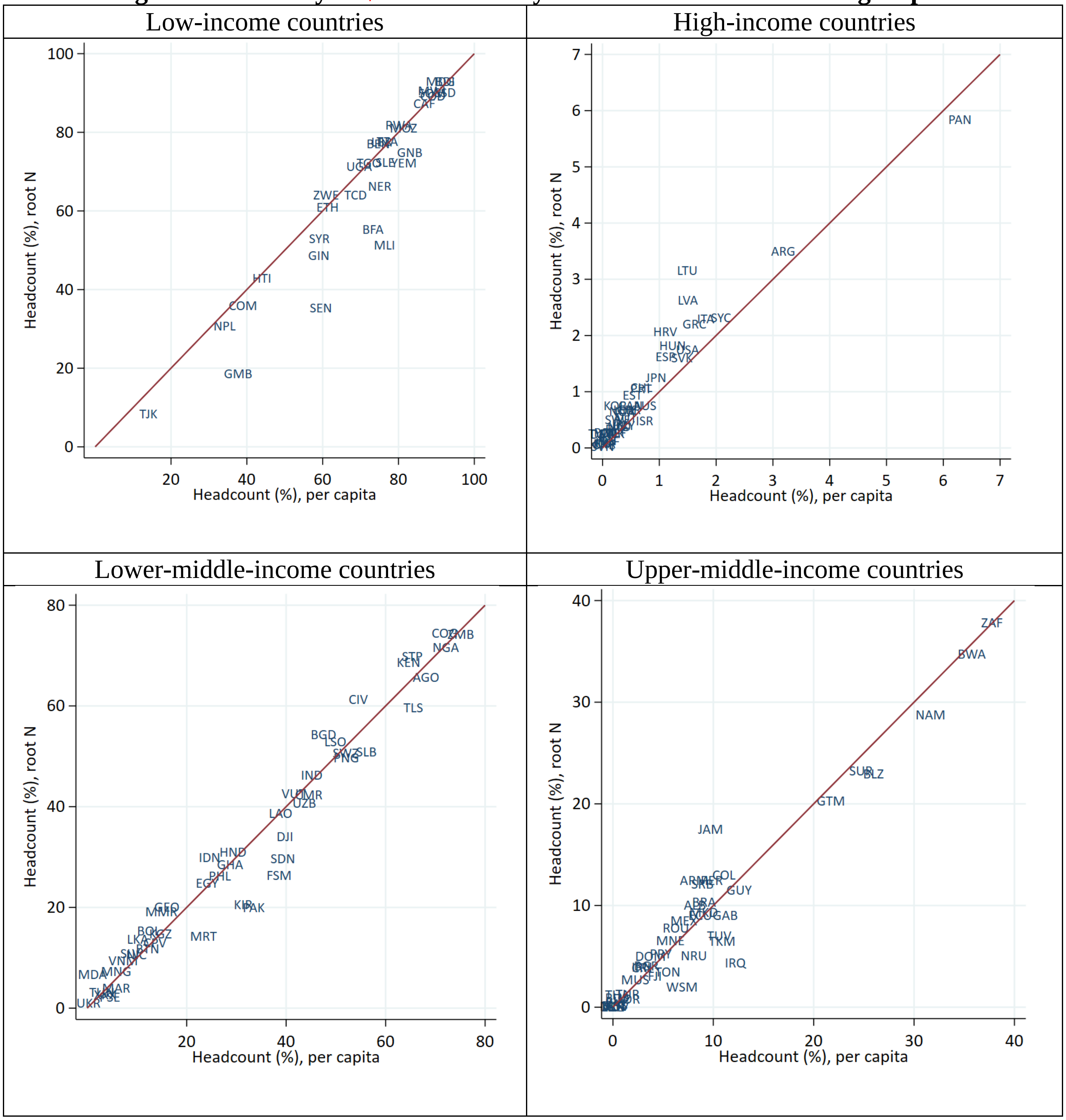


Table A3: Distributional changes in global poverty profiles with root N allocation rule

Region (1)	Per capita poverty rate (%) at **$5.50** (2)	Root N poverty rate (%) at **$12.00** (3)	Change in poverty (pp) (4)	Millions of per capita poor (5)	Millions of root N poor (6)	Change in millions of poor (7)	Absolute deviations in millions of poor (8)
Middle East & North Africa	45.8	43.5	-2.2	150	143	-7.3	19
South Asia	78.5	77.2	-1.3	1379	1357	-22.1	33
Sub-Saharan Africa	86.2	85.5	-0.7	901	894	-7.6	22
World	**49.8**	**49.8**	**0.0**	**2923**	**2923**	**0.0**	**133**
Other High Income	1.3	1.7	0.4	13	18	4.5	5
Europe and Central Asia	12.6	14.2	1.6	62	70	8.0	17
Latin America & Caribbean	23.0	25.0	2.0	134	146	11.6	14
East Asia & Pacific	44.3	46.3	2.0	284	297	13.0	24

Note: Table is arranged in ascending order of ascending order of change in poverty (column 4).

Table A4: Population (in millions) reclassified moving from per capita to root N rule -$5.50

Region (1)	Not poor under both rules (2)	Poor by pc rule, RECLASSIFIED as not poor (3)	Not poor by pc rule, RECLASSIFIED as poor (4)	Poor under both rules (5)	Population (6)
Middle East & North Africa	166	20	12	131	329
South Asia	307	93	71	1286	1757
Sub-Saharan Africa	116	36	28	866	1045
World	**2747**	**195**	**195**	**2728**	**5865**
Other High Income	1002	0	5	13	1020
Europe and Central Asia	412	9	17	53	491
Latin America & Caribbean	425	13	24	122	583
East Asia & Pacific	319	25	38	259	640

Figure A2: Poverty at $5.50 in 2017 by allocation rule and income group

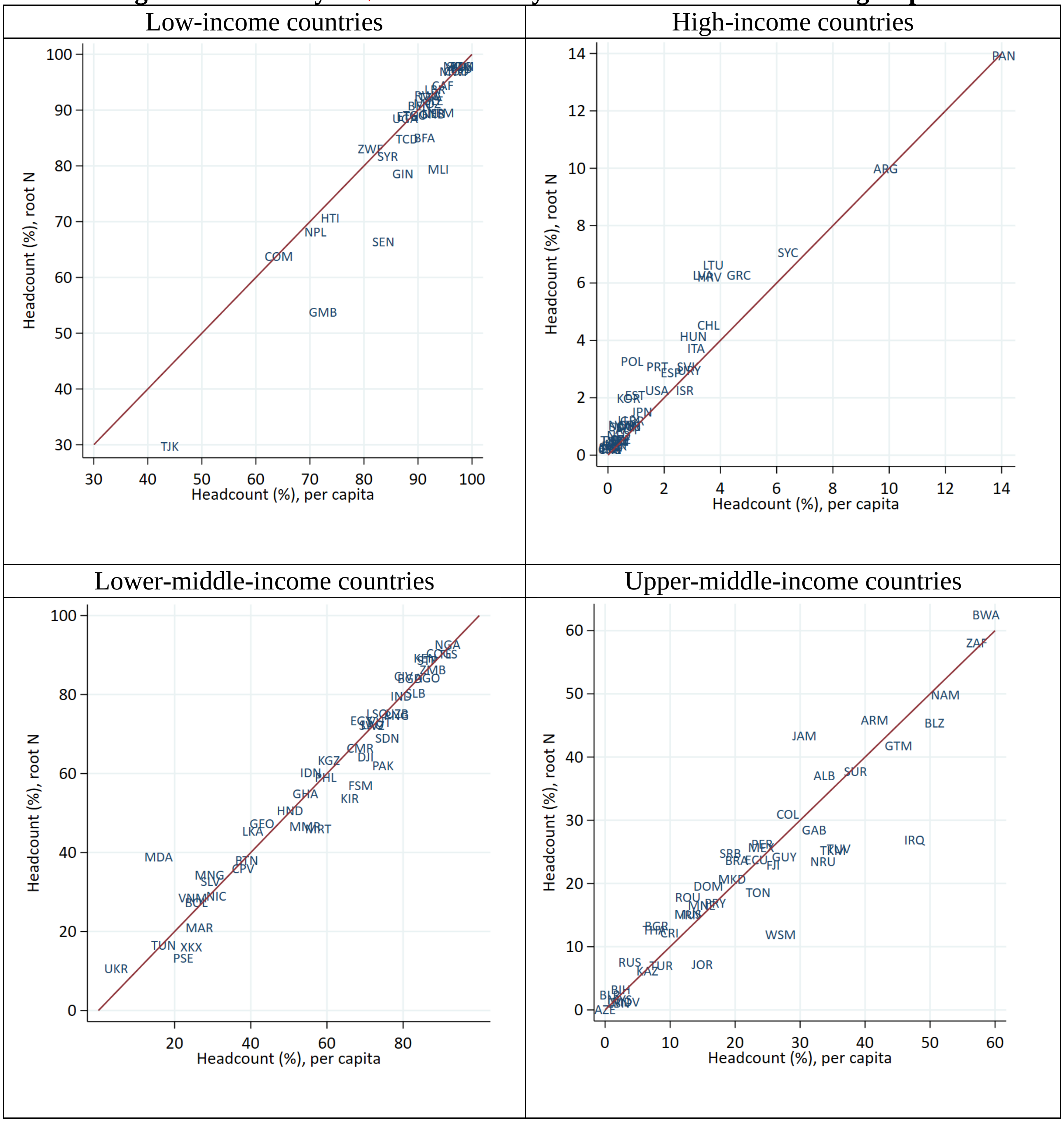


Table A5: Identifying the $1.90 poor based on covariates of poverty

Nigeria 2018/2019

Category **(1)**	**Per capita poor only** **(2)**	**Root N poor only** **(3)**	**Diff. p-value** **(4)**	**Per capita poor** **(5)**	**Root N poor** **(6)**	**Diff. p-value** **(7)**
Years of schooling	-0.001***	-0.009***	0	-0.023***	-0.031***	0
Asset index	-0.004***	-0.039***	0	-0.110***	-0.145***	0
Literacy	-0.003	-0.082***	0	-0.216***	-0.295***	0
Not employed in the agricultural sector	-0.01	-0.130***	0	-0.217***	-0.338***	0
Access to electricity	-0.008***	-0.091***	0	-0.314***	-0.397***	0
Piped drinking water	-0.024***	-0.064***	0.0021	-0.218***	-0.258***	0.0021
Improved sanitation	-0.006**	-0.064***	0	-0.210***	-0.267***	0

Table A6: Identifying the $3.20 poor based on covariates of poverty

Nigeria 2018/2019

Category **(1)**	**Per capita poor only** **(2)**	**Root N poor only** **(3)**	**Diff. p-value** **(4)**	**Per capita poor** **(5)**	**Root N poor** **(6)**	**Diff. p-value** **(7)**
Years of schooling	0.001***	-0.003***	0	-0.025***	-0.029***	0
Asset index	0.008***	-0.010***	0	-0.120***	-0.139***	0
Literacy	0.013***	-0.015**	0.0004	-0.215***	-0.243***	0.0004
Not employed in the agricultural sector	0.017**	-0.035	0.087	-0.258***	-0.310***	0.087
Access to electricity	0.032***	-0.007	0	-0.294***	-0.333***	0
Piped drinking water	0.011	-0.030*	0.0537	-0.301***	-0.342***	0.0537
Improved sanitation	0.014***	-0.003	0.0102	-0.230***	-0.248***	0.01025

Table A7: Identifying the $1.90 poor based on covariates of poverty

Mali 2009

Category (1)	**Per capita poor only** (2)	**Root N poor only** (3)	**Diff. p-value** (4)	**Per capita poor** (5)	**Root N poor** (6)	**Diff. p-value** (7)
Asset ownership	-0.042***	-0.174***	0	-0.391***	-0.523***	0
Literacy	-0.008*	-0.060***	0.0001	-0.205***	-0.257***	0.0001
Access to electricity	-0.020***	-0.144***	0	-0.395***	-0.520***	0
Piped drinking water	-0.002	-0.021*	0.1702	-0.221***	-0.240***	0.1702
Improved sanitation	-0.015***	-0.063***	0.0008	-0.239***	-0.287***	0.0008

Table A8: Identifying the $3.20 poor based on covariates of poverty

Mali 2009

Category (1)	**Per capita poor only** (2)	**Root N poor only** (3)	**Diff. p-value** (4)	**Per capita poor** (5)	**Root N poor** (6)	**Diff. p-value** (7)
Asset ownership	0.006	0.031	0.3504	-0.612***	-0.587***	0.3504
Literacy	0.007*	0.072***	0	-0.254***	-0.189***	0
Access to electricity	0.032***	0.122***	0	-0.514***	-0.424***	0
Piped drinking water	0.018***	0.090***	0	-0.221***	-0.149***	0
Improved sanitation	0.024***	0.051***	0.1046	-0.226***	-0.199***	0.1046

Table A9: Identifying the $1.90 poor based on covariates of poverty

India 2011/2012

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	-0.001***	-0.011***	0	-0.017***	-0.026***	0
Asset index	-0.012***	-0.059***	0	-0.145***	-0.191***	0
Literacy	-0.015***	-0.088***	0	-0.143***	-0.216***	0
Access to electricity	-0.017***	-0.077***	0	-0.243***	-0.302***	0

Table A10: Identifying the $3.20 poor based on covariates of poverty

India 2011/2012

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	0.000	-0.002***	0	-0.034***	-0.036***	0
Asset index	0.005***	0.006**	0.6341	-0.210***	-0.208***	0.6341
Literacy	0.003	-0.002	0.3235	-0.247***	-0.252***	0.3235
Access to electricity	0.014***	0.032***	0.0313	-0.317***	-0.299***	0.0313

Table A11: Identifying the $1.90 poor based on covariates of poverty

Pakistan 2018

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	-0.001***	-0.004***	0	-0.003***	-0.006***	0
Asset ownership	-0.012***	-0.028***	0	-0.036***	-0.052***	0
Literacy	-0.009***	-0.037***	0	-0.034***	-0.062***	0
Not employed in the agricultural sector	-0.006***	-0.024***	0	-0.018***	-0.036***	0
Access to electricity	-0.022***	-0.080***	0	-0.104***	-0.162***	0
Piped drinking water	-0.010***	-0.009*	0.9891	-0.027***	-0.027**	0.9891
Improved sanitation	-0.010***	-0.035***	0	-0.043***	-0.068***	0

Table A12: Identifying the $3.20 poor based on covariates of poverty

Pakistan 2018

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	-0.001***	-0.010***	0	-0.022***	-0.030***	0
Asset ownership	-0.028***	-0.112***	0	-0.268***	-0.353***	0
Literacy	-0.009***	-0.085***	0	-0.205***	-0.281***	0
Not employed in the agricultural sector	-0.007*	-0.057***	0	-0.115***	-0.166***	0
Access to electricity	0.001	-0.060***	0	-0.345***	-0.406***	0
Piped drinking water	-0.003	0.029***	0.0063	-0.055***	-0.024	0.0063
Improved sanitation	-0.006*	-0.066***	0	-0.196***	-0.256***	0

Table A13: Identifying the $1.90 poor based on covariates of poverty

Tajikistan 2015

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Asset index	-0.011***	-0.009***	0.5362	-0.050***	-0.048***	0.5362
Access to electricity	-0.068	-0.009	0.2765	-0.255**	-0.196**	0.2765
Piped drinking water	-0.005	-0.006*	0.789	-0.021*	-0.022**	0.789
Improved sanitation	-0.007	-0.001	0.7581	-0.014	-0.009	0.7581

Table A14: Identifying the $3.20 poor based on covariates of poverty

Tajikistan 2015

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Asset index	-0.024***	-0.027***	0.6774	-0.146***	-0.149***	0.6774
Access to electricity	0.031	-0.025	0.193	-0.301***	-0.357***	0.193
Piped drinking water	-0.014	-0.001	0.315	-0.074***	-0.061**	0.315
Improved sanitation	0.006	-0.011	0.668	-0.066	-0.082	0.668

Table A15: Identifying the $1.90 poor based on covariates of poverty

Indonesia 2017

Category (1)	**Per capita poor only** (2)	**Root N poor only** (3)	**Diff. p-value** (4)	**Per capita poor** (5)	**Root N poor** (6)	**Diff. p-value** (7)
Years of schooling	-0.002***	-0.003***	0	-0.006***	-0.008***	0
Asset index	-0.017***	-0.017***	0.8812	-0.046***	-0.047***	0.8812
Literacy	-0.027***	-0.063***	0	-0.089***	-0.125***	0
Not employed in the agricultural sector	-0.012***	-0.016***	0.0057	-0.034***	-0.039***	0.0057
Access to electricity	-0.041***	-0.016***	0.0084	-0.094***	-0.069***	0.0084
Piped drinking water	-0.005**	-0.003***	0.4166	-0.011***	-0.009***	0.4166
Improved sanitation	-0.021***	-0.025***	0.1131	-0.063***	-0.067***	0.1131

Table A16: Identifying the $3.20 poor based on covariates of poverty

Indonesia 2017

Category (1)	**Per capita poor only** (2)	**Root N poor only** (3)	**Diff. p-value** (4)	**Per capita poor** (5)	**Root N poor** (6)	**Diff. p-value** (7)
Years of schooling	-0.003***	-0.005***	0	-0.025***	-0.027***	0
Asset index	-0.023***	-0.027***	0.0073	-0.178***	-0.182***	0.0073
Literacy	-0.021***	-0.053***	0	-0.230***	-0.263***	0
Not employed in the agricultural sector	-0.016***	-0.025***	0.0015	-0.137***	-0.146***	0.0015
Access to electricity	-0.021***	-0.022***	0.9364	-0.231***	-0.232***	0.9364
Piped drinking water	-0.004	-0.002	0.5648	-0.031***	-0.029***	0.5648
Improved sanitation	-0.020***	-0.031***	0.0002	-0.211***	-0.222***	0.0002

Table A17: Identifying the $1.90 poor based on covariates of poverty

Yemen 2014

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	-0.001***	-0.007***	0	-0.011***	-0.017***	0
Asset index	-0.007***	-0.032***	0	-0.071***	-0.096***	0
Literacy	-0.012*	-0.070***	0	-0.129***	-0.187***	0
Access to electricity	-0.016**	-0.089***	0	-0.205***	-0.278***	0
Piped drinking water	-0.010**	-0.037***	0.0331	-0.091***	-0.118***	0.0331
Improved sanitation	-0.009	-0.067***	0	-0.146***	-0.203***	0

Table A18: Identifying the $3.20 poor based on covariates of poverty

Yemen 2014

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	0.000	-0.002**	0.0417	-0.019***	-0.021***	0.0417
Asset index	-0.001	-0.013***	0.0001	-0.133***	-0.146***	0.0001
Literacy	0.000	-0.003	0.7626	-0.200***	-0.204***	0.7626
Access to electricity	-0.005	0.006	0.394	-0.334***	-0.323***	0.394
Piped drinking water	0.000	0.006	0.661	-0.178***	-0.173***	0.661
Improved sanitation	-0.005	-0.017	0.2762	-0.282***	-0.294***	0.2762

Table A19: Identifying the $1.90 poor based on covariates of poverty

Colombia 2017

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	-0.000***	-0.002***	0	-0.003***	-0.005***	0
Asset ownership	-0.005***	-0.017***	0	-0.042***	-0.053***	0
Literacy	-0.010***	-0.035***	0	-0.056***	-0.080***	0
Not employed in the agricultural sector	-0.007***	-0.014***	0.0001	-0.045***	-0.051***	0.0001
Access to electricity	-0.015***	-0.044***	0.0001	-0.118***	-0.147***	0.0001
Piped drinking water	-0.004**	-0.021***	0.0017	-0.052***	-0.069***	0.0017
Improved sanitation	-0.007***	-0.018***	0	-0.056***	-0.067***	0

Table A20: Identifying the $3.20 poor based on covariates of poverty

Colombia 2017

Category (1)	Per capita poor only (2)	Root N poor only (3)	Diff. p-value (4)	Per capita poor (5)	Root N poor (6)	Diff. p-value (7)
Years of schooling	-0.001***	-0.005***	0	-0.009***	-0.013***	0
Asset ownership	-0.011***	-0.040***	0	-0.114***	-0.142***	0
Literacy	-0.013***	-0.059***	0	-0.136***	-0.182***	0
Not employed in the agricultural sector	-0.011***	-0.032***	0	-0.128***	-0.150***	0
Access to electricity	-0.013***	-0.075***	0	-0.232***	-0.293***	0
Piped drinking water	-0.016***	-0.043***	0.0013	-0.125***	-0.151***	0.0013
Improved sanitation	-0.013***	-0.038***	0	-0.131***	-0.156***	0