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A New Global Subnational Poverty and Inequality Database Based on Harmonized Household Surveys

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Abstract

Subnational data on household welfare help identify and monitor locations with high concentration of poverty and inequality, resulting in more efficient policy interventions. Yet, very few global databases on poverty and inequality exist at the subnational level. Using the World Bank's Global Monitoring Database (GMD) of more than 1,250 harmonized, official household (consumption or income) surveys from 172 economies, we present two new global datasets that focus on poverty and inequality at the subnational level: the Subnational Poverty and Inequality Database (SPID) and the Global Subnational Atlas of Poverty (GSAP). SPID, a (unbalanced) panel data set, allows for analysis of longitudinal changes of subnational poverty and inequality within countries based on direct survey estimates. GSAP, a cross-sectional dataset, offers direct and lined-up estimates for nearly all regions in the world for multiple common years. The datasets can also be matched with other georeferenced datasets, such as on natural disasters or climate change, to provide richer analysis.

JEL classification

I00, O10, Q50

Keywords

subnational, poverty, inequality, household surveys

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1. Background & Summary

Granular subnational data on household welfare helps pinpoint pockets of extreme poverty and inequality at a disaggregated level, leading to cost-effective targeting interventions in areas that are not observed through analysis of national averages alone. For example, natural disasters often disproportionately affect certain regions across the globe (and are often not restricted to country boundaries), so analysis of global, comparable subnational poverty can provide more accurate estimates on their effects. Policymakers are also keen on monitoring regional convergence (or divergence) in living standards to identify lagging regions that require extra investments and support. However, producing subnational welfare data which are comparable across countries—or even within the same countries for different time periods—is challenging for various reasons. Household survey coverage is infrequent in many poorer countries, and data quality can be insufficient in poorer and richer countries alike (Devarajan, 2013; Jerven, 2013; Sandefur and Glassman, 2015; Beegle *et al.*, 2016; Dargent *et al.*, 2018; World Bank, 2021; Dang and Serajuddin, 2020; Auerbach *et al.*, 2025; Dang *et al.*, 2025). Furthermore, subnational statistical regions and definitions of household welfare (consumption or income) aggregates change over time. These issues complicate the construction of a global panel of subnational welfare estimates.

A small, but growing, body of work has sought to fill this gap by compiling subnational development indicators. For instance, Hoffmann *et al.* (2025) analyze Demographic and Health Surveys for 75 countries to reveal persistent gaps in decent living standards at the subnational level. Mikou *et al.* (2024) produce a harmonized, subnational disposable income dataset for Europe, enabling finer analysis of inequality within 42 countries. Wenz *et al.* (2023) introduce the DOSE database of sub-national economic output, covering more than 1,600 regions from 83 countries, which they match with climate data to study climate impacts on regional economies. Regarding multidimensional poverty, Smits and Permanyer (2019) provide a global dataset of education, health and standard of living for 1,625 regions from 161 countries. Suppa and Kanagaratnam (2025) develop a recent global dataset with more multidimensional poverty dimensions 814 regions from 84 countries. These efforts underscore the demand for high-resolution, comparable subnational data on different aspects of welfare and development with global coverage.

We present two new global complementary datasets that present poverty and inequality indicators at the subnational level: the Subnational Poverty and Inequality Database (SPID) and the Global Subnational Atlas of Poverty (GSAP). These datasets are constructed using the World Bank's Global Monitoring Database (GMD)--the Bank's repository of multitopic income and expenditure household surveys used to monitor global poverty and shared prosperity—which comprises of approximately 2,500 harmonized surveys. From this universe, for the most recent versions of the SPID and the GSAP, we retain about 1,250 consumption- or income-based surveys from 172 economies over 1990-2024 for which subnational identifiers and corresponding boundary data are available. While both the SPID and the GSAP are built using a common geospatial framework that defines subnational units, the difference between the two lies in (country and time) coverage and how poverty estimates are computed. The SPID consists of direct estimates from household surveys, thus enabling us to understand the temporal evolution of subnational poverty within countries (with unbalanced panel data). The GSAP, on the other hand, consists of both direct estimates and lined-up (nowcasted) estimates of almost all regions in the world for multiple line-up (common) years (with cross-sectional data). Consequently, when employed together these datasets could offer rich analysis of trends and dynamics of global poverty and inequality. Table 1 provides an overview of the key differences between these two datasets and their recommended use.

Several features distinguish the SPID and GSAP datasets from existing subnational datasets. First, to our knowledge, these represent the first global subnational database on poverty and inequality, which are two key, closely related development outcomes highlighted by the Sustainable Development Goals (SDGs). Analyzing poverty and inequality metrics from the same household surveys provides more consistency and comparability, compared to those obtained from different sources. Second, the GMD that we employ for data construction underlies countries' official poverty and inequality statistics. (The World Bank is the United Nations' custodial agency for monitoring global poverty and inequality). Finally, these two subnational datasets cover between 140 and 172 economies with around 2,200 subnational units, which are double or more the number of countries offered in most existing subnational datasets.

In summary, these datasets serve both academic and policy interests. Some key development questions that these data can help answer include: where are the poorest regions located in the world (or in a country)? Have specific regions seen faster progress in poverty or inequality reduction than others? Furthermore, since aggregate time series data have long been known to cause various aggregation biases (Angrist and Krueger, 1999; Gardes *et al.*, 2005), a particularly useful application of subnational data is in investigating the location-specific impacts of climate change on economic growth (Damania *et al.*, 2020; Kalkuhl and Wenz, 2020). Indeed, despite its infancy, the GSAP and SPID datasets have been combined with georeferenced datasets to study the relationships of poverty and inequality with natural disasters and climate change, as well as various other factors including air pollution and conflicts. (We return to discuss more recent applications in the Usage Notes section).

The SPID and GSAP datasets are typically updated annually to incorporate new surveys and auxiliary data with the annual update of the GMD database (and PIP platform). The latest version of the data (October 2025) are available on the World Bank's Development Data Hub website: the SPID (https://datacatalog.worldbank.org/int/search/dataset/0064796/subnational_poverty_and_inequality_database_spid) and the GSAP (https://datacatalog.worldbank.org/int/search/dataset/0042041/global_subnational_poverty_atlas_gsap). The Geospatial Poverty Portal features interactive maps featuring data from both the SPID and the GSAP (https://pipmaps.worldbank.org/en/data/datatopics/poverty-portal/home).

2. Methods

The construction of the SPID and GSAP datasets involves combining multiple data sources into a harmonized geospatial database. The process consists of the following steps: (1) harmonizing household survey data; (2) defining the subnational geographic units at which the survey is representative and preparing corresponding geospatial boundary data; and (3) computing poverty and inequality indicators for each subnational unit (for each survey year in SPID, or lining up estimates to a common year in the GSAP). Notably, Step 1 is handled by various colleagues at the national statistical offices (NSO) and World Bank, providing the welfare data underlying the World Bank's various official poverty and inequality products including the SPID and the GSAP. Steps 2 and 3 are processes specific to these two datasets.

Figure 1 offers a visual depiction of these data construction steps. We describe these steps below and various quality control checks that were performed in the Technical Validation section.

Step 1: Harmonizing household survey data

Indicators in the SPID and the GSAP are derived from the World Bank's Global Monitoring Database (GMD) – a curated collection of household (income or consumption) surveys from 1980s onward for over 170 countries. The GMD contains microdata obtained from national statistical offices (NSOs) or other reliable sources (such as high-income countries in Luxemburg Income Study (LIS) that offer harmonized variables to facilitate comparability). These household surveys are compiled, processed, and harmonized such that levels and trends in poverty and other key sociodemographic attributes can be reasonably compared across and within countries over time. Within-country inconsistencies across survey rounds that cannot be fully harmonized are explicitly captured through a comparability flag included in the dataset. These harmonized GMD surveys constitute the underlying data used for the World Bank's global poverty monitoring (which are also available in the World Bank's Poverty and Inequality Platform (PIP)).

From each survey, a welfare aggregate (either household consumption per capita or income per capita, depending on the country) is constructed by the NSO and the World Bank's country (or regional statistical) team using standardized methodologies. These vetted and harmonized welfare aggregate data are subsequently combined with non-welfare variables created by regional statistical teams to create the harmonized GMD data. The welfare aggregate in the harmonized GMD data produces poverty and inequality estimates using Purchasing Power Parity (PPP) prices, which are consistent with global poverty rates published by the World Bank.

These welfare aggregates are typically adjusted for within-country price differences using spatial deflators and are comparable for different regions within the same country. Adjustments for price differences over time are made for the same countries (using national Consumer Price Indices (CPI)) and across countries (using PPP exchange rates), ensuring full comparability of welfare and poverty measures across countries and time. All the subnational indicators in the SPID and GSAP datasets are constructed using the vetted and harmonized GMD datasets as described above.

For more details, Figure 1 also provides a breakdown of the typical process under Step 1 where we start from processing raw household survey data to finally obtaining the harmonized welfare data, which is complete with full documentation.

Step 2: Defining subnational units and preparing corresponding geospatial data

A key challenge is to define which geographic units (e.g., regions, states, or provinces) to use for reporting subnational poverty. We use the (smallest) statistical regions at which the official household survey is designed to be representative. This often corresponds with the first administrative level (ADM1, e.g. states/ provinces). In practice, the statistical regions represented by surveys, however, do not always match administrative divisions. Some statistical regions group administrative units together, combine different levels or use entirely different definitions. We maintain consistency with the spatial units supported by a survey's design to report direct estimates of poverty and inequality at the most granular subnational level possible.

The number of subnational units represented by surveys in a particular country may increase or decrease over time, and we track these changes in the database. Some recent surveys have more (fewer) subnational units than previous surveys in the same country because new regions were created (combined) and subsequently incorporated into the survey sampling strategy. Aggregation from finer to coarser administrative units is implemented when lower-level geographic identifiers are consistently available and representative in the survey microdata. In such cases, higher-level estimates are constructed through population-weighted aggregation of lower-level welfare distributions. This approach applies to approximately 10 countries in our database, covering 30 survey rounds. For example, Lao PDR reports four subnational units (statistical regions) in the 2002 and 2007 survey rounds, and 17 and 18 provinces in the 2012 and 2018 survey rounds. To preserve temporal consistency, we construct a harmonized regional series by aggregating the (more recent) provincial data to the (older) four statistical regions, while at the same time separately maintaining a province-level panel for 2012 and 2018. Thus, countries with varying subnational representation over time have multiple observations in the SPID.

We match the geographic identifiers defining statistical regions in surveys to geospatial boundary data derived from several sources: the FAO's Global Administrative Unit Layers (GAUL), Eurostat's Nomenclature of Territorial Units for Statistics (NUTS), the Database of Global Administrative Areas (GADM), United Nations Common Operational Dataset – Administrative Boundaries (COD-AB), and boundary data published by NSOs or other agencies. For each survey, we select the subnational boundary data that best matches survey statistical regions. We primarily use NUTS for Europe and GAUL 2015 for other countries. If no positive match is identified, we consider the alternative boundary data sources. Since automated matching is difficult (due to spelling differences or language issues), matches are manually verified referencing survey documentation. This manual verification process affects approximately 40% of subnational units in the dataset. In the end, each subnational statistical region in the boundary data and surveys is assigned a unique identifier (*geo_code*) that includes the boundary data year, source, level and ID for reference.

In some cases, statistical regions in surveys do not correspond to regions in available geospatial boundary data sources. In these cases, we construct custom boundaries by taking the spatial union or difference of the relevant regions data source. These custom regions are denoted with an "x" suffix in our database (e.g., GAULx) for identification and we document their exact composition. Such modifications account for approximately 10% of subnational units (across 59 countries) in the dataset of around 2,200 subnational areas.

Finally, we perform several topological checks. We edge match subnational boundaries to ensure there are no gaps or overlaps, and that they align with the World Bank Official boundaries at the national (ADM0) level. These national boundaries are also used in the GSAP when survey-based line-up estimates are not available or not representative at the subnational level. Beyond the constructed unique identifier (*geo_code*), which encodes boundary year, source, level, and unit ID, the finalized boundary files preserve the original geo-reference identifiers from the source data. This facilitates interoperability and consistent merging of the SPID and the GSAP with external datasets using the same geographic reference definitions. The availability of boundary geometries facilitates the computation of zonal statistics from spatial and remote sensing datasets, allowing raster-derived indicators to be aggregated to survey-consistent statistical units.

The output of this step is a geospatial database mapping the boundaries of all subnational statistical regions in the GMD survey data across all survey years. These are easily linked to surveys using the unique identifier. For the year-specific GSAP data, we combine the subnational boundaries corresponding with the underlying subset of GMD surveys with national level boundaries to produce global maps. Figure A1 (Appendix A) illustrates the boundary data sources of the 2023 GSAP regions – it shows that the majority of statistical regions use GAUL boundaries (70% of countries), with a smaller share coming from NUTS (16% of countries) and other sources.

Step 3: Computing welfare estimates using household surveys

The primary difference between the SPID and GSAP databases is the construction of welfare estimates. The SPID contains direct estimates of poverty for all available years of survey data. On the other hand, the GSAP provides a common (line-up) year of poverty estimates for all countries, employing now-casting techniques for countries without survey data in the line-up year.

SPID

A set of standardized poverty indicators is computed for each subnational unit using household survey microdata. Monetary poverty rates are calculated at three international poverty lines: \$3.00, \$4.20, and \$8.30 per person per day (in 2021 PPP prices), which correspond to the World Bank's global extreme poverty line and two higher lines for lower-middle and upper-middle income countries. For each survey and each subnational region, we estimate the headcount poverty ratio (i.e., percent of the population living below each poverty line) using sampling weights (Foster, Greer and Thorbecke (FGT), 1984).

Specifically, consider N - a population of income-receiving individual i in a subnational unit, $i = 1, \dots N$, with income y_i. The poverty line is z and the income gap up to the poverty line for this individual is $max(0, z - y_i)$. The FGT class of poverty indices for the subnational unit is given by

$$FGT(y;\alpha) = \sum_{i=1}^{N} \frac{1}{N} \left[\frac{(z-y_i)}{z}\right]^{\alpha} I_i \qquad (1)$$

where $I_i = 1$ if $y_i \leq z$ and $I_i = 0$ otherwise. α is a given parameter, whose first three non-negative integer values are most commonly used. In particular, $FGT(y;0)$ is the subnational unit's headcount poverty ratio.

Regarding inequality, we computed several inequality measures, including the Gini index and the Theil index (GE(1)). The Gini index is defined as follows. Ranking the *cumulative* percentage of the population (from poor to rich) and the *cumulative* percentage of expenditure (or income) for all individuals in a subnational unit. The positions of individual i are respectively x_i and y_i in these rankings. The Gini index for this subnational unit is

$$Gini = 1 - \sum_{i=1}^{N}(x_i - x_{i-1})(y_i + y_{i-1}) \tag{2}$$

The Theil index belongs to the family of generalized entropy (GE) inequality measures and is defined as

$$GE(\gamma) = \frac{1}{\gamma(\gamma-1)}\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{y}}\right)^{\gamma} - 1 \tag{3}$$

where $\bar{y}$ is the subnational unit's mean income (consumption) per person. GE measures vary between zero and infinity, with zero representing an equal distribution and higher values representing higher levels of inequality. γ is a given parameter, whose first three non-negative integer values are most commonly used. We use GE(1) or Theil's T index. (See Haughton and Khandker (2009) for a textbook introduction to these inequality measures).

In addition, we also provide other indicators. These include the subnational unit's mean and median per capita welfare (in 2021 PPP dollars) and a measure of prosperity gap that measures the average shortfall from a prosperity standard of $28/day (Kraay *et al.*, 2023). All the estimates are obtained using population weights.

We also provide estimates for the World Bank's Multidimensional Poverty Measures (MPM) where data permit: specifically, the MPM headcount ratio (the share of people who are poor in multiple dimensions) and six component deprivation indicators (covering monetary poverty, education attainment, school enrolment, electricity, improved sanitation, and improved drinking water). Because the multidimensional measure requires additional survey questions (e.g. on education and basic services), it is only available for a subset of surveys. In the latest SPID version, we report multidimensional poverty for between 7,500 and 9,900 subnational observations, compared to around 16,500 for monetary poverty. All SPID indicators are computed directly from the microdata using standard poverty analysis techniques with survey sampling weights.

GSAP

For the GSAP, our goal is to estimate poverty in each subnational area for a common year (e.g., 2023), using the available survey data from earlier or later years. This involves applying the World Bank's standard "line-up" methodology to adjust national poverty estimates to common reference years as follows

$$y_r = y_s * \prod_{t=s}^{r-1}\left(1 + passthrough * g_{t,t+1}^{NA}\right) \tag{4}$$

In Equation (4), y_r is the extrapolated welfare distribution, y_s is the survey welfare distribution, $g_{t,t+1}^{NA}$ is real GDP per capita growth (or real household final consumption expenditure per capita), and the passthrough rate (passthrough) is less than 1. We use a passthrough rate of 0.7 for surveys with consumption aggregates and a passthrough rate of 1 for surveys with income aggregates (Mahler and Newhouse, 2024). For each country, we select the survey welfare distribution nearest to the line-up year, with preference given to newer surveys when multiple candidates are available.

For example, with the line-up year of 2023, three scenarios are handled: (a) if a survey was conducted in 2023 (or one year before or after) for a country, we use that survey's subnational poverty figures directly for GSAP; (b) if the latest survey is before 2023, we extrapolate forward each subnational welfare distribution to 2023 using growth rates from national accounts; and (c) if the earliest survey is after 2023, we back-cast backward similarly. We provide four line-up years in the GSAP: 2010, 2019, 2021, and 2023.

The extrapolation (or backcasting) assumes distribution-neutral growth; that is, the entire welfare distribution in a region is scaled up or down uniformly according to the growth in real per capita GDP (or household consumption) per capita for the country. Specifically, for each subnational area we multiply household consumption (income) levels in that area by the passthrough-adjusted growth factor between the survey year and the line-up year (e.g., 2023), then recompute the headcount poverty rate for that subnational area.

The GSAP has 10 indicators fewer than the SPID (including multidimensional poverty measures).

3. Data Overview

Figures 3 and 4 show the global maps of country-level estimates of poverty and inequality (Panels A). These country-level estimates, however, mask much variation at the subnational level (Panels B). As an example, Figure 5 further illustrates this point by showing the estimates at both the country level and subnational level for Indonesia over the past 15 years. This figure clearly shows that while subnational poverty and inequality range from 0.4% to 91.1% (headcount poverty) and 18.2% to 82.2% (Gini index), the corresponding ranges for country-level estimates are much smaller at 5.4% to 34.1% and 34.6% to 38.9%.

The subnational data can also better describe changes over time. We further zoom in the Africa region and plot in Figure 6 the annualized country-level changes with poverty and inequality (Panels A and C) next to the subnational changes (Panels B and D). There is much within-country variation at the subnational level. While the country-level changes range from -4.4% to 1.7% for poverty and -1.6% to 1.4% for inequality (Gini index), the subnational changes have a wider range and range from -6.6% to 4.6% for poverty and -3.9% to 1.9% for inequality. Figure A3 (Appendix A) plots the annualized country-level changes with poverty and inequality for the whole world.

4. Data Records

The datasets and associated documentation are publicly available from the World Bank's Development Data Hub. The current release is version 5, published in October 2025, with annual updates planned. The data are also accessible programmatically via the World Bank API. A static snapshot of the latest release (Excel format) has been deposited on Figshare. All data are distributed under the Creative Commons Attribution 4.0 International (CC BY 4.0) license.

The SPID provides a (unbalanced) panel dataset that offers survey-based estimates of poverty, inequality, and multidimensional poverty for subnational units over time. In its latest edition (version 5), the poverty and inequality part of SPID includes estimates for different sub-group populations: age groups (0-5, 6-11, 12-17, 17+), gender (male and female), and all-population. The data includes about 16,000 observations representing 2,211 unique subnational areas from 141 economies, covering roughly 75% of the world's population. On average, each country in the SPID has 10 data points for 28 subnational regions. In the multidimensional part of SPID, the data includes about 10,000 observations representing 2,026 unique subnational areas from 134 countries. These subnational units typically correspond to first-level administrative divisions (e.g. provinces or states), or occasionally more aggregated or disaggregated areas based on the country-specific survey design. More than 90% of the underlying surveys were conducted between 2003 and 2024. Notably, all SPID values are directly computed from actual survey microdata and reflect observed, not modelled, welfare distributions.

(Description of SPID variables)

code	Three-letter country code (ISO-3)
year	Year of survey data
rep_year	Reporting year
survname	Survey name
data	Population groups
data_group	Categories in each population groups
lvlvar	Level of disaggregation
welfaretype	Welfare type (income or consumption)
survey_coverage	Survey coverage
byvar	Data level
comparability	Comparability of data (data with the same number is comparable)
vintage	Data release vintage
sample	Representative area names
geo_code	Geolocation ID to link with shapefiles
poor300	Poverty headcount ratio at $3.00 (2021 PPP) (% of population)
poor420	Poverty headcount ratio at $4.20 (2021 PPP) (% of population)
poor830	Poverty headcount ratio at $8.30 (2021 PPP) (% of population)
mean2021	Survey average consumption or income per capita (2021 PPP $ per day)
gini	Gini index (World Bank estimate)
theil	Theil index (World Bank estimate)
prosgap2021	Average shortfall from a prosperity standard of $28/day (2021 PPP)
dep_poor1	Multidimensional poverty, Monetary poverty (% of population deprived)
dep_educ_com	Multidimensional poverty, Educational attainment (% of population deprived)
dep_educ_enr	Multidimensional poverty, Educational enrollment (% of population deprived)
dep_infra_elec	Multidimensional poverty, Electricity (% of population deprived)
dep_infra_imps	Multidimensional poverty, Sanitation (% of population deprived)
dep_infra_impw	Multidimensional poverty, Drinking water (% of population deprived)
mdpoor_i1	Multidimensional poverty, Headcount ratio (% of population)

In contrast, the GSAP provides a global snapshot of poverty for common reference (line-up) years. The October 2025 edition of the GSAP features headcount poverty ratios in several line-up years (2010, 2019, 2021, and 2023) across 172 economies with about 1,700 subnational areas for

2010, and about 1,900 subnational areas for 2019, 2021, and 2023. Since survey years vary by country, cross-country comparison of subnational poverty based on direct survey estimates in a single year is not possible. The GSAP addresses this challenge by using the World Bank's line-up methodology to estimate poverty for all countries in a single line-up year (e.g., 2023). Employing the same methodology behind the World Bank's official Poverty and Inequality Platform (PIP), the GSAP ensures that subnational poverty rates aggregate consistently to the country-level poverty rates published in the PIP database.

The latest edition of the GSAP dataset (October 2025) achieved near-global coverage: out of 218 World Bank-listed economies, poverty data is available for a total of 172 economies: 132 economies at the subnational level, and 40 economies at the national level only (often due to lack of subnational detail or no recent survey). In total, the GSAP provides poverty estimates (at $3.00, $4.20, $8.30/day, 2021 PPP) for an average of 1,859 subnational units, each corresponding to a geographical area in our global map.

(Description of GSAP variables)

code:	Three-letter country code (ISO-3)
baseyear:	Year of survey data
welfaretype:	Welfare type (income or consumption)
lineupyear:	Line-up year
survname:	Survey name
sample:	Representative area names
poor300_ln:	Poverty rate at $3.00 (2021 PPP, lineup est. of line-up year)
poor420_ln:	Poverty rate at $4.20 (2021 PPP, lineup est. of line-up year)
poor830_ln:	Poverty rate at $8.30 (2021 PPP, lineup est. of line-up year)
prosgap2021:	Prosperity gap (2021 PPP, lineup est. of line-up year)
geo_code:	Geolocation ID to link with shapefiles

We provide in Appendix A the full list of countries, data (survey) years, survey acronyms, and the number and the level of subnational units (Table A1), the number of subnational units over time broken down by seven global regions (Figure A2), and the summary statistics of the main welfare variables (Table A2).

5. Technical Validation

We ensure quality control for the SPID and GSAP datasets by implementing various validation checks, which leverage both internal institutional expertise and external expertise. These include the following.

i. <u>Consistency with country-level aggregates</u>: By construction, our subnational estimates are consistent with official country-level figures. In the SPID, whenever a country's survey data covers 100% of the population across the listed subnational regions, the population-weighted average of the subnational poverty rates equals the country-level poverty rate for that survey. We verify this using the underlying microdata and PIP's country-level results. Any discrepancies (due to rounding or small sample issues) are typically negligible. In the GSAP, the methodology forces consistency: subnational poverty rates aggregate exactly to the official country-level poverty rates used in each PIP release (i.e., the GSAP essentially disaggregates the country-level poverty pie into regional pieces without changing the total). We also compare SPID trends against published regional poverty trends (such as those in World Bank regional reports) to ensure they are consistent. These validation checks provide assurance that our subnational data do not contradict the well-vetted national (country-level) statistics, but they add more spatial detail to them.

ii. Geospatial alignment: We validate that each subnational data record correctly maps to the intended geographic unit. This is done by mapping the welfare estimates using the subnational boundary data to visually inspect them. For example, we map the poverty rates within several countries including Nigeria, India, and Brazil and confirm that the patterns reflected known spatial trends (e.g., higher poverty in northern Nigeria vs. southern Nigeria).

We also ensure that every statistical region has a unique identifier (*geo_code*), and that all regions from the survey data appear on the map. The geospatial data is checked so that there are no duplicate or missing entries – every subnational unit defined in surveys has one geometry and one set of welfare estimates, linked by the *geo_code* identifier. We ensure subnational boundary data is topologically consistent and aligns with national level boundaries defined by the World Bank.

Additionally, we reviewed the distribution of the number of subnational units per country. As shown in Table A1 (Appendix A), most countries have between 2 and 35 subnational units, with a few large federal countries having more (e.g., over 80 for the Philippines, which reports at a lower geographic level). We confirmed that the observed outliers are explained by the country context and differences in survey design.

iii. Temporal consistency and population coverage: We examine the panel aspect of SPID to ensure that we handle it appropriately when regions changed (merged or split). For instance, if a country's survey from 2005 reports poverty for 8 regions and a survey from 2015 for 10 regions due to a split, we either merge the latter's regions to be consistent with those in the former when the sub-region or crosswalk table is available, or we flag the change and use new boundary information. By consulting country-specific documentation (particularly advice from World Bank country economists), we make judgement calls to maximize comparability over time. The result is that SPID's subnational trends over time are "apples-to-apples" for the same *geo_code*. Users can consult the metadata to understand how subnational units change when identifiers vary over time within a country.

We also cross-checked that the share of world population covered by SPID matches expectations. The 140 economies in the SPID account for about 77% of the global population (i.e., missing mainly some high-income countries and a few large low-income ones with no data). Summing up the population represented by all the SPID records (using survey weights and population projections), we confirmed it aligns with around 6.3 billion people out of the total world population of approximately 8.1 billion people in 2024 (United Nations, 2024). This aggregate check helps identify if data from any large-population country is accidentally omitted – none is, aside from those known to be missing (e.g., no data for Afghanistan).

iv. Comparison with other datasets: Although there are few directly comparable global subnational poverty datasets, we compare our data with two related datasets for sanity checks. First, we looked at the Oxford Poverty and Human Development Initiative (OPHI) regional Multidimensional Poverty Index (MPI) data, which covers some overlapping indicators in a subset of countries. Where OPHI's subnational MPI is available, our SPID monetary poverty rankings tend to correlate in expected ways (e.g., regions that OPHI finds to have high multidimensional poverty generally have high monetary poverty in our data). Second, we compared subnational GDP per capita patterns (from Wenz *et al.* 2023) with poverty patterns, to ensure no obvious inversions (one would expect richer regions to have lower poverty). Indeed, in large countries like India, the lowest-poverty states in the SPID correspond to the highest GDP per capita states in the DOSE dataset. While such cross-dataset validation does not offer strict proof, it provides reassurance that our subnational poverty estimates are generally not very different from those in other datasets.

v. Peer review and country feedback: The methodology and preliminary results are circulated internally within the World Bank, especially to regional statistical teams. We incorporate feedback from country teams (including World Bank poverty economists who are familiar with the national data) to refine the data. In a few cases, country experts identified issues such as an outdated survey being used when a newer one is available or suggested alternative ways to merge regions; we updated the dataset accordingly. A preliminary technical note documenting basic features of the SPID/GSAP (Nguyen *et al.*, 2023) was also circulated and carefully reviewed as part of the Global Poverty Monitoring Technical Note series. This ensured the data production process meets the World Bank's quality standards.

vi. Documentation: Finally, because the data are ultimately derived from many different surveys in different time periods across the world, there can be inherent differences (e.g., survey design changes could be made to better reflect current living standards). We include metadata (including survey name, survey year, and survey type) in the data. Nonetheless, the inclusion of only official survey data (not modelled estimates) in the SPID means that the subnational figures should align with country official statistics.

We further discuss below some data notes.

6. Usage Notes

When using the SPID and GSAP data, several important considerations and limitations should be kept in mind:

- *Incomplete country coverage*: These datasets do not include every country. Notably, countries lacking any suitable household survey are absent. In some cases, surveys exist but only report national figures (no subnational breakdown) or the microdata access is restricted – such countries appear in the GSAP only at the national level or not at all. For example, China is included only as a national entry due to data access limitations (i.e., its recent surveys do not permit publishing province-level poverty). A total of 78 economies is missing from the SPID and about 40 from the GSAP (the latter include some high-income small countries without recent poverty data). Users should consult the provided list of countries to see which are covered.

- *Time coverage and frequency*: The SPID is not a yearly time series for each country, but rather a compilation of survey years. Many developing countries conduct household income/expenditure surveys roughly every 3–5 years. As a result, the SPID might have only a few data points per country (the average is 10 observations per country). Some poorer or fragile countries have even sparser data. Thus, the SPID should not be interpreted as capturing short-term annual fluctuations; instead, it provides medium-term trend indications. Moreover, because surveys in different countries occurred in different years, cross-country comparisons for a given year should use the GSAP for consistency, rather than the SPID data for that year.

  The line-up methodology in the GSAP assumes distribution-neutral growth. If inequality was changing in a country between the survey year and the line-up year (e.g., 2019), our subnational extrapolations may be off. For example, if a recession hit some regions harder than others, the uniform growth assumption might misestimate their poverty. The GSAP should thus be seen as an informed projection for the line-up year (2019), not an observed measurement. In general, where possible, users may prefer the SPID's actual survey data for analysis of specific countries/times and use the GSAP for broad cross-country snapshots or mapping.

- *Survey comparability, including administrative boundary change*: While the GMD harmonization imposes a degree of consistency, not all country surveys are strictly comparable over time. Differences in survey questionnaires, sampling, and welfare aggregate construction can introduce biases across countries. We tried to minimize this by using the World Bank's harmonized welfare measures and international poverty lines. Still, caution is warranted, especially when comparing subnational poverty rates across very different countries. Some small countries use income surveys which tend to show higher inequality and potentially different poverty outcomes than consumption-based surveys used elsewhere. We mix income and consumption data out of necessity (following standard practice in global poverty monitoring).

  In addition, constructing a panel of subnational poverty over time requires careful handling of cases where administrative boundaries or survey representativeness changed. In some countries, we have to merge smaller regions or use higher-level groupings to ensure comparability over time. The panel aspect of SPID (covering 2003–2024) is therefore not always balanced – some countries have more frequent survey data than others. Nonetheless, the SPID represents the largest compilation to date of directly observed subnational poverty trends in the developing world.

- *Spatial price differences*: One limitation is that in some countries, the welfare data may not account for cost-of-living differences across regions (spatial deflation). Many surveys do adjust for urban and rural price levels, but not all have the data to fully adjust expenditures across all regions. If a country has large spatial price variation and no adjustment, its poverty map might somewhat overstate poverty in high-cost regions and understate in low-cost regions. Unfortunately, we are constrained by what the original survey data did. Future improvements might incorporate external spatial price indices where available.

- *Uncertainty and error margins*: Especially for smaller regions or when survey sample sizes are limited, the estimates have sampling error. For instance, a poverty rate for a single region might have a confidence interval of a few percentage points. We encourage users to consider those when making comparisons – differences of 1 or 2 percentage points might not be statistically significant.

GSAP and SPID in recent studies

Despite its infancy, to date the GSAP and SPID datasets have been analyzed to study the evolution of income inequality over time (Chrisendo *et al.*, 2025). These datasets are particularly relevant to studies of climate change, and they were combined with climate data to investigate a number of climate change topics. These include the impacts of flood exposure on poverty (Rentschler *et al.*, 2022), exposure of poorer individuals to drought-to-downpour events (Zhang *et al.*, 2023), compound flood-heatwave extremes (Zhao *et al.*, 2024) and different types of climate shocks (Balasubramanian *et al.*, 2025), inequalities in exposure to compound drought-heatwaves between low-income and high-income regions (Zhang *et al.*, 2024), the interaction of poverty and cell phone connectivity and vulnerability of certain communities to climate hazards (Osoro and Oughton, 2023), combining remote sensing and socio-economic data for multi-dimensional disaster risk assessment (Salhab, 2024), and the impacts of global warming on various forms of poverty and inequality (Dang *et al.*, 2024; Dang *et al.*, 2026).

Other studied topics include the relationships between ambient air pollution exposure and poverty (Rentschler and Leonova, 2023) and armed conflicts and poverty (Mueller and Techasunthornwat, 2020). A recent study also benchmarks nightlight data against these data to investigate the validity of nightlights as a proxy for development (Huber and Mayoral, 2024).

Further thoughts for consideration

Despite existing limitations, the SPID and the GSAP offer an advantage that they are based on official and observed data, to the extent possible, and are part of an integrated platform. The Geospatial Poverty Portal allows users to interactively explore the data, overlay it with other indicators, and download custom subsets. Since our data are georeferenced, researchers have merged the SPID and GSAP datasets with various other data sources—such as climate data, conflict event data, or infrastructure location data—to study their relationships with poverty at the subnational level. As more data are available at more disaggregated level, these data can be combined with the SPID and GSAP datasets for richer analysis.

As new surveys become available, we will extend the panel and keep the global atlas up to date. In addition, improvements like incorporating subnational price adjustments or better harmonizing multidimensional indicators are on the research agenda. The SPID and GSAP datasets can contribute to providing a timely, accessible, and policy-relevant view of global poverty's spatial landscape, serving as a foundation for further analysis and action on ending poverty.

7. Data Availability

The latest version of data (October 2025) are available on the World Bank's Development Data Hub website: for the SPID (https://datacatalog.worldbank.org/int/search/dataset/0064796/subnational_poverty_and_inequality_database_spid) and the GSAP (https://datacatalog.worldbank.org/int/search/dataset/0042041/global_subnational_poverty_atlas_gsap). The Geospatial Poverty Portal features interactive maps featuring data from SPID and GSAP (https://pipmaps.worldbank.org/en/data/datatopics/poverty-portal/home).

8. Code Availability

The welfare calculations were performed in Stata using the World Bank's internal data system and poverty calculation code (based on the Poverty and Inequality Platform (PIP) methodology). These scripts are not publicly archived, but follow the established methods as described in the Methods section. All data inputs (household surveys) are either publicly available or available through the World Bank under agreements with national statistics offices. The geospatial boundary data was prepared using R. The development version of the code is hosted at https://github.com/bbrunckh/spid-boundaries. Input boundary data sources are publicly available or were provided to the World Bank under agreements with national statistics offices. Researchers interested in reproducing the exact dataset may contact the authors for further information.

9. Acknowledgements

The development of the SPID and GSAP data was a team effort. We thank the Data for Goals (D4G) team, Global Poverty and Inequality Data (GPID) team, and the six World Bank Regional Statistics Teams for their extensive work in harmonizing survey data, including contributions from Andres Castaneda, Aziz Atamanov, Cameron Haddad, Carolina Diaz-Bonilla, Christoph Lakner, Daniel Mahler, Daylan Alberto Gomez, Diana Marcela Castro, Elizabeth Foster, Gabriel Lara Ibarra, Haoyu Wu, Hernan Winkler, Hugo Nopo, Ifeanyi Edochie, Ikuko Uochi, Jaime Estuardo Romero, Jose Montes, Karen Barreto Herrera, Kelly Yelitza Munoz, Laura Liliana Herrera, Martha Celmira Mendoza, Natsuko Nozaki, Nobuo Yoshida, Reno Dewina, Sergio Olivieri, Veronica Sonia Talledo, and Zurab Sajaia, among others, who assisted in data compilation, methodology design, and review. We are also grateful for comments on earlier drafts from Joao Pedro Azevedo, Benu Bidani, Paul Corral, Hongxi Zhao, Qiong Li, Trong-Anh Trinh, Carlos Sabatino, and many country economists in the Poverty and Equity Global Practice. We are grateful for funding support from the UK Foreign Commonwealth and Development Office (FCDO)'s Data and Evidence for Tackling Extreme Poverty (DEEP) Research Program.

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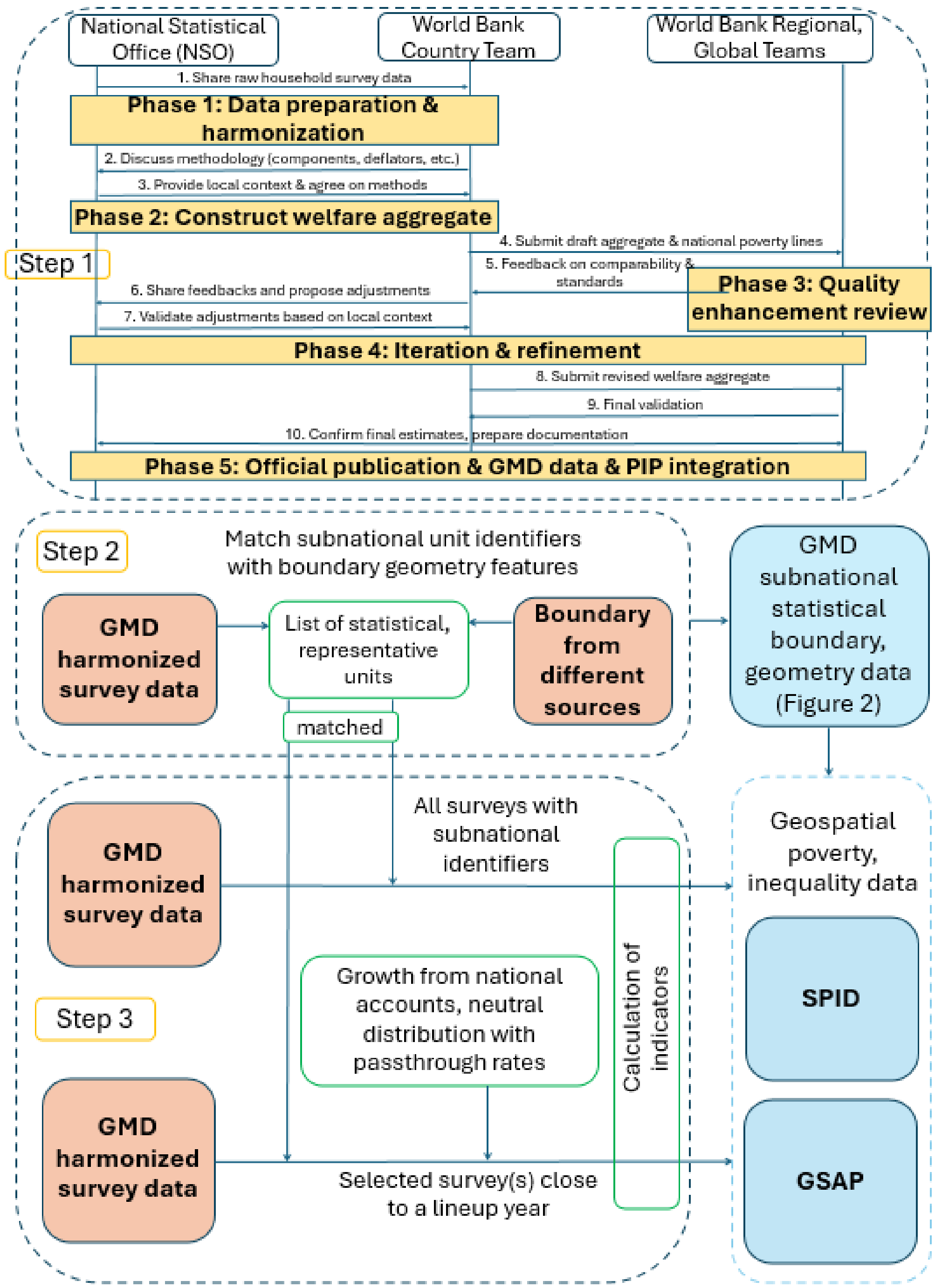
writing – final editing: H.D.

Competing interests
We declare no conflict of interest.

Figures

Figure 1: Data construction process for SPID and GSAP



Note: For the GSAP, there is an additional processing step of adding the lined-up poverty estimates from the World Bank's Global Monitoring Database (GMD) based on household survey data. Step 1 is also the standard procedures employed to generate the harmonized welfare data underlying World Bank's poverty and inequality estimates.

Figure 2: Compiling geospatial feature variables

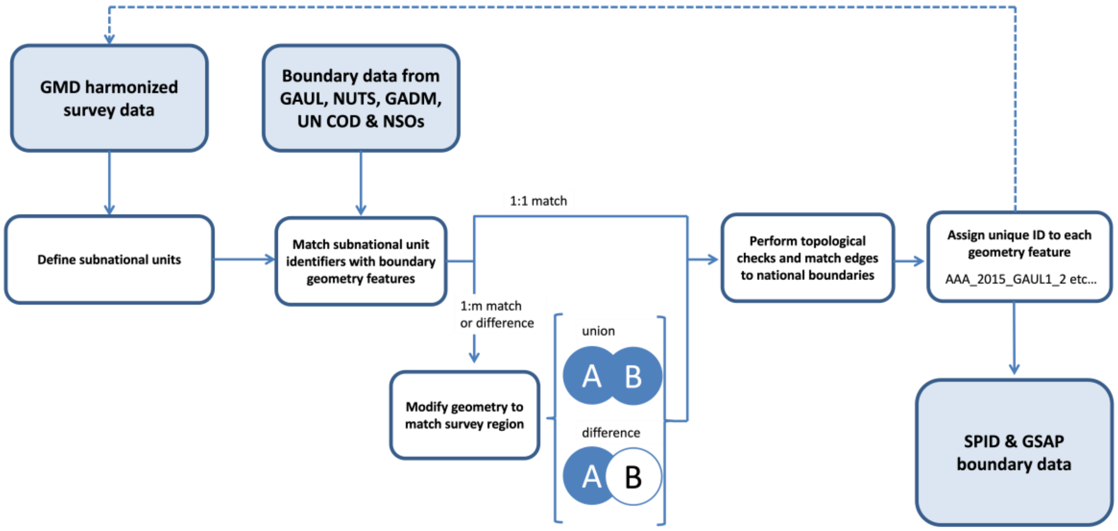
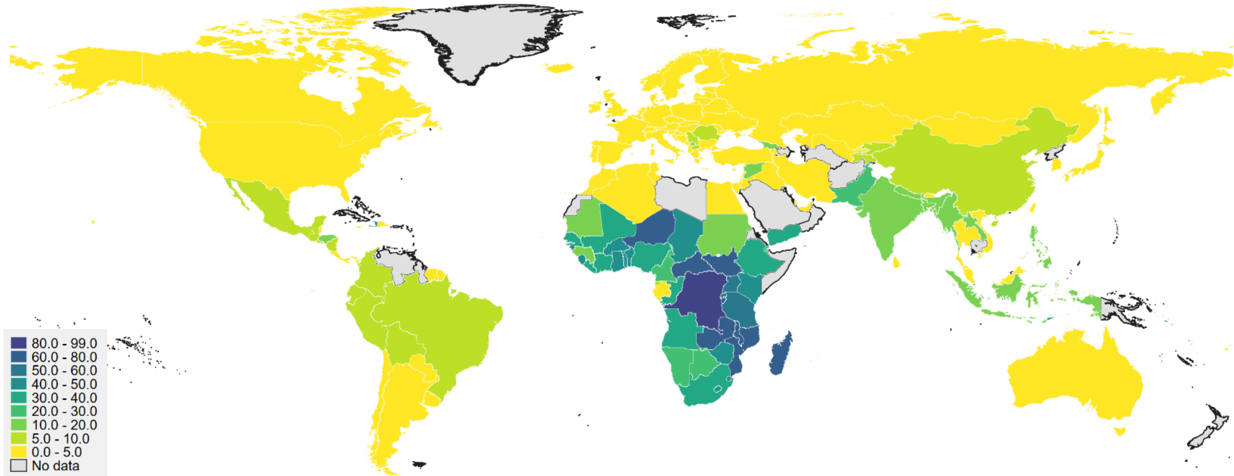
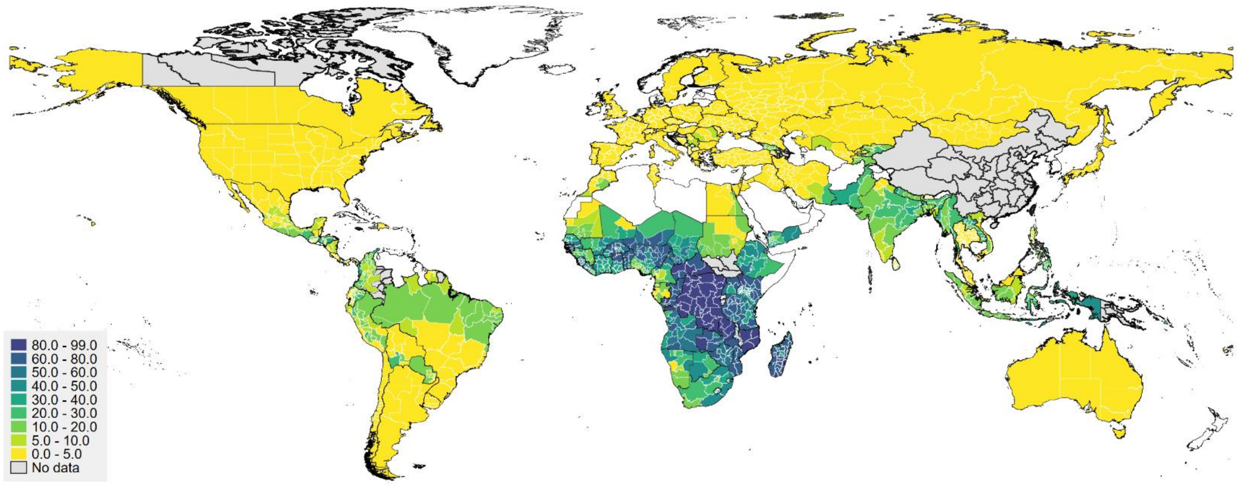


Figure 3. Global poverty: Country-level data (PIP) vs subnational-level data (SPID)

Panel A: Country-level estimates



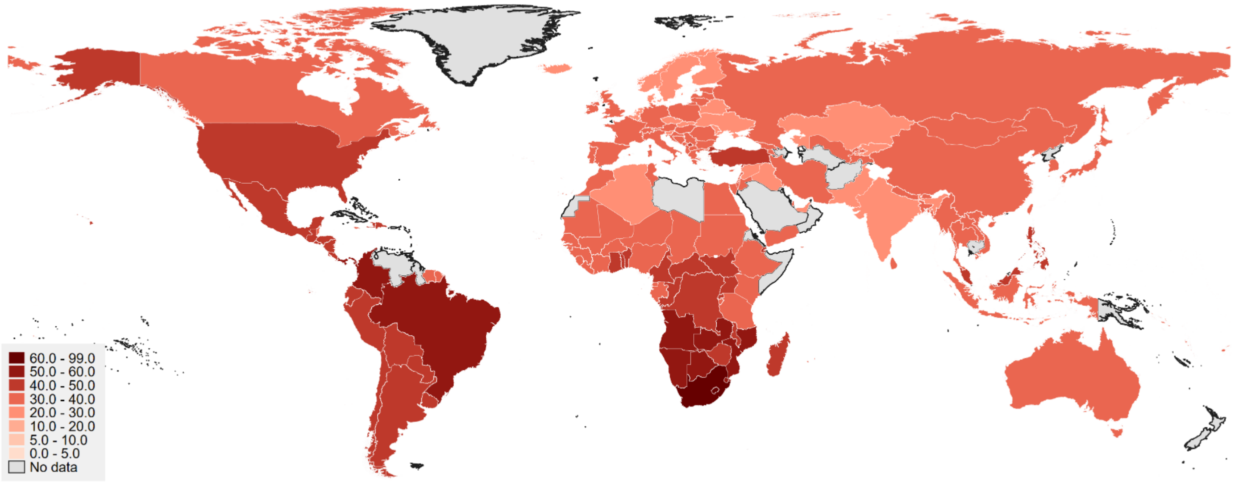
Panel B: Subnational estimates



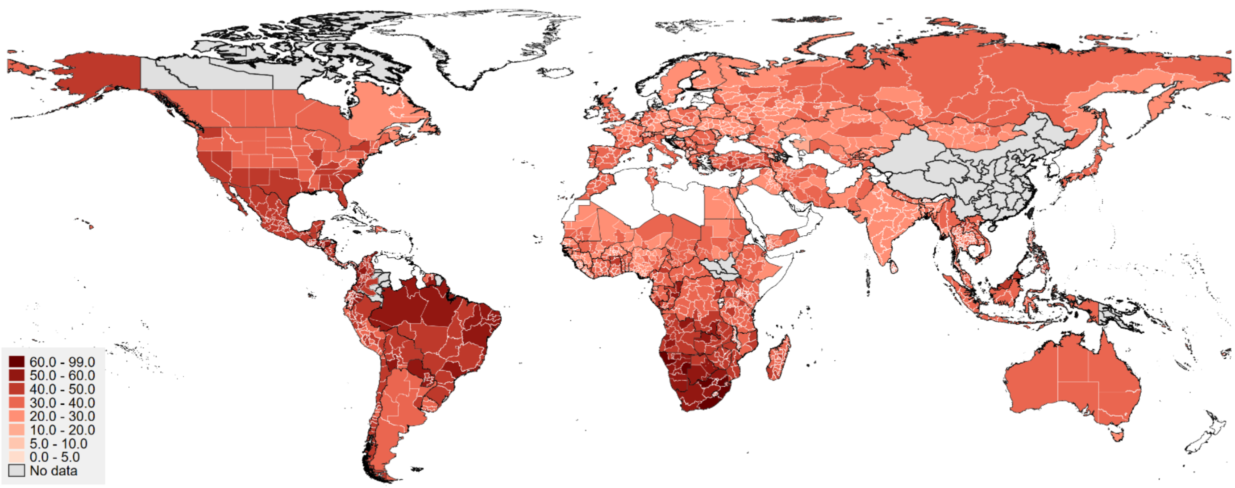
Notes: Poverty is measured by the headcount ratio at $3.00/day, averaged for the period 2010 – 2024.

Figure 4. Global Inequality: Country-level data (PIP) vs subnational-level data (SPID)

Panel A: Country-level estimates



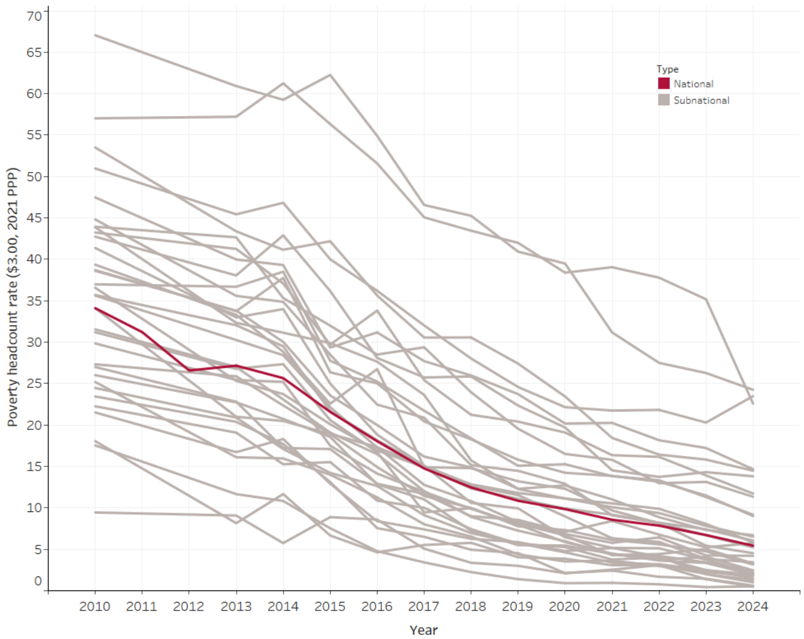
Panel B: Subnational estimates



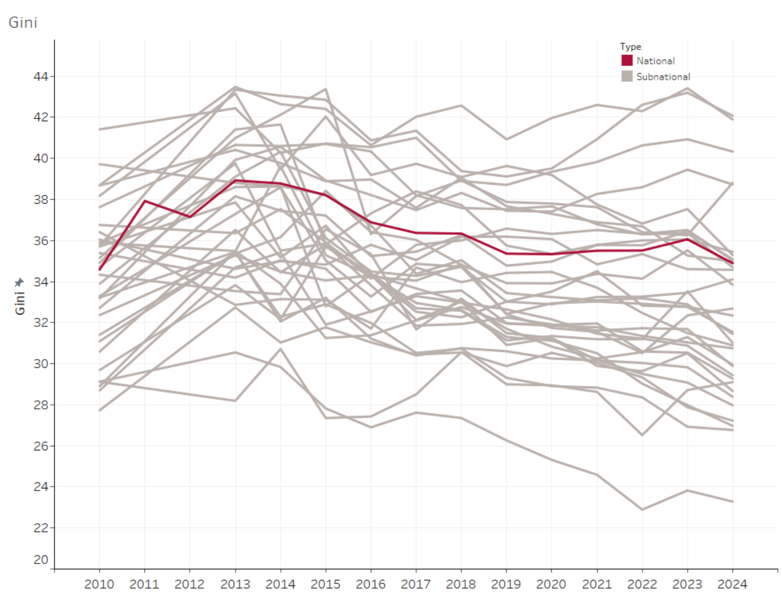
Notes: Inequality is measured by Gini index, averaged for the period 2010 – 2024.

Figure 5. Comparing national and subnational estimates for Indonesia

Panel A: Poverty



Panel B: Inequality



Notes: Poverty is measured by the headcount ratio at $3.00/day, inequality is measured by Gini index.

Figure 6. Annualized changes in poverty ($3.00 a day) and inequality for Africa over the past decade (circa 2010 – circa 2020) (percent)

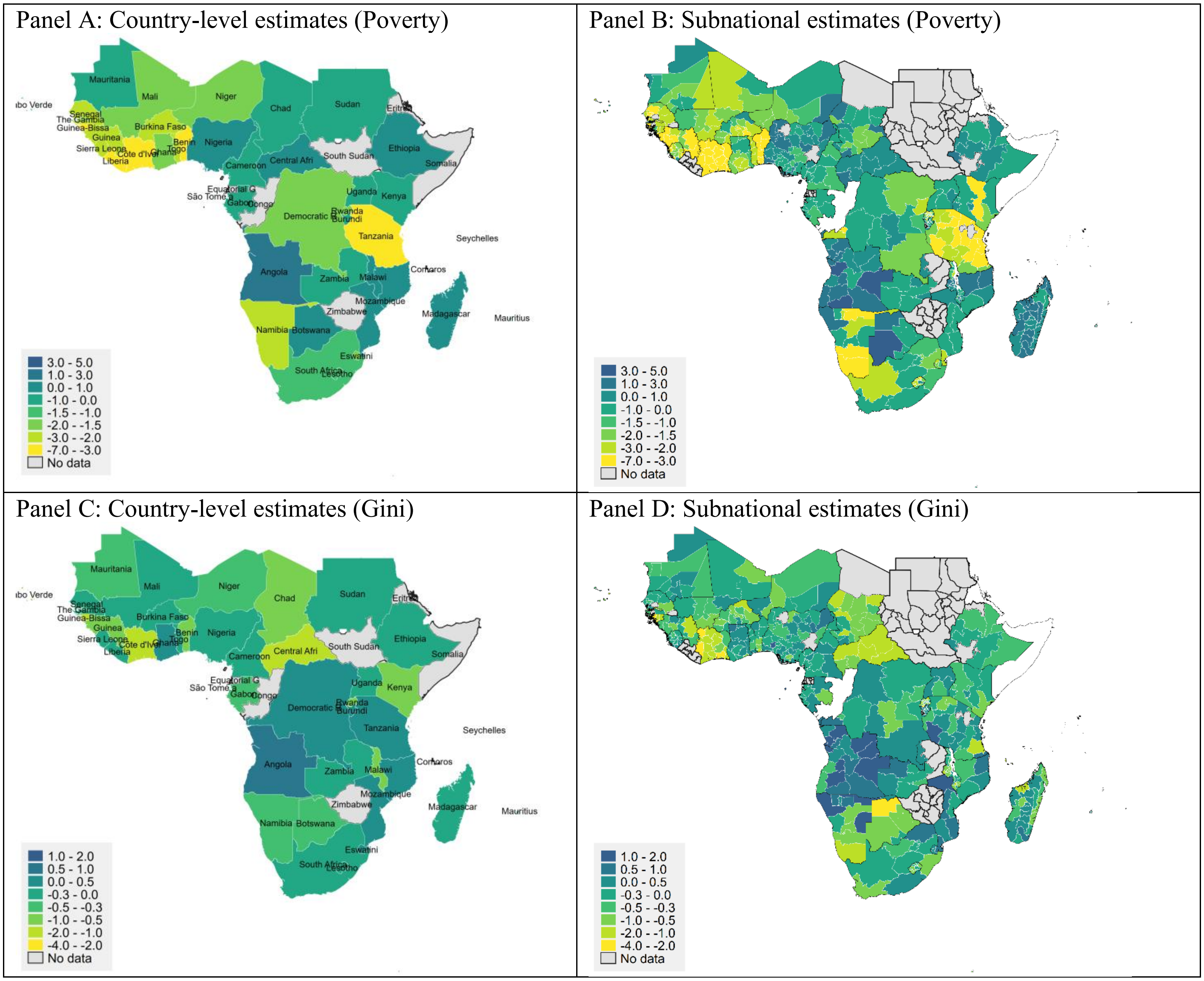


Table 1. Comparison of SPID and GSAP features

	Subnational Poverty and Inequality Database	Global Subnational Atlas of Poverty
Latest version	October 2025 (Version 5.0)	October 2025 (Version 5.0)
Poverty estimates	Direct estimates using GMD. Poverty estimates are available only in the years a country has survey data and matched subnational boundaries. SPID also includes direct estimates at the subnational level for subgroup population such as gender and age cohorts.	All countries have poverty estimates for a common (line-up) year. For countries without microdata in the line-up year, poverty nowcasting is used. Line-up years include: 2010, 2019, 2021, and 2023
Number of indicators	14	4
Country coverage	140	172
Time coverage	1989-2024	2010, 2019, 2021, 2023
Data structure	Unbalanced panel	Cross sections
Recommended use	Panel data analysis (i.e., tracking changes over time for fewer subnational units)	Cross-sectional analysis (i.e., focusing on more subnational units but at a single point in time)

Notes: Features based on the October 2025 editions of SPID and GSAP.

References

1. Devarajan, S. (2013). Africa's statistical tragedy. *Review of Income and Wealth*, *59*, S9-S15.
2. Jerven, M. (2013). *Poor numbers: how we are misled by African development statistics and what to do about it*. Cornell University Press.
3. Sandefur, J., & Glassman, A. (2015). The political economy of bad data: Evidence from African survey and administrative statistics. *Journal of Development Studies*, 51(2), 116-132.
4. Beegle, K., Christiaensen, L., Dabalen, A., & Gaddis, I. (2016). *Poverty in a Rising Africa*. Washington DC: The World Bank.
5. Dargent, E., Lotta, G., Mejía-Guerra, J. A., & Moncada, G. (2018). *The political economy of statistical capacity in Latin America: Who wants to know?* Inter-American Development Bank. https://publications.iadb.org/en/who-wants-know-political-economy-statistical-capacity-latin-america
6. World Bank. (2021). *World Development Report 2021: Data for Better Lives*. World Bank. https://wdr2021.worldbank.org/
7. Dang, H. A. H., & Serajuddin, U. (2020). Tracking the sustainable development goals: Emerging measurement challenges and further reflections. *World Development*, *127*, 104570.
8. Auerbach, J., Bowen, C. M., Citro, C. F., Pierson, S., & Seeskin, Z. H. (2025). The Nation's Data at Risk: The First Annual Report on the Federal Statistical System. *Harvard Data Science Review*, *7*(1).
9. Dang, H. A., Carletto, C., & Jolliffe, D. (2025a). Better Tracking SDG Progress with Fewer Resources? A Call for More Innovative Data Uses. *World Development Perspectives*, 39, 100721.
10. Hoffmann, R., Patange, O., Zimm, C., Pachauri, S., Belmin, C., Pelz, S., ... & Mintz-Woo, K. (2025). Subnational survey data reveal persistent gaps in living standards across 75 low and middle-income countries. *Nature Communications*, *16*(1), 4986.
11. Mikou, M., Vallet, A., & Guivarch, C. (2024). Harmonized disposable income dataset for Europe at subnational level. *Scientific Data*, *11*(1), 308.
12. Wenz, L., Carr, R. D., Kögel, N., Kotz, M., & Kalkuhl, M. (2023). DOSE–Global data set of reported sub-national economic output. *Scientific Data*, *10*(1), 425.
13. Smits, J., & Permanyer, I. (2019). The subnational human development database. *Scientific data*, *6*(1), 1-15.
14. Suppa, N., & Kanagaratnam, U. (2025). The global Multidimensional Poverty Index: Harmonised level estimates and their changes over time. *Scientific Data*, *12*(1), 153.
15. Angrist, J. D. & Krueger, A. B. (1999). Empirical strategies in labor economics. In *Handbook of Labor Economics*, Vol. 3A, 1277–1366 (North-Holland).
16. Gardes, F., Duncan, G. J., Gaubert, P., Gurgand, M. & Starzec, C. (2005). Panel and pseudo-panel estimation of cross-sectional and time series elasticities of food consumption: The case of US and Polish data. *Journal of Business and Economic Statistics*. **23**, 242–253.

17. Damania, R., Desbureaux, S. & Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, **102**, 102335.
18. Kalkuhl, M. & Wenz, L. (2020). The impact of climate conditions on economic production: Evidence from a global panel of regions. *Journal of Environmental Economics and Management,* **103**, 102360.
19. Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, 52(3): 761-766.
20. Haughton, J., & Khandker, S. R. (2009). *Handbook on poverty and inequality*. Washington DC: The World Bank.
21. Kraay, A., Decerf, B., Jolliffe, D., Lakner, C., Ozler, B., Sterck, O., & Yonzan, N. (2023). *A new distribution sensitive index for measuring welfare, poverty, and inequality*. Policy Research Working Paper 10470. Washington DC: The World Bank.
22. Mahler, D. G., & Newhouse, D. (2024). Changes to the Extrapolation Method for Global Poverty Estimation. *Global Poverty Monitoring Technical Note*, *35*.
23. World Bank. (2025). *Poverty and Inequality Platform Methodology Handbook*. Edition 2025-09. Available at https://datanalytics.worldbank.org/PIP-Methodology/.
24. United Nations. (2024). *World Population Prospects 2024: Data Sources*. Available at https://population.un.org/wpp/
25. Nguyen, M. C., Yang, J., Dang, H. A., & Sabatino, C. (2023). *On the construction of the World Bank's Subnational Poverty and Inequality Databases: Documentation* (No. 31). Washington DC: The World Bank.
26. Chrisendo, D., Niva, V., Hoffmann, R., Masoumzadeh Sayyar, S., Rocha, J., Sandström, V., ... & Kummu, M. (2025). Rising income inequality across half of global population and socioecological implications. *Nature Sustainability*, **8**, 1601–1613.
27. Rentschler, J., Salhab, M., & Jafino, B. A. (2022). Flood exposure and poverty in 188 countries. *Nature Communications*, *13*(1), 3527.
28. Zhang, B., Wang, S., Zscheischler, J., & Moradkhani, H. (2023). Higher exposure of poorer people to emerging weather whiplash in a warmer world. *Geophysical Research Letters*, *50*(21), e2023GL105640.
29. Zhao, Q., Gao, L., Meng, Q., & Zhu, M. (2024). Climate warming will exacerbate unequal exposure to compound flood-heatwave extremes. *Earth's Future*, *12*(12), e2024EF005179.
30. Balasubramanian, C., Baquie, S., & Fuchs, A. (2025). *Climate Risk and Poverty in the Middle East and North Africa*. Policy Research Working Paper 11092. Washington, DC: World Bank.
31. Zhang, B., Wang, S., & Slater, L. (2024). Anthropogenic climate change doubled the frequency of compound drought and heatwaves in low-income regions. *Communications Earth & Environment*, *5*(1), 715.
32. Osoro, B., & Oughton, E. (2023). A Global Geospatial Assessment of the Poverty-line Unconnected Population Vulnerable to Climate Hazards. Available at SSRN: https://ssrn.com/abstract=4528192.
33. Salhab, M. (2024). *Can data from space address critical data gaps on earth? Investigating the extent to which holistic disaster risk can be estimated using remote sensing data.* (Doctoral dissertation, University College London).

34. Dang, H. A. H., Hallegatte, S., & Trinh, T. A. (2024). Does global warming worsen poverty and inequality? An updated review. *Journal of Economic Surveys*, *38*(5), 1873-1905.
35. Dang, H. A. H., Hallegatte, S., Nguyen, M. C., & Trinh, T. A. (2026). Impacts of global warming on subnational poverty and inequality. *Nature Climate Change*, 16(2), 207–213.
36. Rentschler, J., & Leonova, N. (2023). Global air pollution exposure and poverty. *Nature Communications*, *14*(1), 4432.
Mueller, H., & Techasunthornwat, C. (2020). *Conflict and poverty*. Policy Research Working Paper 9455. Washington, DC: World Bank.
37. Huber, J. D., & Mayoral, L. (2024). *Economic Development in Pixels: The Limitations of Nightlights and New Spatially Disaggregated Measures of Consumption and Poverty*. BSE Working paper 1433, Barcelona School of Economics.

Appendix A: Additional tables and figures

Table A1. List of countries, survey years and subnational units

No.	Economy	Data year	Survey acronym	Subnational layers	Number of subnational units (modified)	Boundary source
1	Albania	2012, 2014, 2015, 2016, 2017, 2018, 2019, 2020	HBS, LSMS	Prefecture	12	NUTS
2	Angola	2000	HBS	Province	7	GAUL
3	Angola	2008, 2018	IBEP-MICS, IDREA	Province	18	GAUL
4	Argentina	2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EPHC-S2	Statistical region	6 (6)	GAULx
5	Armenia	2005, 2010, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	ILCS	Province	11	GAUL
6	Australia	2010, 2014	SIH-HES-LIS, SIH-LIS	State	7 (1)	GAULx
7	Australia	2016, 2018	SIH-HES-LIS, SIH-LIS	State	8	GAUL
8	Austria	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS1	3	NUTS
9	Azerbaijan	2002, 2003	HBS	Economic region	8 (1)	GAULx
10	Azerbaijan	2004, 2005	HBS	Economic region	10 (1)	GAULx
11	Bangladesh	2000, 2005, 2010, 2016, 2022	HIES	Division (6)	7	GAUL
12	Barbados	2016	BSLC	Parishes	11	GAUL
13	Belarus	1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020	HHS	Region	7	GAUL
14	Belgium	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS1	3	NUTS
15	Belize	2018	HBS	District	6	GAUL
16	Benin	2011, 2015, 2018, 2021	EHCVM, EMICOV	Department	12	GAUL
17	Bhutan	2003, 2007, 2012, 2017, 2022	BLSS	District	20	GAUL

18	Bolivia	2000, 2001, 2002, 2005, 2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	ECH, EH	Department	8 (1)	GAULx
19	Bosnia and Herzegovina	2007, 2011	HBS	Entity	3 (1)	GAULx
20	Botswana	2002, 2009, 2015	BMTHS, CWIS, HIES	Statistical region	7 (5)	DKx
21	Brazil	2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	PNAD, PNADC-E1, PNADC-E5	State	27	GAUL
22	Bulgaria	2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS1	2	NUTS
23	Burkina Faso	2003, 2009, 2014, 2018, 2021	ECVM, EHCVM, EMC	Region	13	GAUL
24	Burundi	2006, 2013	ECVMB, QUIBB	Province	17	GAUL
25	Burundi	2020	EICVMB	Province	18 (3)	GAULx
26	Cabo Verde	2001, 2007, 2015	IDRF, QUIBB	Island	9	GAUL
27	Cameroon	2001, 2007, 2014, 2021	ECAM-II, ECAM-III, ECAM-IV, ECAM-V	Region	10	GAUL
28	Canada	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020	CIS-LIS, SLID-LIS	Province	10	GAUL
29	Central African Republic	2008, 2021	ECASEB, EHCVM	Statistical region	7 (6)	GAULx
30	Chad	2003	ECOSIT-II	Region	12 (7)	GADMx
31	Chad	2011, 2018	ECOSIT-III, EHCVM	Region	20 (1)	GADMx
32	Chad	2022	EHCVM	Region	21 (2)	GADMx
33	Chile	2000, 2006	CASEN	Region	13 (2)	GAULx
34	Chile	2009, 2011, 2013	CASEN	Region	15	GAUL
35	Chile	2015	CASEN	Region	15 (1)	GAULx
36	Chile	2017, 2020, 2022	CASEN	Region	16 (1)	GAULx
37	Colombia	2001	ECH	Department	22 (1)	GAULx
38	Colombia	2002	ECH	Department	23 (1)	GAULx
39	Colombia	2003, 2004, 2005, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	ECH, GEIH	Department	24 (1)	GAULx
40	Comoros	2004, 2013	EESIC, EIM	Region	3	GAUL
41	Congo, Dem. Rep.	2004, 2012	E123	Province (11)	11	GAUL

42	Congo, Dem. Rep.	2020	EGI-ODD	Province (11)	26	GADM
43	Congo, Rep.	2011	ECOM	Department	12	GAUL
44	Costa Rica	1989, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EHPM, ENAHO	Province	6	DK
45	Croatia	2010	EU-SILC	NUTS1	3	NUTS
46	Czechia	2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS2	8	NUTS
47	Côte d'Ivoire	2002	ENV	District	11	DHS
48	Côte d'Ivoire	2015, 2018, 2021	EHCVM, ENV	District	14	GAUL
49	Côte d'Ivoire	2008	ENV	District	19	DK
50	Djibouti	2012, 2017	EDAM	Region	6	GADM
51	Dominican Republic	2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2018, 2019, 2020, 2021, 2022, 2023, 2024	ECNFT-Q03, ENFT	Statistical region	4 (4)	GAULx
52	Ecuador	2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012	ENEMDU	Province	22	GAUL
53	Ecuador	2013, 2018	ENEMDU	Province	24	GAUL
54	Ecuador	2014, 2015, 2016, 2017, 2019	ENEMDU	Province	25	GAUL
55	Egypt, Arab Rep.	2010, 2012, 2015, 2017, 2019, 2021	HIECS	Region	4 (4)	GAULx
56	Egypt, Arab Rep.	2021	HIECS	Governorate	26	GAUL
57	El Salvador	2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2021, 2022, 2023	EHPM	Department	14	GAUL
58	Equatorial Guinea	2022	ENH2	Province	7	GAUL
59	Eswatini	2000, 2009, 2016	HIES	Region	4	GAUL
60	Ethiopia	2004	HICES	Region	9	GAUL
61	Ethiopia	2010, 2015	HICES	Region	11	GAUL
62	Ethiopia	2021	HCES	Region	11 (1)	GAULx
63	Fiji	2002, 2008, 2013, 2019	HIES	Division	4	GAUL
64	Finland	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS2	4	NUTS
65	France	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021	EU-SILC	NUTS2	22	NUTS

66	Gabon	2005, 2017	EGEP	Statistical region	6 (4)	GAULx
67	Gambia, The	2010, 2015, 2020	IHS	Local government areas	8 (2)	GAULx
68	Georgia	2002	HIS	Region	9 (1)	GAULx
69	Georgia	2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	HIS	Region	10 (1)	GAULx
70	Georgia	2023, 2024	HIS	Region	11	GAUL
71	Germany	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020	GSOEP-LIS	State	16	NUTS
72	Ghana	1998, 2005, 2012, 2016	GLSS-IV, GLSS-V, GLSS-VI, GLSS-VII	Region (10)	10	GAUL
73	Greece	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS1	4	NUTS
74	Guatemala	2000	ENCOVI	Developmen t region	8 (6)	GAULx
75	Guatemala	2006, 2014, 2023	ENCOVI	Department	22	GAUL
76	Guinea	2002, 2007, 2012, 2018	EHCVM, EIBEP, ELEP	Region	8	GAUL
77	Guinea-Bissau	2010, 2018, 2021	EHCVM, ILAP-II	Region	9	GAUL
78	Haiti	2012	ECVMAS	Department	10	GAUL
79	Honduras	2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2023, 2024	EPHPM	Statistical region	6 (6)	GAULx
80	Hungary	2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018	EU-SILC	NUTS1	3	NUTS
81	India	1993	NSS-SCH1	State	32 (3)	GAULx
82	India	2004, 2009, 2011	NSS-SCH1, NSS-SCH2	State	35	GAUL
83	India	2022	HCES	State	36 (5)	GAULx
84	Indonesia	2000	SUSENAS	Province	24 (6)	GAULx
85	Indonesia	2002	SUSENAS	Province	26 (2)	GAULx
86	Indonesia	2001	SUSENAS	Province	29 (3)	GAULx
87	Indonesia	2006	SUSENAS	Province	30 (2)	GAULx
88	Indonesia	2003, 2004	SUSENAS	Province	30 (3)	GAULx
89	Indonesia	2005	SUSENAS	Province	31 (2)	GAULx
90	Indonesia	2007, 2008, 2009, 2010, 2013, 2014, 2015, 2016, 2017, 2018,	SUSENAS	Province	33	GAUL

		2019, 2020, 2021, 2022, 2023, 2024				
91	Iran, Islamic Rep.	2009	HEIS	Province	30 (3)	GAULx
92	Iran, Islamic Rep.	2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	HEIS	Province	31 (5)	GAULx
93	Iraq	2006, 2012, 2023	IHSES	Governorate	18	GAUL
94	Israel	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021	HES-LIS	District	6	GAUL
95	Italy	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS1	5	NUTS
96	Japan	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020	JHPS-KHPS-LIS	Region	8 (7)	GAULx
97	Jordan	2006, 2008, 2010	HEIS	Statistical region	4 (3)	GAULx
98	Kazakhstan	2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018	HBS	Oblast	16 (1)	GAULx
99	Kazakhstan	2019, 2020, 2021	HBS	Oblast	17 (2)	GAULx
100	Kenya	1994, 1997, 2005, 2015	IHBS, WMS-II, WMS-III	Province (former)	8	GAUL
101	Kenya	2015, 2021, 2022	IHBS, KCHS	County	47	GADM
102	Kosovo	2009, 2010, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	HBS, SILC-C	District	7	GADM
103	Kyrgyz Republic	1998	KPMS	Oblast	7	GAUL
104	Kyrgyz Republic	2010	KIHS	Oblast	8	GAUL
105	Kyrgyz Republic	2013, 2015, 2017, 2018, 2019, 2020, 2021, 2022, 2023	KIHS	Oblast	9	GADM
106	Lao PDR	2002, 2007, 2012, 2018	LECS	Statistical region	4 (3)	GAULx
107	Lao PDR	2012	LECS	Province	17	GAUL
108	Lao PDR	2018	LECS	Province	18	GADM
109	Lebanon	2022	LHS	Governorate	5 (1)	GAULx
110	Lebanon	2011	HBS	Governorate	6	GAUL
111	Lesotho	2002, 2017	CMSHBS, HBS	District	10	GAUL
112	Liberia	2007	CWIQ	Statistical region	6 (5)	GAULx
113	Liberia	2014, 2016	HIES	County	16 (1)	GAULx
114	Madagascar	2005, 2010, 2012, 2021	ENSOMD, EPM	Region	22	GAUL

115	Malawi	1997	IHS-I	District	25	GAUL
116	Malawi	2004	IHS-II	District	26	GAUL
117	Malawi	2010	IHS-III	District	27	GAUL
118	Malawi	2016, 2019	IHS-IV, IHS-V	District	28	GAUL
119	Malaysia	2009, 2012, 2014, 2016, 2019, 2022	HIESBA, HIS	State	14	GAUL
120	Maldives	2002, 2009	HIES	Statistical region	2 (1)	GAULx
121	Maldives	2019	HIES	Atoll	18	GAUL
122	Maldives	2016	HIES	Atoll	20	GAUL
123	Mali	2006, 2009, 2021	EHCVM, ELIM	Region	9	GAUL
124	Mali	2018	EHCVM	Region	10 (1)	GAULx
125	Mauritania	2000, 2004, 2008, 2014, 2019	EPCV	Region	13	GAUL
126	Mauritius	2006, 2012, 2017	HBS	District	10	GAUL
127	Mexico	1989, 1992, 1994, 1996, 1998, 2000, 2002, 2004, 2005, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020, 2022	ENIGH, ENIGHNS	State	32	GAUL
128	Moldova	2007, 2010, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	HBS	Region	4 (3)	GAULx
129	Mongolia	2010, 2011, 2012, 2014, 2016, 2018, 2022	HSES	Statistical region	5 (4)	GAULx
130	Mongolia	2016, 2018, 2022	HSES	Province	22	GAUL
131	Montenegro	2014	HBS	Statistical region	3 (3)	GAULx
132	Montenegro	2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022	SILC-C	Statistical region	4 (3)	GAULx
133	Morocco	2013	ENCDM	Region	10	DK
134	Morocco	2000, 2006	ENCDM, ENNVM	Region	14 (3)	GAULx
135	Mozambique	2002, 2008, 2014, 2019, 2022	IAF, IOF	Province	11 (1)	GAULx
136	Myanmar	2015, 2017	MLCS, MPLCS	Agro-ecological zone	5 (4)	GAULx
137	Myanmar	2017	MLCS	Subdivision	15	GADM
138	Namibia	2003, 2009, 2015	NHIES	Region	13	GAUL
139	Nepal	1995, 2003, 2010	LSS-I, LSS-II, LSS-III	Development region	5	GAUL
140	Nepal	2022	LSS-IV	Province	7	DK
141	Nicaragua	2001, 2005, 2009, 2014	EMNV	Statistical region	4 (3)	GAULx
142	Niger	2005, 2007, 2011, 2014, 2018, 2021	ECVMA, EHCVM, ENBCM, ENCVM	Region	8	GAUL
143	Nigeria	2022	LSS	State	35	GAUL
144	Nigeria	2018	LSS	State	36	GAUL
145	Nigeria	2003, 2010	GHSP-W1, LSS	State	37	GAUL

146	North Macedonia	2004	HBS	Region	2 (1)	NUTSx
147	North Macedonia	2005, 2008, 2018, 2019, 2020	HBS, SILC-C	Region	8	NUTS
148	Pakistan	2001, 2004, 2005, 2007, 2010, 2011, 2013, 2015, 2018	HIES, PIHS	Division	4 (2)	GAULx
149	Panama	2000	EH	Province	9	GAUL
150	Panama	2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014	EH	Province	12	GAUL
151	Panama	2015, 2016, 2017, 2018, 2019, 2021, 2023, 2024	EH	Province	13 (2)	GAULx
152	Papua New Guinea	2009	HIES	Region	5 (4)	GAULx
153	Paraguay	2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014	EIH, EPH	Statistical region	7 (2)	GAULx
154	Paraguay	2018, 2019, 2020, 2021	EPH	Statistical region	8 (2)	GAULx
155	Paraguay	2015, 2016, 2017, 2022, 2023, 2024	EPH, EPHC	Department	16 (1)	GAULx
156	Peru	1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	ENAHO	Region	25	GAUL
157	Philippines	2000	FIES	Region	16 (1)	GAULx
158	Philippines	2003, 2006, 2009, 2012, 2015, 2018, 2021, 2023	FIES	Region	17	GAUL
159	Philippines	2018, 2021, 2023	FIES	Province	81 (1)	GAULx
160	Poland	2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017	EU-SILC	NUTS1	6	NUTS
161	Poland	2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2018, 2019, 2020, 2022, 2023, 2024	EU-SILC, HBS	NUTS1	7	NUTS
162	Portugal	2018, 2019, 2020, 2021, 2022, 2023	EU-SILC	NUTS2	7	NUTS
163	Portugal	2024	EU-SILC	NUTS2	9	NUTS
164	Romania	2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC, HBS	NUTS1	4	NUTS
165	Russian Federation	2007, 2012	HBS	Statistical region	8	DK
166	Russian Federation	2010	HBS	Oblast	79 (7)	GAULx
167	Russian Federation	2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	HBS, VNDN	Oblast	80 (7)	GAULx
168	Rwanda	2000, 2005, 2010, 2013, 2016, 2023	EICV-I, EICV-II,	District	30	GAUL

			EICV-III, EICV-IV, EICV-V, EICV7			
169	Samoa	2008, 2013	HIES	Statistical region	4	DK
170	Senegal	2005	ESPS-I	Region	11	GAUL
171	Senegal	2011, 2018, 2021	EHCVM, ESPS-II	Region	14	GAUL
172	Serbia	2017, 2018, 2020, 2021	EU-SILC	NUTS1/2	2	NUTS
173	Serbia	2004, 2005, 2006, 2007, 2008, 2009, 2010, 2015, 2018	HBS	NUTS1/2	3 (1)	NUTSx
174	Serbia	2013, 2019, 2022, 2023	EU-SILC, HBS	NUTS1/2	4	NUTS
175	Seychelles	2006	HBS	Region	6	GAUL
176	Seychelles	2013, 2018	HBS	Region	6 (1)	DKx
177	Sierra Leone	2003, 2011, 2018	SLIHS	District	13	GAUL
178	Solomon Islands	2012	HIES	Province	10	GADM
179	South Africa	2005, 2010, 2014	IES, LCS	Province	9	GAUL
180	South Sudan	2009	NBHS	Statistical region	3 (3)	GAULx
181	Spain	2004, 2005	EU-SILC	NUTS2	18	NUTS
182	Spain	2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS2	19	NUTS
183	Sri Lanka	2002	HIES	District	17	GAUL
184	Sri Lanka	2006	HIES	District	19	GAUL
185	Sri Lanka	2009	HIES	District	22	GAUL
186	Sri Lanka	2012, 2016, 2019	HIES	District	25	GAUL
187	Sudan	2009	NBHS	State	15	GAUL
188	Sudan	2014	NBHS	State	18	GADM
189	Suriname	2022	SSLC	Domain	3	DK
190	Sweden	2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024	EU-SILC	NUTS1	3	NUTS
191	Switzerland	2020, 2021, 2022, 2023	EU-SILC	NUTS1	7	NUTS
192	São Tomé and Príncipe	2000, 2010, 2017	IOF	Province	2	GAUL
193	Tajikistan	2009, 2015, 2021, 2022, 2023, 2024	HBS, HSITAFIEN, TLSS	Region	5	GADM
194	Tanzania	2000	HBS	Region	20 (5)	GAULx
195	Tanzania	2007, 2011	HBS	Region	21 (5)	GAULx
196	Tanzania	2018	HBS	Region	26	GADM
197	Thailand	2000, 2002, 2004, 2007, 2009	SES	Statistical region	5 (5)	GAULx
198	Thailand	2006, 2008, 2009, 2010, 2011	SES	Province	76	GAUL
199	Thailand	2012, 2013, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	SES	Province	77 (2)	GAULx

200	Timor-Leste	2007	TLSLS	Statistical region	5 (4)	GAULx
201	Timor-Leste	2014	TLSLS	Municipality	13	GAUL
202	Togo	2006, 2011, 2015, 2018, 2021	EHCVM, QUIBB	Region	6 (1)	GAULx
203	Tonga	2021	HIES	Division	5	GADM
204	Tunisia	2005, 2010, 2015, 2021	NSHBCSL	Region	7 (6)	GAULx
205	Türkiye	2023	SILC-C	NUTS2	25	NUTS
206	Türkiye	2018, 2019, 2020, 2021, 2022	SILC-C	NUTS2	26	NUTS
207	Uganda	2002, 2005, 2009, 2012, 2016, 2019	UNHS	Region	4 (4)	GAULx
208	Ukraine	2014, 2015, 2016, 2017, 2018, 2019, 2020	HLCS	Oblast	25 (1)	GADMx
209	Ukraine	2005, 2007, 2010, 2013	HLCS	Oblast	27 (1)	GADMx
210	United Kingdom	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021	FRS-LIS	NUTS1	12	NUTS
211	United States	2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023	CPS-ASEC-LIS	State	51	GAUL
212	Uruguay	1992, 1995, 1996, 1997, 1998, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2021, 2022, 2023, 2024	ECH, ECH-S2	Statistical region	5 (5)	GAULx
213	Uzbekistan	2003, 2021, 2022, 2023, 2024	HBS	Region	14	GAUL
214	Vanuatu	2010, 2019	HIES, NSDP	Province	6	GAUL
215	Viet Nam	2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020, 2022	VHLSS	Region	6 (6)	GAULx
216	West Bank and Gaza	2004, 2005, 2006, 2007, 2009, 2010, 2011, 2016, 2023	PECS	State	2 (2)	GAULx
217	Yemen, Rep.	2005	HBS	Governorate	21	GAUL
218	Yemen, Rep.	2014	HBS	Governorate	22 (2)	GAULx
219	Zambia	2004, 2006, 2010	LCMS-IV, LCMS-V, LCMS-VI	Province	9	GAUL
220	Zambia	2015, 2022	LCMS-VII, LCMS-VIII	Province	10 (3)	GAULx
221	Zimbabwe	2017, 2019	PICES	Province	10	GAUL

Table A2. Summary statistics

	Mean	Std. Dev.	Min	Max	Number of subnational observations	Number of countries
			Panel A - SPID			
All sample						
Poverty rate at $3.00 (2021 PPP)	13.85	21.42	0.00	99.75	16,512	140
Poverty rate at $4.20 (2021 PPP)	21.58	27.12	0.00	100.00	16,512	140
Poverty rate at $8.30 (2021 PPP)	42.40	33.85	0.00	100.00	16,512	140
Mean (2021 PPP)	20.93	20.21	0.64	137.78	16,512	140
Prosperity gap (2021 PPP)	5.08	4.87	0.37	58.71	16,512	140
GINI index	36.74	8.79	13.37	96.54	16,512	140
Theil Index	27.22	16.88	3.14	631.41	16,512	140
Age groups						
0-5						
Poverty rate at $3.00 (2021 PPP)	15.00	21.54	0.00	100.00	15,733	140
Poverty rate at $4.20 (2021 PPP)	23.84	27.55	0.00	100.00	15,733	140
Poverty rate at $8.30 (2021 PPP)	47.66	34.16	0.00	100.00	15,733	140
Mean (2021 PPP)	16.32	14.86	0.80	118.57	15,733	140
Prosperity gap (2021 PPP)	5.47	4.73	0.38	49.20	15,733	140
GINI index	34.10	9.22	0.00	82.32	15,733	140
Theil Index	23.24	15.50	0.00	304.39	15,733	140
06-11						
Poverty rate at $3.00 (2021 PPP)	15.05	21.67	0.00	100.00	15,735	140
Poverty rate at $4.20 (2021 PPP)	23.92	27.68	0.00	100.00	15,735	140
Poverty rate at $8.30 (2021 PPP)	47.62	34.18	0.00	100.00	15,735	140
Mean (2021 PPP)	16.37	14.83	0.86	112.83	15,735	140
Prosperity gap (2021 PPP)	5.45	4.73	0.43	47.88	15,735	140
GINI index	34.33	9.14	0.00	89.52	15,735	140
Theil Index	23.61	15.23	0.00	368.92	15,735	140
12-17						
Poverty rate at $3.00 (2021 PPP)	13.67	20.38	0.00	99.86	15,736	140
Poverty rate at $4.20 (2021 PPP)	22.17	26.52	0.00	100.00	15,736	140
Poverty rate at $8.30 (2021 PPP)	45.56	33.76	0.00	100.00	15,736	140
Mean (2021 PPP)	17.20	15.78	0.86	126.92	15,736	140
Prosperity gap (2021 PPP)	5.14	4.45	0.40	46.34	15,736	140
GINI index	34.20	8.94	1.36	78.19	15,736	140
Theil Index	23.31	14.53	0.04	213.49	15,736	140
17+						
Poverty rate at $3.00 (2021 PPP)	10.65	17.82	0.00	99.66	15,736	140
Poverty rate at $4.20 (2021 PPP)	17.58	23.83	0.00	100.00	15,736	140
Poverty rate at $8.30 (2021 PPP)	37.77	32.30	0.00	100.00	15,736	140
Mean (2021 PPP)	23.39	22.02	0.89	147.65	15,736	140
Prosperity gap (2021 PPP)	4.36	3.98	0.34	42.54	15,736	140
GINI index	36.65	8.72	13.71	83.20	15,736	140
Theil Index	26.99	15.84	3.20	313.21	15,736	140
Gender						

Female						
Poverty rate at $3.00 (2021 PPP)	12.15	19.32	0.00	99.74	15,850	140
Poverty rate at $4.20 (2021 PPP)	19.64	25.29	0.00	100.00	15,850	140
Poverty rate at $8.30 (2021 PPP)	40.59	33.03	0.00	100.00	15,850	140
Mean (2021 PPP)	21.34	19.99	0.88	130.12	15,850	140
Prosperity gap (2021 PPP)	4.71	4.29	0.36	44.71	15,850	140
GINI index	36.45	8.75	11.56	76.86	15,850	140
Theil Index	26.50	15.45	2.51	289.48	15,850	140
Male						
Poverty rate at $3.00 (2021 PPP)	12.06	19.21	0.00	99.75	15,850	140
Poverty rate at $4.20 (2021 PPP)	19.48	25.18	0.00	100.00	15,850	140
Poverty rate at $8.30 (2021 PPP)	40.43	32.95	0.00	100.00	15,850	140
Mean (2021 PPP)	21.85	20.73	0.87	146.39	15,850	140
Prosperity gap (2021 PPP)	4.69	4.27	0.38	45.50	15,850	140
GINI index	36.84	8.90	13.39	85.32	15,850	140
Theil Index	27.44	16.42	2.96	363.04	15,850	140

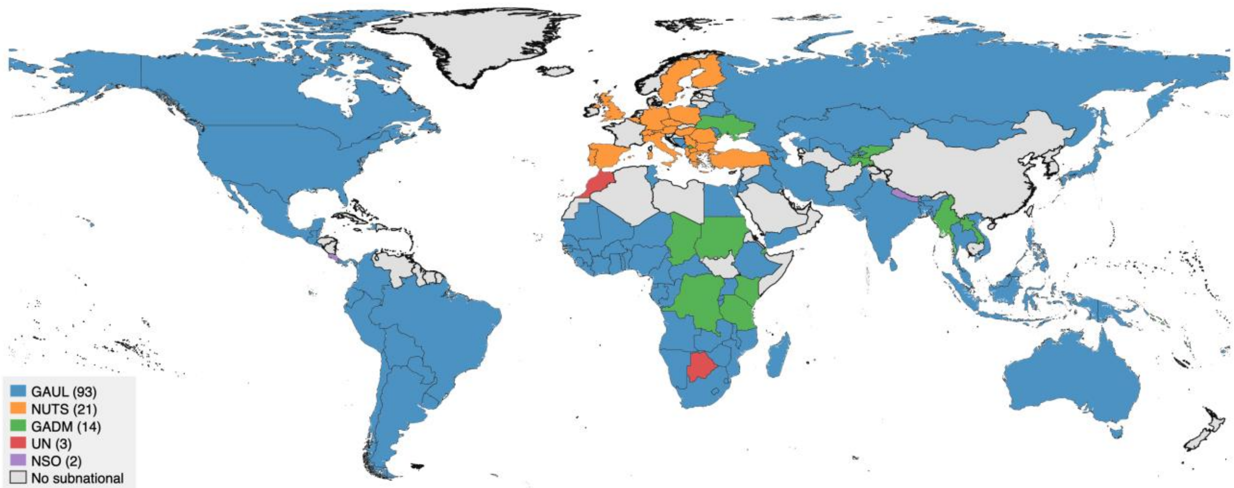
Table A2 (continued)

	Mean	Std. Dev.	Min	Max	Number of subnational observations	Number of countries
				Panel B - SPID		
Multi-dimensional poverty						
Monetary	10.43	18.82	0.00	98.70	9,889	134
Enrollment	10.25	15.64	0.00	95.49	9,778	134
Education Attainment	5.67	11.17	0.00	83.82	7,480	112
Electricity	8.59	20.95	0.00	100.00	9,851	134
Sanitation	16.26	24.02	0.00	100.00	9,368	132
Water	8.87	14.25	0.00	90.40	8,657	127
MPM	13.34	22.59	0.00	99.24	9,889	134
				Panel C - GSAP		
2023						
Poverty rate at $3.00 (2021 PPP)	18.45	25.73	0.00	97.35	1,914	172
Poverty rate at $4.20 (2021 PPP)	28.10	31.81	0.00	99.46	1,914	172
Poverty rate at $8.30 (2021 PPP)	49.96	37.34	0.00	100.00	1,914	172
Prosperity gap (2021 PPP	5.97	5.54	0.37	37.94	1,914	172
2021						
Poverty rate at $3.00 (2021 PPP)	19.27	25.92	0.00	98.36	1,904	172
Poverty rate at $4.20 (2021 PPP)	29.24	31.75	0.00	99.70	1,904	172
Poverty rate at $8.30 (2021 PPP)	51.96	36.63	0.00	100.00	1,904	172
Prosperity gap (2021 PPP	6.16	5.67	0.40	40.81	1,904	172
2019						
Poverty rate at $3.00 (2021 PPP)	18.70	25.47	0.00	98.14	1,904	172
Poverty rate at $4.20 (2021 PPP)	28.55	31.38	0.00	99.46	1,904	172
Poverty rate at $8.30 (2021 PPP)	51.09	36.47	0.00	100.00	1,904	172
Prosperity gap (2021 PPP	6.05	5.44	0.46	39.77	1,904	172
2010						
Poverty rate at $3.00 (2021 PPP)	24.15	28.01	0.00	99.40	1,714	172
Poverty rate at $4.20 (2021 PPP)	34.73	33.15	0.00	99.92	1,714	172

Poverty rate at $8.30 (2021 PPP)	56.86	35.83	0.00	100.00	1,714	172
Prosperity gap (2021 PPP	7.13	6.01	0.43	37.34	1,714	172

Note: Number of subnational observations is the total observation of country-year-subnational units.

Figure A1. Subnational boundary data sources, GSAP 2023



Note: The legend indicates the number of economies using each source of boundary data in brackets.

Figure A2. Number of subnational units over time

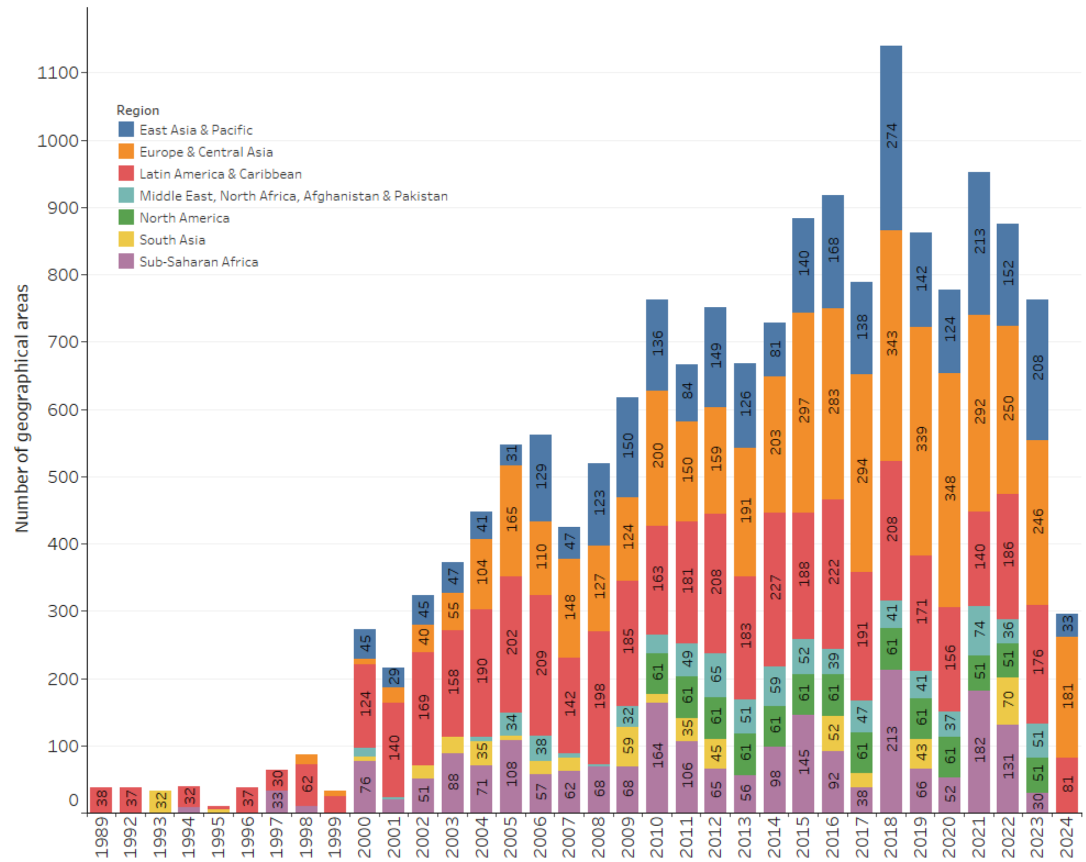
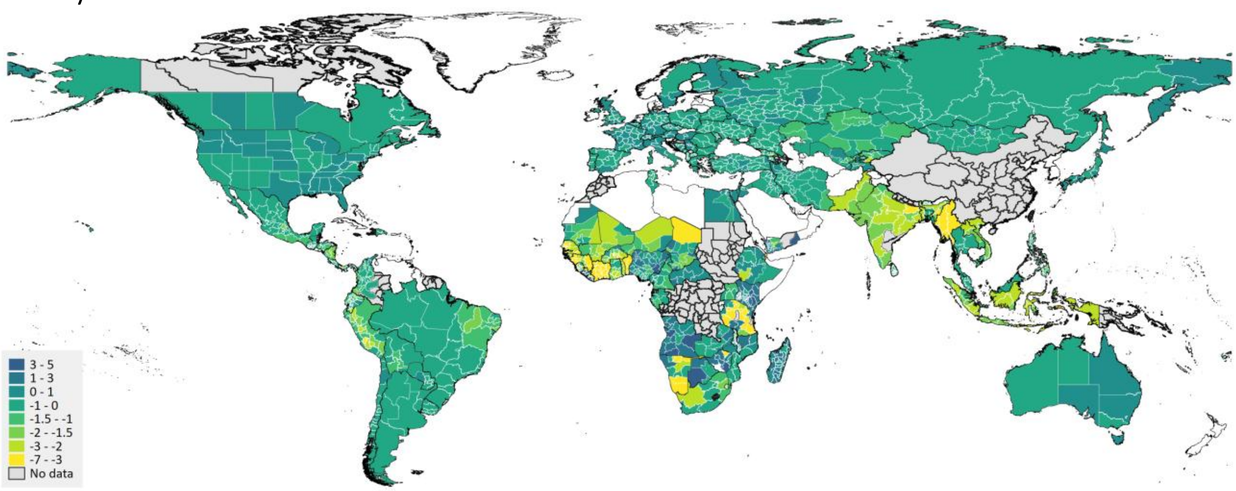


Figure A3. Annualized changes in global poverty ($3.00 a day) and inequality over the past decade (circa 2010 – circa 2020) (percent)

Poverty



Inequality