World Development 179 (2024) 106593

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Regular Research Article

Identifying the poor – Accounting for household economies of scale in global poverty estimates

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ARTICLE INFO

JEL classification:
I32
O10
O20

Keywords:
Global poverty
Household economies of scale
Sustainable development goals

ABSTRACT

Estimates of the number of people living in extreme poverty, as reported by the World Bank, figure prominently in international development dialogue and policy. An assumption underpinning these 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 changing this assumption. The analysis rests on nationally representative household surveys from 162 countries covering 97.5 percent of the population estimated to be in extreme poverty in 2019. We compare current-method estimates with a constant-elasticity scale adjustment that divides total household consumption or income not by household size but by the square-root of household size. While the regional profile of extreme poverty is robust to this change, the determination of who is poor changes substantially – the poverty status of 264 million people changes. We then discuss evidence suggesting that the assumption of economies of scale more closely aligns with non-consumption measures of poverty. Specifically, we draw from existing literature of subjective assessments of poverty and wellbeing, along with new empirical evidence from examining the partial correlation (conditional on household size) between the two measures of poverty and a set of presumed poverty covariates (i.e., years of schooling, literacy, asset index, working in agriculture, access to electricity, piped drinking water, improved sanitation).

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.[3] 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, 2022). In 2015, extreme poverty as measured by living on less than the IPL (then set at $1.90 per day) was less than 3 percent in more than half the countries of the world (Jolliffe & Prydz, 2021)). Progress in reducing extreme poverty has slowed dramatically (World Bank, 2018, 2020a) and it has 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

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[3] 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 $2.15 in 2017 PPPs.

https://doi.org/10.1016/j.worlddev.2024.106593
Accepted 28 February 2024
Available online 30 March 2024

farming (Desiere & Jolliffe, 2018) and nonfarm enterprises (Haggblade et al., 2010), both of which tend to be household-level activities. Consumption is similarly measured 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.[4] 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.[5] Decades ago, when this decision to use a per capita allocation of household resources was made, Deaton and Zaidi (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 a good working understanding of its strengths and weaknesses, when it is sound (in most cases), and when it is likely to be misleading…" While analysts may have a working understanding of its strengths and weaknesses, very little is understood about both the sensitivity of the regional profile of extreme poverty to this assumption and the potential extent of reclassifying who is poor to changing the assumption.

Ferreira et al. (2016, 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."[6] The Global Consumption and Income Project (GCIP) database[7] 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.

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 if 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 (Fig. 1) and regions (Table 1). In terms of average household size, the data used in our analysis indicate that average household size across 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. 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).[8] 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.[9] 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.

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 a commonly used 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 264 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 schooling, literacy, asset index, working in the non-agricultural sector, 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.

[4] https://worldbank.github.io/PIP-Methodology/welfareaggregate.html#equivalence-scale.

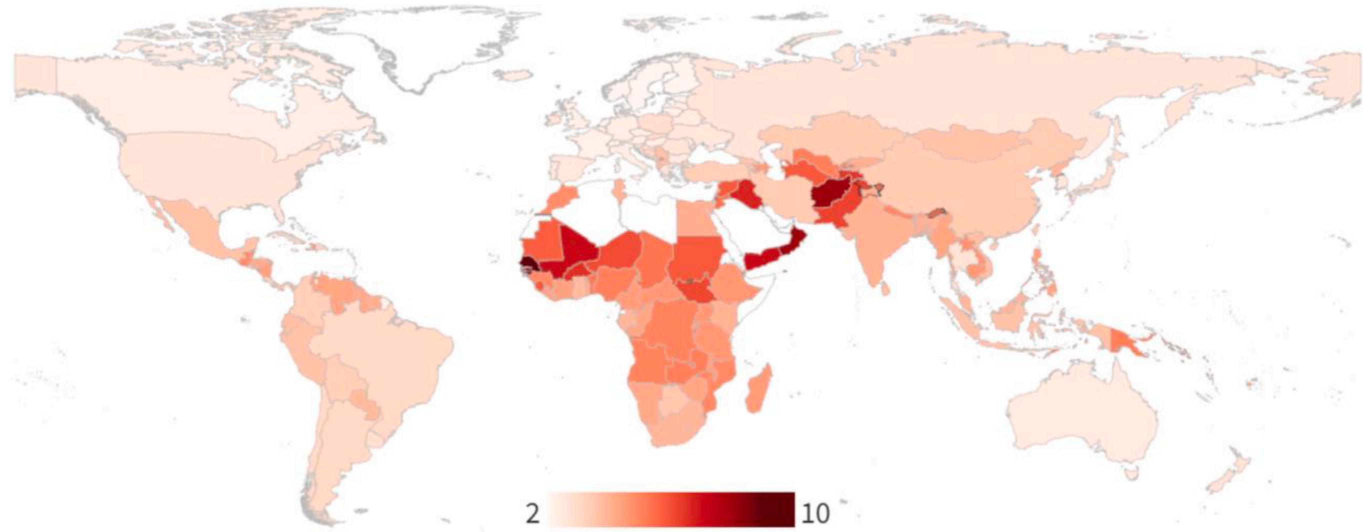
[5] Evidence in economics and non-economics fields (such as demography, sociology and neuroscience) suggests that these assumptions do not hold in practice. For example, Lloyd and Desai (1992) find that children in large households, particularly in Sub-Saharan Africa, usually benefit from the pooled resources of not only their parents but other relations in the extended family structure. Not only for children, but care-giving tasks for the elderly can be distributed more lightly among other members of a large household (Brodaty & Donkin, 2009; Toledano-Toledano et al., 2020). When thinking more broadly about poverty beyond the monetary dimension, it may be argued that larger households would likely be better off because they offer social support, which improves the overall mental health of household members (Melchiorre et al., 2013). Further, the recent rise in solo living exposes single-person households—often consisting of men and the elderly—to higher housing costs, labor market risks, isolation, and mental health issues (Bennett & Dixon, 2006; Forward et al., 2022; Mortelmans et al., 2023).

[6] For an example of a global profile of poverty based on a subset of data using the per-capita allocation of household resources, see Castañeda et al. (2018).

[7] https://gcip.info/.

[8] Other data sources indicate similar 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).

[9] 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.].



Sources: Global Monitoring Database (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/14090969/ The GMD and LIS are the main data sources, and supplementary data from DESA for 21 countries have been added to improve data coverage. Countries with missing data are left blank without a color.

Fig. 1. Average household size across countries. Sources: Global Monitoring Database (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/14090969/ The GMD and LIS are the main data sources, and supplementary data from DESA for 21 countries have been added to improve data coverage. Countries with missing data are left blank without a color.

Table 1
Household size by region, circa 2019.

Region(1)	Household size(2)	Year (3)	Households (in millions)(4)	Countries (5)
Middle East & North Africa	5.1	2014	74	11
Sub-Saharan Africa	4.9	2017	213	45
East Asia & Pacific	4.8	2018	178	20
South Asia	4.6	2019	425	7
World	**4.0**	**2019**	**1654**	**162**
Latin America & Caribbean	3.6	2019	182	22
Europe & Central Asia	3.3	2019	166	30
Other High Income	2.4	2019	417	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) shows the median year of the surveys from each region, revealing for example that the survey data from the Middle East and North Africa is substantially older than from other regions. The table is arranged in descending order of average household size.

2. Methods and data

2.1. 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 $(A+\alpha C)^{\theta}$ where α adjusts for differences in needs between adults and children (or in other words, converts children into adult equivalents) and θ adjusts for economies of scale in household size. If $\theta = 0$, 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$\alpha = 1$ and $\theta = 1$, and household needs are equal to household size. Smeeding (2016) notes that setting$\alpha = 1$ and θ 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 & Smeeding, 2005). Lanjouw and Ravallion (1995) also demonstrate how changing the value of θ 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 reported global profile of poverty, we have sufficient data on the number of household members to cover 97.5 percent of the population of people living in extreme poverty (as currently estimated). Data on the age composition of individuals in the households are missing from several countries and dropping those countries would reduce our coverage to less than 75 percent of those in extreme poverty.[10] With our desire to maximize country and population coverage, we choose to focus on the class of single-parameter models, and examine changing the single parameter, θ, which describes the elasticity of needs to household size.[11] The per-capita allocation sets $\theta = 1$ which would be defensible if households only consumed non-shareable 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. Yet, it has been the case for some time now that budget shares allocated to food have been declining across most all countries of the world (Traub, 1992, Table 2), and the assumption of setting $\theta = 1$ has become 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, Fig. 1.4). While there is variation in values used for θ, Johnson and Torrey (2004) note that adjusting needs by the square root of household size (i.e., α=1, θ = 0.5) is becoming common in international poverty comparisons.[12] 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.

2.2. 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 micro-level income and consumption data from 153 countries. (For details, see World Bank, 2020a, Appendix 1A.) In addition, we supplement the GMD data with household survey data from the Luxembourg Income Study (LIS) for 9 countries.[13] 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 2023 update to the World Bank's global poverty estimates as described in Castaneda Aguilar et al. (2023). 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.[14] 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 8.5 percent in 2019 based on the 168 countries (Castaneda Aguilar et al., 2023). The primary reason the global

Table 2
Poverty lines in 2017 PPP dollars.

Panel A Income classification	Per-capitapoverty line ($) (2)	Square-root poverty lines ($)		
		Ravallion (2015)(3)	World Bank(4)	Fixed Headcount (5)
Low-income countries (LIC)	2.15	4.86	5.20	4.93
Lower-middle-income (LMIC)	3.65	7.70	8.53	8.17
Upper-middle-income (UMIC)	6.85	13.39	14.40	14.49
Panel B		Poverty lines accounting for country-specificeconomies of scale parameter ($)		
		Ravallion (2015)	World Bank	Fixed Headcount
Low-income countries (LIC)	2.15	4.56	5.12	4.67
Lower-middle-income (LMIC)	3.65	7.51	7.98	7.82
Upper-middle-income (UMIC)	6.85	13.72	14.50	14.15

Source: Authors' calculations from the Global Monitoring Database (GMD) and the Poverty and Inequality Platform (PIP).
Notes: Ravallion's (2015) approach of setting the poverty line starts with the per-capita poverty lines of the World Bank in column (2). The per-capita poverty line is adjusted with an adjustment factor such that the poverty status of the pivot household remains unchanged when moving from the per-capita poverty line to the line that accounts for economies of scale. The pivot household is the one closest to the per-capita poverty line. In this case, the pivot household size is the average household size of those households living within 10% of the poverty line in the 2019 global welfare distribution. The poverty line that accounts for economies of scale is derived as the per-capita poverty line multiplied by the ratio of (a) pivot household size to (b) pivot household size to the power of the economies of scale parameter (which is 0.5 for all countries). The World Bank approach of setting the square-root poverty lines uses the same methodology that was used in deriving the World Bank's per-capita poverty lines (see Jolliffe et al. (2022) for more details). The poverty lines reported in column (4) are the median values of the PPP-adjusted harmonized national poverty lines by income group. The poverty lines in column (5) are based on our approach of fixing the global headcount. Panel B repeats each of these three approaches but allows the household-economies-of-scale parameter to vary for each country. The food share of a country from national accounts data, plus half of the nonfood share, is used as a proxy for the share of private consumption in total household consumption. The economies of scale parameter is a function of the country's average household size and average share of private consumption in the household (see Eq. (4)).

[10] Newhouse et al. (2017) focus on estimating child poverty rates and account for both adult equivalence and household economies of scale in their estimates. They show that over a relatively large set of candidate parameters for adult-equivalence and household economies of scale, the child poverty rate never falls below 17 percent and is always higher than the adult poverty rate. They also demonstrate that the estimated child poverty rate of 19.5 percent based on the per-capita indicator is fairly robust to allowing for adjustments for adult equivalence and economies of scale.

[11] While we have data on age for 90 percent of the countries used in this analysis, those countries without data on age represent a substantial portion of the poor (more than 20 percent). Given our interest in commenting on the estimates that are currently influencing public discourse, perceptions and policy, we view this loss of population coverage as particularly damaging. We also note again Rainwater and Smeeding's (2005) view that the single parameter model (i.e., what we are using in this paper), is the most commonly used approach for international comparisons.

[12] 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).

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

[14] 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.

estimate reported in this paper is higher 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 over 6 billion people or more than 3/4th of the world's population. The coverage of people estimated to be living in extreme poverty, the population that is relevant for this analysis, is much larger – the data cover 97.5 percent of this 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 2017 constant local prices using Consumer Price Indices from each country, and then convert the resulting vector into internationally comparable US dollars using 2017 purchasing power parity exchange rates (PPPs).[15] 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 are able to extract data on covariates of poverty for a small subset of the 162 countries and use these data to investigate the performance of the square-root allocation rule of household consumption in identifying the poor, relative to the per-capita allocation rule. We use detailed micro-level data from the latest available surveys from Nigeria, Mali, India, Pakistan, Colombia, Tajikistan, Indonesia, and Yemen for circa 2017.[16] We wanted this analysis to have regional diversity but to also have two countries each from Sub-Saharan Africa and South Asia—the two 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 covariates of poverty, including completed years of schooling, asset ownership, literacy, access to electricity, agriculture as source of income, piped drinking water and improved sanitation.

In addition to select nonmonetary covariates of poverty, we estimate asset indices in each country as a proxy for wealth using principal components analysis (PCA). 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 Filmer & Pritchett, 2001; Vyas & Kumaranayake, 2006; Filmer & Scott, 2012; Harttgen & 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 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 Appendix Table A1.) 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 A1 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).

3. Results

3.1. *Comparing poverty profiles under the per-capita and square-root allocation rules*

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. To assess this, it is important to recognize that this assumption affects both how household resources are allocated to the individual and also the determination of the international poverty line. The \$2.15 line (in 2017 PPPs) is estimated based on assuming there are no economies of scale. We consider six different approaches to estimating the IPL when assuming that there are positive economies of scale (i.e., θ is less than 1). For the first three approaches, we set $\theta = 0.5$ for all countries. That is to say, we divide household resources by the square root of household size to allocate resources to the individual. We then repeat these three approaches but allow θ to vary for each country.

The first approach is adapted from Ravallion's (2015) idea of solving for the economies-of-scale poverty line that results in the "pivot" household being identified as poor under both poverty lines (and not poor for those households ranked just above the pivot household). The pivot household is a (demographic) type of household – one whose poverty status does not depend on the value of the scale parameter θ. We estimate the household size of the pivot household as the average household size for the households with per capita consumption that is within ten percent of the per-capita IPL (i.e., those whose consumption falls in the range of \$1.935, \$2.365). The pivot household size varies by the per-capita poverty line assumed. For the \$2.15 line, it is 5.11 (it is 4.46 and 3.82 for the \$3.65 and \$6.85 lines, respectively). We find that \$4.86 maintains the same poverty classification for the pivot household when household resources are divided by the square-root of household size as the IPL of \$2.15 when household resources are divided by household size (Table 2, panel A, column 3). We repeat this exercise for the higher-valued lines of \$3.65 and \$6.85 frequently reported on by the World Bank. Table 3 (Panel A, columns 2 and 3) indicate that when estimating global poverty based on allocating resources by the square-root of household size and the poverty line of \$4.87, the global poverty headcount falls from 10.6 to 10.2 percent (or 22 million fewer people are identified as being poor).

The second approach we consider mimics the methodology used by the World Bank in their derivation of the per-capita, international poverty line (Jolliffe, Mahler, Lakner, Atamanov, & Tetteh-Baah, 2022). For most countries in the world, the World Bank has the reported number of people who are poor in each country as assessed by their national poverty line, and they also have the corresponding vector of household resources (either in terms of consumption or income) in per-capita terms. They do not have the value of the national poverty lines that produced the poverty headcount, nor do they have information for each country on whether the national poverty line adjusts for economies of scale or differing needs of children. Using the headcount and the vector of per-capita resources, one can back out the value of the national poverty line in per-capita terms regardless of whether the country sets their threshold in per-capita terms or not (Jolliffe, D., Prydz, 2016). Each of these lines, in principle, reflects country-level assessments of what it is needed to realize basic needs (assuming household resources are all private goods within the household and shared on a per-capita basis). The per-capita, international poverty line (i.e., \$2.15 in 2017 PPPs) for counting the number of people in extreme poverty is then just the median value of these per-capita lines in all low-income countries. We repeat this exercise except convert the per-capita vector of household resources into a square-root allocation equivalent vector (i.e., multiply

[15] 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.].

[16] The latest survey year varies across these countries. The surveys years are 2018–19 for Nigeria, 2009–10 for Mali, 2011–12 for India, 2018–19 for Pakistan, 2015 for Tajikistan, 2017 for Indonesia, Yemen for 2014, and 2017 for Colombia.

Table 3
Changes in regional and global poverty profiles in 2019 – LIC poverty lines.

Region (1)	Per- capita poverty rate (%)(2)	Square-root poverty rate (%)(3)	Change (pp) (4)	Per- capita poor (millions)(5)	Square-root poor (millions) (6)	Change (millions) (7)	Absolute deviations in poor (millions)(8)
Panel A: Ravallion's (2015) approach							
Sub-Saharan Africa	34.9	30.6	−4.3	384	337	−47	50
MENA	10.0	8.1	−1.9	36	29	−7	7
World	**10.6**	**10.2**	**−0.4**	**643**	**620**	**−22**	**116**
Europe & Central Asia	2.3	1.9	−0.3	11	10	−2	2
Other High Income	0.6	0.7	0.1	6	7	1	1
Latin America	4.3	4.8	0.4	26	28	3	4
East Asia & Pacific	3.4	3.9	0.6	22	26	4	8
South Asia	8.6	10.1	1.4	158	184	26	43
Panel B: World Bank's approach							
Sub-Saharan Africa	34.9	34.0	−0.9	384	374	−10	33
MENA	10.0	9.1	−0.9	36	32	−3	5
Europe & Central Asia	2.3	2.3	0.0	11	11	0	1
Other High Income	0.6	0.7	0.1	6	7	1	1
Latin America	4.3	5.4	1.0	26	32	6	6
World	**10.6**	**12.0**	**1.4**	**643**	**727**	**85**	**150**
East Asia & Pacific	3.4	5.1	1.7	22	34	11	12
South Asia	8.6	13.0	4.4	158	237	79	92
Panel C: Fixed Headcount							
Sub-Saharan Africa	34.9	31.3	−3.6	384	345	−39	44
MENA	10.0	8.4	−1.7	36	30	−6	7
Europe & Central Asia	2.3	2.0	−0.3	11	10	−1	2
World	**10.6**	**10.6**	**0.0**	**643**	**643**	**0**	**120**
Other High Income	0.6	0.7	0.1	6	7	1	1
Latin America	4.3	4.9	0.6	26	29	3	5
East Asia & Pacific	3.4	4.2	0.8	22	27	5	9
South Asia	8.6	10.7	2.0	158	195	37	53

Source: Authors' calculations from the Global Monitoring Database (GMD) and Luxembourg Income Study (LIS).
Notes: MENA is Middle East and North Africa, Latin America includes the Caribbean..This table reports poverty estimated with the 2017 PPPs for the 2019 reference year. For countries with no surveys conducted exactly in 2019, the poverty estimates are extrapolated from the latest survey if conducted before 2019, otherwise extrapolated or interpolated from the closest surveys before and after 2019. 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. Some of the results may not add up due to rounding.

the vector by household size, then divide by the square-root of household size) and derive the corresponding square-root national poverty lines.

Table 2 (panel A, column 4) reports that the median national poverty line for LICs when resources are allocated based on the square-root rule is $5.20. (Table 2 also reports median values of national poverty lines based on square-root allocations for lower-middle-income countries (LMICs) and for upper-middle-income countries (UMICs). Table 3 (Panel B, columns 2 and 3) indicates that when estimating global poverty based on allocating resources by the square-root of household size and the poverty line of $5.20, the global poverty headcount increases from 10.6 to 12 percent (or 85 million more people are identified as being poor).

While both of these approaches are completely valid ways of solving for the value of the international poverty line under a rule that allocates household resources by the square-root of household size, both approaches change the profile of poverty both through changing the overall level of poverty and through changing the distribution of poverty assignments. In order to disentangle these effects, we consider a third approach where we solve for the square-root poverty line that fixes the global headcount at the same level as measured with the per-capita international poverty line. More specifically, let the global poverty rate in a reference year (in our analysis, this is 2019) be given as:

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

where z is the value of the IPL in per-capita, per-day terms (expressed in 2017 PPP US dollars).[17] P^* is the global poverty rate obtained from a global welfare probability density function, $f(y(.))$ of daily consumption per capita, *y(pc)*, in 2017 PPPs. For our sample of 162 countries, P^* is

[17] We first examine the IPL value of $2.15 (2017 PPPs) and then also consider the reported higher values lines of $3.65 and $6.85 (Jolliffe et al., 2022).

equal to 10.6 percent (Table 3). We then solve for the value of $\widehat{z}$ on the density function of consumption that has been allocated to the individual based on the square root of household size, $f(y(rn))$:

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

Thus, the equivalent "square-root" poverty line ($\widehat{z}$) 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 \$4.93 in 2017 PPPs (Table 2, Panel A, column 5).[18]

The substantial increase in the value of all of the square-root poverty lines, 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.[19]

All three approaches are similar conceptually – In the Ravallion approach, poverty is held constant for the pivot household, in our version of the World Bank approach, national poverty rates are held constant, and in this last approach, the global poverty rate is held constant. In terms of understanding the sensitivity of the distribution of poverty to incorporating economies of scale, an advantage of holding the global headcount fixed is that all of the observed changes are due to differences in how poverty is distributed, not to the overall level of poverty.

Table 3 reveals that qualitatively, the findings are very similar across the three approaches. To describe how the distribution of poverty changes (as distinct from the level of poverty) from assuming economies of scale in household consumption, we focus on panel C, which reports on the approach that fixes the global headcount. By design, both the \$2.15 per capita and the \$4.93 square-root lines result in a global poverty rate of 10.6, or 643 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 34.9 percent under the per capita line to 31.3 percent under the square-root line. The change of 3.6 percent points represents 39 million fewer people living in poverty in Sub-Saharan Africa than are measured with per-capita allocation of resources. The changes in South Asia and the Middle East and North Africa regions are 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 regional profile of poverty is not so sharply changed. If only concerned about regional patterns of poverty, learning that the percentage point change in poverty is two points or less in all regions except for Sub-Saharan Africa is reasonably informative of the sensitivity of the global poverty estimates to assuming 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 change in the number of people who are poor in each region. By design, the sum of these changes over all regions is zero, but the sum of the absolute value of the changes across the regions indicates a change in the regional profiles of 92 million people when switching from the per-capita to the square-root allocation. These changes at the regional level reflect a shift of about fourteen percent of the total population of poor people (92 million out of the estimated 643 million poor people).

Furthermore, the work to eradicate extreme poverty is largely undertaken at the country level and not at the regional level. Poverty reduction policies and programs are typically national or subnational programs. An examination of 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 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 an increase of six million people while another country in that same region had a decline of four million people. The sum of changes in that region is two million people, and that is descriptive of how the profile of poverty changes across regions from assuming household economies of scale in consumption. But, if we are interested in understanding how the profile of poverty changes across countries, the sum of the absolute value of changes for these two countries is more informative. 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 regional effect.

The data reveal that in South Asia, the total change for the region is an increase in the number of people living in extreme poverty of 37 million people when switching from the per-capita to the square-root allocation (Table 3, panel C, column 7). 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 53 million people (a count which is equal to one third of the poverty headcount for South Asia). Across all regions, the sum of the absolute value of the change in the number of poor people in each country is 120 million people, or about 18 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 changes at the regional level. When we shift to examining the change in the number of poor people in each country, we observe a sizeable change in the distribution of poverty.

Just as looking at changes to regional average poverty rates masks significant changes at the country level, it is also the case that looking at the 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 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 again South Asia. We noted that there are 37 million more poor people in the region and the sum of the absolute value of all changes at the country level is 53 million people (Table 3, panel C, columns 7 and 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 4 indicates that in South Asia, when shifting from the per-capita to the square-root allocation of resources, 38 million people who are poor under the per-capita rule are not poor under the square-root rule and 75 million people who are not poor under the per-capita rule are reclassified as poor under the square-root rule (panel C, columns 3 and 4). In terms of the magnitude of the total number of people experiencing a reclassification of their poverty status, 113 million

[18] When we carry out this analysis at higher-value lines (i.e., \$3.65 and \$6.85), the corresponding values of the square-root poverty lines are \$8.17 and \$14.49.

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

Table 4
People reclassified moving from per capita to square root rule (millions).

Region (1)	Not poor under both rules(2)	RECLASSIFIEDPoor by pc rule, not poor under sq rule (3)	RECLASSIFIED Not poor by pc rule, poor under sq rule(4)	Poor under both rules(5)	Population (6)
Panel A: Ravallion's (2015) **approach**					
Sub-Saharan Africa	684	80	32	304	1101
Middle East & North Africa	318	9	2	27	356
World	**5293**	**141**	**119**	**501**	**6055**
Europe & Central Asia	482	3	1	8	495
Other High Income	1021	0	1	6	1028
Latin America & Caribbean	563	3	6	23	595
East Asia & Pacific	625	6	10	16	657
South Asia	1599	40	67	117	1824
Panel B: World Bank's approach					
Sub-Saharan Africa	669	58	47	326	1101
Middle East & North Africa	317	7	3	29	356
Europe & Central Asia	482	2	2	9	495
Other High Income	1021	0	1	6	1028
Latin America & Caribbean	561	2	8	24	595
World	**5230**	**98**	**182**	**545**	**6055**
East Asia & Pacific	619	4	16	18	657
South Asia	1562	25	105	132	1824
Panel C: Own approach					
Sub-Saharan Africa	681	75	35	309	1101
Middle East & North Africa	318	8	2	27	356
Europe & Central Asia	482	3	2	8	495
World	**5280**	**132**	**132**	**510**	**6055**
Other High Income	1021	0	1	6	1028
Latin America & Caribbean	563	3	6	23	595
East Asia & Pacific	623	6	11	16	657
South Asia	1591	38	75	120	1824

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 2019 reference year. These results are based on the full sample of 162 countries covered in the paper. Some of the results may not add up due to rounding.

people is more than 70 percent of the current headcount of people in extreme poverty (based on the per-capita rule). Over all 162 countries in our analysis, the poverty status of 264 million people changes when switching from the per-capita to square-root allocation of resources. This is equal to more than 40 percent of the total population of poor people as estimated by either of these rules.[20]

3.2. Extension: Allowing the economies of scale parameter to vary for each country

We motivate the importance of reconsidering the assumption of no economies of scale in household size by noting that food budget shares have been declining over time. While food shares may at one time been high enough to accept as an approximation that most all consumption in the household was rival (i.e., if one person consumed the item, no one else could also consume it), we argue that this may no longer be the case. Up to now though, we have assigned the same economies of scale parameter (i.e., the square root of household size) to all countries. Given that variation in consumption patterns across countries (in particular, variation in food shares), we relax this assumption in this sub-section by assuming the economies of scale parameter is a function of the proportion of private and public goods in total household consumption.[21] In particular, we assume household consumption consists of either purely private or public goods.[22] Private goods cannot be shared, while public goods are shareable. The implication of this is that an individual's consumption, x_i, of total household consumption, x_h, can be described as:

$$x_i = \frac{x_h}{n^\theta} = pvt\frac{x_h}{n} + (1 - \rho vt)x_h \tag{3}$$

where n is household size, pvt is the share of total household consumption that is private, and θ is the economies-of-scale parameter.

[20] Appendix Tables A3 and A4 present the results from repeating this analysis for the LMIC line of \$3.65 and Appendix Tables A5 and A6 present the analysis based on the UMIC line of \$6.85. As the global headcount increases, the relative magnitude of poverty reclassifications drops as a proportion of the increasing global headcount.

[21] The authors are deeply grateful to Sergio Olivieri for his framing of this analysis.

[22] We are grateful to an anonymous referee for noting the literature that develops a more theoretical foundation for the parameterization of economies of scale, somewhat similar to what we aim to do here. Examples of this include Biewen and Juhasz (2017) and de Ree, Alessie and Pradhan (2013). Both use subjective measures of wellbeing and satisfaction to derive scale parameters.

Table 5
Changes in regional and global poverty profiles in 2019 – LIC poverty lines. *Allowing for country-specific economies of scale.*

Region (1)	Per- capita poverty rate (%)(2)	Square-root poverty rate (%)(3)	Change (pp) (4)	Per- capita poor (millions)(5)	Square-root poor (millions) (6)	Change (millions) (7)	Absolute deviations in poor (millions)(8)
Panel A: Ravallion's (2015) approach							
Sub-Saharan Africa	34.9	31.5	−3.4	384	347	−37	52
MENA	10.0	8.1	−1.9	36	29	−7	7
World	**10.6**	**10.1**	**−0.6**	**643**	**609**	**−34**	**101**
Europe & Central Asia	2.3	2.0	−0.2	11	10	−1	2
Latin America	4.3	4.1	−0.2	26	24	−1	2
Other High Income	0.6	0.6	0.0	6	7	0	0
East Asia & Pacific	3.4	3.7	0.4	22	24	2	7
South Asia	8.6	9.2	0.6	158	168	10	31
Panel B: World Bank's approach							
MENA	10.0	9.8	−0.3	36	35	−1	5
Other High Income	0.6	0.7	0.1	6	7	1	1
Europe & Central Asia	2.3	2.7	0.5	11	14	2	3
Latin America	4.3	5.0	0.7	26	30	4	5
World	**10.6**	**13.0**	**2.4**	**643**	**790**	**147**	**202**
East Asia & Pacific	3.4	5.8	2.4	22	38	16	16
Sub-Saharan Africa	34.9	37.4	2.5	384	411	27	57
South Asia	8.6	14.0	5.4	158	255	98	116
Panel C: Own approach							
Sub-Saharan Africa	34.9	32.7	−2.2	384	360	−24	48
MENA	10.0	8.5	−1.6	36	30	−6	6
Europe & Central Asia	2.3	2.2	−0.1	11	11	−1	1
Latin America	4.3	4.3	−0.1	26	25	0	2
World	**10.6**	**10.6**	0.0	**643**	**643**	**0**	**111**
Other High Income	0.6	0.7	0.1	6	7	1	1
East Asia & Pacific	3.4	4.1	0.7	22	27	5	8
South Asia	8.6	10.1	1.4	158	183	26	46

Source: Authors' calculations from the Global Monitoring Database (GMD) and Luxembourg Income Study (LIS).
Notes: MENA is Middle East and North Africa, Latin America includes the Caribbean. This table reports poverty estimated with the 2017 PPPs for the 2019 reference year. For countries with no surveys conducted exactly in 2019, the poverty estimates are extrapolated from the latest survey if conducted before 2019, otherwise extrapolated or interpolated from the closest surveys before and after 2019. 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. Some of the results may not add up due to rounding.

Solving for θ gives,

$$\theta = \frac{-\ln\left(1 - pvt + \frac{pvt}{n}\right)}{\ln(n)} \tag{4}$$

From (4), it is clear that if all household consumption is private (pvt = 1), then θ = 1 and total household resources are assigned following the per-capita allocation rule. If all consumption within the household is public, then θ = 0 and every individual is assigned the total level of their household consumption. More generally though, the economies of scale parameter is a function of household size and the household budget share for private consumption goods. As an example, for a household with 4 people whose total household consumption consists of two-thirds private goods, then θ = 0.5 (meaning total household consumption is divided by the square-root of household size).

For each country, we estimate average household size and average budget share allocated to private goods to produce a country-specific economies of scale parameter. We largely do not have data on the average household budget share for private consumption and need to make fairly crude assumptions to estimate this. We first extract estimates of food shares from national accounts data and assume that all food consumed is private.[23] While food is a prototypical example of a private good, there are other items in household consumption besides food that

[23] The IMF database (https://data.imf.org/regular.aspx?key=61017820) is our source for food shares and this provides estimates for food shares in 2019 for 123 countries. Results for 2017 and 2019 are reported in Appendix Table A2. We impute food shares for missing values based on the following model: $FS_i = \beta_0 + \beta_1 cons_i + \beta_2 hsize_i + \sum_{j=1}^{J} \partial_j reg_{ij} + \sum_{k=1}^{K} \gamma_k inc_{ik} + \sum_{l=1}^{L} \delta_l (reg_{ij} * inc_{ik})_l + e_i$where:$FS_i$ is the food share of country *i* in the selected survey year$cons_i$ is the survey-based mean consumption per capita for country $ihsize_i$ is the survey-based average household size for country $ireg_{ij}$ is a dummy variable indicating that country *i* belongs to region $jinc_{ik}$ is a dummy variable indicating that country *i* belongs to income group ke_i is an error term.

Table 6
People reclassified moving from per capita to square root rule (millions). *Allowing for country-specific economies of scale.*

Region (1)	Not poor under both rules(2)	RECLASSIFIEDPoor by pc rule, not poor under sq rule (3)	RECLASSIFIED Not poor by pc rule, poor under sq rule(4)	Poor under both rules(5)	Population (6)
Panel A: Ravallion's (2015) approach					
Sub-Saharan Africa	683	71	34	313	1101
Middle East & North Africa	319	8	2	27	356
World	**5308**	**138**	**104**	**505**	**6055**
Europe & Central Asia	482	3	1	9	495
Latin America & Caribbean	565	5	3	21	595
Other High Income	1022	0	0	6	1028
East Asia & Pacific	626	6	9	16	657
South Asia	1612	44	54	113	1824
Panel B: World Bank's approach					
Middle East & North Africa	316	5	4	31	356
Other High Income	1021	0	1	6	1028
Europe & Central Asia	480	1	4	10	495
Latin America & Caribbean	562	3	7	23	595
World	**5192**	**73**	**221**	**569**	**6055**
East Asia & Pacific	615	3	19	19	657
Sub-Saharan Africa	649	40	68	344	1101
South Asia	1547	21	119	137	1824
Panel C: Own approach					
Sub-Saharan Africa	677	64	40	320	1101
Middle East & North Africa	318	8	2	28	356
Europe & Central Asia	482	2	2	9	495
Latin America & Caribbean	565	5	4	21	595
World	**5289**	**123**	**123**	**519**	**6055**
Other High Income	1022	0	1	6	1028
East Asia & Pacific	624	6	10	16	657
South Asia	1601	39	65	119	1824

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 2019 reference year. These results are based on the full sample of 162 countries covered in the paper. Some of the results may not add up due to rounding.

are private. And there are many goods that are somewhat public and somewhat private (such as clothing which can be shared by siblings but not at the same time; and which are worn out over time). To account for this, we make the ad hoc assumption that one half of the nonfood share is private and the other half is public.

With the country-specific estimates of the household economies of scale parameter, we then repeat each of the three approaches to estimating the corresponding economies-of-scale poverty line (hereafter referred to as the scaled poverty line). For the Ravallion pivot-household approach, the scaled poverty line results in a slightly lower estimate of global poverty (Table 5, panel A).[24] For our approach that mimics the World Bank derivation of the per-capita line, the scaled poverty line results in a higher global poverty rate of 13 percent (this compares to 12 percent in Table 3, Panel B where we do not allow for variation in scales across countries).

When we consider the approach that fixes the global headcount of poverty for the scaled line to be the same as that for the per-capita line, we again find results that are similar to the findings from the square-root rule. The first is that regional poverty rates are largely unchanged under the scaled poverty line with the largest change being a drop of 2.2 percentage points in Sub-Saharan Africa (Table 5, panel C, column 4). As with the square-root findings, this relatively small change in the rates of regional poverty masks a lot of change. The absolute sum of the regional poverty headcounts is 63 million people or just under 10 percent the count of poor people as assessed by the per-capita rule (Table 5, panel C, column 7). Further, the absolute sum of changes at the country level is 111 million people or 17 percent of the count of per-capita poor people (Table 5, panel C, column 8). Finally, just as with the findings for the square-root rule, 246 million people (which is 38 percent of the global poverty headcount) have their poverty status reclassified when changing from the per-capita to the scaled poverty line (Table 6, panel C, columns 3 and 4).

Across all three of these approaches, there is little qualitative difference between the estimates based on the square-root poverty line (i.e., θ = 5 for all countries) as opposed to the country-specific, scaled poverty lines (i.e., θ varies across countries). An examination of the distribution of the economies of scale parameter reveals why the findings are so similar. The estimated global average of the economies of scale parameter is 0.5 when each country is equally weighted and 0.51 when the country-specific scale parameters are population weighted. In addition to being centered on 0.5, the dispersion of the scale parameters is quite narrow. The interquartile range (i.e., the 25th to the 75th percentile) of the economies of scale parameter is 0.46, 0.53 when each

[24] 10.1 percent as compared to 10.2 for the square-root line.

Table 7
Summary statistics on covariates of poverty.

Category	Nigeria2018	Mali2009	India 2011	Pakistan 2018	Tajikistan 2015	Indonesia 2017	Yemen2014	Colombia 2017
Years of schooling	7.0		5.5	5.2		8.1	6.1	8.2
Asset index	2.51		2.12		1.74	2.14	2.68	
Asset ownership: computer or landline		0.04		0.14				0.43
Literacy	0.72	0.35	0.68	0.58		0.94	0.71	0.93
Not employed in the agricultural sector	0.92			0.70		0.64		0.80
Access to electricity	0.64	0.43	0.80	0.91	0.98	0.98	0.65	0.98
Piped drinking water	0.03	0.64		0.17	0.49	0.10	0.48	0.98
Improved sanitation	0.58	0.34		0.75	0.96	0.74	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.

country is equally weighted, and 0.47, 0.53 for the population weighted estimates. While we emphasize that our assumptions underpinning the estimated economies of scale parameters are relatively crude, it is nonetheless surprising the extent to which they align with the uniform assignment of the square-root allocation rule to each country.

3.3. Extension: assessing the performance of the square-root allocation rule

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. There is an inherent estimation challenge in assessing the correlation between the two poverty indicators and the poverty covariates. Changing from assuming no economies of scale to positive economies of scale alters by definition the correlation between household size and the poverty indicators and covariates in a way that affects (i.e., confounds) comparisons of the coefficients for this exercise. The poverty covariates are constructed based on some implicit assumption on household economies of scale. For example, access to electricity assumes that this characteristic is a pure public good within the household (i.e., $\theta = 0$). How the poverty covariates correlate with the poverty measures will shift as the assumption of household economies of scale switches. Unconditional correlations of the variables will in part reflect assumptions being made about the household economies of scale parameter used for each.

In lieu of trying to directly disentangle household size from the measures, we instead assess the partial correlation between the poverty measures and poverty covariates – conditional on the effect that household size has on each – and estimate the following specification:

$$P^{a}_{h,c} = \beta_0 + \beta_1 (Y_{h,c}) + \beta_2 (N_{h,c}) + \varepsilon_{h,c} \tag{5}$$

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 rule. Y is variously one of the poverty covariates (e.g., years of schooling of the household head) and N is household size.

The eight countries examined in this part of the analysis 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 covariates.[25] 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 251 million people living in extreme poverty or almost 40 percent of the total poverty population in this analysis.

Table 7 shows the dispersion in the selected covariates 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 (averaging 5.5 years or less of schooling).[26] Fig. 2 reveals that the age profile of the poor changes substantially when switching from the per-capita to the square-root allocation of resources. For each of the countries, the proportion of the poor that are adults increases under the square-root allocation.

In estimating Eq. (5), 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 the same samples and specifications, except for switching the allocation rule from per-capita to square-root in $P^{a}_{i,c}$ across the models. To identify those who

[25] 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).

[26] Variation across countries in this figure should be interpreted with caution given the differences in survey years.

are poor under the square-root allocation rule, we solve for the value of the square-root poverty line that ensures 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. More specifically, for each country we solve Eq. (2) to derive the value of the square-root allocation poverty lines that produces the same poverty rate as with the $2.15 IPL for each country (Table 8). We repeat this for the higher-valued poverty line of $3.65 (Appendix Table A7).

Except for years of schooling and the asset index, all of the other the poverty covariates examined in Table 9 are binary variables. The advantage of binary indicators as opposed to continuous variables is that the units are comparable across countries.[27] 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 9 and 10 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.[28] The only difference is that in Table 9 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 is one). In Table 10, 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 is the count 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 column (2) 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 $2.15 poverty line). All nonpoor individuals are zero, and all individuals who are identified as poor under both allocations are zero. Column (3) 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) reports 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 $\alpha = 0.01$. 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 9 and 10). The p-value is less than 0.01 for all comparisons.[29] 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 (conditioning on household size). 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.

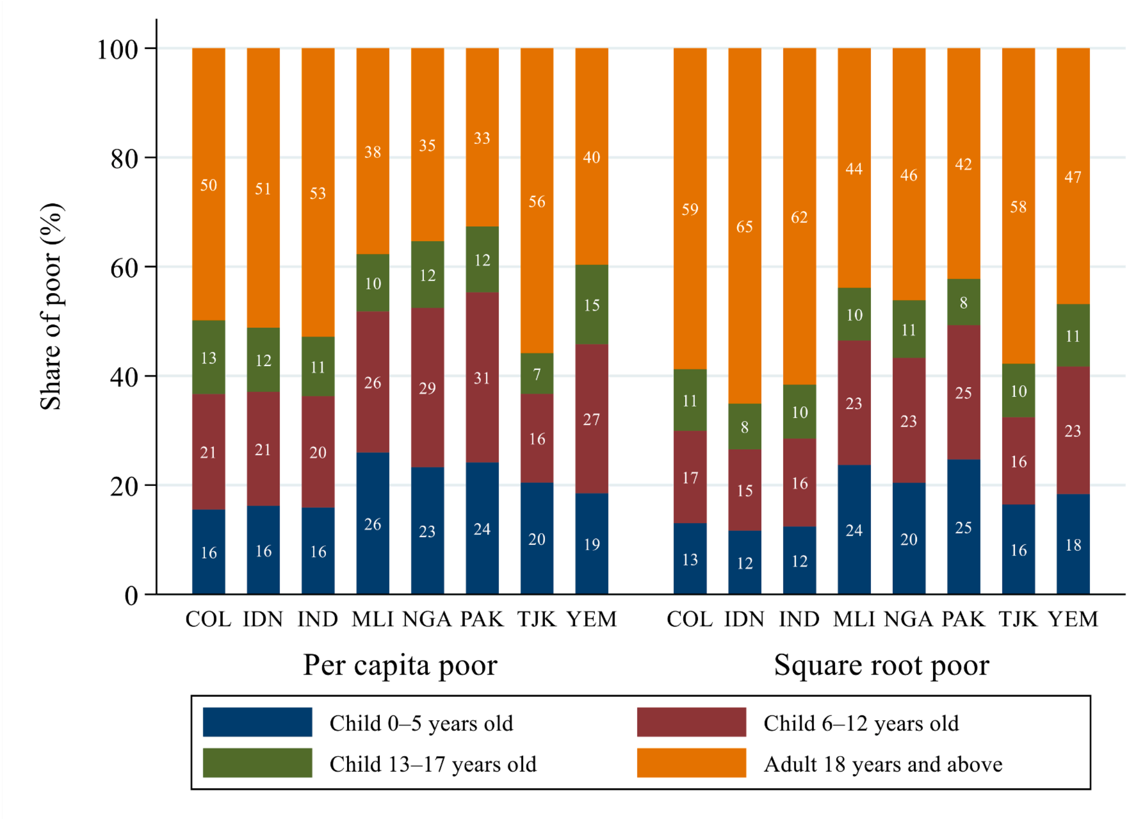
When considering the differences between columns (5) and (6), it is useful to note that the differences are statistically significant despite there being significant overlap between the two samples of who is identified as poor (the majority of people who are classified as poor under one measure are also poor under the other). Columns (2) and (3) in contrast, identify those individuals who are classified as poor only under one measure (either the per-capita or square-root allocation). It continues to be the case that the magnitude of the correlation between the poverty covariates and the square-root identifier of poverty is greater, but the differences when the overlap in the sample is eliminated are substantial.

We interpret the findings from Tables 9 and 10 as strongly supportive of the conclusion that the square-root allocation rule performs at least as well as the per-capita rule. Moreover, the finding that the partial correlation between the square-root allocation and the poverty correlates is larger than that found for the per-capital allocation, appears to hold in the space of public health investments (e.g., access to 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 square-root and per-capita indicators are highly correlated by examining 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 across the two regressions (particular for the comparisons where the per-capita and square-root samples have substantial overlap, column 7). Appendix Tables A8 and A9 also explore the sensitivity of the finding to the value of the IPL of $2.15 by replicating the test of equality but with the poverty line set at the higher value of $3.65. The findings from these tables suggest there is little sensitivity to increasing the value of the IPL. Whereas all 32 differences were

[27] One caveat to this claim is the binary indicator for piped drinking water. How this variable is defined does vary substantially across countries, and this variation does harm cross-country comparability. In future work, we intend to expand the coverage of countries, and focus only on variables that are more fully harmonized across surveys.

[28] Appendix Table A10 provides the estimates for each country instead of the pooled estimates presented in Tables 9 and 10.

[29] Each of the p-values in columns (4) and (7) of Tables 9 and 10 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.



Sources: Global Monitoring Data (GMD), Luxembourg Income Study (LIS)
Notes: This chart shows the share of the per-capita and square-root poor by age cohort. Four age cohorts are identified, namely children between up to 5 years, between 6 and 12 years, between 13 and 17 years, and adults.

Fig. 2. Age Distribution of the Poor. *Comparisons under the per-capita and square-root allocation.* Sources: Global Monitoring Data (GMD), Luxembourg Income Study (LIS) Notes: This chart shows the share of the per-capita and square-root poor by age cohort. Four age cohorts are identified, namely children between up to 5 years, between 6 and 12 years, between 13 and 17 years, and adults.

Table 8
Country-level poverty status at $2.15 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 (2017 USD PPP)(7)
Nigeria	2018.75	30.9	30.9	62.4	62.4	5.615
Mali	2009.89	48.2	48.2	7.5	7.5	7.639
India	2011.5	22.5	22.5	153.9	153.9	4.916
Pakistan	2018.5	4.9	4.9	10.9	10.9	5.968
Tajikistan	2015	6.1	6.1	0.5	0.5	5.889
Indonesia	2017	6.6	6.6	8.6	8.6	4.522
Yemen	2014	19.8	19.8	5.5	5.5	6.124
Colombia	2017	4.3	4.3	2.1	2.1	4.535

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.

statistically significant when the IPL is $2.15, at $3.65, 28 of the 32 differences are statistically significant (p-values < 0.01) and indicate stronger correlation with the square-root measure.

The finding that the partial correlation between the square-root poverty measure and the poverty covariates is consistently greater in absolute value can be viewed as one piece of evidence suggesting that the square-root measure better identifies the poor. We view existing literature from country studies on subjective assessments of poverty and wellbeing as providing further evidence that household economies of scale are significantly greater than what is implied by the per-capita measure. These studies on subjective wellbeing, coming from countries at varying levels of development, point towards economies of scale that are close to the square-root assumption. The studies reflect a variety of methodological approaches; for example, one approach is based on asking respondents to identify the least amount of income their household would need to meet absolute minimum basic needs, along with asking whether their income was adequate to meet these needs. By combining the answers to these questions with measured household

Table 9
Identifying the $2.15 poor based on covariates of poverty *(Pooled data across countries with equal weights for each country).*

Category (1)	Per capita poor only (2)	Square-root poor only (3)	Diff. p-value (4)	Per capita poor (5)	Square-root poor (6)	Diff. p-value (7)	Obs (8)
Years of schooling	−0.019***	−0.108***	0	−0.174***	−0.264***	0	683,505
Asset index	−0.037***	−0.153***	0	−0.378***	−0.494***	0	431,436
Asset ownership	0.001	−0.122***	0	−0.118***	−0.242***	0	264,698
Literacy	0.000	−0.125***	0	−0.151***	−0.276***	0	694,463
Not employed in the agricultural sector	−0.004***	−0.029***	0	−0.034***	−0.059***	0	450,521
Access to electricity	−0.011***	−0.158***	0	−0.279***	−0.426***	0	697,583
Piped drinking water	−0.006***	−0.012***	0	−0.048***	−0.053***	0	595,934
Improved sanitation	−0.008***	−0.114***	0	−0.196***	−0.302***	0	595,936

Source: Authors' calculations from the Global Monitoring Database (GMD).
Notes: This table shows the results of regressing an indicator variable of being poor on the poverty covariates (in some cases, the actual values of the covariates, in two cases, the percentile rankings) while controlling for household size. See Section 3b in the paper for more details. Percentile rankings (scaled to range between 0,1) are used for 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 $2.15 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 10
Identifying the $2.15 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)	Square-root poor only (3)	Diff. p-value (4)	Per capita poor (5)	Square-root poor (6)	Diff. p-value (7)	Obs (8)
Years of schooling	−0.024***	−0.164***	0	−0.265***	−0.405***	0	683,505
Asset index	−0.048***	−0.204***	0	−0.484***	−0.640***	0	431,436
Asset ownership	−0.003***	−0.096***	0	−0.096***	−0.190***	0	264,698
Literacy	−0.013***	−0.094***	0	−0.149***	−0.231***	0	694,463
Not employed in the agricultural sector	−0.007***	−0.032***	0	−0.041***	−0.066***	0	450,521
Access to electricity	−0.015***	−0.093***	0	−0.252***	−0.330***	0	697,583
Piped drinking water	−0.017***	−0.015***	0.336	−0.100***	−0.097***	0.336	595,934
Improved sanitation	−0.009***	−0.082***	0	−0.174***	−0.246***	0	595,936

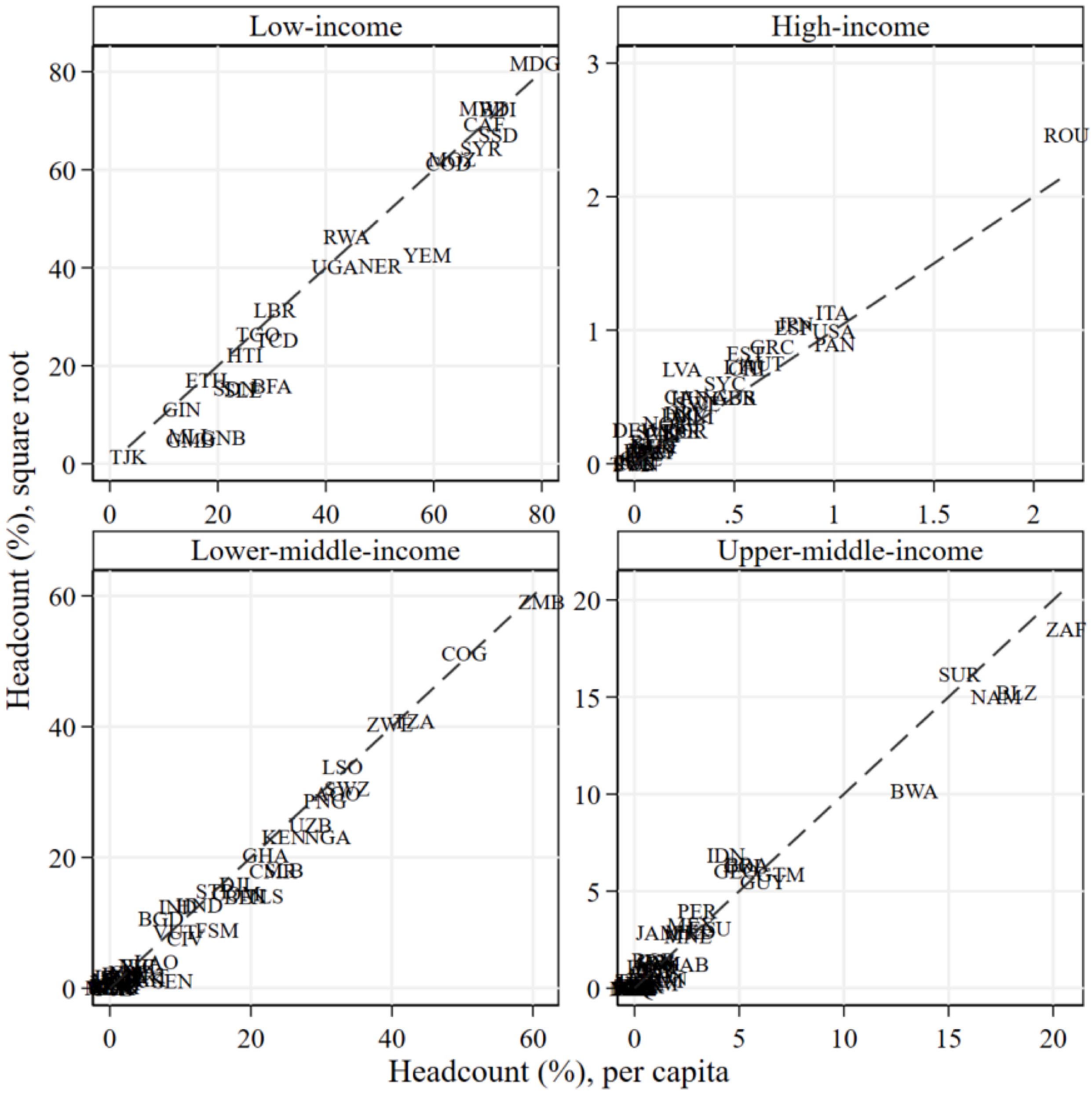
Source: Authors' calculations from the Global Monitoring Database (GMD).
Notes: This table shows the results of regressing an indicator variable of being poor on the poverty covariates (in some cases, the actual values of the covariates, in two cases, the percentile rankings) while controlling for household size. See Section 3b in the paper for more details. Percentile rankings (scaled to range between 0,1) are used for 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 $2.15 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.

income, one can construct a subjective poverty line that will vary with household size.[30]

The variation between the subjective poverty line and household size will then directly reveal an empirical estimate of household economies of scale. One example of this application is from Pradhan and Ravallion (2000) who find an estimated economies of scale parameter of 0.47 for Nepal, a low-income country.[31] Bishop et al. (2006) use data from urban China during the 1990s when the country was transitioning between low- and lower-middle-income status. Using a slightly different methodological approach, they estimate a poverty line based on subjective assessments of poverty for families with children and similarly find an economies of scale parameter that corresponds with the square-root rule. Rojas (2007) using data from Mexico (an upper-middle income country) on subjective wellbeing, estimates household economies of scale parameters for Mexico of 0.48 (based on a single parameter model)

[30] The answers to "…income needed to meet minimum basic needs?" are typically increasing in value as household income increases, but the expected value of this line increases at a diminishing rate. In this case, there will then be a point on this line that bisects measured household income (for a fixed household size) and the subjective assessment of the cost of minimum needs. This point will reflect a subjective estimated cost of basic needs where most people with income less than this value will have reported that they cannot make ends meet (and vice versa). It will also be the case that the estimated cost of basic needs will vary for households of different sizes.

[31] Though they state that they were surprised by this estimate.



Notes: The dashed line is a 45-degree line.

Fig. 3. Extreme poverty in 2019 by allocation rule and income group. Notes: The dashed line is a 45-degree line.

and 0.51 (based on a more flexible model). Pradhan and Ravallion, as well as Rojas, both argue that viewing economies of scale as a concern for only high-income countries is an untenable assumption. Pradhan and Ravallion in particular refer to many reasons why economies of scale exist in low- and middle-income countries.

4. Conclusion

Eradicating extreme poverty figures prominently in 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 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 two 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 have been tenable. But in a world that has grown richer and is experiencing declining budget shares for food, increasing shares for shelter; and in consideration of the 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 surveys from 162 countries covering more than 3/4th of the world's population, and 97.5 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 discussion focuses on the analysis based on the square-root allocation poverty line that maintains the same global poverty headcount as the per-capita poverty line. While the value of this line more than doubles, the changes to the percent of poor in each region of the world are relatively small (i.e., two percentage points or less in all regions except for Sub-Saharan Africa where extreme poverty fall by 3.6 percentage points due to large households with more children). The analysis shows though that these relatively small changes in the regional poverty headcounts mask significant variation at the country level. Fig. 3 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.[32] In considering the absolute sum of changes across countries (not regions), country-level poverty headcounts change by 92 million people (or about 14 percent of the total count of people living in extreme poverty).

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 indicates 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 264 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 more than 40 percent of the total population of people estimated to be in extreme poverty.

We also examine if there is any evidence that the partial correlation of 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, $2.15 poverty line, the square root measure of poverty was more highly correlated with each of the poverty covariates (conditioning on household size). Our interpretation of these findings is that the decision to allocate household consumption on a per-capita basis is problematic in a world where food shares are declining, and it is an assumption that has significant implications for identifying who is living in extreme poverty.

CRediT authorship contribution statement

Dean Jolliffe: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Samuel Kofi Tetteh-Baah:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

The authors wish to thank Andres Castaneda Aguilar, Shatakshee Dhongde, Thesia Garner, Charles Yuji Horioka, Stephen Jenkins, Christoph Lakner, Daniel Mahler, Martha Mendoza, Minh Cong Nguyen, Sergio Olivieri, Marta Schoch, Umar Serajuddin, Tim Smeeding, Nishant Yonzan and participants at the 2022 IARIW conference for feedback on initial drafts of this work. The authors gratefully acknowledge financial support from the World Bank's Research Support Budget; the Republic of Korea, through the Korea Development Institute School of Public Policy and Management (KDIS) and its Knowledge Partnership with the World Bank; the Knowledge for Change Program (KCP); and the UK government through the Data and Evidence for Tackling Extreme Poverty (DEEP) Research Programme. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2024.106593.

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[32] Appendix Figs. A1 and A2 show that this finding also holds at the higher-value lines of $3.65 and $6.85.

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