Where is Poverty Concentrated? The New Evidence based on Globally Consistent Urban and Poverty Measurements[*] [†]

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Abstract

The incomparability of urban definitions across countries has hindered the breakdown of global poverty in urban and rural areas. This paper compares subnational poverty statistics across countries by integrating globally consistent definitions of urban areas into the World Bank's official global poverty measurement framework. Analyzing 20 low- and middle-income countries—mainly in Sub-Saharan Africa—the paper shows that poverty rates tend to be lower in more densely populated urban areas. However, the analysis demonstrates that poor populations are more concentrated in urban areas than previously thought. The findings underscore the importance of consistent urban definitions in cross-country poverty analysis and encourage rethinking geographically targeted policies to accelerate poverty reduction.

Keywords: Global poverty; urban poverty; urbanization; cost of living; Sub-Saharan Africa

JEL Codes: I32, R12, O18

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1 Introduction

Reducing global poverty is the first Sustainable Development Goal (SDG).[1] As a custodian agency to monitor the progress, the World Bank measures and monitors global poverty across countries based on income or consumption expenditures in household budget surveys and the international poverty lines (Ferreira et al., 2016; World Bank, 2022; Ravallion et al., 1991; World Bank 1990). Current global poverty measurement practice implicitly adopts official national definitions of urban areas, which have been shown to vary widely across countries (Roberts et al., 2017; Satterthwaite, 2007; World Bank, 2009; Dijkstra et al., 2021). This has created a challenge to disaggregate global poverty by urban and rural areas in a globally comparable way. The lack of globally consistent information on urban poverty hinders efficient and effective resource allocations to achieve the SDGs. The national governments may be unable to optimally allocate resources between urban and rural areas and between different types of urban areas within their countries. The resource allocations across countries by international organizations can be constrained as well. Unfortunately, only a few attempts have been made to measure and analyze global poverty from an urban/rural perspective, with Ravallion, Chen, and Sangraula (2007) as an exceptional early example examining how global poverty has urbanized. At best, cross-country comparisons have been made based on poverty measures using national poverty lines (for example, Ferré, Ferreira, and Lanjouw 2012).

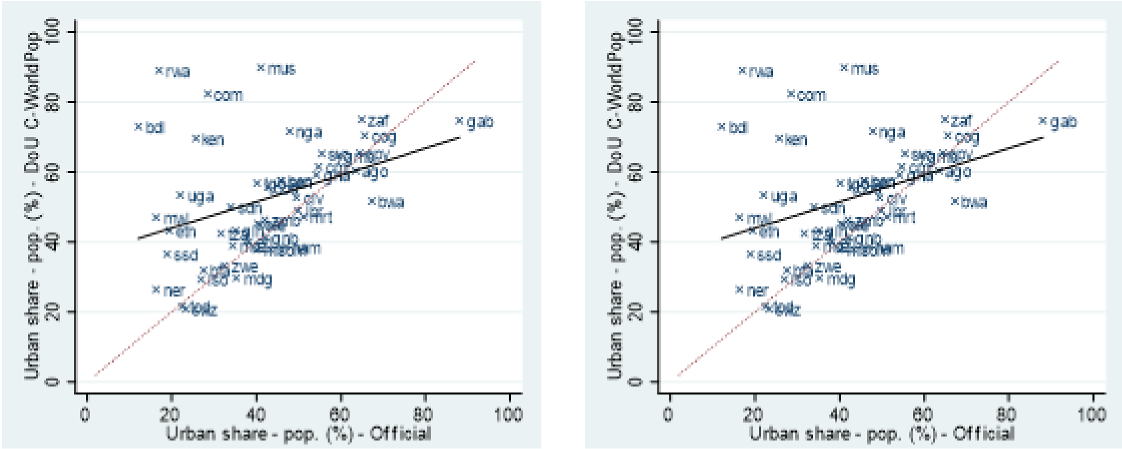
Building on recent work by Combes et al. (2023), this paper attempts to provide new evidence on poverty distributions within and between countries based on globally consistent urban and rural poverty measurements.[2] Combes et al. (2023) is a new effort to consistently delineate urban areas across countries based on two different approaches: the Degree of Urbanization (DOU) and Dartboard (DB) approaches. The DOU approach classifies cells in a gridded population layer into different urban and rural categories by applying unique population and population density thresholds to all countries (Dijkstra et al., 2021). The DB approach also classifies gridded population cells. However, instead of uniformly applying the same absolute thresholds to all countries, it statistically distinguishes different urban and rural categories based on each country's population density distribution (de Bellefon et al., 2021). In other words, the DOU is an absolute measure, whereas the DB is a relative measure. These new measures suggest that official urban definitions tend to underestimate urban population shares in Sub-Saharan Africa (Figure A2). Moreover, the DOU and DB approaches distinguish multiple types of urban areas rather than relying solely on a simple urban-rural dichotomy that paints an overly simplified picture of urbanization (Cattaneo et al., 2022). The novel dataset created for this study by integrating new urban classifications into household budget surveys covers 221,000 households, comprising around 1 million individuals from 20 low- and middle-income countries from different parts of the world.

Based on this new global database of urban poverty, we first examine a set of questions about poverty incidence across different types of geographic areas. One of the fundamental questions is *whether and to what extent poverty incidence is lower in urban than rural areas.* In general, labor productivity tends to be higher in denser areas thanks to agglomeration effects (Duranton, 2015; Duranton & Puga, 2004; Glaeser & Gottlieb, 2009; Gollin et al., 2002; Grover et al., 2021; Michaels et al., 2012) and the sorting of higher ability individuals into these areas (Combes et al., 2008). However, monetary poverty is not necessarily lower in urban areas than in rural areas once the higher urban cost of living is considered. For example, compared to cities elsewhere, the cost of living in African cities is high relative to their country's GDP levels (Nakamura et al.,2019). Our newly created cross-country dataset confirms that the cost of living is higher in urban areas—notably denser urban areas—than in rural areas. Urban poverty can prevail and be as severe as rural poverty when crowding and negative congestion externalities from

[1]Target 1.1 aims to 'eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day'. The latest extreme poverty line is $2.15 per day in 2017 Purchasing Power Parity (PPP) terms (World Bank 2022).

[2]The preliminary findings from 7 countries are reported in Combes et al. (2022).

Figure 1: Urban population shares in Sub-Saharan Africa by different definitions



(a) DOU vs. official urban definitions

(b) DB vs. official urban definitions

Source: Combes et al. 2022
Note: Dotted lines are 45-degree lines. DOU: Degree of urbanization. DB:Dartboard.

density outweigh its benefits (Marx et al., 2013; Lucci et al., 2018). Similarly, it is an empirical question of whether poverty and density are negatively correlated not only between urban and rural areas but also within urban areas, as both income and cost of living can vary a lot at a lower geographic scale and typically between the centers of large cities and their suburbs.[3]

The second set of questions to be addressed refer to the spatial distributions of poverty— *Where is the mass of poverty, as defined by the total number of poor populations, concentrated? Is the mass of poverty still concentrated predominantly in rural areas?* Global extreme poverty is known to be concentrated in Sub-Saharan Africa (World Bank 2022). Despite the massive increase in urban population, it is still assumed that extreme poverty is concentrated in *rural* areas. For example, Castaneda et al. (2018) analyze 89 developing countries, estimating that around 80 percent of extremely poor populations live in rural areas. Beegle and Christiaensen (2019) report that 82 percent of extremely poor populations in Sub-Saharan Africa live in rural areas. However, hard evidence is lacking due to the lack of geographic disaggregation in global poverty based on a globally consistent classification of urban and rural areas. It is also essential to know in which types of urban areas poverty is concentrated—for example, major cities or secondary towns. Some recent studies point to the critical role of secondary towns in poverty reduction (Gibson et al., 2023; Gibson et al., 2017; Christiaensen & Todo, 2014). A proper understanding of urban/rural poverty distributions is crucial, given the persistent debates over the unique nature of Africa's urbanization and its implications for economic growth and poverty reduction.[4] Such information is also necessary to design policies that effectively facilitate structural transformation and boost productivity, improve living standards, and ultimately reduce poverty.

Our analysis underscores the need to address urban poverty to accelerate global poverty reduction. The results confirm that urban poverty rates are lower than rural poverty in all 20 countries studied based on globally consistent urban definitions and poverty measures. Poverty incidence in dense urban areas is particularly low, whereas poverty rates in low-density urban areas are closer to those in rural areas. The patterns hold even after controlling for observed individual household characteristics. The use of DOU/DB approaches, instead of relying on each country's

[3]As for non-monetary measures, both Gollin, Kirchberger, and Lagakos (2021) and Henderson et al. (2021) find that various living condition indicators positively correlate with population density in Africa. Ameye and de Weerdt (2020) find that the prevalence of child stunting first improves with increasing city size but worsens for cities with a population of over one million.

[4]Such studies include, but are not limited to, Bryan, Glaeser, and Tsivanidis 2020; Castells-Quintana and Wenban-Smith 2020; Gollin, Jedwab, and Vollrath 2016; Henderson, Storeygard, and Deichmann 2017; Jedwab, Christiaensen, and Gindelsky 2015; Fay and Opal 2000; Henderson, Storeygard, and Roberts 2013.

official urban definition, increases urban poverty rates in most countries. However, the choice of DOU (absolute) or DB (relative) approach does not matter much. The most striking result is that while rural areas accommodate more than half of the poor populations in many countries, the mass of poverty is more concentrated in urban areas than previously thought. We also find that, unlike poverty rates, the choice of DOU or DB approach to delineating urban areas makes a critical difference to the spatial distribution of poor populations.

The remainder of the paper is structured as follows. Section 2 provides a brief background on the framework of global poverty measurement and urban delineation—the variation in urban definitions across countries and pros and cons of different urban delineation methodologies. Section 3 describes the data used in this paper. Section 4 presents the empirical approach to integrating the new globally consistent urban classifications into the global poverty framework. Section 5 reports the results, followed by a discussion and conclusions in Section 6.

2 Global poverty measurement and urban delineation

2.1 Global poverty measurement

Global poverty is measured based on individual or household welfare proxies – either consumption expenditures or income –, international poverty lines, and price indexes to adjust for within- and between-country price differences.[5] Based on household budget surveys, consumption expenditures are aggregated for each household and converted to per capita consumption expenditures by dividing by the number of members in each household (Deaton & Zaidi, 2002; Mancini & Vecchi, 2022). The World Bank sets different thresholds in international poverty lines: the extreme poverty line ($2.15 per capita per day in 2017 PPP terms), the lower-middle-income poverty line ($3.65), and the upper-middle-income poverty line ($6.85) (World Bank 2022).[6] Household consumption expenditures must be deflated by price indexes to be comparable to the international poverty lines. The purchasing power parity (PPP) index is used to adjust for currency exchange ratios and price level differences across countries. The consumer price index (CPI) is also used to adjust for price differences over time, whereas a spatial deflator adjusts for subnational price differentials (Amendola et al., 2023; Nakamura & Yoshida, 2022). Precisely, the poverty status of an individual is measured as follows. Real consumption expenditures of individual i in region r in country C at year t, which we denote as $REXP^{C}_{i,r,t}$, is calculated as:

$$REXP^{C}_{i,r,t} = NEXP_{i,r,t} \times (\pi^{CN}_{r,t})^{-1} \tag{1}$$

where $NEXP_i$ is the nominal consumption expenditure of the individual and π^{CN}_{r} is a spatial price deflator that adjusts for cost-of-living differences between region r and the national level (N). To determine an individual's poverty status, the level of consumption expenditure can be further converted as follows so that both it and the global poverty line are expressed in US$ in 2017 PPP terms:

$$NEXP_{irt} \times (\pi^{CN}_{rt})^{-1} \times (CPI^{C}_{2017,\ t})^{-1} \times (PPP_{C,\ 2017})^{-1} \lesseqgtr IPL_{2017} \tag{2}$$

where $CPI^{C}_{2017,\ t}$ adjusts for the price differences between the survey year t and 2017 in country C; $PPP_{C,\ 2017}$ adjusts for the differences in the currency exchange ratios and price levels between country C and the United States in 2017; and IPL_{2017} is one of the international poverty lines expressed in US$ in 2017 PPP terms. Poverty rates are measured as the percentage of the population in poverty at the national and sub-national levels.

[5] For the sake of simplicity, we mention consumption, instead of income, as a welfare measure in the remainder of this paper.

[6] The international poverty line is derived as the median of the national poverty lines of low-income countries, while the higher absolute poverty lines are the median national poverty lines of lower-middle-income and upper-middle-income countries.

Although great care is taken in its application, the global poverty measurement methodology presented above entails several methodological challenges. First, each country defines urban areas by its own definition. Because these definitions vary significantly, comparisons of urban (and rural) poverty across countries are inconsistent and unreliable. Additionally, although much attention has been paid to accounting for differences in the cost of living *between* countries (for example, Ravallion, 2018; Deaton, 2011), there has been relatively less focus on adjusting the costs of living across subnational areas *within* countries in the context of global poverty measurement. This is, however, crucial when estimating urban and rural poverty, as living expenses can vary significantly between urban and rural areas (Nakamura & Yoshida, 2021; Jolliffe, 2006; Jolliffe et al., 2004; Bidani & Ravallion, 1993). As demonstrated in this paper, failing to account for the subnational cost of living differences leads to a systematic underestimation of urban poverty, making standard poverty and welfare estimates inaccurate. Furthermore, and related, housing costs are often excluded from spatial price deflators. At the same time, these costs vary the most across locations, thus leading to an underestimation of the cost of living in urban areas.[7] As a result, urban households may appear to have higher living standards than they do, and urban poverty is often underestimated.

Ravallion, Chen, and Sangraula (2007) and Ferré, Ferreira, and Lanjouw (2012) are the key predecessors to our study, delving into the spatial dimension of poverty from a global perspective. Ravallion, Chen, and Sangraula (2007) is a milestone study investigating whether global poverty had urbanized based on more than 200 household surveys from about 90 countries from 1993 to 2002. The study was innovative in various aspects. First, it applied global poverty lines to measure poverty. Second, it addressed the cost-of-living differences between urban and rural areas by taking the ratio of each country's urban and rural poverty lines.[8] Third, using multiple data points over time for many countries, the authors analyzed dynamic aspects of urbanization and poverty reduction and heterogeneity across world regions. Nevertheless, Ravallion, Chen, and Sangraula (2007) suffer from a possible bias from incomparable urban definitions across countries. Ferré, Ferreira, and Lanjouw (2012) is a second study investigating the relationship between poverty and city size in eight low- and middle-income countries.[9] Applying a small area estimation method to impute poverty for disaggregated geographic units, they find that poverty incidence is higher in smaller towns and that the mass of poverty is also concentrated there. While providing insightful results, their approach has several limitations, such as the use of each country's national poverty line instead of global poverty lines, no distinction in cost of living by city size, and—as in Ravallion, Chen, and Sangraula (2007)—no application of a consistent urban definition across countries.

2.2 Urban delineation

Accurately and consistently defining urban areas is a fundamental step in providing accurate and consistent estimates of urban (and rural) poverty across countries. Until recently, there has been little attention in urban economics on consistently defining cities and urban areas across countries (Combes et al., 2023; Duranton, 2021; Roberts et al., 2017). These definitions vary significantly across countries; however, most include at least one of four essential criteria to define urban areas. The most used criterion is population size, with most countries using a minimum population threshold as part of their definition of urban areas. In addition, some countries consider the availability of urban infrastructure and services, the structure of the local economy, and/or population density (Roberts et al., 2017). However, many countries do not

[7] A counterargument here is that higher housing costs in urban than in rural areas for properties that share the same structural characteristics (i.e., size, number of rooms, etc.) reflect, at least in part, the existence of superior urban amenities, including access to basic services, which are welfare-enhancing. To the extent that this is the case, it is unclear how to incorporate the value of these amenities into the welfare measure.

[8] More precisely, Ravallion, Chen, and Sangraula (2007) create another global poverty line for each country based on the ratio of the country's urban and rural poverty lines. Essentially, this is equivalent to deflating household consumption expenditures by a spatial deflator derived as the ratio. The poverty lines used for the analysis are constructed following the cost-of-basic-needs approach (Ravallion & Bidani, 1994) in most countries.

[9] Albania, Brazil, Kazakhstan, Kenya, Mexico, Morocco, Thailand, and Sri Lanka.

use explicit criteria to delineate cities (Roberts et al., 2017; Dijkstra et al., 2021). This lack of a consistent and global definition of urban areas may result in statistical artifacts, ultimately hindering policy recommendations and potentially their effectiveness.[10]

In response to the challenges posed by inaccurate and inconsistent urban delineation, and thanks to the growing availability of high-resolution global gridded population datasets and satellite imagery, recent research has emphasized the importance of developing new methodologies for accurately and consistently defining urban areas across countries.[11] According to Combes et al. (2023), two methodologies have emerged as the leading approaches for consistent urban delineation. The Degree of Urbanization (DOU) method, introduced by Dijkstra and Poelman (2014) and extended globally by Dijkstra et al. (2021), defines cities based on two primary absolute thresholds: a population size and a population density threshold. The method is straightforward to implement and has been applied globally by a coalition of international organizations led by the European Commission. The method was also endorsed by the United Nations Statistical Commission in March 2020 as a recommended method of international comparisons of urban areas (Dijkstra et al., 2021). In contrast, the dartboard approach, introduced by de Bellefon et al. (2021), defines cities in relative terms, using local density thresholds endogenously determined based on a country's spatial population distribution.

Under the DOU approach, each cell of a gridded population dataset, such as WorldPop and GHSPOP, can be classified as belonging to either an urban center (city), urban cluster (towns and suburbs), or rural area (Table 1; also see Panel A of Figure A1 in Annex for an example of Greater Accra, Ghana).[12] A cell is part of an urban center if it belongs to a spatially contiguous set of grid cells in which each cell has a population density of at least 1,500 people per km^2 and the aggregate population of the set is at least 50,000. Urban clusters, meanwhile, are sets of grid cells in which each cell has a population density of at least 300 people per km^{2,} and the set has an aggregate population of at least 5,000. Rural areas are areas not classified as either urban centers or clusters.

The DB approach classifies areas into three types: cities, themselves made of cores and suburbs; rural towns; and other rural areas (1; also see Panel B of Figure A1 in Annex for an example of Greater Accra, Ghana; for a more in-depth description, see Combes et al. 2021). An area is first screened if it is part of a contiguous set of cells for which the population density of each cell exceeds the 95$^{\text{th}}$ percentile of a counterfactual distribution of grid cells, where the counterfactual distribution is generated under the assumption of a random spatial distribution of population. Cities are screened areas that possess at least one *core*, where cores are identified as contiguous second-order urban pixels based on the comparison with a counterfactual population random distribution within urban areas. Suburbs are non-core parts of cities, whereas towns are screened areas with no core—classified as part of rural areas. Areas not classified as either of the above are considered rural.

[10]As an example, Latin American countries have significantly lower GDP per capita than expected based on their urbanization levels and are also "over-urbanized" relative to the size of their agricultural sectors. Roberts et al. (2017) demonstrate that these patterns are an illusion resulting from systematic biases in the measurement of urbanization levels, and disappear when adopting a consistent definition of urban areas across countries.

[11]These new methods tend to adopt either a functional or, more commonly, a morphological approach to delineating urban areas (Duranton, 2021). Functional approaches identify a city's geographical extent based on the strength of spatial economic interactions with the typical focus being on delineating cities based on the strength of commuting flows. By contrast, morphological approaches identify a city's geographical extent based on its physical extent. Examples of more functional based approaches to the globally consistent definition of urban areas include Uchida and Nelson (2009; see also World Bank 2009) and Moreno-Monroy, Schiavina, and Veneri (2021). Meanwhile, examples of morphological approaches include those that identify a city's physical extent using built-up area data (Heinrigs, 2020; OECD/SWAC 2020; OECD/UN ECA/AfDB 2022), gridded population data (Dijkstra & Poelman, 2014; Dijkstra et al., 2021), and nighttime lights data (Balk et al., 2006; Zhang & Seto, 2011; Brecht et al., 2013; Zhou et al., 2015; Ellis & Roberts, 2016; Ch et al., 2021; Dingel et al., 2021).

[12]These three types of area correspond to "Level 1" of the DOU. "Level 2" of the DOU further disaggregates the number of types of urban area using different population density and overall population thresholds (see Dijkstra et al., 2021).

Table 1: Urban-rural classifications in DOU and DB approaches

Classification	Definition
Degree of urbanization approach (Dijkstra et al., 2021)	
Urban areas	Urban centers and urban clusters.
Urban centers	Spatially contiguous sets of 1km^2 grid cells for which the population density of each cell $\geq$ 1,500 people per km^2 and aggregate settlement population $\geq$ 50,000.
Urban clusters	Spatially contiguous sets of 1km^2 grid cells for which the population density of each cell $\geq$ 300 people per km^2 and aggregate settlement population $\geq$ 5,000.
Rural areas	Areas not classified as either urban centers or urban clusters.
Dartboard approach (de Bellefon et al., 2021)	
Urban areas (Cities)	Sets of contiguous pixels with population density $> 95^{\text{th}}$ percentile of the counterfactual with a core.
Cores	Urban cores are identified as contiguous second-order urban pixels with population density $> 95^{\text{th}}$ percentile of counterfactuals within urban areas.
Suburbs	Non-core parts of cities.
Rural areas	
Towns	Sets of contiguous pixels with population density $> 95^{\text{th}}$ percentile of the counterfactual with no core.
Other rural areas	Areas not classified as cities or towns.

Note: See Combes et al. (2023) for details.

3 Data

For this study, we prepare a new dataset, the Global Urban Poverty Database, by integrating two types of data: i) high-resolution gridded population data to construct urban classifications and ii) detailed household-level data to construct poverty measures.

3.1 Gridded population layers

We use the GHSPOP and WorldPop gridded population datasets for 2015, with a resolution of 1km and 250m, respectively. Where available, we use WorldPop data from years closer to the household budget survey (HBS) interview year. Both GHSPOP—created by the European Commission—and WorldPop—produced by the University of Southampton—are open-source datasets, covering most countries globally for multiple years.[13] Both datasets are prepared by allocating each country's census-based population across gridded cells within a given administrative area. For GHSPOP, the population is evenly distributed across grid cells that contain built-up areas (Florczyk et al., 2019). For WorldPop, a machine learning approach—the random forest method—is first used to calculate weights for each grid cell. These calculations are based on several spatial input layers, including land cover, nighttime lights, and (social) infrastructure data. Second, these weights are used to distribute the population across grid cells, where the constrained WorldPop constrains the distribution of the population to grid cells that contain built-up areas. (Stevens et al., 2015)

Our primary choice of input population layer in this study is WorldPop, with GHSPOP as an alternative data source. While GHSPOP is an official dataset created by the European Commission and was used to develop the DOU method, WorldPop—particularly constrained

[13]GHSPOP data is available on the following European Commission website: https://ghsl.jrc.ec.europa.eu/ghs_pop2019.php. WorldPop data is available here: https://www.worldpop.org/project/categories?id=3

Table 2: List of Analyzed Countries

Region	Country
Sub-Saharan Africa (17)	Angola, Burkina Faso, Chad, Cote d'Ivoire, Ethiopia Gabon, Ghana, Guinea, Guinea Bissau, Lesotho, Mauritania, Malawi, Niger, Senegal, Tanzania, Uganda
North Africa and the Middle East (1)	Egypt*
South Asia (1)	Bangladesh
East Asia and Pacific (1)	Vietnam
Latin America and the Caribbean (1)	Colombia

Note: Egypt in our database has only information about poverty status and urban classifications at the individual level.

WorldPop—appears to better reflect the true spatial distributions of populations, at least to the extent that a detailed map of all building footprints is used for the development of constrained layers in Sub-Saharan Africa.[14] When choosing the resolution, we need to account for two opposing factors: computational speed and precision of the constructed urban classifications. While we stick to a 1km resolution for GHSPOP as the development of the DOU is associated with it, we use a resolution of 250 meters for WorldPop, which is four times more precise but still computationally feasible. The results of our analyses based on GHSPOP are reported in Appendix B.

3.2 Household budget surveys

We use each country's household budget survey (HBS) data collected circa 2015, corresponding to the years of WorldPop and GHSPOP in our study. The key data requirements are the information about the location identifiers of individual households, enumeration areas (EAs), or other geographic units in HBS. This study uses HBS data from 20 countries that contain such information: Angola, Burkina Faso, Chad, Cote d'Ivoire, Ethiopia, Gabon, Ghana, Guinea, Guinea Bissau, Lesotho, Mauritania, Malawi, Niger, Senegal, Tanzania, and Uganda from Sub-Saharan Africa; Egypt, Bangladesh, Vietnam, and Colombia from outside Sub-Saharan Africa (Table 2). Among the case countries in our study, household-level GPS coordinates are available for six of the 20 countries: Ethiopia, Gabon, Lesotho, Mauritania, Malawi, and Tanzania. For the remaining 13 countries, GPS coordinates are available for enumeration areas (EA) or other administrative units.[15]

Table 3 summarizes household-level information in our data pooled across 20 countries.[16] Each HBS contains information about household per capita consumption expenditures, with which global poverty can be estimated.[17] The spatially deflated per capita consumption expenditures were right-skewed with a mean of \$5.30 (in 2017 PPP terms) and a standard deviation of 8.04. We use the consumption expenditure measures prepared for global poverty monitoring by the World Bank, aside from the adjustments through the reclassification of urban areas and the update of spatial deflators (explained in Section 4). For a few countries, such as Ghana, Tanzania, and Egypt, we further modify consumption expenditures by adding housing rents, as missing housing rents in consumption aggregates is particularly concerning to our study given its urban

[14] See Combes et al. (2023) for details.

[15] Namely, Angola, Bangladesh, Burkina Faso, Chad, Cote d'Ivoire, Egypt, Ghana, Guinea, Guinea-Bissau, Niger, Senegal, Uganda, and Vietnam.

[16] Egypt in our database has only information about poverty status and urban classifications at the individual level. Country-level summary information is presented in Table A1 in Appendix A.

[17] As explained in Section 2.1, consumption expenditures are first aggregated for each household and then divided by the number of members to obtain per capita expenditures. It is assumed that individuals in the same household have the same welfare level and poverty status.

-v- rural focus. This modification makes global poverty rates in those countries lower than what is currently reported by the World Bank.[18] In addition, our data also include various variables related to demographics (household size, household head's age, sex, and marital status), education (literacy and highest education level achieved by the household head), and employment (employment status and economic sector of the household heads), as well as access to basic services, such as improved water, improved sanitation, and electricity.

4 Empirical approach

4.1 Updating urban classification

Given that official national definitions of urban areas vary widely, one must choose a consistent approach for comparisons across countries. We build on the analysis of Combes et al. (2023), employing the DOU and DB approaches. As discussed above, the DOU applies standard population and population density thresholds to all countries. As such, some highly dense countries—such as Egypt and Bangladesh—are classified as being almost entirely urban. While such results are certainly informative for global comparison, the DB approach can provide more nuanced insights by looking, in a consistent manner across countries, at the relative density distribution in each country. Since the absolute and relative approaches complement each other, we use both the DOU and the DB approaches.

We first apply the DOU and DB classifications to WorldPop and GHSPOP gridded population layers and then overlay them with geo-located HBS data. When a country's HBS contains GPS information, it is straightforward to overlay gridded layers. For countries that lack GPS information in their HBS, we overlay at the lowest possible geographic unit level. The population shares of each DOU/DB category are calculated for each geographic unit, and sampling weights in HBS are modified with those population shares when producing aggregated statistics, such as poverty rates at the national and sub-national levels. When we need a binary indicator for households for each type of DOU and DB area in a country's HBS—a typical case is a regression analysis—we apply a "threshold" approach. Hence, for each geographic area, we obtained the number of people residing in grid cells of a particular type. If most of the area's population lives in rural locations, the area is considered rural. Otherwise, areas are classified as urban. Concerning the DOU approach, we classify all households in a geographic area as located in an urban center if more of the population lives in cells classified as centers than clusters. The whole area is classified as an urban cluster if more of the population lives in clusters. As for DB indicators, if the share of the population in core areas is larger than that in towns and suburbs, the area is considered a core area. Similarly, we also classify areas as suburbs and towns.

Henderson, Liu, Peng, and Storeygard (2019) also employ one of the two urban definitions our study uses (Degree of Urbanization definition) and gridded population data (GHSPOP). In addition, both studies take a microdata approach, though Henderson et al. (2019) primarily rely on the Demographic and Health Survey (DHS), while our study uses official household budget surveys. The DHS is a valuable source to analyze a range of demographic and health outcomes, generally more detailed than what is included in HBS data. However, HBS data also contains vital demographic variables and, similar to the DHS, access to basic services. The most important is a consumption (or income) variable to measure poverty, which is absent in the DHS data.

4.2 Integrating new urban classifications into global poverty measurement

We conduct poverty analysis applying DOU and DB classifications instead of official but inconsistently defined urban/rural classifications previously contained in HBS. This involves several steps. First, we update the spatial deflators in HBS using DOU and DB classifications to convert nominal consumption expenditures to real ones (equation [1]). The spatial deflators allow us

[18] It is a case-by-case whether the modification results in an increase in poverty or a decrease in poverty, as the addition of housing rents to consumption aggregates can be offset by updated spatial deflators that adjust for housing price variations across sub-national areas.

Table 3: Summary Statistics of pooled household-level data

	N	Mean	Median	SD	Min	Max
DOU urban classification:						
Urban center	454,728	0.27	0.00	0.44	0	1
Urban cluster	454,728	0.33	0.00	0.47	0	1
Rural	454,728	0.40	0.00	0.49	0	1
DB urban classification:						
Core	454,728	0.28	0.00	0.45	0	1
Suburb	454,728	0.21	0.00	0.41	0	1
Town	454,728	0.13	0.00	0.34	0	1
Other rural	454,728	0.50	1.00	0.50	0	1
Consumption (per day in 2017 PPP terms):						
Real per capita consumption expenditures	453,632	5.62	3.56	9.48	0	2,290
Nominal per capita consumption expenditures	454,631	5.35	3.21	10.05	0	2,522
Spatial deflator						
Spatial deflator	453,659	1.00	0.99	0.13	1	2
Demographic:						
Household size	454,728	5.70	5.00	3.26	1	62
Age of household head	454,623	43.15	43.00	17.04	0	119
Household head is male	454,674	0.81	1.00	0.39	0	1
Marital status (of household head):						
Married	454,664	0.80	1.00	0.40	0	1
Never married	454,664	0.03	0.00	0.17	0	1
Living together	454,664	0.05	0.00	0.21	0	1
Divorced/Seperated	454,664	0.04	0.00	0.20	0	1
Widowed	454,664	0.08	0.00	0.28	0	1
Education (of household head):						
No education	438,551	0.33	0.00	0.47	0	1
Primary incomplete	438,551	0.20	0.00	0.40	0	1
Primary complete	438,551	0.15	0.00	0.36	0	1
Secondary incomplete	438,551	0.20	0.00	0.40	0	1
Secondary complete	438,551	0.06	0.00	0.24	0	1
Post secondary but not university	438,551	0.02	0.00	0.13	0	1
University incomplete and complete	438,551	0.03	0.00	0.18	0	1
Can read and write	442,262	0.56	1.00	0.50	0	1
Employment (of household head):						
Not in labor force	432,935	0.14	0.00	0.34	0	1
Unemployed	432,935	0.02	0.00	0.14	0	1
Employed in Agriculture	432,935	0.44	0.00	0.50	0	1
Employed in Industry	432,935	0.13	0.00	0.33	0	1
Employed in Services	432,935	0.28	0.00	0.45	0	1
Access to basic services						
Improved water	454,639	0.80	1.00	0.40	0	1
Improved sanitation facility	454,637	0.40	0.00	0.49	0	1
Access to electricity	443,585	0.64	1.00	0.48	0	1

Source: Global Urban Poverty Database.
Note: The statistics above are based on the household-level data pooled for 19 countries. Real per capita consumption expenditures are deflated using a spatial deflator calculated using the WorldPop 250m dataset and the DOU method.

to capture price variations across subnational areas. An approach is to construct new spatial deflators for all countries based on the same methodology and price data. However, such an approach is not feasible as price data availability varies across countries. Instead, we update the spatial deflators used for the official global poverty estimation.[19] This approach provides

[19]However, for countries where global poverty is estimated using nominal consumption—Bangladesh, Egypt, Ethiopia, Ghana, and Tanzania—we use the spatial deflator used for poverty estimation with the national poverty lines.

consistency with the current methodology of global poverty measurement. The resulting poverty changes are only due to the reallocation of households between urban and rural areas associated with the move from official to consistent urban definitions.

Second, we modify the existing spatial deflators by recalculating them based on the new DOU/DB classification. For example, Tanzania's official spatial deflator is a Paasche price index constructed based on food unit values for 26 Provinces with no urban and rural distinction. We use alternative geographic divisions: urban centers, urban clusters, and rural areas for six regions for DOU; and cores, suburbs, towns, and rural areas for six regions for DB.[20] For most countries, we only replicate all the steps in calculating spatial deflators by changing their geographic divisions.[21]

Many countries adjust only for food prices with spatial deflators. Notably, housing prices are often not accounted for in spatial deflation. However, ignoring housing costs is problematic when analyzing the distribution of poverty between urban and rural areas. Housing costs tend to be higher in urban areas than in rural areas and can lead to a substantial underestimation of poverty across urban areas.[22] Thus, we add housing prices to the spatial deflators. Spatial variations in non-housing non-food prices are hard to capture accurately, as we often lack detailed information on product specifications and unit values in market price surveys. In contrast, reasonably good housing characteristics and price information are typically available in the HBS data. We estimate a housing price index using the HBS data and add it to the spatial deflators.[23] The updated spatial deflators for 20 countries clearly show that the cost of living is higher in urban areas—particularly in dense urban areas—than in rural areas (Figure 2).

4.3 4-3. Analysis with the new global dataset

To investigate whether and to what extent density is associated with household welfare, we regress household consumption expenditures—a proxy measure of household welfare—on location and other characteristics. The association between welfare and location can be driven merely by the difference in household characteristics. Hence, for example, if more educated households "sort" towards urban and away from rural areas, urban areas may have lower poverty rates simply because they are composed of more educated households. Thus, we investigate to what extent household welfare is determined by location characteristics after controlling for household characteristics. The main specifications are expressed as follows:

$$\ln EXP_{ijjc} = \alpha + DOU_{jrc}\beta_1 + X_{ijrc}\beta_2 + SPDEF_{jrc}\beta_3 + \gamma_c + \varepsilon_{ijrc} \tag{3}$$

[20]We group 26 Provinces into six regions because it is impossible to distinguish DOU/DB categories within each Province due to the limited HBS sample size. Also, we classify all households in Dar es Salaam as urban centers (DOU) or cores (DB) when constructing spatial deflators due to only a limited number of households living in other DOU/DB categories in Dar es Salaam.

[21]Constructing a poverty line for each subnational region is a common practice. Poverty is measured based on nominal consumption aggregate—instead of real consumption aggregate—with regional poverty lines that take account of the cost-of-living differences across regions. Bangladesh and Egypt employ such a regional poverty line approach. We reconstruct regional poverty lines for those countries by changing the geographic divisions. For example, Bangladesh's official poverty lines are constructed for 16 geographic domains (City Corporation, urban, and rural areas for six regions). In the case of the DOU classification, we reclassify them into urban centers, urban clusters, and rural areas for six regions. Then, the ratio of the regional poverty lines is calculated as a new spatial price deflator that is applied to the consumption aggregate when measuring poverty with international poverty lines.

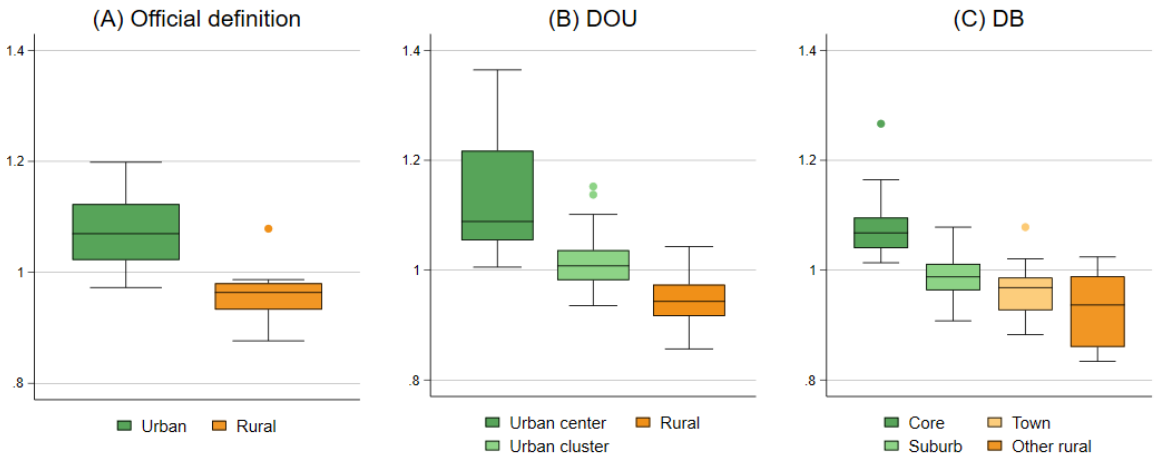
[22]It is true, though, that compared to richer countries, households in poor countries tend to allocate less budget to housing (see Figure A3 in Appendix A).

[23]The housing price index is calculated by estimating the following hedonic regression model with HBS data:

$$\ln (RENT_{i,j}) = \alpha + \beta_1 X_{i,j} + \beta_2 LOCATION_{j(1)} + \varepsilon_{i,j}$$

where $RENT_{i,j}$ is either observed or imputed rents for household i in location j, $X_{i,j}$ is a vector of housing characteristics, and $LOCATION_{j(1)}$ is the geographic domain to distinguish prices relative to the base location j =1. $\widehat{\beta_2}$ is the log of a housing price index. Distinguishing housing prices between urban and rural areas is challenging if rent observations are limited in the latter.

Figure 2: Cost of living index across subnational areas in 20 countries



Source: Global Urban Poverty Database.
Note: DOU: Degree of urbanization. DB: Dartboard. The cost-of-living index is prepared as a spatial deflator for each country in this study. It is normalized to 1 for each country. WorldPop 250m is used for both the DOU and DB methods.

$$\ln EXP_{ijjc} = \alpha + DB_{jrc}\beta_1 + X_{ijrc}\beta_2 + SPDEF_{jrc}\beta_3 + \gamma_c + \varepsilon_{ijrc} \tag{4}$$

where $\ln EXP_{ijjc}$ is the natural logarithm of the consumption expenditures of household i in location j, sub-national region r, and country c.; DOU_{jrc} and DB_{jrc} are vector of dummies indicating the type of DOU and DB areas, respectively, with other rural areas as the reference category; X_{ijrc} is a vector of household characteristics, such as household heads' age, sex, and education; γ_c is a country fixed effect; and ε_{ijrc} is an individual-level error term. We also add spatial deflators ($SPDEF$). With the control of spatial price differentials, we look at the association between household locations and real consumption expenditures. The vector of parameters β_1 shows which types of DOU and DB areas are positively/negatively correlated with household welfare.

Our poverty-specific regressions are specified as follows:

$$POV_{ijrc} = \alpha + DOU_{jrc}\beta_1 + X_{ijrc}\beta_2 + \gamma_c + \varepsilon_{ijrc} \tag{5}$$

$$POV_{ijrc} = \alpha + DB_{jrc}\beta_1 + X_{ijrc}\beta_2 + \gamma_c + \varepsilon_{ijrc} \tag{6}$$

where POV_{ijrc} indicates the poverty status (1=poor; 0=nonpoor) of household i in location j, sub-national region r, and country c. We estimate them as linear probability models (LPM).

It is important to note that a potential endogeneity problem remains that may lead to the importance of location being overstated, even after adding a vector of household characteristics due to unobserved characteristics – for example, a household's unobserved "ability" and/or "grit" – that are correlated with both locations and welfare levels. Moreover, households may endogenously choose where to locate depending on the local poverty rate, thereby affecting an area's density and, therefore, potentially, its urban status. Unfortunately, the cross-sectional nature of our dataset does not allow for the inclusion of household fixed effects. Appealing to instrumental variables or structural econometrics is beyond the scope of the present paper. Nevertheless, it remains essential to describe the contribution of the different factors, urbanization, region, and individual characteristics, to the variations in poverty.[24]

[24] It is worth noting that equation 5 is a version of a specification commonly used to estimate agglomeration

Table 4: Household characteristics by location

		Official definition		DOU			DB			
	All	Urban	Rural	Urban center	Urban cluster	Rural	Core	Suburb	Town	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demographic:										
Household size	5.70	5.40	5.84	5.33	5.19	6.42	5.89	5.51	6.69	5.34
Age of household head	43.15	44.50	42.53	45.14	45.09	39.99	43.05	40.34	44.08	44.43
Household head is male	0.81	0.75	0.84	0.77	0.84	0.81	0.76	0.80	0.82	0.86
Education (of household head):										
No education	0.33	0.19	0.39	0.22	0.32	0.43	0.23	0.30	0.47	0.38
Primary complete or incomplete	0.35	0.28	0.38	0.27	0.35	0.40	0.31	0.40	0.33	0.36
Secondary complete or incomplete	0.27	0.40	0.21	0.40	0.29	0.14	0.35	0.26	0.18	0.24
Tertiary complete or incomplete	0.05	0.12	0.02	0.11	0.04	0.02	0.11	0.03	0.03	0.02
Employment (of household head):										
Not in labor force	0.14	0.16	0.13	0.18	0.14	0.11	0.14	0.13	0.12	0.14
Unemployed	0.02	0.03	0.01	0.03	0.01	0.02	0.03	0.01	0.02	0.02
Employed in Agriculture	0.44	0.12	0.59	0.10	0.44	0.69	0.20	0.51	0.63	0.52
Employed in Industry	0.13	0.18	0.10	0.20	0.14	0.06	0.16	0.14	0.07	0.11
Employed in Services	0.28	0.51	0.17	0.49	0.27	0.13	0.47	0.21	0.17	0.21
Access to basic services										
Improved water	0.80	0.90	0.76	0.94	0.89	0.63	0.87	0.76	0.68	0.82
Improved sanitation facility	0.40	0.53	0.34	0.57	0.47	0.21	0.47	0.38	0.26	0.39
Access to electricity	0.64	0.88	0.53	0.90	0.69	0.40	0.77	0.59	0.47	0.62

Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods

5 Results

5.1 Household characteristics by location

We first examine household characteristics across DOU and DB areas (Table 4). In the DOU classification (columns 4 to 6), the household head's education level is highest in urban centers, followed by urban clusters and rural areas. Nearly half of the household heads in urban centers work in the service sector, while rural household heads predominantly work in agriculture. However, there are considerable variations across countries, as shown in Figure 3. Access to basic services, such as water, sanitation, and electricity, is better in denser areas, consistent with previous findings (such as Henderson et al., 2019). In the case of the DB classification (columns 7 to 10), the gaps in household characteristics between urban cores and other areas are narrower. In several indicators, people in rural towns appear worse off than those in other rural areas. Households in SSA countries have lower education levels and are more likely to work in agriculture, with limited access to basic services (**Table A2** in Appendix A).

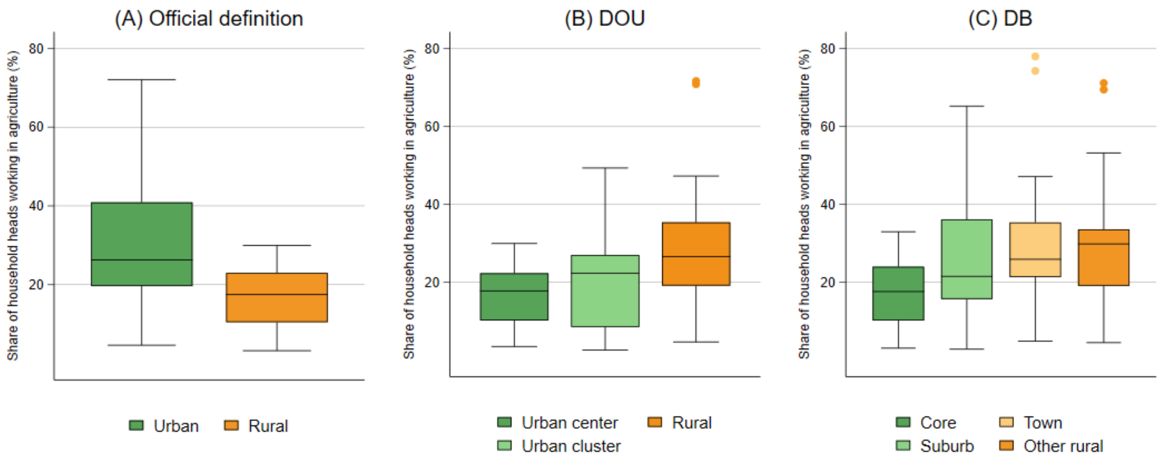
Based on our microdata approach, we can also analyze the profile of the extreme poor by location.[25] The comparison of the characteristics of poor households across DOU classifications in columns 2 to 5 in Table 5 highlights some distinct features.[26] Compared to the rural poor, the urban poor tend to be slightly better educated. For example, 40 percent of poor household heads in urban areas did not complete any education, as opposed to 49 percent among rural poor households. Employment patterns of the poor are very different between urban and rural areas as well. The majority of the poor rural household heads work in agriculture, whereas in

effects based on the log of nominal wages on the left-hand side and the log of the population at the city or metropolitan areas on the right-hand side (Combes & Gobillon, 2015). The endogeneity problems described here are similar to those that characterize the empirical agglomeration economies literature.

[25] To emphasize, this is a clear advantage of our approach. Neither satellite-based analysis nor a microdata approach with non-official household budget surveys (such as DHS) can disaggregate outcomes by poverty status.

[26] Though the levels are different (e.g., lower education levels, higher shares of agriculture, and lower access to basic services), the overall patterns are similar when only households in SSA countries are analyzed. The results focusing on SSA countries are presented in Table A3 in the Appendix A.

Figure 3: Share of household heads working in agriculture by location



Source: Global Urban Poverty Database.
Note: Each boxplot shows the share of household heads working in agriculture over different geographic areas in 19 countries. WorldPop 250m is used for the DOU and DB methods.

urban centers, around half of poor heads work in the industry and service sectors. It is also striking to see differences between urban centers and urban clusters. For instance, about 60 percent of the poor household heads in urban clusters still work in the agriculture sector, as opposed to 21 percent in urban centers. In terms of access to basic services, not surprisingly, the rural poor are the most deprived group. The urban poor households enjoy improved access to water at a similar level to the non-poor households (around 85 percent). However, their access to improved sanitation is extremely low—only around 24 percent, even in the urban centers. Access to electricity is scant among the poor households in urban clusters (36 percent). In the case of the DB classifications in columns 6 to 10, the characteristics of the poor are relatively similar between urban and rural areas.

5.2 Poverty incidence

Are poverty rates lower in urban areas than in rural areas?

The comparisons of poverty rates across different types of geographic areas in 20 countries (Figure 4) show that poverty rates tend to be lower in denser areas irrespective of whether we consider the $2.15 or $3.65 global poverty line, or the method of urban delineation (official, DOU or DB) used. With the extreme poverty line of $2.15 (Panel A), urban poverty rates are overall lower than rural poverty rates when urban areas are defined based on each country's official definition. With the DOU approach, poverty rates are lowest in urban centers, followed by urban clusters and rural areas. In the case of the DB approach, poverty rates are lowest in urban cores, followed by suburbs, towns, and rural areas. These patterns are maintained when a higher poverty line is used (Panel B). This negative correlation between density and poverty is observed in almost all countries, as shown in Figure A4 in the Appendix A.

It is also interesting to see that poverty rates in denser urban areas—urban centers in the DOU and urban cores in the DB—are a lot lower than in the other types of area, while less dense urban areas—urban clusters in the DOU and rural towns in the DB—tend to have poverty rates relatively close to low-density rural areas. This is particularly the case for towns, partly because towns are classified with no population threshold in the DB approach.

Adoption of DOU and DB approaches increases urban poverty rates, as more rural households are reclassified into urban households, consistent with Combes et al. (2023) finding that, relative to both the DOU and DB approaches, official national definitions of urban areas tend to understate levels of urbanization in African countries. Figure 5 compares urban poverty rates based on

Table 5: Profile of the poor by location

	All	Poor by DOU: Urban	Urban center	Urban cluster	Urban Rural	Poor by DB: Urban	Core	Suburb	Town	Other Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demographic:										
Household size	5.70	6.37	6.36	6.37	7.48	7.37	7.39	6.88	7.94	6.49
Age of household head	43.15	42.49	42.79	42.37	40.27	40.53	41.11	36.95	44.21	42.12
Household head is male	0.81	0.81	0.77	0.83	0.81	0.79	0.75	0.80	0.82	0.83
No education	0.33	0.40	0.38	0.41	0.49	0.45	0.39	0.41	0.55	0.47
Primary complete or incomplete	0.35	0.44	0.43	0.44	0.44	0.45	0.46	0.50	0.37	0.43
Secondary complete or incomplete	0.27	0.15	0.18	0.13	0.07	0.10	0.14	0.08	0.08	0.10
Tertiary complete or incomplete	0.05	0.01	0.02	0.01	0.00	0.01	0.02	0.01	0.00	0.00
Employment (of household head):										
Not in labor force	0.14	0.15	0.18	0.14	0.14	0.14	0.14	0.14	0.13	0.15
Unemployed	0.02	0.04	0.07	0.03	0.02	0.03	0.05	0.02	0.02	0.02
Employed in Agriculture	0.44	0.46	0.21	0.57	0.73	0.62	0.46	0.67	0.71	0.62
Employed in Industry	0.13	0.11	0.16	0.08	0.04	0.06	0.09	0.05	0.04	0.07
Employed in Services	0.28	0.24	0.38	0.18	0.07	0.15	0.26	0.11	0.09	0.13
Access to basic services										
Improved water	0.80	0.85	0.91	0.82	0.59	0.66	0.76	0.63	0.61	0.73
Improved sanitation facility	0.40	0.24	0.29	0.22	0.16	0.18	0.23	0.14	0.18	0.22
Access to electricity	0.64	0.44	0.63	0.36	0.20	0.29	0.39	0.24	0.25	0.31

Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Poverty is measured using the $2.15 poverty line.

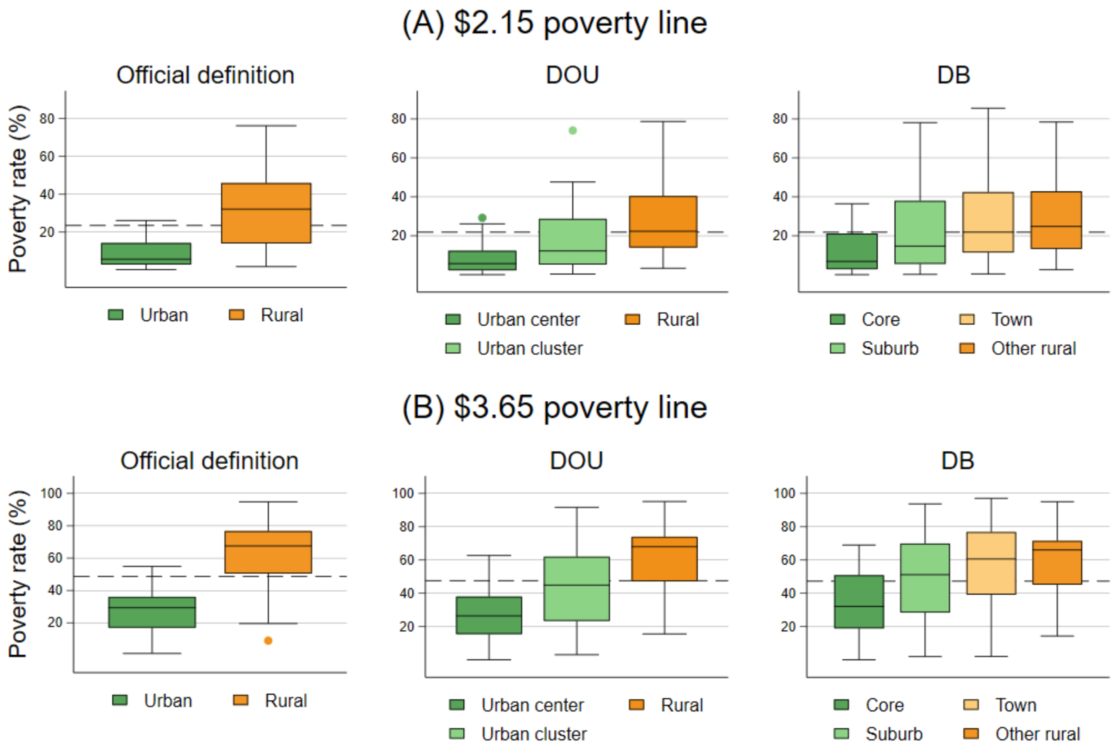
the official urban definitions (x-axis) and DOU or DB definitions (y-axis). Countries closer to the 45-degree line have similar poverty rates for both definitions. Several countries have higher urban poverty rates in DOU, or DB approaches than the official urban definition, as they appear above the 45-degree line. For example, the urban poverty rate in Malawi (MWI) is more than 50 percent in DOU and DB approaches, a profound increase from 20 percent with the official urban definition. A few other countries, such as Niger (NER) and Uganda (UGA), also have substantial increases. The comparison of urban poverty rates in DOU and DB approaches in Panel C show that most countries have similar poverty rates between the two approaches, with a handful of countries (such as Malawi, Niger, Tchado [TCD], etc.) having higher poverty rates with the DB approach. Therefore, the choice between the DOU and DB approaches does not seem to impact poverty rates significantly.

While the negative cross-country correlation between poverty rates and GDP per capita is well known (see Figure A1 in Appendix A), whether such a correlation is observed for urban and rural poverty rates is unknown. Figure 6 shows a linear relationship between urban and rural poverty rates observed across countries: countries with lower urban poverty rates also tend to have lower rural poverty rates. As this already implies, when urban areas are defined by the DOU or DB methods, urban and rural poverty rates tend to be lower in countries with higher per capita GDP levels (Figure A8 in Appendix A).

Is poverty driven by the difference between urban and rural areas or across subnational regions?

The results from Equations (3) and (4) estimation are summarized in Table 6 and Table 7 for DOU and DB classifications, respectively. In both cases, the dependent variable is the log of nominal per capita household expenditures. Columns 1 to 4 exclude spatial deflators, while columns 5 to 8 include these deflators. Three types of controls are added with different combinations across columns: demographic (household size, household head's age, sex, and marital status), education (household head's highest level of education attainment), and employment characteristics (household head's employment status and economic sectors). Note that while adding education variables is to control for the sorting of population, differences in employment status could be a cause of being less poor in denser areas. Full results are reported in Table A4

Figure 4: Poverty rates by subnational areas



Source: Global Urban Poverty Database.
Note: Each boxplot shows the distributions of poverty rates over different geographic areas in 20 countries. WorldPop 250m is used for the DOU and DB methods. The dashed lines represent the average national poverty rate in the sample.

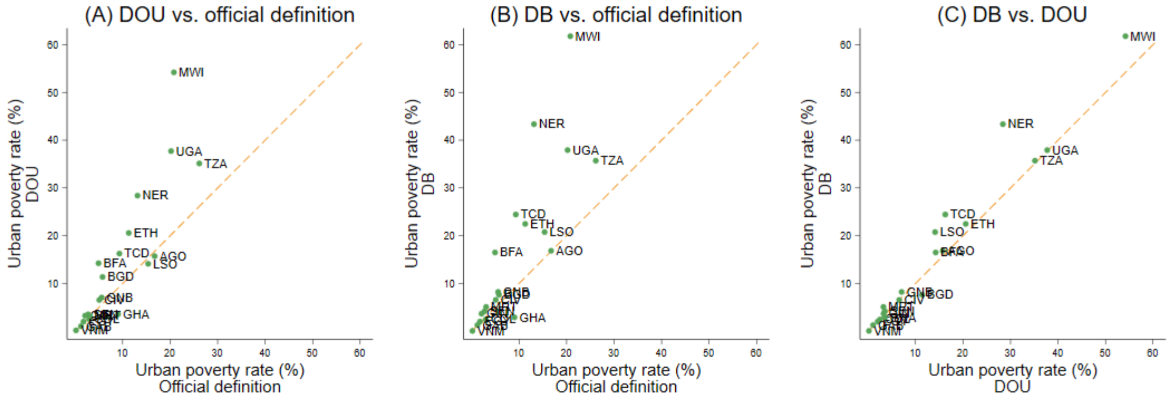
and Table A5 in the Appendix A.

The results indicate that irrespective of whether we use the DOU or DB approach to define urban areas, household consumption is higher in urban areas—particularly dense urban areas—even after controlling for observed household characteristics. Adding spatial deflators and each type of control reduces the coefficient estimates for urban categories. With control of demographic and education characteristics, the nominal consumption is 69.2 percent higher in urban centers and 16.2 percent higher in urban clusters than rural areas (column 2 in Table 6). Further controlling for employment differences reduces the location premium to 53.9 percent in urban centers and 11.6 percent in urban clusters, respectively (column 3). The coefficient estimate for urban centers remains high even after limiting the sample to urban households (column 4). With additional control of spatial prices, real welfare in urban centers is higher by 53.0 percent (without employment controls in column 6) and 41.6 percent (with employment controls in column 7) than in rural areas. The welfare premium in low-dense urban clusters becomes small with all the controls: only 8.7 percent in column 7.

Similarly, with the DB approach, urban households—primarily those in urban cores—appear to have higher consumption expenditures. After controlling for household characteristics (except employment differences) and spatial price differentials, the real consumption of households in urban cores and suburbs is 40.2 percent and 7.6 percent higher than those in other rural areas (column 6 in Table 7). Additional control of employment differences reduces the premium to 31.1 percent in urban cores and 5.2 percent in suburbs, respectively (column 7). The real expenditures of households in rural towns are not clearly different from those in other rural areas.

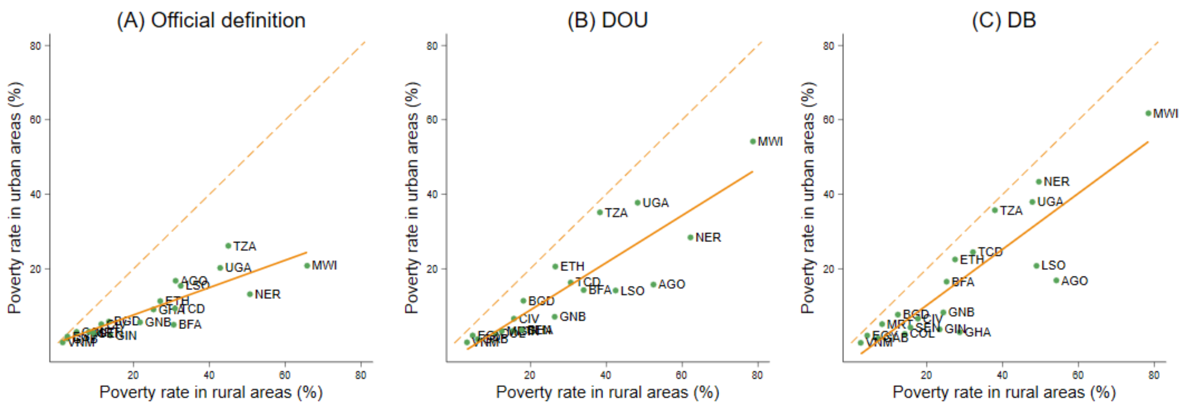
Is urban poverty lower even after controlling for individual and household characteristics?

Figure 5: Comparison of urban poverty rates between official and DOU/DB urban definitions



Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Urban areas include the categories “Urban center” and “Urban cluster” for the DOU method and the categories “Core” and “Suburb” for the DB method. Dashed lines are 45-degree lines. Poverty is measured using the $2.15 poverty line.

Figure 6: Comparison of urban and rural poverty rates



Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Dashed lines are 45-degree lines. Urban areas include the categories “Urban center” and “Urban cluster” for the DOU method and the categories “Core” and “Suburb” for the DB method. Dashed lines are 45-degree lines. Poverty is measured using the $2.15 poverty line.

Table 8 reports the results of estimating equations (5) and (6), where the dependent variable is the poverty status of each household (1=poor; 0=non-poor). The table presents the results for three poverty lines: $2.15, $3.65, and $6.85. The first three columns correspond to the $2.15 poverty line, the next three to the $3.65 poverty line, and the last three to the $6.85 poverty line. In Panel A, the location’s DOU urban classification is the main explanatory variable. Panel B presents the results for the DB method.

In line with the pattern observed in Figure 4, Table 8 indicates that compared to rural areas (the excluded category), DOU and DB urban areas—particularly dense urban areas—have significantly lower poverty rates. The pattern remains the same regardless of the poverty line ($2.15, $3.65, or $6.85). However, estimated coefficients are somewhat larger for higher poverty lines. While the coefficient estimates for urban cores are all significantly negative, we find some positive and statistically insignificant coefficients for suburbs and rural towns, implying not-so-apparent differences from other rural areas regarding poverty. Living in urban centers and urban clusters, compared to living in a rural area, is associated with a 9.2 and 3.8 percentage points lower likelihood of being extreme poor, respectively (Column 2, using the $2.15 poverty line and

Table 6: Estimation results of regressions on log expenditures with DOU classifications

	Log of per capita nominal consumption expenditures							
	(1) All	(2) All	(3) All	(4) Urban	(5) All	(6) All	(7) All	(8) Urban
Urban center	0.756***	0.526***	0.431***	0.369***	0.602***	0.425***	0.348***	0.295***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)	(0.007)
Urban cluster	0.269***	0.151***	0.110***		0.215***	0.118***	0.083***	
	(0.007)	(0.006)	(0.006)		(0.007)	(0.006)	(0.006)	
Spatial deflator					0.771***	0.544***	0.475***	0.599***
					(0.027)	(0.025)	(0.024)	(0.033)
Demographic	*No*	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Education	*No*	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Employment	*No*	*No*	*Yes*	*No*	*No*	*No*	*Yes*	*No*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.630	0.714	0.726	0.653	0.636	0.717	0.728	0.657
Nr. of countries	19	19	19	19	19	19	19	19
Nr. of hh	453683	437458	419519	292650	452684	436491	418586	292538

Source: Global Urban Poverty Database.
Note: *** p < 0.01, ** p < 0.05, *** p < 0.1. Robust standard errors in parentheses. WorldPop 250m is used for the DOU method. The dependent variable is the log of per capita consumption expenditures, expressed in PPP and not spatially deflated. Only urban households ("Urban center" or "Urban cluster") are included in specifications (4) and (8). The baseline category is "Rural" in all specifications, except (4) and (8), where it is "Urban cluster". Demographic control variables include household size and household head's age, sex, and marital status. Education is a categorical control variable that summarizes the education of the household head in seven categories. Employment is a categorical control variable that summarizes the household head's labor status and employment sector.

demographic and education controls). Living in urban cores is associated with a 6.2 percentage points lower likelihood of living in extreme poverty—similar to urban centers.

5.3 Spatial distribution of poverty

Where is the mass of poverty concentrated?

Updating official urban definitions with DOU/DB definitions increases the share of urban areas in the distribution of poor populations. Figure 7 shows that in the 20 countries studied, extreme poverty is mainly concentrated in rural areas when each country's official definition defines urban areas. In 15 out of 20 countries, more than 80 percent of poor populations live in rural areas. We then look at the results with the $2.15 poverty line. Based on the DOU approach, the share of rural areas declines, reducing the number of countries with more than 80 percent of poor populations living in rural areas from 15 to 9 countries. The median share of urban areas goes up from 13 percent in the original urban definition to 22 percent in the DOU definition. See Figure A6 in the Appendix A for each country's urban/rural shares.

The reasons why global poverty is still concentrated in rural areas in many countries are 1) most of a country's population still resides in rural areas (e.g., Chad), 2) poverty incidence is substantially high in rural areas (e.g., Niger), and/or 3) global poverty does not exist anymore in urban areas (e.g., Vietnam) (Figure A10 in Appendix A). Interestingly, the relationship between the share of poor populations in urban areas and the level of per capita GDP is less clear (Figure A9 in Annex). We loosely observe such a correlation with the DOU results but not the DB results. This is because higher GDP per capita is associated with higher urban population shares but with lower urban poverty rates, making the relationship between a country's level of development and the share of its poor population that resides in urban areas ambiguous.

Based on the DB approach (Figure 7), the spatial distribution of poor populations shows substantially higher urban and lower rural shares compared to the results with the official urban definitions. In 15 out of 20 countries, more than half of poor populations reside in urban areas. The patterns above hold with a higher poverty line (Panel B). See Figure A7 in the Appendix A for each country's urban/rural shares. It is worth highlighting that within DB urban areas,

Table 7: Estimation results of regressions on log expenditures with DB classifications

	Log of per capita nominal consumption expenditures							
	(1) All	(2) All	(3) All	(4) Urban	(5) All	(6) All	(7) All	(8) Urban
Core	0.618*** (0.007)	0.429*** (0.006)	0.346*** (0.007)	0.311*** (0.007)	0.477*** (0.008)	0.338*** (0.007)	0.271*** (0.008)	0.243*** (0.008)
Suburb	0.167*** (0.007)	0.106*** (0.006)	0.076*** (0.007)		0.116*** (0.007)	0.073*** (0.006)	0.051*** (0.007)	
Town	0.067*** (0.007)	0.036*** (0.007)	0.033*** (0.007)		0.023*** (0.007)	0.006 (0.007)	0.009 (0.007)	
Spatial deflator					0.788*** (0.021)	0.542*** (0.020)	0.480*** (0.020)	0.617*** (0.028)
Demographic	*No*	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Education	*No*	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Employment	*No*	*No*	*Yes*	*No*	*No*	*No*	*Yes*	*No*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.616	0.707	0.721	0.767	0.623	0.710	0.723	0.770
Nr. of countries	19	19	19	19	19	19	19	19
Nr. of hh	453683	437458	419519	267655	452789	436564	418633	267397

Source: Global Urban Poverty Database.
Note: *** $p < 0.01$, ** $p < 0.05$, *** $p < 0.1$. Robust standard errors in parentheses. WorldPop 250m is used for the DB method. The dependent variable is the log of per capita consumption expenditures, expressed in PPP and not spatially deflated. Only urban households ("Core" or "Suburb") are included in specifications (4) and (8). The baseline category is "Other rural" in all specifications, except (4) and (8), where it is "Suburb". Demographic control variables include household size and household head's age, sex, and marital status. Education is a categorical control variable that summarizes the education of the household head in seven categories. Employment is a categorical control variable that summarizes the household head's labor status and employment sector.

low-density urban areas (i.e., towns) accommodate a large share of poor populations—even higher than rural areas in many countries. In addition, poverty is more concentrated in urban cores than in suburbs. While poverty rates tend to be lower in the suburbs, relatively high population shares in urban cores contribute to the greater mass of poverty there. A higher poverty line makes the difference even starker between dense and less dense urban areas. Density reduces the probability of being poor. For this reason, dense areas attract more people, leading to a more significant concentration of poor populations.

The change in the urban share of poor populations based on the update of urban definitions differs between the DOU and DB approaches (Figure 8). In the case of the shift from the official urban definitions to the DOU approach (Panel A), a few countries show substantial increases in urban shares of the poor. The largest increase is for Bangladesh, from less than 20 percent to nearly 100 percent. This is mainly because almost 100 percent of the country is urban, according to the DOU approach. Uganda, Tanzania, and Ethiopia show relatively significant increases as well. By contrast, in the case of the DB approach (Panel B), most countries increase the urban share of poor populations from 20 to 40 percent in the official urban definitions to 60 to 80 percent in the DB definition. It is also clear that the urban shares of poor populations are higher in most countries when the DB approach is used compared to the DOU approach (Panel C). It is important to emphasize that the choice of DOU and DB approaches significantly changes the spatial distributions of poverty. This was not the case for poverty incidence, as observed in an earlier section. This is because the DB approach, by being relative and specific to each country, is less sensitive to the overall average population density of the country and better captures the local variations in population density within the individual countries, even when they have a pretty high or low average population density.

The cross-comparison of urban and poverty status of individuals across the three urban definitions confirms that changes in spatial distributions of poverty are due to the reclassification of the poor from rural to urban. Table 9 summarizes the reclassifications with and without spatial deflators. Bangladesh is excluded from this analysis as it is an outlier. We first look at the pure results of reclassification without considering the effect of spatial deflation. Regarding the switch from the official urban definition to the DOU approach (Panel A), around a third of the non-poor rural

Table 8: Estimation results of regressions on household poverty status

	Poverty status (1 = poor, 0 = non-poor)								
	(1) $2.15	(2) $2.15	(3) $2.15	(4) $3.65	(5) $3.65	(6) $3.65	(7) $6.85	(8) $6.85	(9) $6.85
Panel A: DOU									
Urban center	-0.151***	-0.092***	-0.056***	-0.280***	-0.170***	-0.118***	-0.236***	-0.149***	-0.122***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Urban cluster	-0.070***	-0.038***	-0.021***	-0.109***	-0.052***	-0.029***	-0.086***	-0.046***	-0.035***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: DB									
Core	-0.109***	-0.062***	-0.033***	-0.198***	-0.106***	-0.063***	-0.192***	-0.119***	-0.094***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Suburb	-0.015***	0.003	0.013***	-0.055***	-0.026***	-0.011**	-0.063***	-0.040***	-0.033***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Town	0.039***	0.048***	0.047***	0.017***	0.030***	0.030***	-0.022***	-0.010***	-0.009**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Demographic	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Education	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Employment	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.180	0.233	0.207	0.238	0.331	0.334	0.329	0.410	0.418
Nr. of countries	19	19	19	19	19	19	19	19	19
Nr. of hh	453993	437766	419821	453993	437766	419821	453993	437766	419821

Source: Global Urban Poverty Database.
Note: *** $p < 0.01$, ** $p < 0.05$, *** $p < 0.1$. Robust standard errors in parentheses. WorldPop 250m is used for the DOU and DB method. The dependent variable is a dummy variable taking the value one if a household's per capita expenditure expressed in PPP and spatially deflated falls below the poverty line. The baseline category is "Rural" in all specifications in Panel A, and "Other rural" in all specifications in Panel B. Demographic control variables include household size and household head's age, sex, and marital status. Education is a categorical control variable that summarizes the education of the household head in seven categories. Employment is a categorical control variable that summarizes the household head's labor status and employment sector.

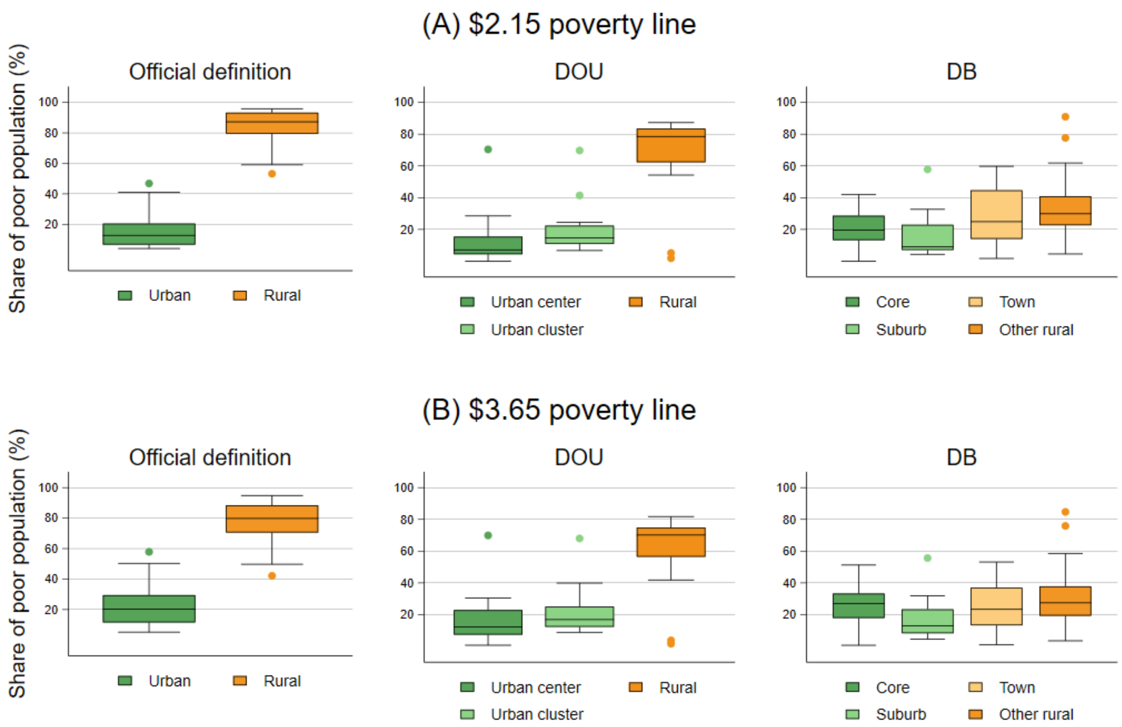
population and 17 percent of the poor rural population are reclassified from rural to urban areas, respectively. At the same time, 11 percent of the urban non-poor population and 23 percent of the urban poor households are reclassified into the rural non-poor and rural poor populations, respectively. The scale of rural-to-urban reclassification is massive in the case of the switch from the official urban definitions to the DB approach: 47 percent among the non-poor and 55 percent among the poor (Panel B). Spatial deflation mainly reduces poverty in rural areas due to their relatively low prices. The overall pattern does not change when the sample is restricted to SSA countries (see Table A6 in the Appendix A).

5.4 Spatial inequality

Aside from poverty, the spatial dimension of inequality is a crucial issue in assessing welfare distributions in low- and middle-income countries. Household-level consumption expenditures in the dataset created for this study allow us to measure inequality based on various standard indicators. This paper focuses on the Gini coefficient, the most used inequality indicator in welfare analysis.

Gini coefficients range from 30 to 51 nationally among the countries analyzed for this study (Figure 9). Urban Gini coefficients are higher than rural Gini coefficients in most countries, except for a few cases, such as Gabon and Mauritania in DOU and DB definitions and Vietnam in the DOU definition. That urban inequality is higher is not surprising as urban areas tend to accommodate very wealthy populations. We find no clear pattern between Gini coefficients,

Figure 7: Comparison of urban and rural poverty rates



Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Each boxplot shows the distribution of the share of the poor population over different geographic areas in 20 countries.

national or subnational, and a country's GDP per capita level.[27]

We examine to what extent inequality is explained by 1) inequality within urban and rural areas, respectively, and 2) inequality between urban and rural groups, following Pyatt (1976). The results of decomposing Gini coefficients into between- and within-group factors in Figure 10 show that the within-group inequality is higher in all countries, particularly in the case of the DB approach. In other words, urban inequality is dominating.

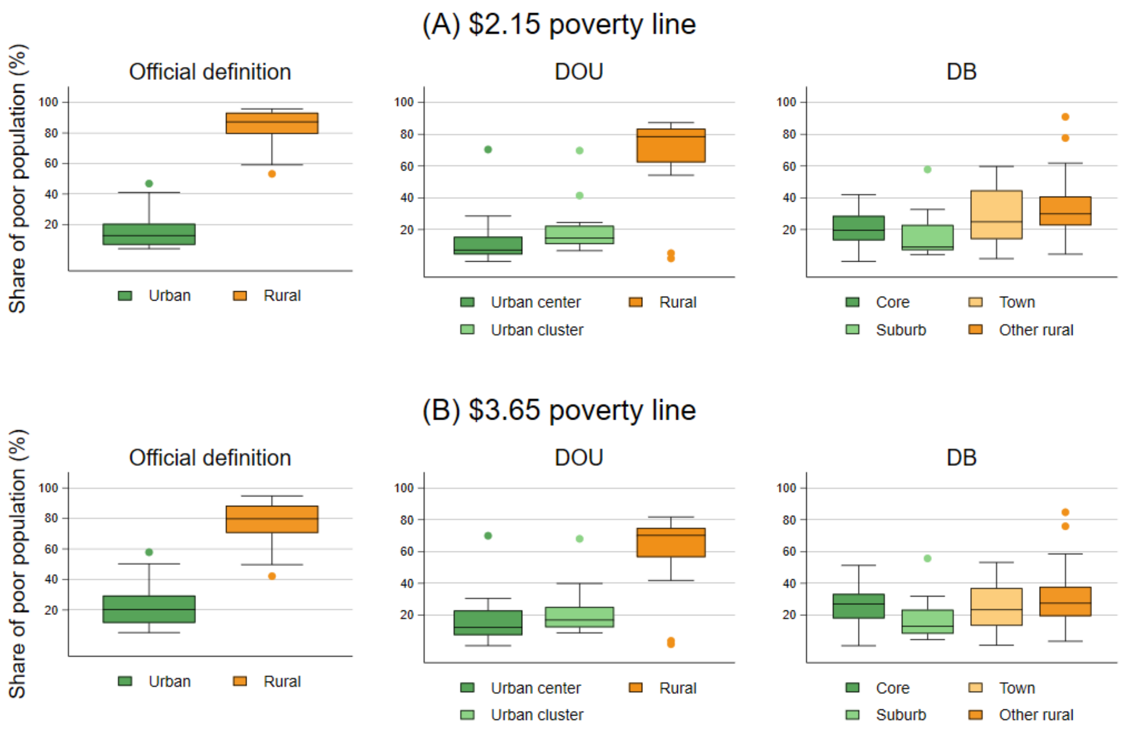
Not surprisingly, the consumption gains by urban households, relative to rural households, are driven by differences in endowments instead of the differences in returns to the endowments. The difference in consumption levels between urban and rural households can be decomposed to the difference in endowments (i.e., observed household characteristics) and the returns to endowments based on the Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973). We conducted such a decomposition analysis for each country. The decomposition results in Figure 11 show that the differences in endowments account for a large part of the consumption gaps between urban and rural areas. The endowment difference also dominates when the consumption gaps between dense and less dense urban areas are analyzed.

5.5 Non-monetary poverty

The last, but not the least, when analyzing poverty, we should also consider its non-monetary aspects. It especially important for amenities that can be roughly considered public goods. In this section we analyze how access to improved water source, sanitation facilities and electricity vary across space. It is obvious that poor households are critically dependent on public infrastructure,

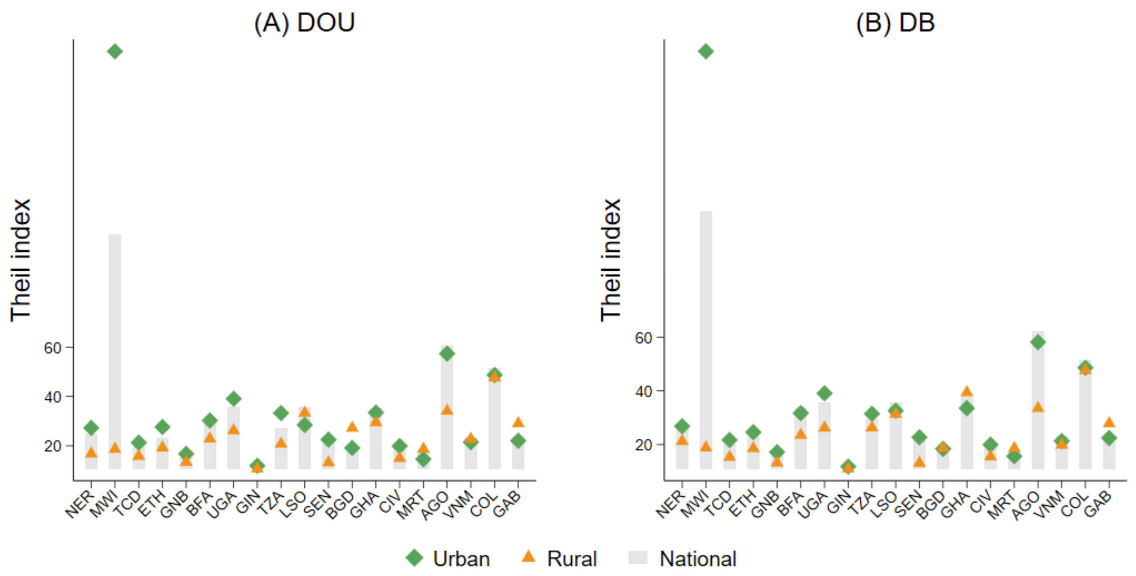
[27]This is partly because of the coverage of countries in this paper, primarily focusing on low-income countries. In general, a Kuznets curve (Kuznets 1955) is observed for world countries (see Panel D in Figure A1), indicating that inequality widens as the economy grows and then declines at the high-income stage.

Figure 8: Comparison of urban and rural poverty rates



Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Dashed lines are 45-degree lines. Urban areas include the categories "Urban center" and "Urban cluster" for the DOU method and the categories "Core" and "Suburb" for the DB method. Dashed lines are 45-degree lines. Poverty is measured using the $2.15 poverty line.

Figure 9: Theil indexes at the national and sub-national levels



Source: Global Urban Poverty Database.
Note: Countries are sorted in ascending order of log of GDP per capita, measured in PPP (constant 2017 international $). WorldPop 250m is used for the DOU and DB methods. Urban areas include the categories "Urban center" and "Urban cluster" for the DOU method and the categories "Core" and "Suburb" for the DB method. See Figure A11 for the same chart with countries reordered by the highest to the lowest Theil indexes.

Table 9: Urban and poverty status changes

(A) Original definitions to DOU		Non-spatially deflated				Spatially deflated			
Poverty status:		Non-poor		Poor		Non-poor		Poor	
DOU:		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Official urban definition:									
Non	Urban	88.8	11.2	0.0	0.0	87.8	11.2	0.9	0.0
	Rural	33.6	66.4	0.0	0.0	31.5	65.8	1.0	1.6
Poor	Urban	0.0	0.0	77.3	22.7	4.9	2.5	74.7	17.8
	Rural	0.0	0.0	17.1	82.9	0.1	3.1	17.5	79.3

(B) Original definitions to DB		Non-spatially deflated				Spatially deflated			
Poverty status:		Non-poor		Poor		Non-poor		Poor	
DOU:		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Official urban definition:									
Non	Urban	89.0	4.5	0.0	6.5	93.1	6.5	0.4	0.0
	Rural	46.7	20.0	0.0	33.2	64.6	32.2	2.5	0.7
Poor	Urban	0.0	0.0	91.6	8.4	6.5	1.0	85.9	6.6
	Rural	0.0	0.0	54.7	45.3	1.4	2.3	63.9	32.4

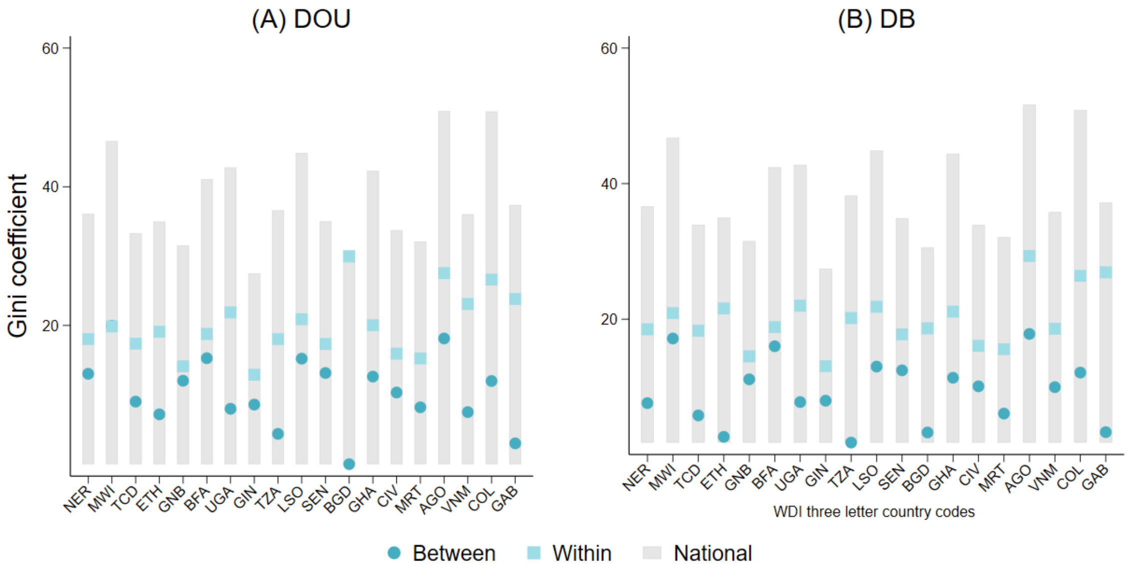
(C) DOU to DB		Non-spatially deflated				Spatially deflated			
Poverty status:		Non-poor		Poor		Non-poor		Poor	
DB:		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
DOU:									
Non	Urban	90.9	2.6	0.0	6.5	93.1	6.6	0.3	0.0
	Rural	29.4	27.9	0.0	42.7	56.0	41.4	2.0	0.6
Poor	Urban	0.0	0.0	96.6	3.4	6.9	0.3	90.1	2.8
	Rural	0.0	0.0	43.9	56.1	1.1	2.2	58.3	38.5

Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Poverty is measured using the $2.15 poverty line. 18 countries are included. Bangladesh is an outlier and is not included. In Panel (A), welfare is deflated using official spatial deflators. In Panel (B) and (C), welfare is deflated using our updated spatial deflators.

as they might lack funds to substitute it privately. Nevertheless, governments do not always possess enough funds to provide universal access to these basic services (Yakubenko, 2020). Given this constraint, it appears logical to first develop infrastructure in the regions with high population density. Below we analyze whether individual access to basic amenities depends on the type of location.

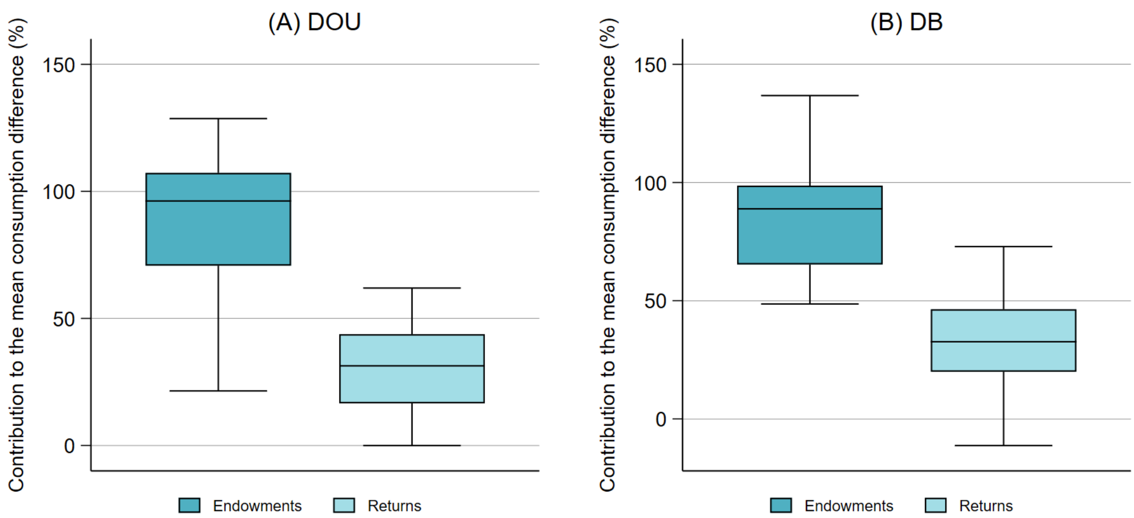
As we predicted, regressions presented in Table 10 suggest that households residing in less densely populated areas are generally less likely to have access to improved water source, sanitation facility and electricity. The only exception is a slightly better access to sanitation in Suburbs compared to Cores under DB delineation (column 6 of Panel B). However, this result might be driven by the existence of densely populated, but extremely underdeveloped slum areas, where infrastructure development can be constrained due to a lack of unoccupied space. In other cases we see a significant negative effect of a reduction in density of access. This effect is not only stable across types of amenities we consider and delineation, but also robust to inclusion of various controls. First of all, in columns (2), (5), (8) we demonstrate that lower access to water, sanitation and electricity cannot be fully explained by higher incomes in more densely populated areas. Moreover, our results are robust to inclusion of demographic characteristics, educational

Figure 10: Theil indexes at the national and sub-national levels



Source: Global Urban Poverty Database.
Note: Countries are sorted in ascending order of log of GDP per capita, measured in PPP (constant 2017 international $). WorldPop 250m is used for the DOU and DB methods. Following Pyatt (1976), the Theil index is decomposed into within, between, and interaction terms. For the sake of presentation, interaction terms are not shown. See Figure A12 for the same chart with countries reordered by the highest to the lowest Theil indexes.

Figure 11: Decomposition of consumption difference between urban and rural areas



Source: Global Urban Poverty Database.
Note: Each boxplot shows the distribution of percentage contribution of (1) endowments and (2) returns to the mean differences in the log per capita consumption expenditures between urban and rural areas in 18 countries based on the Oaxaca-Blinder decomposition. The share of interactions is not shown for the sake of presentation. WorldPop 250m is used for the DOU and DB methods.

controls and employment of the household head. Overall, estimates presented in Table 10 go in line with our previous findings: residents of less densely populated areas are more vulnerable, even when we consider non-monetary poverty.

Table 10: Access to basic amenities and location

	water			sanitation			electricity		
Panel A: DOU									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Urban cluster	−0.032***	−0.024***	−0.011***	−0.052***	−0.019***	0.005	−0.154***	−0.126***	−0.090***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Rural	−0.159***	−0.142***	−0.111***	−0.176***	−0.122***	−0.082***	−0.310***	−0.254***	−0.177***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
Log of real exp.		0.037***	0.024***		0.132***	0.125***		0.126***	0.107***
		(0.002)	(0.003)		(0.002)	(0.003)		(0.002)	(0.003)
Demographic	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Education	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Employment	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.245	0.248	0.258	0.340	0.364	0.407	0.384	0.407	0.414
Nr. of countries	19	19	19	19	19	19	19	19	19
Nr. of hh	414161	412989	379118	414159	412987	379115	403152	401980	375834
Panel B: DB									
Suburbs	−0.079***	−0.069***	−0.049***	−0.035***	0.001	0.026***	−0.129***	−0.096***	−0.060***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Towns	−0.095***	−0.084***	−0.047***	−0.081***	−0.042***	−0.009*	−0.181***	−0.144***	−0.087***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Rural	−0.125***	−0.111***	−0.078***	−0.105***	−0.056***	−0.022***	−0.229***	−0.183***	−0.121***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Log of real exp.		0.037***	0.023***		0.137***	0.128***		0.131***	0.108***
		(0.002)	(0.003)		(0.002)	(0.003)		(0.002)	(0.003)
Demographic	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Education	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Employment	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.240	0.244	0.254	0.334	0.360	0.405	0.375	0.400	0.410
Nr. of countries	19	19	19	19	19	19	19	19	19
Nr. of hh	414161	412989	379118	414159	412987	379115	403152	401980	375834

Source: Global Urban Poverty Database.
Note: *** $p < 0.01$, ** $p < 0.05$, *** $p < 0.1$. Robust standard errors are in parentheses. WorldPop 250m is used for the DOU and DB method. The dependent variable is a dummy variable taking the value one if a household has access to a respective amenity. The baseline category is "Urban center" in all specifications in Panel A, and "Cores" in all specifications in Panel B. Demographic control variables include household size and household head's age, sex, and marital status. Education is a categorical control variable that summarizes the education of the household head in seven categories. Employment is a categorical control variable that summarizes the household head's labor status and employment sector.

5.6 Employment across locations

Finally, we also consider employment patterns across locations. When one studies poverty, it is important to consider whether individuals have equal job opportunities. To see if locations systematically affect employment, we look at shares of household members working in agriculture and service sector. We also control for a standard set of demographic characteristics and educational variables. Interestingly, our results presented in Table 11 are robust to inclusion of employment variables of a household head. Overall, the results appear rather predictable: more sparsely populated areas host relatively more agricultural workers, while more densely populated provide more jobs in the service sector. As was demonstrated above, employment patterns alone cannot fully explain poverty, however, this factor can substantially contribute to the problem.

6 Discussion and conclusion

This study produces globally comparable urban and rural poverty statistics for the first time with a novel dataset created for 20 low- and middle-income countries—mainly in Sub-Saharan Africa—by integrating globally consistent urban delineation approaches into the framework of global poverty measurement.

Our analysis underscores the need to address urban poverty to accelerate global poverty reduction. Based on globally consistent urban and poverty measures, we find that urban poverty rates are lower than rural poverty in all the studied countries. Poverty incidence in dense urban areas is particularly low, whereas poverty rates in low-density urban areas are closer to those in rural areas. The patterns hold including country fixed effects and controlling for household characteristics. The use of DOU/DB approaches, instead of relying on each country's official urban definition, increases urban poverty rates in most countries. However, the choice of DOU or DB approaches does not matter much. Regarding spatial distributions of poverty, the poor

Table 11: Employment shares across locations

Panel A: DOU	agriculture				services			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Urban cluster	0.299***	0.294***	0.264***	0.094***	−0.221***	−0.217***	−0.181***	−0.064***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.006)	(0.004)
Rural	0.538***	0.531***	0.467***	0.159***	−0.404***	−0.397***	−0.326***	−0.111***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
Demographic	*No*	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Education	*No*	*No*	*Yes*	*Yes*	*No*	*No*	*Yes*	*Yes*
Employment	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*Yes*
Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.380	0.388	0.412	0.793	0.225	0.229	0.267	0.732
Nr. of countries	19	19	19	19	19	19	19	19
Nr. of hh	352819	352770	340100	336518	352819	352770	340100	336518
Panel B: DB								
Suburbs	0.227***	0.222***	0.189***	0.067***	−0.210***	−0.205***	−0.170***	−0.063***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)
Towns	0.335***	0.329***	0.291***	0.094***	−0.261***	−0.256***	−0.214***	−0.067***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)
Rural	0.424***	0.417***	0.372***	0.125***	−0.308***	−0.302***	−0.249***	−0.081***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)
Demographic	*No*	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Education	*No*	*No*	*Yes*	*Yes*	*No*	*No*	*Yes*	*Yes*
Employment	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*Yes*
Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.363	0.371	0.399	0.792	0.212	0.216	0.258	0.731
Nr. of countries	19	19	19	19	19	19	19	19
Nr. of hh	352819	352770	340100	336518	352819	352770	340100	336518

Source: Global Urban Poverty Database.
Note: *** $p < 0.01$, ** $p < 0.05$, *** $p < 0.1$. Robust standard errors are in parentheses. WorldPop 250m is used for the DOU and DB method. The dependent variable is a share of household workers employed in a respective sector. The baseline category is "Urban center" in all specifications in Panel A, and "Cores" in all specifications in Panel B. Demographic control variables include household size and household head's age, sex, and marital status. Education is a categorical control variable that summarizes the education of the household head in seven categories. Employment is a categorical control variable that summarizes the household head's labor status and employment sector.

population is concentrated more in urban areas than previously thought, with the lower incidence of poverty being more than compensated by the much larger number of people living there. In many studied countries, more than half of poor populations live in DOU/DB urban areas, with dense urban areas accommodating a large share of these poor populations. We also find that, unlike poverty rates, the choice of DOU and DB approaches makes a critical difference in the spatial distribution of poverty, the mass of poverty being even more concentrated in urban areas according to the fact that the DB approach, by being specific to each country, better captures the local variations of population density, especially for the countries that have either pretty high or pretty low average population density.

Our study offers important implications from both methodological and policy perspectives. Methodologically, the proposed approach makes it possible to disaggregate official global poverty statistics into globally consistent urban and rural areas and more nuanced geographic categories in the spectrum of the urban-rural continuum. This is the first study attempting such an endeavor. The results also demonstrate that choosing absolute (DOU) and relative (DB) measures of urban areas matters for estimating spatial distributions of poor populations. We do not exclusively recommend one over the other, as both the DOU and DB approaches have advantages depending on the purpose of the analyses. Our study also highlights the importance of better understanding the spatial distribution of poverty at a global scale to allocate resources more efficiently and effectively to reduce extreme poverty and achieve the SDGs. Our analyses suggest that global poverty is more concentrated in urban—and especially dense urban—areas than previously thought. Although it does not automatically mean that investing more in urban areas is the most efficient and effective way to reduce global poverty, the findings still imply the need to pay serious attention to urban poverty in low- and middle-income countries, while simultaneously highlighting the benefits of urbanization for overall poverty reduction.

While innovative, our approach encompasses several imitations. First, our data are only cross-sectional in nature. This implies that we cannot fully control for unobserved heterogeneity to account for sorting on, for example, ability by adding household fixed effects. Adding more time points to our dataset is theoretically possible, as GHSPOP and WorldPop are available for other years. However, the comparability of those datasets and consumption and poverty measures in HBS over time needs to be carefully assessed, which is beyond this study's scope. Data availability in HBS is a crucial methodological issue for the proposed approach, as it can analyze only countries where the location information of geographically disaggregated units is available in the HBS. The second potential limitation is the inconsistency in the spatial deflation approach in the current global poverty monitoring system. Global poverty is measured in many countries without adjusting for subnational cost of living differences. We apply spatial deflators to such countries; nevertheless, spatial deflation approaches are not consistent across countries. Third, the data quality of underlying population layers and HBS can affect our results. The lack of availability of recently conducted population census—uncommon in low-income countries—particularly threatens the quality of gridded population datasets.[28] Finally, we have not estimated non-monetary poverty and its linkage with monetary poverty. Our approach makes it straightforward to analyze non-monetary poverty outcomes, such as access to water, sanitation, and electricity if such information is available in HBS. Moreover, it is possible to compute a multidimensional poverty index at globally comparable urban/rural areas by incorporating monetary and non-monetary poverty dimensions.

[28]For example, Ethiopia's latest population census was conducted in 2007.

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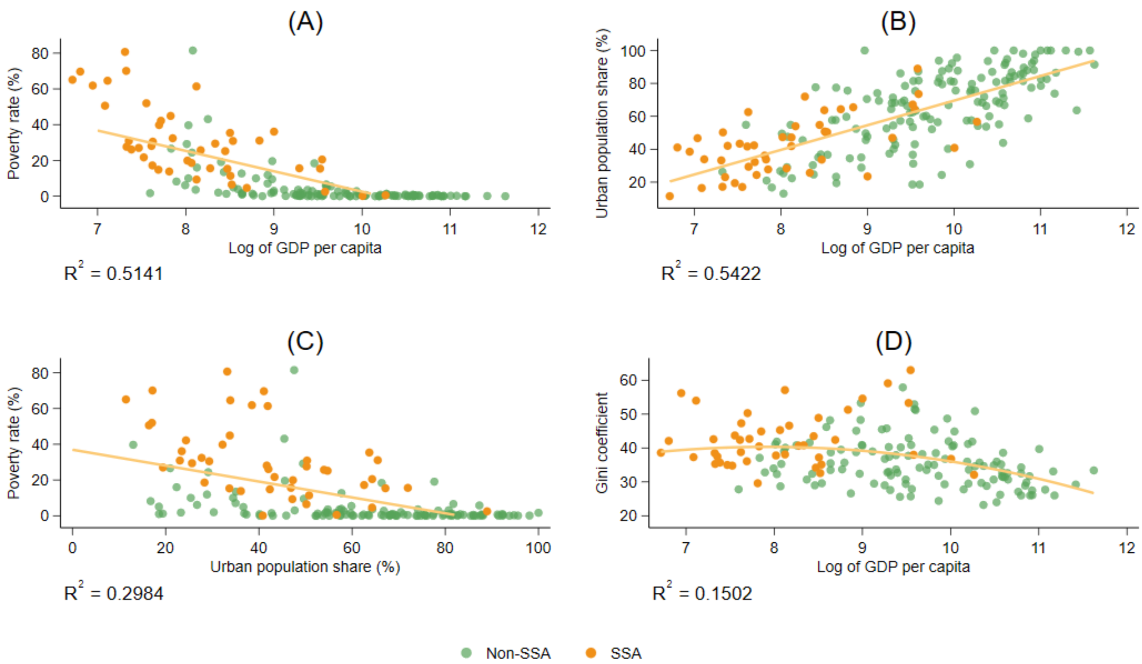
Appendix

A Additional figures and tables

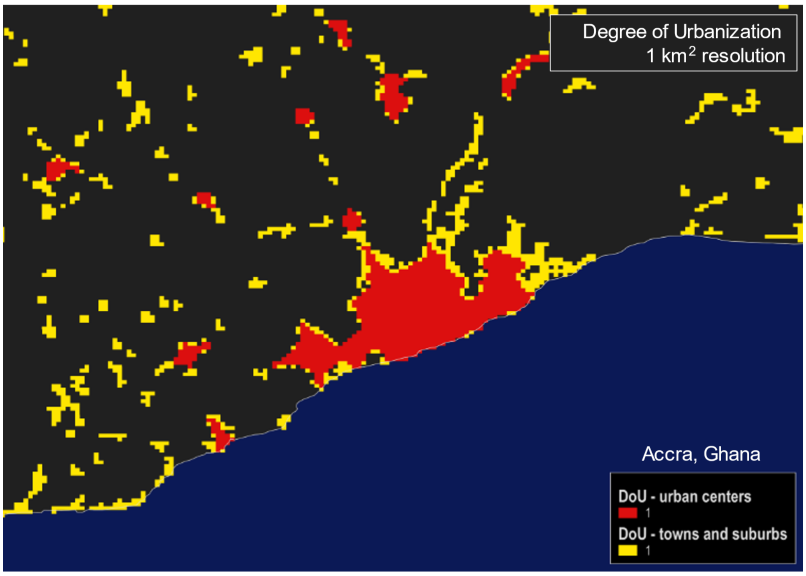
Figure A1: Urbanization, poverty, and inequality



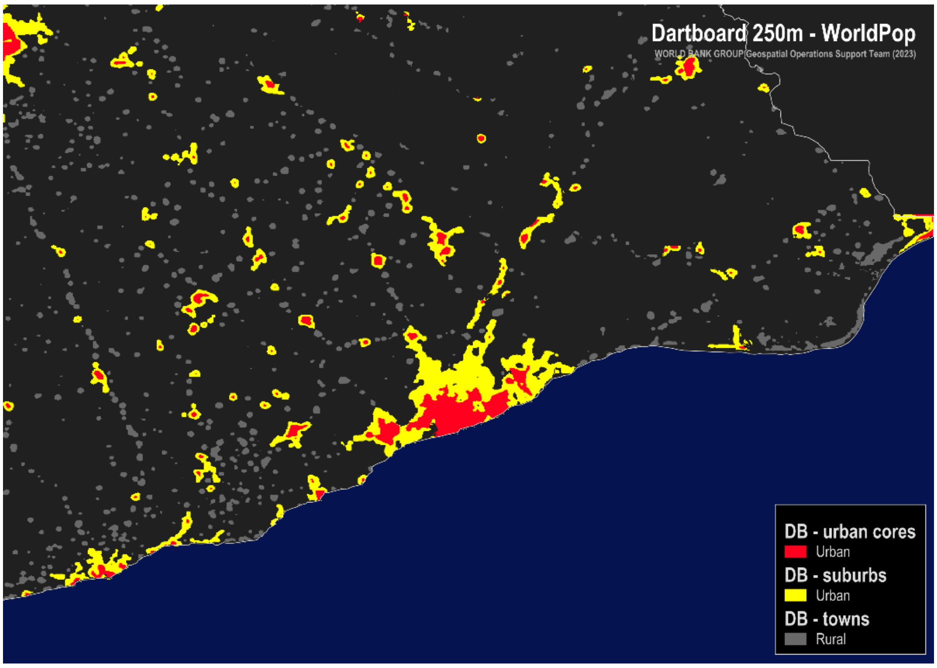
Source: World Development Indicators (World Bank)
Note: Data is derived from World Development Indicators, selecting the most recent year with available data. 163 countries are included in panel (A), (C) and (D), and 193 countries are included in panel (B). Poverty is measured using the \$2.15 poverty line. GDP per capita is measured in PPP (constant 2017 international \$).

Figure A2: Greater Accra, Ghana, by DOU and DB

(a) DOU

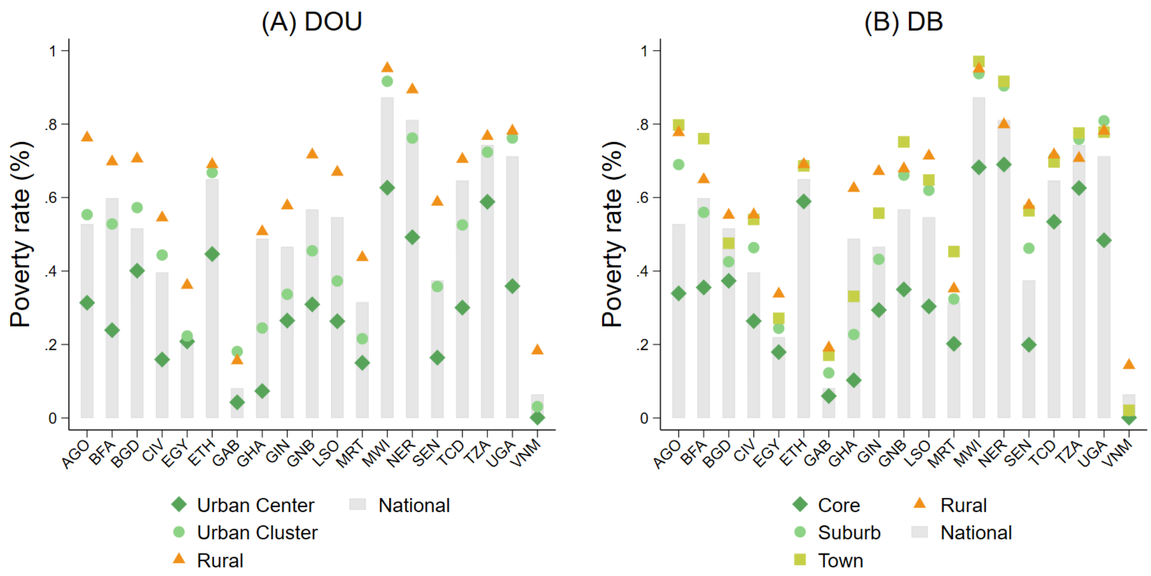


(b) DB



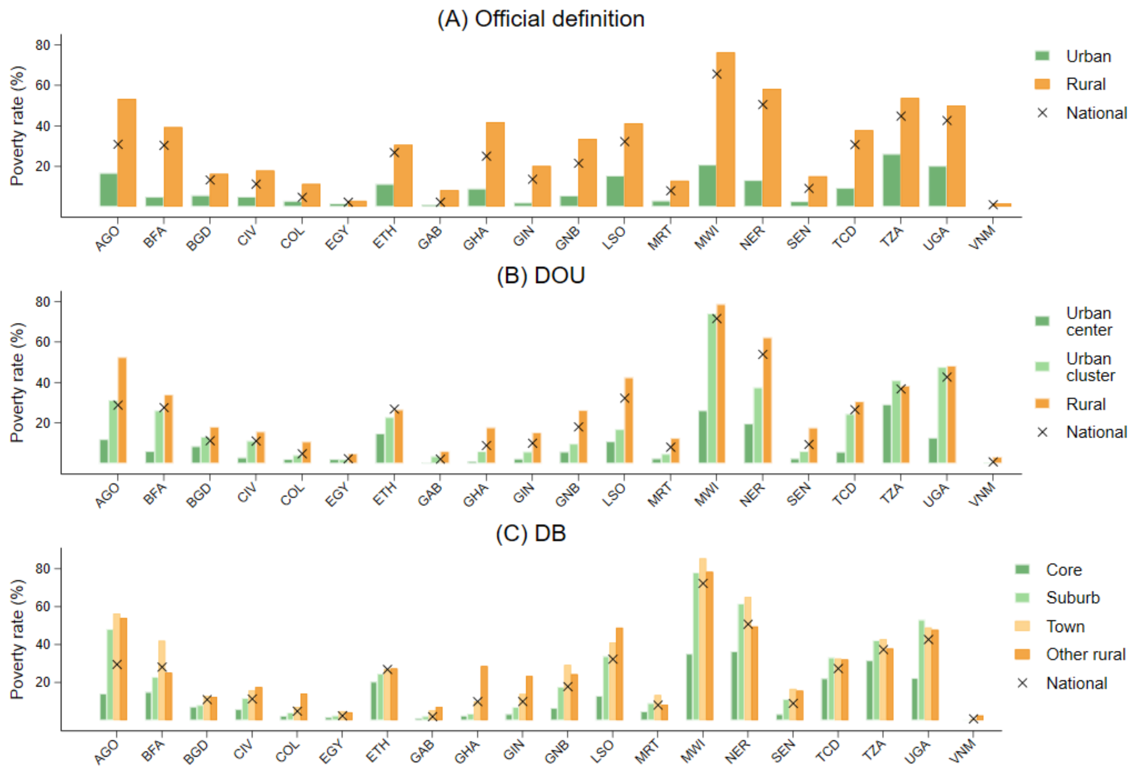
Source: WorldPop.
Note: Rural areas in black.

Figure A3: The share of household budget on housing in 12 low- and middle-income countries



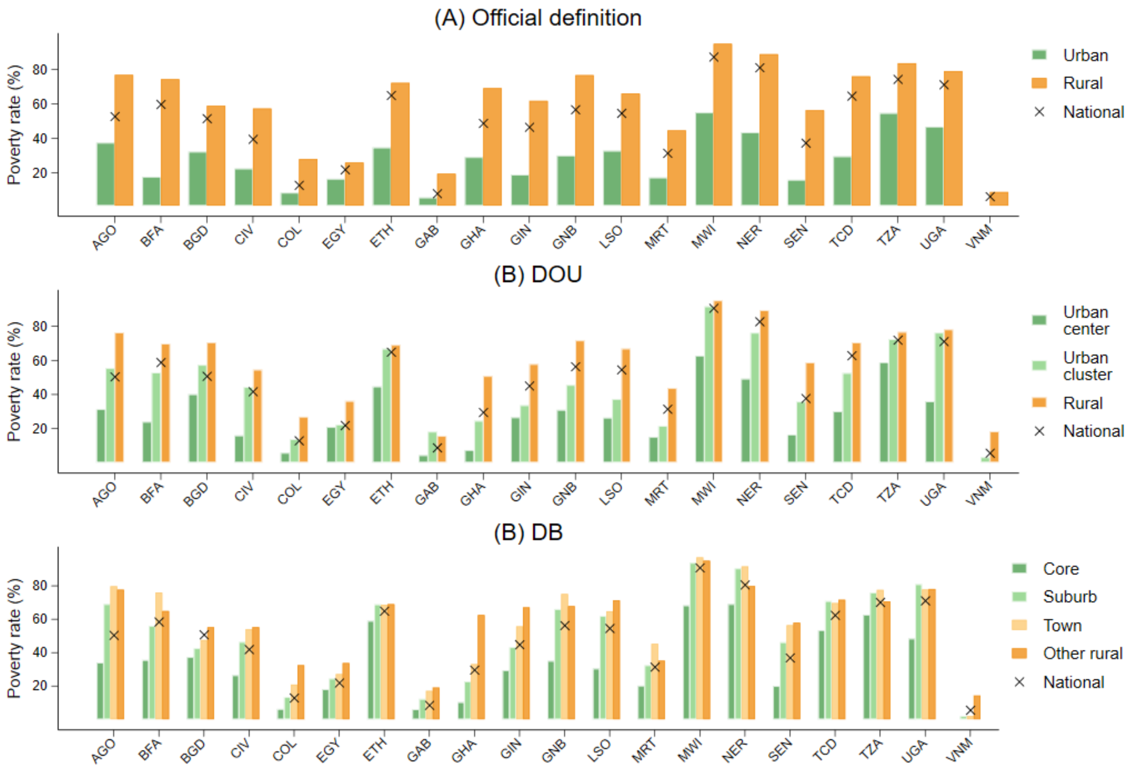
Source: Authors' calculations using each country's household budget survey.

Figure A4: Poverty rates by subnational areas, $2.15 poverty line



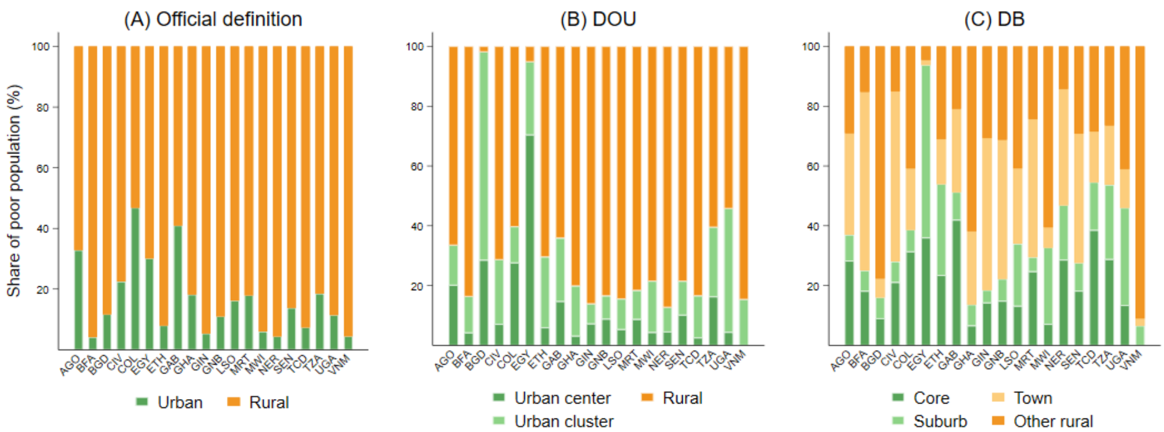
Source: Global Urban Poverty Database.
Note: For the DOU and DB methods, WorldPop 250m is used.

Figure A5: Poverty rates by subnational areas, \$3.65 poverty line



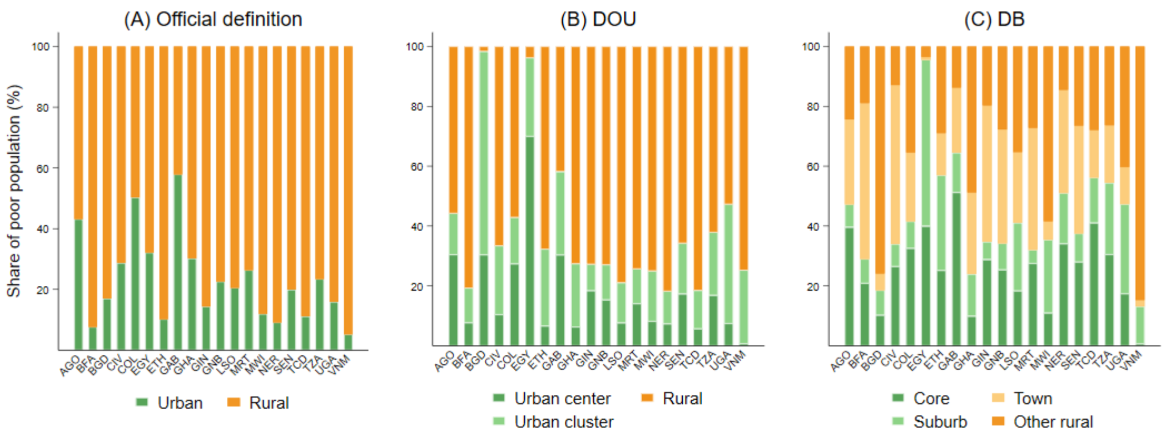
Source: Global Urban Poverty Database.
Note: For the DOU and DB methods, WorldPop 250m is used.

Figure A6: Distributions of poor populations across subnational areas, \$2.15 poverty line



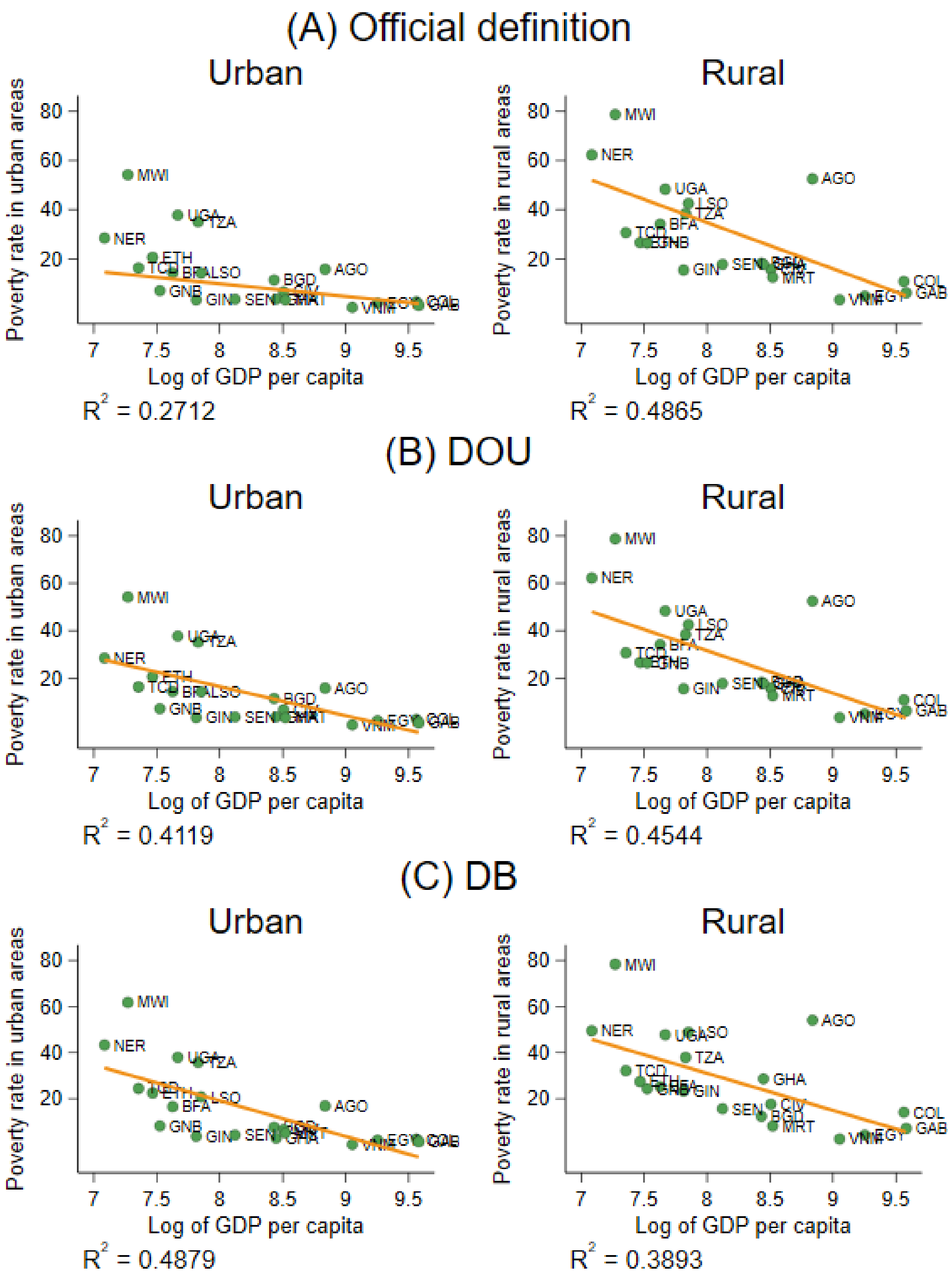
Source: Global Urban Poverty Database.
Note: For the DOU and DB methods, WorldPop 250m is used.

Figure A7: Distributions of poor populations across subnational areas, $3.65 poverty line



Source: Global Urban Poverty Database.
Note: For the DOU and DB methods, WorldPop 250m is used.

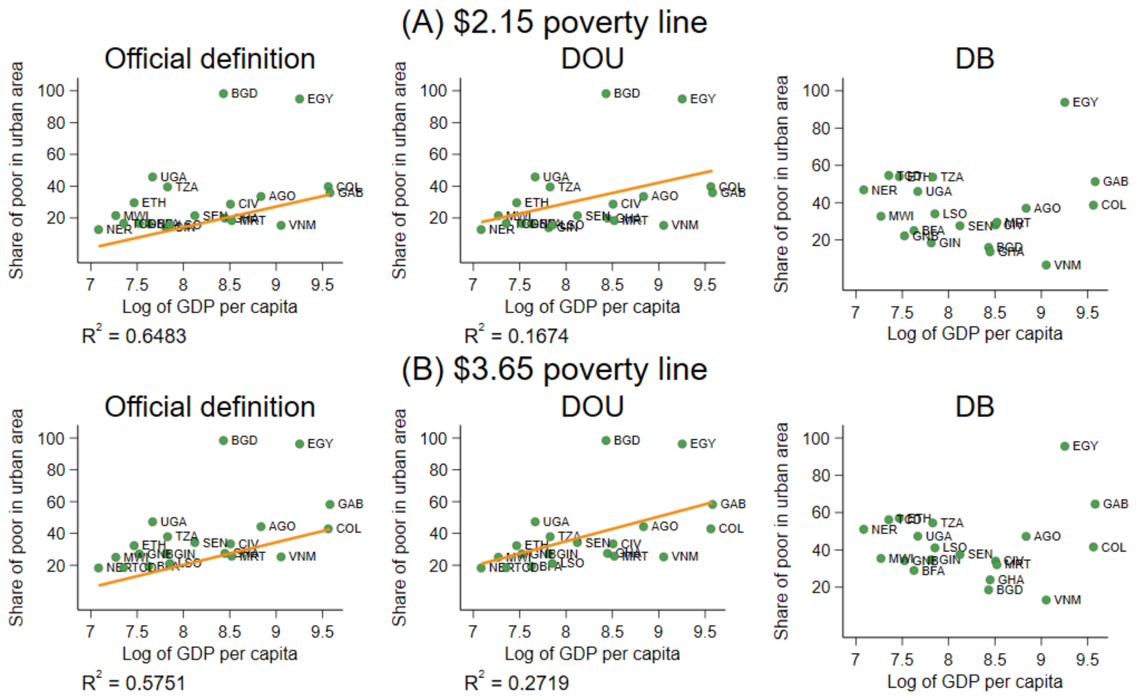
Figure A8: Urban/rural poverty rates and GDP



Source: Global Urban Poverty Database.

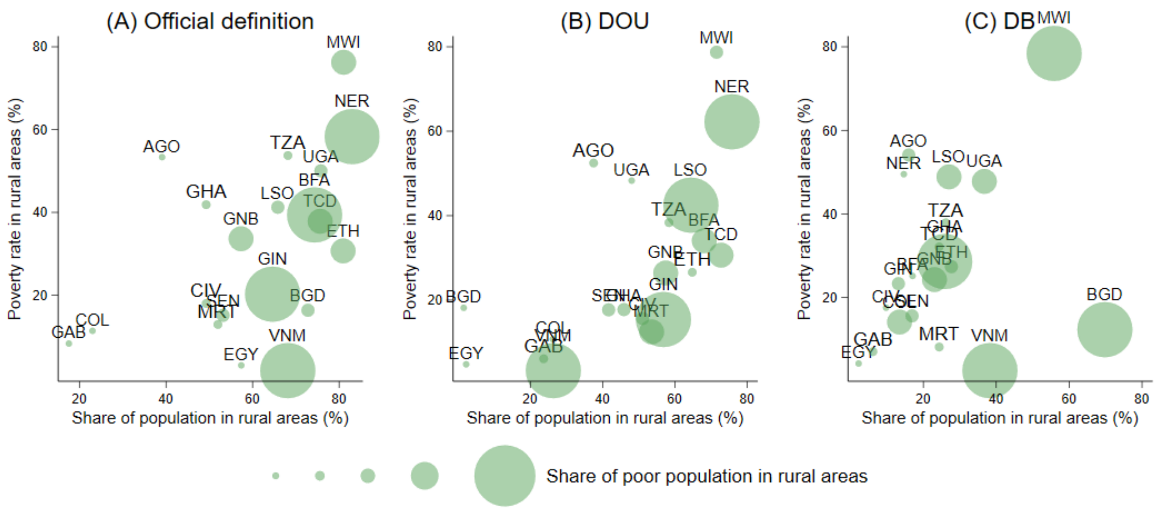
Note: GDP per capita is measured in PPP (constant 2017 international \$). For the DOU and DB methods, WorldPop 250m is used. Urban areas include the categories "Urban center" and "Urban cluster" for the DOU method, and the categories "Core" and "Suburb" for the DB method. Poverty is measured using the \$2.15 poverty line.

Figure A9: Share of poor in urban areas and GDP



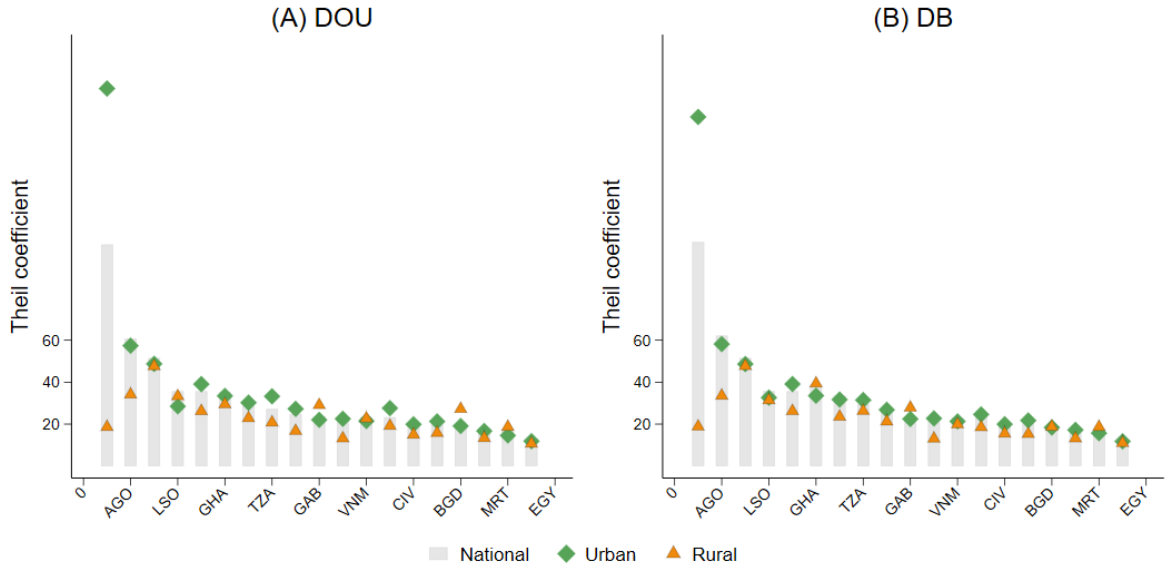
Source: Global Urban Poverty Database.
Note: Bangladesh and Egypt are outliers and are not included. GDP per capita is measured in PPP (constant 2017 international \$). For the DOU and DB methods, WorldPop 250m is used. Urban areas include the categories "Urban center" and "Urban cluster" for the DOU method, and the categories "Core" and "Suburb" for the DB method.

Figure A10: Poverty rates, population shares, and poor population shares in rural areas



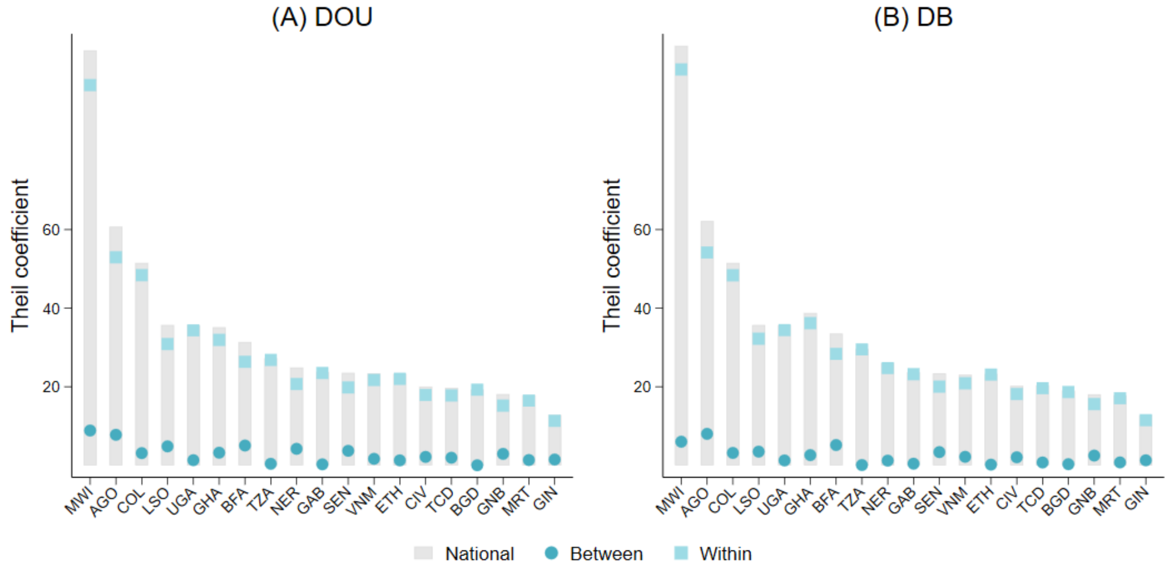
Source: Global Urban Poverty Database.
Note: The size of each circle is proportional to the share of the poor population in rural areas for each country. WorldPop 250m is used for the DOU and DB methods. Poverty is measured using the \$2.15 poverty line.

Figure A11: Theil coefficients in national, urban, and rural areas



Source: Global Urban Poverty Database.
Note: For the DOU and DB methods, WorldPop 250m is used. For the DOU and DB methods, WorldPop 250m is used. Urban areas include the categories "Urban center" and "Urban cluster" for the DOU method, and the categories "Core" and "Suburb" for the DB method.

Figure A12: Decomposition of Theil coefficients



Source: Global Urban Poverty Database.
Note: For the DOU and DB methods, WorldPop 250m is used. Following Pyatt (1976), the Gini coefficient is decomposed to within, between, and interaction terms. For the sake of presentation, interaction terms are not shown.

Table A1: Summary statistics by country

	AGO	BFA	BGD	CIV	COL	ETH	GAB	GHA	GIN	GNB
Number of households	11,822	6,651	45,812	11,589	232,160	30,255	7,914	14,009	8,243	5,291
Survey years	2018/19	2018/19	2016	2018/19	2015	2015/16	2017	2016/17	2018/19	2018/19
Lowest geographic unit available	Bairro	PSU	Mauza	PSU	Section	HH	HH	PSU	PSU	PSU
DOU urban classification:										
Urban center	0.49	0.20	0.39	0.27	0.49	0.10	0.63	0.24	0.31	0.28
Urban cluster	0.13	0.12	0.60	0.22	0.11	0.17	0.14	0.24	0.12	0.15
Rural	0.38	0.68	0.02	0.51	0.41	0.74	0.24	0.52	0.57	0.57
DB urban classification:										
Core	0.60	0.34	0.14	0.42	0.53	0.26	0.74	0.27	0.44	0.41
Suburb	0.05	0.08	0.10	0.07	0.06	0.46	0.09	0.16	0.06	0.08
Town	0.19	0.41	0.05	0.41	0.11	0.11	0.11	0.24	0.37	0.29
Other rural	0.35	0.58	0.76	0.51	0.41	0.28	0.17	0.56	0.50	0.52
Consumption (per day USD in 2017 PPP terms):										
Real per capita consumption expenditures	5.67	4.42	4.44	5.11	19.47	3.70	11.83	4.01	4.44	4.10
Nominal per capita consumption expenditures	5.90	4.67	4.47	5.19	19.18	0.99	11.88	4.03	4.49	4.22
Demographic:										
Household size	6.44	8.93	4.68	6.21	3.37	5.76	5.90	5.64	6.26	11.34
Age of household head	42.87	48.63	44.64	44.92	47.89	22.53	44.88	46.97	46.28	49.21
Household head is male	0.74	0.91	0.90	0.84	0.65	0.80	0.71	0.71	0.83	0.83
Marital status (of household head):										
Married	0.10	0.90	0.94	0.78	0.27	0.84	0.27	0.65	0.89	0.80
Never married	0.04	0.02	0.02	0.15	0.10	0.02	0.25	0.06	0.02	0.06
Living together	0.66	0.01	0.00	0.00	0.34	0.00	0.38	0.10	0.00	0.01
Divorced/Seperated	0.12	0.01	0.01	0.02	0.19	0.04	0.03	0.09	0.01	0.02
Widowed	0.09	0.06	0.04	0.06	0.09	0.09	0.07	0.10	0.08	0.10
Education (of household head):										
No education	0.16	0.76	0.42	0.50	0.07	0.51	0.19	0.27	0.55	0.40
Primary incomplete	0.30	0.10	0.13	0.19	0.18	0.33	0.09	0.11	0.13	0.28
Primary complete	0.05	0.03	0.12	0.03	0.16	0.05	0.08	0.04	0.00	0.09
Secondary incomplete	0.40	0.08	0.24	0.18	0.16	0.04	0.42	0.41	0.17	0.07
Secondary complete	0.02	0.00	0.04	0.03	0.21	0.02	0.07	0.06	0.02	0.08
Post secondary but not university	0.00	0.00	0.00	0.03	0.10	0.03	0.00	0.07	0.00	0.00
University incomplete and complete	0.06	0.03	0.04	0.05	0.11	0.03	0.16	0.05	0.12	0.07
Can read and write	0.75	0.32	0.54	0.53	0.93	0.46	0.91	0.52	0.40	0.57
Employment (of household head):										
Not in labor force	0.09	0.07	0.17	0.08	0.19	0.08	0.21	0.02	0.06	0.09
Unemployed	0.06	0.00	0.01	0.00	0.04	0.00	0.04	0.02	0.01	0.00
Employed in Agriculture	0.34	0.66	0.32	0.52	0.15	0.72	0.14	0.42	0.41	0.47
Employed in Industry	0.09	0.08	0.18	0.09	0.16	0.05	0.14	0.14	0.15	0.10
Employed in Services	0.42	0.18	0.32	0.31	0.46	0.15	0.48	0.40	0.38	0.34
Access to basic services										
Improved water	0.68	0.81	0.97	0.78	0.98	0.57	0.88	0.59	0.79	0.78
Improved sanitation facility	0.46	0.30	0.46	0.33	0.88	0.04	0.32	0.20	0.29	0.37
Access to electricity	0.47	0.53	0.76	0.80	0.98	0.36	0.91	0.81	0.44	0.58

Source: Global Urban Poverty Database.

Note: Real per capita consumption expenditures are deflated using a spatial deflator calculated based on the WorldPop 250m dataset and the DOU method.

Table A2: Household characteristics by location (SSA only)

	All	Official definition: Urban	Official definition: Rural	DOU: Urban center	DOU: Urban cluster	DOU: Rural	DB: Core	DB: Suburb	DB: Town	DB: Other Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demographic:										
Household size	6.55	6.18	6.71	6.31	6.41	6.67	6.52	6.11	7.07	6.59
Age of household head	40.31	42.51	39.30	43.29	41.00	39.04	41.40	34.81	43.60	41.46
Household head is male	0.78	0.73	0.81	0.73	0.76	0.81	0.75	0.79	0.81	0.80
Education (of household head):										
No education	0.37	0.20	0.45	0.18	0.29	0.47	0.26	0.40	0.51	0.40
Primary complete or incomplete	0.39	0.33	0.42	0.31	0.44	0.40	0.34	0.45	0.34	0.44
Secondary complete or incomplete	0.18	0.33	0.11	0.35	0.20	0.11	0.28	0.12	0.14	0.13
Tertiary complete or incomplete	0.06	0.15	0.02	0.16	0.07	0.02	0.12	0.04	0.02	0.03
Employment (of household head):										
Not in labor force	0.12	0.13	0.11	0.14	0.11	0.11	0.12	0.11	0.10	0.13
Unemployed	0.03	0.04	0.02	0.05	0.02	0.02	0.04	0.02	0.02	0.03
Employed in Agriculture	0.52	0.14	0.71	0.07	0.48	0.70	0.26	0.66	0.70	0.65
Employed in Industry	0.08	0.14	0.05	0.15	0.09	0.05	0.12	0.06	0.05	0.05
Employed in Services	0.26	0.55	0.12	0.58	0.30	0.13	0.46	0.16	0.13	0.15
Access to basic services										
Improved water	0.69	0.84	0.62	0.88	0.75	0.61	0.82	0.63	0.63	0.60
Improved sanitation facility	0.24	0.40	0.17	0.46	0.27	0.16	0.37	0.15	0.20	0.19
Access to electricity	0.48	0.82	0.32	0.85	0.53	0.33	0.69	0.36	0.39	0.34

Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods.

Table A3: Household characteristics by location (SSA only)

	All	Poor by DOU: Urban	Poor by DOU: Urban center	Poor by DOU: Urban cluster	Poor by DOU: Rural	Poor by DB: Urban	Poor by DB: Core	Poor by DB: Suburb	Poor by DB: Town	Poor by DB: Other Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demographic:										
Household size	6.55	7.05	6.97	7.09	7.50	7.49	7.56	6.95	8.07	7.06
Age of household head	40.31	42.15	42.82	41.87	40.20	40.40	41.12	36.56	44.26	41.62
Household head is male	0.78	0.74	0.69	0.77	0.81	0.79	0.75	0.80	0.82	0.79
Education (of household head):										
No education	0.37	0.29	0.25	0.30	0.49	0.44	0.37	0.40	0.55	0.40
Primary complete or incomplete	0.39	0.55	0.54	0.56	0.44	0.46	0.47	0.51	0.38	0.51
Secondary complete or incomplete	0.18	0.15	0.19	0.13	0.07	0.09	0.14	0.07	0.07	0.08
Tertiary complete or incomplete	0.06	0.02	0.02	0.01	0.00	0.01	0.02	0.01	0.00	0.00
Employment (of household head):										
Not in labor force	0.12	0.16	0.19	0.14	0.14	0.14	0.14	0.14	0.13	0.17
Unemployed	0.03	0.05	0.09	0.03	0.02	0.03	0.05	0.02	0.02	0.03
Employed in Agriculture	0.52	0.49	0.19	0.61	0.73	0.64	0.49	0.70	0.73	0.68
Employed in Industry	0.08	0.08	0.12	0.06	0.04	0.05	0.08	0.04	0.04	0.04
Employed in Services	0.26	0.23	0.40	0.16	0.07	0.14	0.24	0.10	0.07	0.08
Access to basic services										
Improved water	0.69	0.77	0.86	0.73	0.59	0.65	0.74	0.61	0.59	0.63
Improved sanitation facility	0.24	0.25	0.32	0.21	0.16	0.18	0.23	0.14	0.17	0.20
Access to electricity	0.48	0.37	0.56	0.29	0.20	0.26	0.35	0.22	0.23	0.20

Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Poverty is measured using the $2.15 poverty line.

Table A4: Estimation results of regressions on log expenditures with control variables: DOU

	Log of per capita nominal consumption expenditures							
	(1) All	(2) All	(3) All	(4) Urban	(5) All	(6) All	(7) All	(8) Urban
Urban center	0.756***	0.526***	0.431***	0.369***	0.602***	0.425***	0.348***	0.295***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)	(0.007)
Urban cluster	0.269***	0.151***	0.110***		0.215***	0.118***	0.083***	
	(0.007)	(0.006)	(0.006)		(0.007)	(0.006)	(0.006)	
Spatial deflator					0.771***	0.544***	0.475***	0.599***
					(0.027)	(0.025)	(0.024)	(0.033)
Demographic:								
Household size		−0.078***	−0.081***	−0.075***		−0.078***	−0.080***	−0.074***
		(0.002)	(0.002)	(0.003)		(0.002)	(0.002)	(0.003)
Age of head of hh		0.007***	0.007***	0.007***		0.007***	0.007***	0.007***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Sex of head of hh		−0.049***	−0.039***	−0.085***		−0.046***	−0.036***	−0.082***
		(0.007)	(0.007)	(0.009)		(0.007)	(0.007)	(0.009)
Marital status (of head of hh):								
Never married		0.243***	0.226***	0.201***		0.244***	0.228***	0.203***
		(0.011)	(0.011)	(0.013)		(0.011)	(0.011)	(0.013)
Living together		−0.083***	−0.088***	−0.119***		−0.090***	−0.094***	−0.123***
		(0.014)	(0.014)	(0.019)		(0.014)	(0.014)	(0.019)
Divorced/Separated		−0.008	−0.024*	−0.085***		−0.006	−0.021*	−0.084***
		(0.012)	(0.013)	(0.017)		(0.012)	(0.013)	(0.017)
Widowed		−0.025***	−0.030***	−0.076***		−0.023**	−0.028***	−0.075***
		(0.010)	(0.010)	(0.012)		(0.010)	(0.010)	(0.012)
Education (of head of hh):								
Primary incomplete		0.094***	0.081***	0.077***		0.090***	0.078***	0.077***
		(0.006)	(0.007)	(0.008)		(0.006)	(0.007)	(0.008)
Primary complete		0.240***	0.217***	0.217***		0.231***	0.209***	0.212***
		(0.007)	(0.008)	(0.009)		(0.007)	(0.008)	(0.009)
Secondary incomplete		0.385***	0.349***	0.355***		0.369***	0.336***	0.340***
		(0.006)	(0.007)	(0.007)		(0.006)	(0.007)	(0.007)
Secondary complete		0.662***	0.596***	0.619***		0.643***	0.582***	0.605***
		(0.011)	(0.011)	(0.012)		(0.011)	(0.011)	(0.012)
Post secondary but not university		0.773***	0.674***	0.731***		0.762***	0.667***	0.723***
		(0.015)	(0.015)	(0.019)		(0.015)	(0.015)	(0.018)
University incomplete and complete		0.920***	0.835***	0.866***		0.902***	0.821***	0.850***
		(0.013)	(0.013)	(0.013)		(0.013)	(0.013)	(0.013)
Employment (of head of hh):								
Unemployed			0.034**				0.034**	
			(0.016)				(0.016)	
Not in labor force			0.130***				0.126***	
			(0.008)				(0.008)	
Employed in Industry			0.160***				0.149***	
			(0.007)				(0.007)	
Employed in Services			0.234***				0.225***	
			(0.006)				(0.006)	
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.630	0.714	0.726	0.653	0.636	0.717	0.728	0.657
Nr. of countries	19	19	19	19	19	19	19	19
Nr. of hh	453683	437458	419519	292650	452684	436491	418586	292538

Source: Global Urban Poverty Database.

Note: *** $p < 0.01$, ** $p < 0.05$, *** $p < 0.1$. Robust standard errors in parentheses. WorldPop 250m is used for the DOU method. The dependent variable is the log of per capita consumption expenditures, expressed in PPP and not spatially deflated. Only urban households ("Urban center" or "Urban cluster") are included in specifications (4) and (8). The baseline category is "Rural" in all specifications, except (4) and (8), where it is "Urban cluster". Baseline categories for the control variables are the following: "Married" for marital status of household head, "No education" for education of household head, and "Employed in Agriculture" for employment of household head. Robust standard errors are in parentheses. Observations are weighted using population weights.

Table A5: Estimation results of regressions on log expenditures with control variables: DB

	Log of per capita nominal consumption expenditures							
	(1) All	(2) All	(3) All	(4) Urban	(5) All	(6) All	(7) All	(8) Urban
Core	0.618***	0.429***	0.346***	0.311***	0.477***	0.338***	0.271***	0.243***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Suburb	0.167***	0.106***	0.076***		0.116***	0.073***	0.051***	
	(0.007)	(0.006)	(0.007)		(0.007)	(0.006)	(0.007)	
Town	0.067***	0.036***	0.033***		0.023***	0.006	0.009	
	(0.007)	(0.007)	(0.007)		(0.007)	(0.007)	(0.007)	
Spatial deflator					0.788***	0.542***	0.480***	0.617***
					(0.021)	(0.020)	(0.020)	(0.028)
Demographic:								
Household size		−0.079***	−0.081***	−0.090***		−0.079***	−0.081***	−0.090***
		(0.002)	(0.002)	(0.003)		(0.002)	(0.002)	(0.003)
Age of head of hh		0.007***	0.007***	0.007***		0.007***	0.007***	0.007***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Sex of head of hh		−0.061***	−0.043***	−0.060***		−0.056***	−0.039***	−0.056***
		(0.007)	(0.007)	(0.010)		(0.007)	(0.007)	(0.010)
Marital status (of head of hh):								
Never married		0.251***	0.230***	0.266***		0.253***	0.233***	0.262***
		(0.011)	(0.011)	(0.015)		(0.011)	(0.011)	(0.015)
Living together		−0.075***	−0.083***	−0.079***		−0.085***	−0.090***	−0.088***
		(0.015)	(0.015)	(0.020)		(0.015)	(0.015)	(0.020)
Divorced/Separated		−0.009	−0.024*	−0.012		−0.004	−0.018	−0.011
		(0.012)	(0.013)	(0.017)		(0.012)	(0.013)	(0.017)
Widowed		−0.025**	−0.030***	0.005		−0.022**	−0.027**	0.002
		(0.010)	(0.010)	(0.014)		(0.010)	(0.010)	(0.013)
Education (of head of hh):								
Primary incomplete		0.101***	0.086***	0.115***		0.097***	0.084***	0.109***
		(0.007)	(0.007)	(0.010)		(0.007)	(0.007)	(0.010)
Primary complete		0.255***	0.227***	0.298***		0.247***	0.220***	0.285***
		(0.008)	(0.008)	(0.013)		(0.008)	(0.008)	(0.013)
Secondary incomplete		0.409***	0.364***	0.456***		0.393***	0.351***	0.428***
		(0.006)	(0.007)	(0.010)		(0.006)	(0.007)	(0.010)
Secondary complete		0.693***	0.614***	0.709***		0.673***	0.598***	0.686***
		(0.011)	(0.011)	(0.015)		(0.011)	(0.011)	(0.015)
Post secondary but not university		0.806***	0.688***	0.830***		0.794***	0.681***	0.807***
		(0.016)	(0.016)	(0.020)		(0.016)	(0.016)	(0.020)
University incomplete and complete		0.957***	0.855***	1.020***		0.936***	0.839***	0.990***
		(0.013)	(0.013)	(0.015)		(0.013)	(0.013)	(0.015)
Employment (of head of hh):								
Unemployed			0.066***				0.065***	
			(0.016)				(0.016)	
Not in labor force			0.162***				0.153***	
			(0.008)				(0.008)	
Employed in Industry			0.189***				0.174***	
			(0.007)				(0.007)	
Employed in Services			0.261***				0.250***	
			(0.006)				(0.006)	
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R2	0.616	0.707	0.721	0.767	0.623	0.710	0.723	0.770
Nr. of countries	19	19	19	19	19	19	19	19
Nr. of hh	453683	437458	419519	267655	452789	436564	418633	267397

Source: Global Urban Poverty Database.
Note: *** $p < 0.01$, ** $p < 0.05$, *** $p < 0.1$. Robust standard errors are in parentheses. WorldPop 250m is used for the DB methods. The dependent variable is the log of per capita consumption expenditures, expressed in PPP and not spatially deflated. Only urban households ("Core" or "Suburb") are included in specifications (4) and (8). The baseline category is "Other rural" in all specifications, except (4) and (8), where it is "Suburb". Baseline categories are the following: "Married" for the marital status of the household head, "No education" for the education of the household head, and "Employed in Agriculture" for the employment of the household head. Observations are weighted using population weights.

Table A6: Urban and poverty status changes (SSA only)

(A) Original definitions to DOU		**Non-spatially deflated**				**Spatially deflated**			
Poverty status:		Non-poor		Poor		Non-poor		Poor	
DOU:		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Official urban definition:									
Non	Urban	87.4	12.6	0.0	0.0	86.0	12.7	1.3	0.1
	Rural	21.0	79.0	0.0	0.0	19.0	77.4	1.4	2.2
Poor	Urban	0.0	0.0	77.5	22.5	4.8	2.5	75.1	17.6
	Rural	0.0	0.0	17.1	82.9	0.1	3.0	17.6	79.3

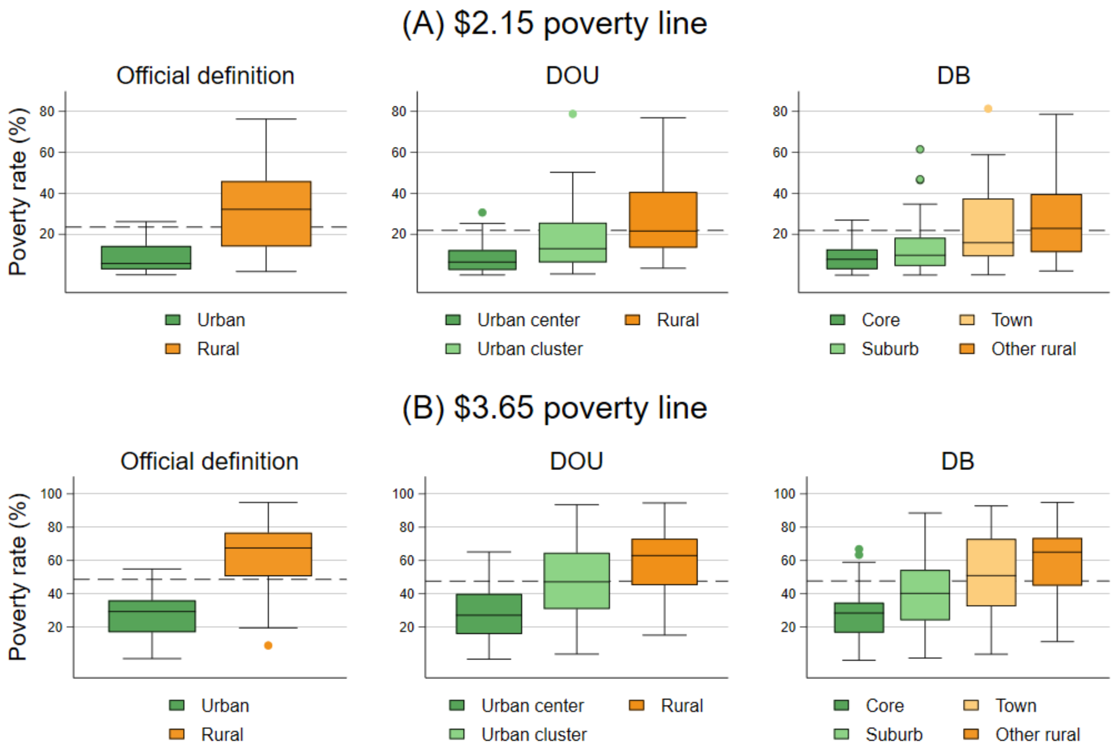
(B) Original definitions to DB		**Non-spatially deflated**				**Spatially deflated**			
Poverty status:		Non-poor		Poor		Non-poor		Poor	
DOU:		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Official urban definition:									
Non	Urban	90.1	3.4	0.0	6.5	92.9	6.5	0.5	0.0
	Rural	46.5	27.2	0.0	26.3	70.2	25.3	3.4	1.0
Poor	Urban	0.0	0.0	91.8	8.2	6.3	1.0	86.2	6.5
	Rural	0.0	0.0	55.5	44.5	1.4	2.2	64.6	31.8

(C) DOU to DB		**Non-spatially deflated**				**Spatially deflated**			
Poverty status:		Non-poor		Poor		Non-poor		Poor	
DB:		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
DOU:									
Non	Urban	96.3	1.8	0.0	1.9	97.6	1.9	0.5	0.0
	Rural	34.6	32.0	0.0	33.3	64.7	32.3	2.3	0.7
Poor	Urban	0.0	0.0	96.9	3.1	7.0	0.3	90.3	2.4
	Rural	0.0	0.0	44.7	55.3	1.1	2.2	58.9	37.9

Source: Global Urban Poverty Database.
Note: WorldPop 250m is used for the DOU and DB methods. Poverty is measured using the $2.15 poverty line. 16 sub-saharan countries are included. In Panel (A), welfare is deflated using official spatial deflators. In Panel (B) and (C), welfare is deflated using our updated spatial deflators.

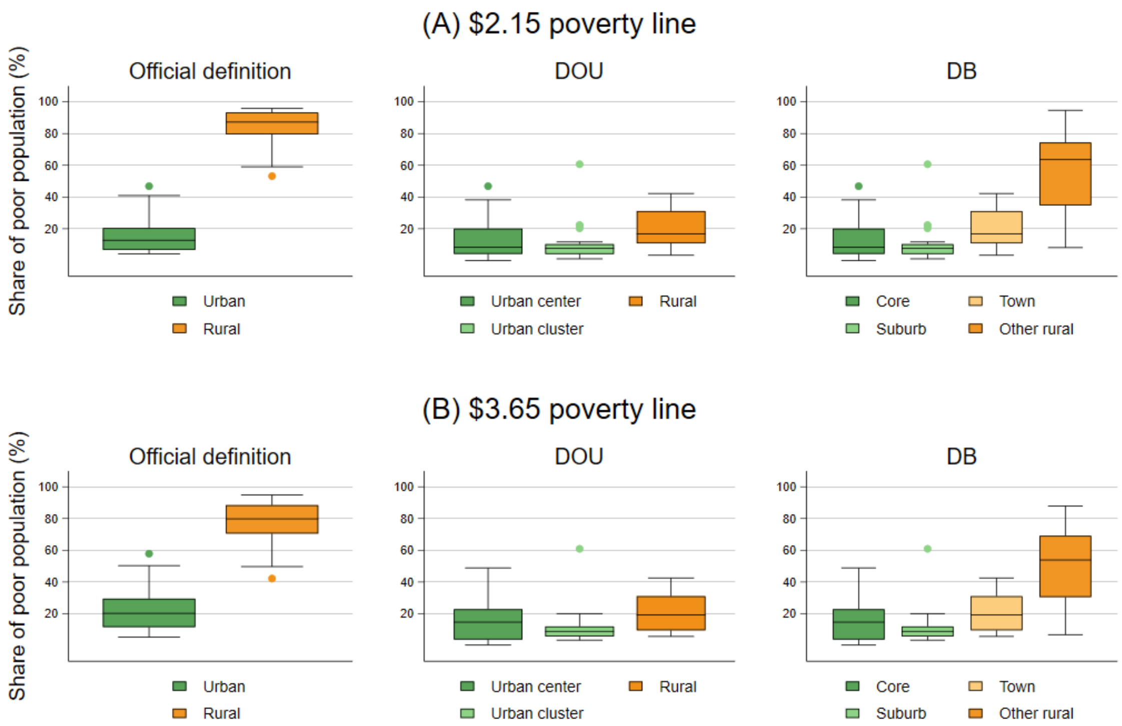
B Results based on GHSPOP

Figure B1: Poverty rates by subnational areas



Source: Global Urban Poverty Database.
Note: Each boxplot shows the distributions of poverty rates over different geographic areas in 20 countries. GHSPOP 1km is used for the DOU and DB methods. The dashed lines represent the average national poverty rate in the sample.

Figure B2: Distribution of poor population across urban versus rural areas



Source: Global Urban Poverty Database.
Note: Each boxplot shows the distributions of poverty rates over different geographic areas in 20 countries. GHSPOP 1km is used for the DOU and DB methods. The dashed lines represent the average national poverty rate in the sample.