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Why Does Data Deprivation Persist? Exploring the Factors Behind Incomplete Poverty Data

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Why Does Data Deprivation Persist?

Exploring the Factors Behind Incomplete Poverty Data

Abstract

This paper examines the factors influencing the availability of official poverty statistics Despite broad recognition of its importance, many countries remain deprived of poverty data. This study analyzes how statistical capacity and political characteristics are associated with the availability of monetary and multidimensional poverty measures. Descriptive and regression results reveal contrasting patterns: monetary poverty estimates are strongly linked to statistical capacity and political institutions, while multidimensional poverty estimates appear less dependent on these factors. The findings highlight the need to move beyond the prevailing view that improving statistical capacity alone can overcome data deprivation and call for deeper understanding of the political and institutional dynamics shaping the availability of official poverty statistics.

Keywords: Poverty Measurement, Monetary Poverty, Multidimensional Poverty, Data Deprivation, Statistical Capacity, Political Economy of Statistics, Sustainable Development Goals

JEL Codes: I32, O15, C83, H83, P48

Introduction

Poverty reduction has long been a central focus of international development. The Millennium Development Goals (MDGs) set a target to halve extreme poverty globally between 1990 and 2015—a goal that was achieved five years ahead of schedule. The Sustainable Development Goals (SDGs) continue to prioritize poverty reduction as a fundamental challenge to sustainable development. SDG 1 explicitly calls for the eradication of poverty in all its forms by 2030 while ensuring that no one is left behind (United Nations, 2023).

Poverty is multifaceted and must therefore be measured in multiple ways. Today, the two most widely used poverty measures are monetary poverty and multidimensional poverty. Globally, the World Bank has overseen the monitoring of monetary poverty since the introduction of the dollar-a-day measure (World Bank, 1990). The Oxford Poverty and Human Development Initiative (OPHI) serves as the custodian of the global Multidimensional Poverty Index (MPI), which now covers more than 100 low- and middle-income countries (Oxford Poverty and Human Development Initiative, 2025).

Poverty measurement is essential for understanding the state of the poor (Deaton, 2016; Jerven & Johnston, 2015). Data on poverty is often the only available means for policy-makers to understand the state of the poor. Without timely and accurate poverty data, their situation would remain invisible, and governments and the international community are left with no evidence base to allocate limited resources to poverty reduction programs. Moreover, the poor are frequently deprived of political agency to advocate for their rights, making poverty data a critical tool through which policymakers can recognize and address the deprivation they experience (Serajuddin et al., 2015)

Despite the strong commitment by the international community to eradicate poverty, the availability of poverty estimates has been limited. The World Development Report of 1979 showed data on poverty and inequality from only 17 developing countries, which surprised the then World Bank president Robert McNamara (Ravallion, 2016). Even at the onset of the SDG era, around half of the world's countries faced data deprivation—a situation in which a country lacks recent and comparable monetary poverty data to monitor progress toward SDG 1 (Serajuddin et al., 2015). Lack of comparable data over time is a much bigger challenge for poverty data than other indicators such as GDP (Devarajan, 2013).

The existing literature emphasizes the need to strengthen the statistical capacity of developing countries to end data deprivation (Alkire, 2014; Dang & Serajuddin, 2020;

Serajuddin et al., 2015). In 2015, the World Bank committed to supporting the 78 poorest countries to implement a multi-topic household survey every three years until 2030 (Kilic et al., 2017). Improving statistical capacity in developing countries has become an urgent priority for international organizations such as the World Bank (Oechslin & Steiner, 2022).

This paper empirically tests these arguments. The overarching objective of this paper is to examine the factors that influence the availability of official poverty statistics, with two main parts. First, it provides the first comprehensive update on the state of data deprivation since Serajuddin et al. (2015), with the aim of assessing the current landscape of poverty data availability. Second, this paper empirically examines the roles of statistical capacity in explaining cross-country variations in the availability of official poverty statistics. As highlighted in the emerging literature on data manipulation, the quality of official statistics can be shaped not only by technical capacity of national statistics offices but also by a range of political characteristics of governments (Briviba et al., 2024; Devarajan, 2013; Jerven & Johnston, 2015; Kerner et al., 2017; Martínez, 2022; Oechslin & Steiner, 2022; Sandefur & Glassman, 2015). On the one hand, one could argue that, unlike GDP estimates —which are primarily produced by national statistical offices— poverty statistics are less susceptible to manipulation because of the strong technical involvement of international organizations such as the World Bank and the Oxford Poverty and Human Development Initiative (OPHI). At the same time, incentives to influence official statistics may manifest differently in this context. Political factors linked to the manipulation of GDP such as over-reporting of growth, may also be associated with other forms of interference, including suppressing the publication of official statistics (Georgiou, 2021) or postponing household survey operations (Devarajan, 2013). Such practices could negatively affect the impartiality of public data (Jolliffe et al., 2023) and potentially reduce the number of official poverty statistics available in the public domain. To the extent that this is the case, improving statistical capacity and conducting additional household surveys will not, on their own, be sufficient to improve the availability of official poverty statistics.

Regression analysis reveals that the factors associated with the availability of monetary poverty estimates differ markedly from those linked to multidimensional poverty. In cross-country regressions, the availability of monetary poverty estimates is significantly and positively correlated with several political factors highlighted in the literature on data manipulation, even after controlling for statistical capacity. These factors include the Electoral Democracy Index, Polity V (an indicator of democracy and autocracy), the Freedom House score (which measures political rights and civil liberties), the World Bank's Worldwide Governance Indicators, and the autocracy gradient, defined as the

elasticity of GDP growth to nighttime light growth (Martínez, 2022). By contrast, the availability of multidimensional poverty estimates shows no significant correlation with political characteristics. However, panel regressions suggest that positive changes in political factors are associated with a greater likelihood of publishing a multidimensional poverty estimate, but not a monetary poverty estimate.

The main finding of this paper is that markedly different mechanisms shape the availability of the two poverty measures. Where political characteristics are positively correlated with data availability—as in the case of monetary poverty—countries that score lower on these indicators, such as those with weaker democratic institutions or restricted political and civil liberties, are less likely to release monetary poverty estimates. Ironically, in many of these contexts, household survey–based poverty estimates may be among the few available tools for shedding light on the conditions of the poor, yet such data are less likely to be made public. This pattern runs directly counter to the spirit of the Sustainable Development Goals, particularly the commitment to "leave no one behind."

This paper contributes to the existing literature in three main ways. First, it provides the first comprehensive update on the state of poverty data availability since Serajuddin et al. (2015), who documented that about half of the world's countries were deprived of sufficient monetary poverty data. Our analysis shows that the availability of monetary poverty estimates has not improved, apart from a few high-income countries that further increased the already high frequency of their reporting. Second, the paper analyzes the availability of multidimensional poverty data and demonstrates that the factors associated with its availability are markedly different from those associated with monetary poverty estimates. Despite its shorter history and more limited geographical coverage, multidimensional poverty measurement has become substantially more common, particularly in South Asia and Sub-Saharan Africa. Third, the paper contributes to the emerging literature on data manipulation by highlighting the correlation between the availability of poverty data and political economy factors. Regression results show that countries with weaker democracy, and more limited political rights and civil liberties are less likely to publish monetary poverty estimates. By contrast, no such correlation is observed for the availability of multidimensional poverty estimates. To the best of our knowledge, this is the first attempt to test the availability of poverty data from this perspective.

The remainder of the paper is structured as follows. The next section reviews the background and existing literature to frame the research questions. We then provide a brief description of the data, followed by descriptive and regression analyses that

examine the factors associated with poverty data availability and discuss the implications of the findings, including avenues for further research. The final section concludes.

Background

The demand for development data has grown in both scale and scope. The World Development Report, the World Bank's annual flagship publication, was titled "Data for Better Lives" in 2021 and was dedicated to discussing the critical roles data plays for development (World Bank, 2021). With the adoption of the SDGs, the scope of data required for monitoring progress expanded substantially beyond what was needed under the Millenium Development Goals (MDGs), as the number of indicators increased significantly (Dang & Serajuddin, 2020). The geographical coverage of data also broadened during the SDG era, since the SDG encompasses all UN member countries rather than only the developing countries that were the scope of the MDG.

Despite this increased demand, data remains scarce in much of the world. At the onset of the SDG era, nearly half of all countries lacked sufficient data to monitor poverty (Serajuddin et al., 2015) , with the shortage particularly acute in Sub-Saharan Africa (Devarajan, 2013). The scarcity of data extends beyond poverty estimates. For example, the availability of gender-related SDG indicators remains limited in many countries (Beegle et al., 2023, 2025). Even when data is available, quality is a major concern. As Jerven (2013) details, macroeconomic statistics, such as Gross Domestic Products (GDP), can be unreliable due to outdated methodologies, weak statistical capacity and missing underlying data.

This scarcity may seem surprising, as it contrasts with the common narrative in global poverty reports that emphasize improvements in poverty data availability over time. For instance, the World Development Report of 1979 presented poverty and inequality data from only 17 developing countries, which shocked then–World Bank president Robert McNamara (Ravallion, 2016). Two decades later, Chen & Ravallion (2001) reported global poverty estimates drawing on 297 household surveys from 88 countries. The most recent update by the World Bank notes that the Poverty and Inequality Platform (PIP), the database used for global poverty monitoring, now contains 2,400 surveys from 172 countries and economies (Alfani et al., 2025). Yet a closer look at country-level poverty data availability in Serajuddin et al. (2015) and in the updated analysis presented later in this paper shows that there is considerable heterogeneity in poverty data availability

across countries and across different types of poverty measures.

Much of the existing literature suggests that improving statistical capacity is the key to improve the availability of poverty data (Alkire, 2014; Dang et al., 2023; Dang & Serajuddin, 2020; Kilic et al., 2017; Serajuddin et al., 2015). Statistical capacity encompasses many aspects related to data and statistics, such as data use, openness of data, data quality, production of underlying data such as household surveys and censuses. It also includes the overarching governance structure that creates an enabling environment in which data actors produce, use and exchange data and data analytics. The World Bank's Statistical Performance Indicators (SPI) and its predecessor, the Statistical Capacity Index (SCI), have been the most comprehensive metrics of statistical capacity across countries.

While the SPI primarily consists of dimensions related to the production and use of data and statistics, an important aspect of official statistics is their vulnerability to political influence (Beker, 2021). Numerous cases have shown governments engaging in various forms of data falsification. (Georgiou, 2021), for instance, documents qualitative accounts of the misreporting of the consumer price index in Argentina, public financial statistics in Greece, and GDP and public finance statistics in Jourdan. Impartiality is a critical element in defining the value of official statistics (Jolliffe et al., 2023), yet politics often undermines the independence and neutrality of statistical agencies. Until recently, however, evidence of misreporting or manipulation was limited, largely because of the difficulty of obtaining solid proof of such misconduct. Data limitations were the primary bottleneck in proving data manipulation.

Recent years witnessed a growing number of quantitative studies that have addressed this gap by exploiting discrepancies between multiple data sources intended to yield the same or similar results. Sandefur & Glassman (2015) documented systematic inconsistencies in health and education statistics between administrative records and household survey estimates in African countries, concluding that incentives to report favorable results for meeting milestones biased the administrative data upward. Kerner et al. (2017) identified discrepancies in GNI per capita across different vintages of the same data sources. They compared GNI per capita from the latest version of the World Development Indicators, which incorporates frequent revisions, with that from the printed edition of the World Bank's statistical atlas, which includes few or no revisions. It was the latter—the less frequently revised vintage—that exhibited discontinuities

around the IDA threshold, above which countries lose eligibility for concessional finance from the World Bank Group. Using province-level data in China, Wallace (2014) detected signs of GDP manipulation as indicated by divergent patterns between GDP growth and electricity production and consumption during provincial leadership turnovers.

The advent of new data sources has opened further opportunities to gain a more holistic understanding about the prevalence of data manipulation. Since Henderson et al. (2012) introduced nighttime light intensity data as a proxy for economic activity, many studies compared GDP growth with changes in night light to identify irregularities. Magee & Doces (2015) demonstrated that GDP growth rates are consistently higher in autocracies than in democracies. Using night light growth as a benchmark, Martínez (2022) showed that the same amount of night light growth leads to much higher GDP growth in autocratic governments, suggesting they overstate GDP growth by about 35 percent on average. Briviba et al. (2024) analyzed the roles of institutional factors in GDP manipulation and found that economic openness and democracy serve as a deterrent to such manipulation, while decentralization tends to increase overreporting of GDP growth. These recent studies rest on the assumption that measurement errors in night light data are orthogonal to country-specific characteristics including political factors and the ability to control or preempt data manipulation.

Somewhat surprisingly, there has been a complete absence of discussion around data manipulation when it comes to official poverty statistics. For one, this is likely because international organizations such as the World Bank are heavily involved in the production and quality control of official poverty statistics (Alfani et al., 2025). Second, unlike GDP estimates for which night light data can serve as a point of reference, no such alternative exists for poverty estimates, at least for now, be it monetary poverty or multidimensional poverty. This lack of comparison by no means indicates that poverty estimates are free from biases and manipulation but has deprived researchers from empirically testing for such biases thus far.

Yet incentives to influence official statistics are pervasive (Devarajan, 2013; Jerven & Johnston, 2015; Magee & Doces, 2015; Sandefur & Glassman, 2015) and may manifest differently in this context. Political factors linked to over-reporting of GDP growth, for example, may also be associated with other forms of interference, including suppressing the publication of official statistics (Devarajan, 2013; Georgiou, 2021). There is a dearth of empirical studies that specifically looked at the association between data availability and political factors in this emerging literature. A rare exception is Hollyer et al. (2011) who used the availability of economic indicators reported in the World Development

Indicators and tested its statistical correlation with political regime types. They found that a transition from autocracy to democracy increases the share of reported indicators by 13 percentage points, although the availability of official poverty statistics was not their main focus.

To summarize the discussion so far, demand for data in international development is rising, driven in part by the SDG framework, which substantially expanded both thematic areas and geographic coverage compared to the MDGs. Yet the supply of data has hardly kept pace. Limited data availability is a serious constraint to proper SDG monitoring and to policy actions that should be grounded in evidence. At the onset of the SDG era, about half of the countries worldwide lacked sufficient data to track monetary poverty trends. The existing literature suggests that improving statistical capacity, including the availability of underlying household survey data, is critical to addressing this form of data deprivation. Recent evidence, however, indicates that official statistics are also vulnerable to political influence and that statistical capacity is closely correlated with countries' political characteristics. What remains largely absent from this growing literature is an empirical examination of the relationship between the availability of poverty data and country-specific characteristics beyond statistical capacity.

This paper examines the factors associated with the availability of official poverty statistics through two complementary approaches. First, it provides a comprehensive update on the state of data deprivation since Serajuddin et al. (2015), assessing the availability of both monetary and multidimensional poverty data. By comparing these two measures—each governed by different institutional arrangements—we aim to shed light on the constraints that limit the coverage and frequency of official poverty data. Second, the paper empirically investigates the roles of statistical capacity and political characteristics in explaining cross-country variation in the availability of poverty statistics.

Data

This study uses publicly available data compiled from various sources. The variables of interest in this study are the availability of monetary and multidimensional poverty estimates. For monetary poverty estimates, we rely on data from the World Development Indicators (World Bank, 2025f).[1] A country-year is counted as having a monetary

[1] WDI data are downloaded using wbopendata command in Stata (Azevedo, 2011).

poverty estimate if a poverty headcount ratio is available at either the national or international poverty line. This includes cases where only national estimates are reported outside the Poverty and Inequality Platform (World Bank, 2025b). Multidimensional poverty data are taken from the Global MPI 2024 (OPHI). While a similar distinction exists between national and global multidimensional poverty estimates, national estimates are a proper subset of global estimates in the latest records.

As a measure of statistical capacity, we primarily rely on data from the World Bank's Statistical Performance Indicators (SPI), supplemented with the earlier Statistical Capacity Index (SCI) for years not covered by the SPI. Political characteristics are drawn from four widely used sources. The electoral democracy index provides granular indicators of democratic institutions and practices. Polity5 measures regime type on an autocracy–democracy scale. Freedom House scores countries on political rights and civil liberties. The Worldwide Governance Indicators (WGI) summarize six dimensions of governance, including voice and accountability, government effectiveness, and control of corruption. We also utilize the autocracy gradient (Martínez, 2022), which measures the elasticity of GDP growth with respect to night light growth, as a proxy for susceptibility to data manipulation. We do not have a preferred measure of political characteristics from this list a priori, as they are all commonly used variables in the literature. In the descriptive analysis and regression analysis that follow, we present results using the variables with the electoral democracy index due to its wider temporal and geographical coverage. Results using other policy variables are presented as a robustness check. This is because the cross-country data is limited in sample size by nature and limited coverage in certain variables may induce selection bias into the already small sample. All of these variables are highly correlated with each other. Additional control variables such as GDP per capita and population are also obtained from the World Development Indicators. Country characteristics such as income classification (World Bank, 2025e), fragile and conflict-affected status (World Bank, 2025a), small states (World Bank, 2025c) and landlocked countries (Wikipedia, n.d.) are obtained from respective sources.

The State of Poverty Data Availability

Descriptive Analysis

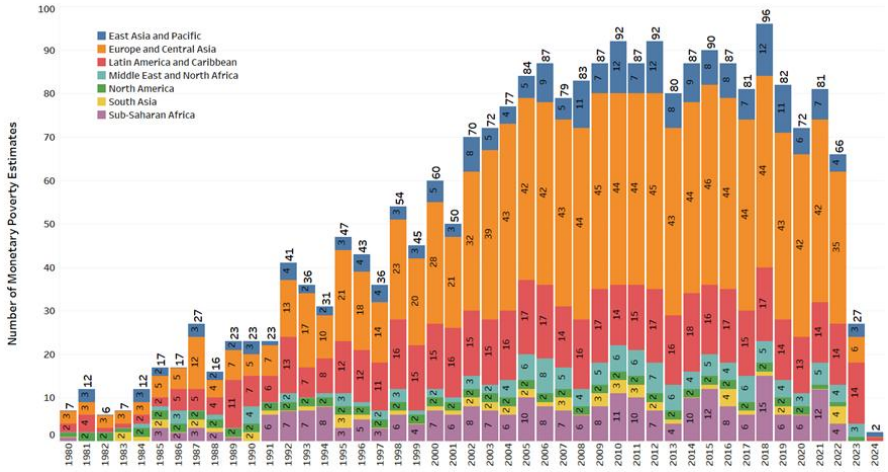
The global availability of monetary poverty estimates has expanded considerably over the past four decades, but this progress has stalled in recent years. In 1979, the *World Development Report* documented poverty and inequality measures for only 17

developing countries (Ravallion, 2016). By the mid-2000s, coverage had improved substantially, with 80–90 countries reporting at least one monetary poverty estimate per year (Figure 1). Since then, however, this growth has plateaued, even as the demand for timely, high-frequency data has increased with the monitoring requirements of the Sustainable Development Goals (SDGs). This stagnation is at least partly attributable to the COVID-19 pandemic and the resulting disruptions in household survey operations since 2020.

The geographic distribution of poverty estimates highlights systematic imbalances. Around 50 percent of all available monetary poverty estimates originate from Europe and Central Asia, despite the region accounting for only about 1 percent of the global poor at the $3.00-a-day threshold. In contrast, Sub-Saharan Africa—home to over 70 percent of the world's poor—saw fewer than 10 countries producing annual estimates in the 2010s. This represents roughly 10 percent of the global total, illustrating the extent to which regions with the highest poverty incidence remain underrepresented in global poverty monitoring.

The availability of multidimensional poverty estimates has a much shorter history than that of monetary poverty, yet its coverage has expanded markedly, particularly in South Asia and Sub-Saharan Africa. No multidimensional poverty estimates were available prior to 2000. Since then, however, the number of estimates has increased substantially, with coverage reaching as many as 30 countries in certain years and averaging around 20 countries annually since 2010. Although this volume remains roughly one quarter of that for monetary poverty, the expansion of multidimensional measures represents a notable shift in the global poverty monitoring landscape.

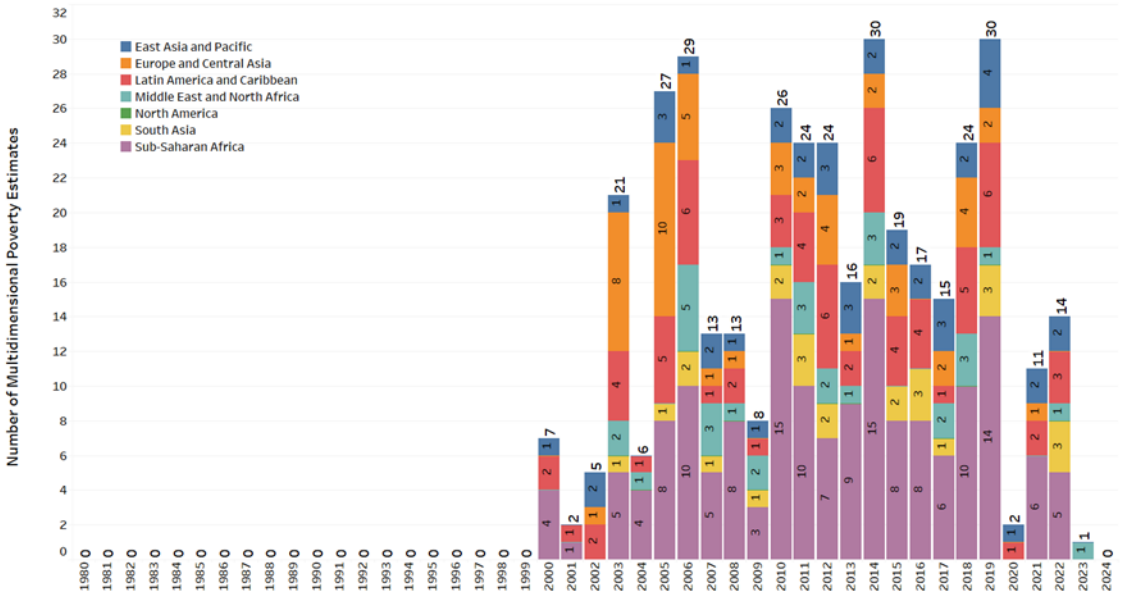
Figure 1: The number of monetary poverty estimates (1960-2024)



Source: Authors' calculation using (World Bank, 2025f)

Unlike monetary poverty estimates, which are concentrated in richer regions, the distribution of multidimensional poverty estimates is disproportionately tilted toward poorer countries (Figure 2). Sub-Saharan Africa alone accounts for roughly one-third to one-half of all available multidimensional estimates. Low-income countries also play a central role, representing between 23 and 50 percent of total estimates during the 2010s. This pattern contrasts sharply with monetary poverty data, where low-income countries made up less than 10 percent of the total in most years of the 2010s (not shown). Conversely, very few multidimensional poverty estimates are reported for high-income countries, which accounted for around 40 percent of monetary poverty estimates during the same period (not shown). This finding is partially consistent with Beegle et al. (2023), who show that poorer countries perform no worse than richer countries in reporting gender-related indicators under the SDG framework.

Figure 2: The number of multidimensional poverty estimates (2000-2024)

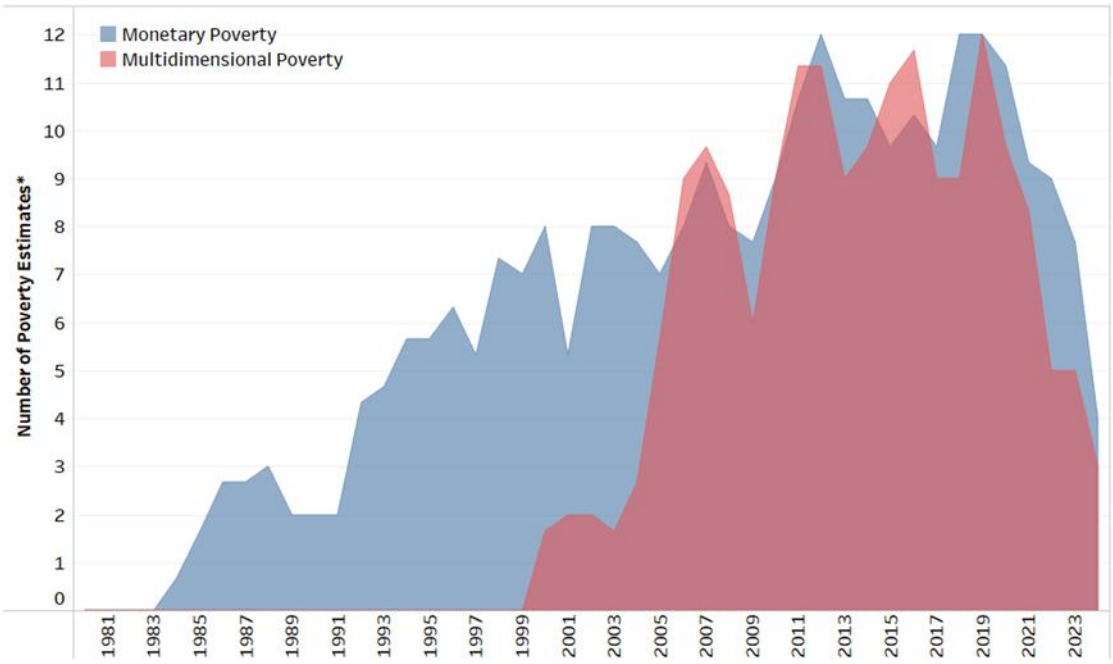


Source: Authors' calculation using Oxford Poverty and Human Development Initiative (2025)

The expansion of multidimensional poverty measurement has been particularly important for countries historically lacking reliable poverty statistics. Serajuddin et al. (2015) identified 77 "data-deprived" countries that lacked sufficient monetary poverty estimates to monitor trends over time. Figure 3 illustrates the availability of monetary and multidimensional poverty estimates in these countries, drawing on the same data presented in Figures 1 and 2. As discussed, multidimensional poverty has a much more recent history than that of monetary poverty, but its availability increased substantially during the 2000s. On average, only about 10 countries out of 77 produce poverty

estimates each year during the 2010s—whether monetary or multidimensional—underscoring the dire state of data deprivation. Although monetary poverty estimates are far more numerous at the global level, multidimensional poverty estimates slightly outnumber monetary ones within the set of "data-deprived" countries. Multidimensional poverty estimates are increasingly filling gaps in poverty monitoring where monetary estimates remain scarce.

Figure 3 The number of monetary and multidimensional poverty estimates in 77 Data Deprived Countries (1995-2024) according to Serajuddin et al. (2015)



Authors' calculation using World Bank (2025f) and Oxford Poverty and Human Development Initiative (2025).

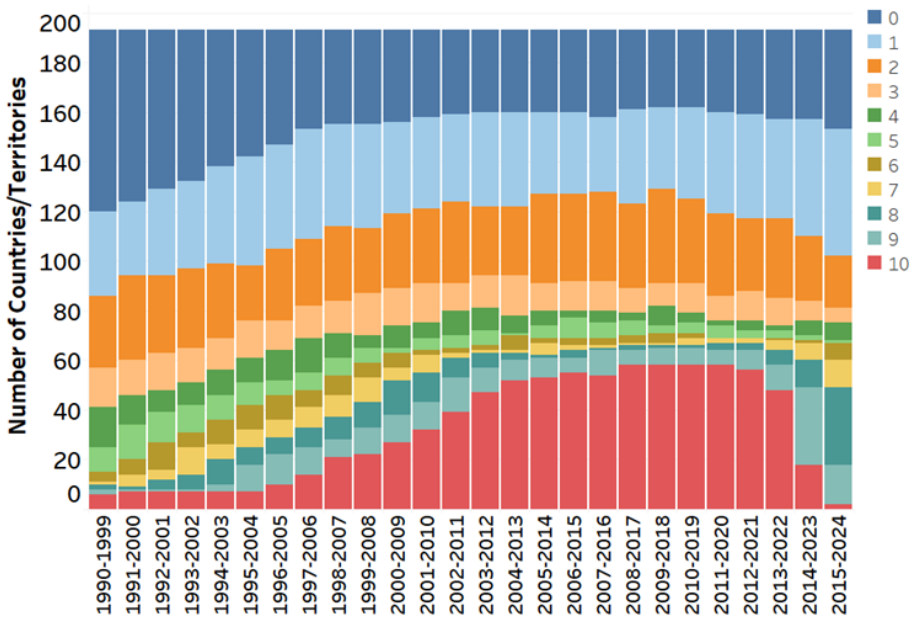
* Three-year moving average (current and two previous years)

It is also important to consider the frequency with which poverty estimates are produced over time. While the annual number of estimates provides a sense of global coverage, a country's ability to monitor poverty trends depends on consistent and regular measurement (Jolliffe et al., 2023). Figure 4 summarizes the availability of monetary poverty estimates for all 198 United Nations member states, covering the periods 1990–1999 through 2015–2024. The results show little progress over the last two decades. The number of countries with more than two monetary poverty estimates within a 10-year period has not changed since 2000–2009. Between 2000 and 2009, a total of 104 countries had two or fewer monetary poverty estimates; the corresponding figure for

2010–2019 is nearly identical at 102 countries, the most recent decade before COVID-19 disrupted household survey operations worldwide. While this analysis extends coverage to all 198 UN member states—compared with the 155 countries and territories examined in Serajuddin et al. (2015)—reproducing Figure 4 using the smaller sample yields essentially the same results.

The limited progress in measurement frequency further reinforces the earlier discussion that the availability of monetary poverty remains skewed toward richer countries. The only notable improvement can be observed in the set of countries producing annual monetary poverty estimates, defined as 10 estimates within a 10-year window, highlighted in red in Figure 4. Between 2010 and 2019, however, roughly two-thirds of these countries were in Europe and Central Asia, while none were in South Asia or Sub-Saharan Africa. In effect, the availability of monetary poverty estimates has improved mainly in the least poor regions, whereas the number of data-deprived countries has not declined over the past 20 years. As a result, richer countries benefit from more frequent updates to their poverty statistics, while poorer countries remain deprived of reliable and timely data.

Figure 4 Availability of Monetary Poverty Estimates (10-year Analysis)



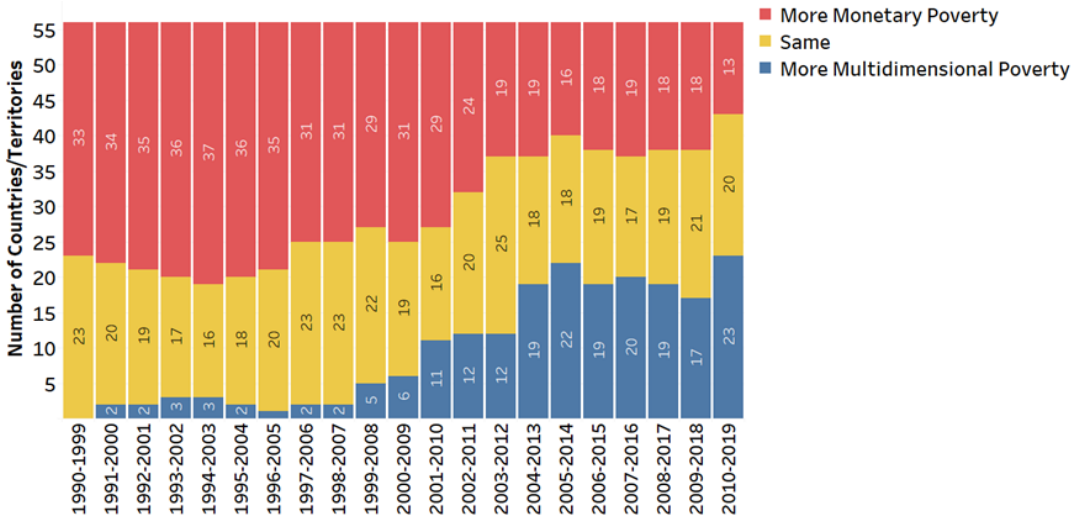
Source: Authors' calculation using World Bank (2025f)

The contrasting patterns in the availability of monetary and multidimensional poverty estimates across countries over the last two decades carry important implications for the current landscape of poverty data. Figure 5 illustrates these patterns by classifying

countries in South Asia and Sub-Saharan Africa into three groups according to the relative availability of monetary and multidimensional poverty estimates over 10-year periods: countries with more monetary estimates (red), more multidimensional estimates (blue), and an equal number of both (yellow).

During the 2000–2009 period, monetary poverty estimates were more prevalent: 31 out of 56 countries in the two regions reported more monetary estimates than multidimensional ones. Since then, however, the trend has almost reversed. Between 2010 and 2019, only 13 countries reported more monetary estimates, while 23 countries produced more multidimensional estimates and another 20 reported the same number of each. Thus, in the decade preceding the COVID-19 pandemic, a majority of countries in South Asia and Sub-Saharan Africa generated more multidimensional than monetary poverty estimates. Taken together, these results suggest that an increasing number of countries in the world's poorest regions are relying primarily on multidimensional poverty measures to monitor poverty trends.

Figure 5 Relative availability of monetary and multidimensional poverty estimates in South Asia and Sub-Saharan Africa



Authors' calculation using World Bank (2025f) and Oxford Poverty and Human Development Initiative (2025).

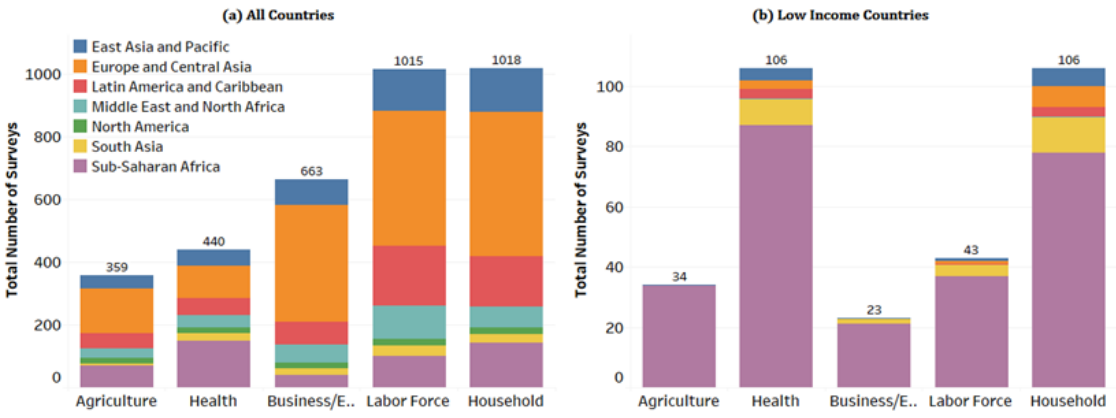
Since virtually all poverty estimates are derived from household survey data[2], the availability of such surveys follows patterns similar to those observed for monetary and multidimensional poverty estimates. Figure 6 summarizes the number of household surveys conducted between 2010 and 2019 for (a) all countries and (b) low-income

[2] There are few notable exceptions. See Alfani, et. al. (2025) for details.

countries (LICs), based on the World Bank's Statistical Performance Indicators database (World Bank, 2025d). During this period, more than 1,000 household surveys collected income and expenditure information for monetary poverty estimation. However, their distribution was highly uneven: approximately 45 percent of these surveys were concentrated in Europe and Central Asia. In contrast, only 440 health surveys—essential for estimating multidimensional poverty—were conducted over the same period (Panel (a)).

The landscape of survey availability looks very different when the analysis is restricted to low-income countries (LICs). Over the 2010–2019 period, LICs conducted an equal number of health surveys and household surveys—106 each (Panel (b)). Health surveys, which serve as the basis for multidimensional poverty measures, are considerably more pro-poor in their orientation than household surveys used for monetary poverty measurement, mirroring the broader contrast between multidimensional and monetary poverty estimates. Figure 6 classifies countries by their income status at the time the surveys were conducted, even if they have since graduated to middle-income status. When focusing only on those countries that remain classified as LICs in 2025, the gap widens further: 83 health surveys were conducted compared to 77 household surveys (not shown).

Figure 6 The Number of Household Surveys by Types (2010-2019)



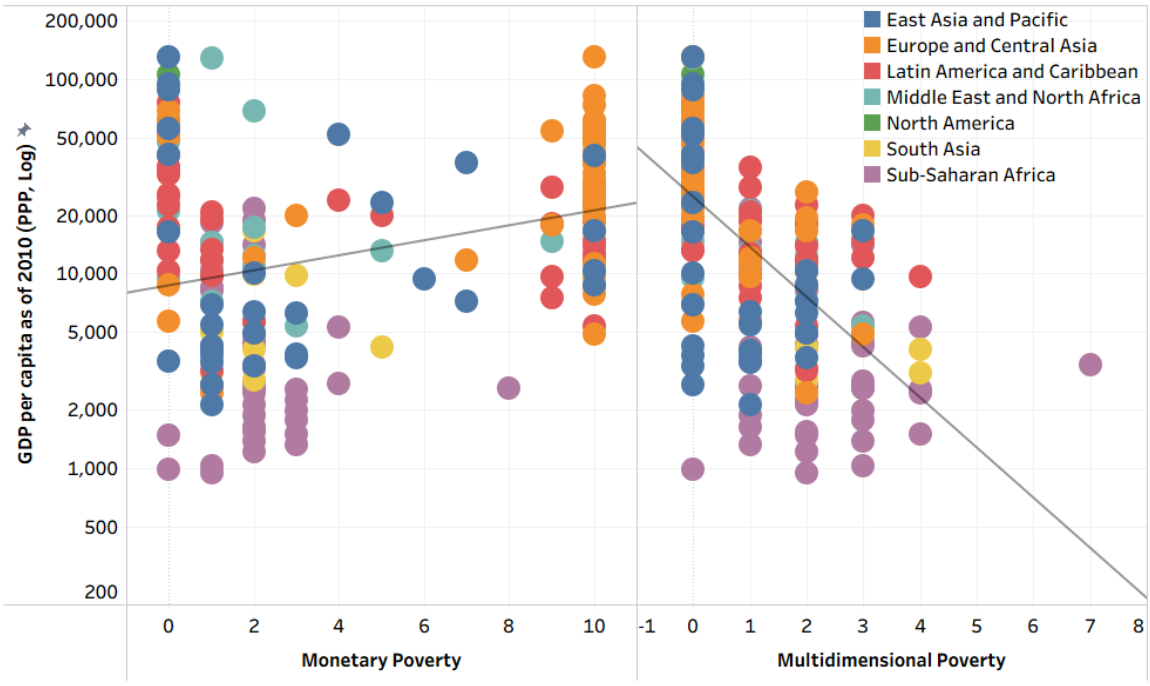
Source: Authors' calculation using World Bank (2025d).

A simple regression analysis of Gross Domestic Product (GDP) per capita on the availability of different types of poverty estimates provides further support for the preceding arguments. Figure 7 plots GDPIper capita as of 2010 in natural logarithm against the number of monetary poverty estimates (left panel) and multidimensional

poverty estimates (right panel) during the 2010–2019 period. The relationship is positive in the case of monetary poverty: countries with higher levels of GDP per capita tend to produce more monetary poverty estimates. The opposite pattern emerges for multidimensional poverty, where countries with lower GDP per capita are more likely to report a greater number of multidimensional poverty estimates.

While assessing the "pro-poor" nature of poverty data availability using poverty status is inherently endogenous—since countries cannot be classified by poverty without the very data under study—the use of GDP per capita as an independent benchmark yields consistent results. The results are robust when GDP per capita as of 2019 is used and when the data from other 10-year periods are used. These correlations reinforce the finding that monetary poverty measurement remains concentrated in richer countries, while multidimensional poverty measures have become more common in poorer countries.

Figure 7 GDP per capita and Poverty Data Availability (2010-2019)



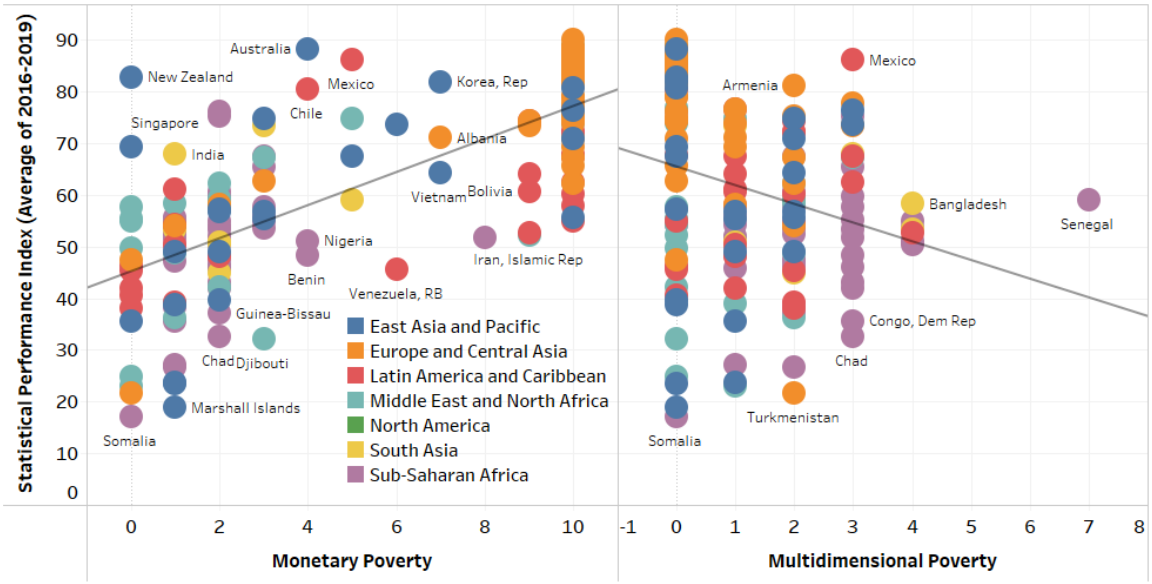
Authors's calculation using World Bank (2025b). The horizontal axis shows the number of monetary poverty estimates (left) and multidimensional poverty estimates in the 10-year period from 2010 to 2019.

Figure 8 plots the World Bank's Statistical Performance Index (SPI) against the number of monetary poverty estimates (left panel) and multidimensional poverty estimates (right panel). Much like the earlier correlation with GDP per capita, the two measures of

poverty exhibit contrasting associations with statistical capacity. Countries with higher SPI tend to produce more monetary poverty estimates, while those with lower SPI are more likely to produce multidimensional poverty estimates.

This pattern challenges a common presumption in the literature—that improvements in statistical capacity necessarily translate into more frequent poverty measurement. While a positive correlation may plausibly suggest such a causal link for monetary poverty, the negative association between statistical capacity and multidimensional poverty estimates calls this logic into question. The evidence here shows that countries with relatively low statistical capacity are nonetheless able to generate more multidimensional poverty estimates.

Figure 8 Statistical Performance Indicators and Poverty Data Availability



Authors' calculation using World Bank (2025d) and World Bank (2025f).

The horizontal axis shows the number of monetary poverty estimates (left) and multidimensional poverty estimates in the 10-year period from 2010 to 2019. The average Statistical Performance Indicators from 2016 to 2019 are used.

The conventional view that ending data deprivation requires first strengthening statistical capacity does not hold uniformly. In practice, countries with weaker statistical capacity have been able to generate more multidimensional poverty data, suggesting alternative pathways for overcoming data gaps. However, the analysis thus far relies on descriptive statistics and simple regression models, where the observed correlations may be influenced by confounding factors. The next section extends the analysis by

incorporating additional covariates used in the existing studies to test the results presented so far.

Regression Analysis

This section presents results from regression models that examine factors that explain the variation in the availability of monetary and multidimensional poverty estimates. We estimate two models, each run twice with the availability of monetary poverty and multidimensional poverty as the dependent variables.[3] First, using the 10-year data summarized in Figures 8 and 9, we estimate linear regression models to understand cross-country differences. Second, we employ Poisson Pseudo-Maximum Likelihood (PPML) models with country and year fixed effects using a country-year panel, where the dependent variable is a binary indicator of whether a poverty estimate is available in a given year. Finally, we estimate PPML models with a three-year window panel, in which the dependent variable reflects the number of poverty estimates available during each period, again including country and period fixed effects.

The linear model provides insights into cross-sectional variation, while the latter two models exploit within-country variation over time. Across all models, the main explanatory variables of interest are countries' statistical capacity and political characteristics. We focus on the electoral democracy index as the key proxy for political institutions, given its superior geographic and temporal coverage. Results based on alternative measures—including Polity V, Freedom House scores, and the Worldwide Governance Indicators—are qualitatively similar. Consistent with the literature, we employ parsimonious specifications to minimize sample selection bias that may arise from including additional covariates with limited coverage (Hollyer et al., 2011).

We restrict the analysis to data up to 2019 for two reasons. First, the COVID-19 pandemic severely disrupted household survey operations, and including the pandemic years risks confounding the relationships of interest. Second, a quick descriptive analysis of WDI data and its vintages demonstrates that it usually takes up to three to four years for all poverty estimates to be published in the World Development Indicators since the household survey is fielded. This means that, at the time of writing, we can reasonably expect all available poverty estimates to have been published up to around 2021–2022, which still falls within the period affected by the pandemic. Descriptive results in Figures 1 and 2

[3] We also estimated seemingly unrelated regression models. However, the correlation between the error terms of the two equations was not statistically significant, indicating that it is appropriate to estimate the models separately.

seem to confirm this view. For these reasons, all regression analyses that follow are restricted to data up to 2019.

Tables 1 and 2 report the linear regression results, with the dependent variable defined as the number of monetary and multidimensional poverty estimates over 2010–2019, respectively. Statistical performance indicators are positive and significant across all five models, while the electoral democracy index is positive and significant in Models 2–4. These results suggest that countries with stronger statistical capacity and higher electoral democracy scores are more likely to publish monetary poverty estimates, while those with weaker capacity and less democratic institutions are less likely to do so. The findings remain robust when controlling for log GDP per capita and log population (Model 3); indicators for small states, landlocked countries, and fragile states (Model 4); and the total amount of aid financing and number of aid projects (both in logs). Among these additional controls, only log GDP per capita shows a positive and significant coefficient, consistent with the descriptive patterns in Figure 8.

The analysis of multidimensional poverty yields markedly different results compared to those for monetary poverty. Table 2 presents the corresponding regression results using the number of multidimensional poverty estimates as the dependent variable. The patterns contrast sharply with those in Table 1. Statistical capacity is negative and significant in the most parsimonious specifications (Models 1 and 2) but insignificant in the others. The electoral democracy index is also not statistically significant in any model. These results suggest that, unlike monetary poverty estimates, neither statistical capacity nor electoral democracy is systematically associated with the number of multidimensional poverty estimates. By contrast, log GDP per capita is negative and significant in Models 3–5, indicating that countries with lower income levels are likely to publish more multidimensional poverty estimates. This finding is consistent with the descriptive patterns in Figure 8. Another notable difference between Tables 1 and 2 is the explanatory power of the statistical performance indicator. In Table 1, the most parsimonious model, where the statistical performance indicator is the sole regressor, yields an adjusted R-squared of 0.56. In Table 2, the same model produces an adjusted R-squared of only 0.04, underscoring that different underlying factors drive the availability of the two poverty measures.

Table 1 Cross-country regression on the availability of Monetary Poverty Estimates

Dependent Variable = Number of Monetary Poverty Estimates (2010-2019)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Statistical Performance Indicators (average from 2016 to 2019)	0.181***	0.161***	0.145***	0.131***	0.135***
	(0.010)	(0.015)	(0.019)	(0.020)	(0.021)
Electoral democracy index		2.525**	2.818**	3.259***	3.446***
		(1.123)	(1.150)	(1.179)	(1.188)
Log of GDP per capita (PPP) as of 2010			0.287	0.412*	0.744**
			(0.220)	(0.244)	(0.333)
Log of Population as of 2010			0.197	0.065	0.035
			(0.156)	(0.215)	(0.217)
Small States				-1.167	-1.073
				(0.847)	(0.848)
Landlocked Country/Territory				0.536	0.575
				(0.559)	(0.553)
Fragile States				-0.012	0.022
				(0.057)	(0.062)
Log of SDG financing - disbursement as of 2010					-0.060
					(0.208)
Log of SDG financing - total projects as of 2010					0.331
					(0.641)
Constant	-6.82***	-6.76***	-11.8***	-10.05**	-13.9***
	(0.598)	(0.687)	(2.896)	(4.059)	(5.104)
Adj. R-sq.	0.561	0.559	0.568	0.569	0.568
Observations	186	168	165	165	165

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

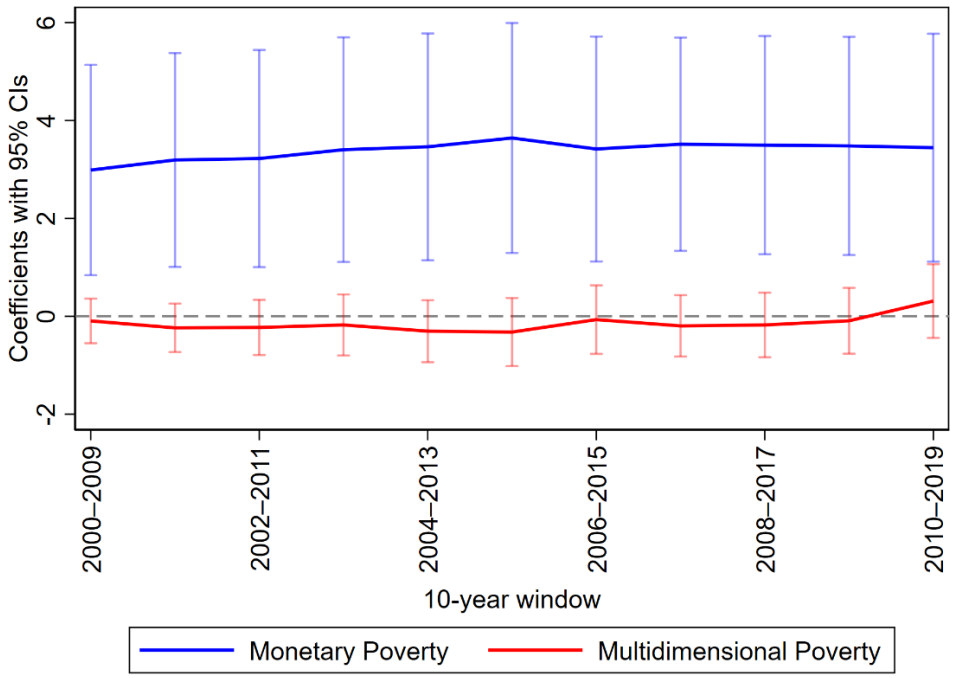
Table 2 Cross-country regression on the availability of Multidimensional Poverty Estimates

Dependent Variable = Number of Multidimensional Poverty Estimates (2010-2019)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Statistical Performance Indicators (average from 2016 to 2019)	-0.016***	-0.021***	0.001	-0.002	0.003
	(0.005)	(0.007)	(0.008)	(0.008)	(0.009)
Electoral democracy index		-0.544	0.055	0.092	0.311
		(0.470)	(0.388)	(0.390)	(0.384)
Log of GDP per capita (PPP) as of 2010			-0.711***	-0.738***	-0.347**
			(0.088)	(0.114)	(0.146)
Log of Population as of 2010			0.090**	0.104*	0.070
			(0.046)	(0.057)	(0.056)
Small States				0.069	0.180
				(0.273)	(0.274)
Landlocked Country/Territory				0.078	0.123
				(0.253)	(0.245)
Fragile States				-0.039	0.001
				(0.036)	(0.035)
Log of SDG financing - disbursement as of 2010					-0.071
					(0.069)
Log of SDG financing - total projects as of 2010					0.391*
					(0.217)
Constant	2.198***	2.913***	6.435***	6.657***	2.120
	(0.329)	(0.390)	(1.089)	(1.732)	(1.979)
Adj. R-sq.	0.040	0.104	0.416	0.413	0.473
Observations	186	168	165	165	165

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

While Tables 1 and 2 present results for 2010–2019, the coefficient estimates for the electoral democracy index are robust across different periods. Figure 9 summarizes the Model 5 coefficients from Tables 1 and 2 using alternative 10-year windows beginning with 2000–2009. For monetary poverty, the electoral democracy index remains positive and significant across all periods. In contrast, the coefficients for multidimensional poverty are negative and statistically insignificant. These findings highlight a persistent association between political characteristics and the availability of monetary, but not multidimensional, poverty data.

Figure 9: Coefficient Estimates for Electoral Democracy Index



Source: Authors' calculation.

Up to this point, the analysis has focused on cross-country variation in poverty data availability. We now turn to within-country dynamics using country–year panel data. Table 3 reports Poisson Pseudo-Maximum Likelihood estimates with country and year fixed effects, testing the correlation between changes in statistical performance, electoral democracy, and the availability of poverty estimates. In Models 1–3, the dependent variable is a binary indicator equal to one when a monetary poverty estimate is available; in Models 4–6, the dependent variable is the corresponding indicator for multidimensional poverty. Because the dependent variable is binary, these regressions capture the likelihood that a poverty estimate is available in a given country–year.

Here again, the two poverty measures exhibit contrasting results. In the monetary poverty regressions, the statistical performance indicator has a negative coefficient and is only marginally significant in Model 3, while the electoral democracy index is not statistically significant in any specification. In the multidimensional poverty regressions, by contrast, the statistical performance indicator is insignificant, but the electoral democracy index is positive and significant, even after controlling for log GDP per capita, log population, and fragility status. These results suggest that within-country changes in political characteristics are more closely associated with the availability of multidimensional poverty estimates, whereas statistical capacity plays little role.

The results in Table 3 are robust to both the choice of estimator and the measure of political characteristics. Estimating the same models with linear probability models yields essentially identical results: the electoral democracy index is positive and significant in the multidimensional poverty regressions but not in the monetary poverty regressions. Tables A1 and A2 report robustness checks using alternative measures of political institutions. In Table A1, the Polity V score—which ranges from –10 (fully institutionalized autocracy) to +10 (fully institutionalized democracy)—is positive and significant in the multidimensional poverty regressions and insignificant in the monetary poverty regressions. In Table A2, the Freedom House scores—ranging from 1 (most free) to 7 (least free)—are negative and significant in the multidimensional poverty regressions and insignificant in the monetary poverty regressions. The change in sign is consistent with the scale of the measure, since lower Freedom House scores indicate greater freedom, whereas higher values on the electoral democracy index and Polity V score denote more democratic institutions.

Table 3: Poisson Pseudo-Maximum Likelihood Estimates with Country and Year Fixed Effects (Country–Year Panel)

Dependent Variable	Availability of Monetary Poverty Estimates			Availability of Multidimensional Poverty Estimates		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Statistical Performance Indicators	-0.000	-0.000	-0.008*	0.009	0.010	0.007
	(0.005)	(0.005)	(0.004)	(0.007)	(0.007)	(0.008)
Electoral democracy index		0.441	0.124		2.281***	2.110**
		(0.322)	(0.303)		(0.704)	(0.893)
Log of GDP per capita			0.707*			0.554
			(0.387)			(0.502)
Log of Population			-0.193			0.241
			(0.479)			(1.034)
Fragility Status (=1 if Fragile State, 0 otherwise)			0.081			-0.175
			(0.192)			(0.204)
Constant	-0.444	-0.671	-3.548	-2.165***	-3.253***	-11.655
	(0.351)	(0.442)	(9.309)	(0.437)	(0.590)	(18.367)
Observations	2192	2057	1788	1811	1729	1480

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The dependent variables are binary variables that take a value of 1 when a poverty estimate is available in a given country/year, and 0 otherwise. All regressions include country and year fixed effects.

Discussions

Several factors may help explain the contrasting associations observed between monetary and multidimensional poverty estimates. First, governments are likely to perceive the two poverty measures differently. On the one hand, publishing monetary poverty estimates can be politically sensitive, since new estimates are often compared with earlier ones and may draw public attention to whether poverty has increased or declined. By contrast, multidimensional poverty measures are relatively recent and often lack long historical series, which may make governments more willing to release them, at least in the early stages. The first publication of a Multidimensional Poverty Index (MPI) may thus be perceived as less politically risky than updating monetary poverty figures. Moreover, multidimensional poverty estimates are constructed as weighted averages of deprivations in education, health, and living standards. Because many of these component indicators—such as school attendance, access to sanitation, and access to safe drinking water—are already reported separately in surveys like DHS and MICS, the likelihood of "surprises" in the final MPI is lower. For policymakers, these deprivations are also more actionable, as they point directly to specific policy interventions. In contrast, reducing monetary poverty involves more complex mechanisms and lacks clear, single-policy solutions. These conceptual differences, while intended to make the two measures complementary, may also shape how governments perceive and manage their publication.

Second, differences in the institutional arrangements for producing these measures may shape governments' incentives. The production of multidimensional poverty estimates is more decentralized. Data collection for Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) is implemented by USAID and UNICEF in partnership with national statistical agencies. Data analysis and reporting are typically undertaken by the Oxford Poverty and Human Development Initiative (OPHI), with UNDP support for the global Multidimensional Poverty Report. In contrast, monetary poverty estimation is more centralized and is largely managed by the World Bank. The World Bank provides financial and technical support for multi-topic household surveys, conducts the bulk of the analysis, and often drafts the resulting reports. Because monetary poverty requires detailed expenditure data, it cannot be derived from DHS or MICS; instead, the World Bank frequently supports Living Standards Measurement Study (LSMS)–type surveys, even where these are not officially recognized as LSMS. While the Bank also invests in capacity-building for national statistical agencies, in practice much of the analytical burden falls on Bank staff and consultants.

These structural differences may have implications for the political economy of data production. When governments are reluctant to publish results, it is less clear whom they can pressure in the multidimensional poverty framework, since different organizations are responsible for different stages of survey implementation, analysis, and reporting. By contrast, for monetary poverty, the World Bank is the primary counterpart throughout the process. Given the World Bank's wider lending relationship with most governments, poverty data can become entangled in broader negotiations. Governments may not directly pressure the World Bank to suppress poverty figures, but subtle signals during lending discussions may lead the World Bank to prioritize project approvals over contentious data releases. As Ravallion (2016) reminds us, the World Bank is not exclusively a poverty-minimizing institution, and tensions between its roles as lender and knowledge producer may, at times, affect the dissemination of poverty data.

To be clear, this paper does not provide evidence of manipulation or suppression of official poverty statistics, nor is it intended to do so. Its motivation lies in the fact that poverty data remain severely limited in parts of the world, despite broad recognition by the international community of the need to address this form of data deprivation. The aim is to generate a more nuanced understanding of poverty data availability, moving beyond the prevailing narrative that improving statistical capacity alone is sufficient. The analysis shows that poverty data availability can increase even in countries with weak statistical capacity, as illustrated by the case of multidimensional poverty. Both descriptive and regression evidence suggest that the availability of multidimensional poverty estimates is less dependent on countries' statistical capacity or political characteristics, pointing to an alternative pathway for expanding poverty data availability.

The discussion in this section about institutional arrangements and the ways governments may perceive different poverty measures reflects informed practitioner insights from international development experience. These interpretations, however, remain hypotheses and require further substantiation through in-depth qualitative research that can illuminate the dynamics behind the production of monetary and multidimensional poverty data. Unlike the literature on GDP manipulation—which often identifies direct incentives for governments to misreport economic output—the availability of poverty data is shaped by a more complex interplay of domestic politics, donor engagement, and institutional arrangements. While the findings here reveal robust correlations between political characteristics and the availability of poverty estimates, they do not establish causality. Poverty data production involves multiple

actors, financing constraints, and bureaucratic decisions that complicate causal attribution. Instead, the results are best interpreted as consistent with the view that political institutions influence the broader environment in which poverty data are produced and disseminated.

This study represents one of the first systematic attempts to highlight the need for a deeper understanding of these dynamics in order to improve the availability of both monetary and multidimensional poverty data. Finally, while this paper emphasizes their differences, these two measures are ultimately complementary. Taken together, they offer a more holistic view of the lived realities of the poor. Yet the sobering reality remains: many countries long known to be deprived of poverty estimates continue to face this deprivation even today—ten years into the SDG era and with only five years remaining before its conclusion.

Conclusion

This paper addressed a persistent gap in the global data landscape: the scarcity of poverty statistics despite their central role in monitoring development progress. Most of the existing literature emphasizes improving statistical capacity as the primary solution to data deprivation. At the same time, recent studies have examined how governments manipulate economic indicators such as GDP, yet no prior work has analyzed the availability of poverty data in this political economy literature. This study asked whether poverty data availability depends mainly on statistical capacity, or whether political and institutional factors also matter. Using a cross-country dataset of monetary and multidimensional poverty estimates, we combined descriptive analysis with regression models to explore these associations.

The results reveal clear contrasts. Monetary poverty estimates are closely linked to statistical capacity and political institutions, while multidimensional poverty estimates appear less constrained by these factors. This suggests that poverty data can expand even in weak-capacity settings, though the mechanisms remain unclear. These findings should not be read as evidence of manipulation or suppression; rather, they underscore the need for a more nuanced understanding of how poverty data are produced. By highlighting robust correlations between political characteristics and data availability, this paper represents one of the first systematic efforts to situate poverty statistics within the political economy of data. Ultimately, monetary and multidimensional measures are complementary, together providing a fuller account of poverty. Yet the fact that many countries remain deprived of both measures—even a decade into the SDG era and just five years before its end—underscores the urgency of addressing this persistent form of data deprivation.

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Appendix

Table A1: Poisson Pseudo-Maximum Likelihood Estimates with Country and Year Fixed Effects (Country–Year Panel) with Polity V score

Dependent Variable	Availability of Monetary Poverty Estimate			Availability of Multidimensional Poverty Estimate		
Statistical Capacity Index	-0.000	0.002	-0.002	0.009	0.019**	0.017*
	(0.005)	(0.004)	(0.004)	(0.007)	(0.008)	(0.009)
Polity V		0.005	0.000		0.080***	0.075***
		(0.013)	(0.012)		(0.029)	(0.028)
Log of GDP per capita			0.350			-0.149
			(0.305)			(0.421)
Log of Population			-0.190			0.935
			(0.479)			(0.793)
Constant	-0.444	-0.630*	-0.495	-2.165***	-3.093***	-17.002
	(0.351)	(0.363)	(8.876)	(0.437)	(0.590)	(14.643)
Adj. R-sq.						
Observations	2192	1791	1747	1811	1517	1488

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The dependent variables are binary variables that take a value of 1 when a poverty estimate is available in a given country/year, and 0 otherwise. All regressions include country and year fixed effects.

Table A2: Poisson Pseudo-Maximum Likelihood Estimates with Country and Year Fixed Effects (Country–Year Panel) with Freedom House Score

Dependent Variable	Availability of Monetary Poverty Estimate			Availability of Multidimensional Poverty Estimate		
Statistical Capacity Index	-0.000	0.002	-0.003	0.009	0.013*	0.011
	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Freedom House Score		-0.051	-0.015		-0.197**	-0.196**
		(0.060)	(0.053)		(0.094)	(0.093)
Log of GDP per capita			0.330			0.241
			(0.298)			(0.387)
Log of Population			-0.069			1.248*
			(0.438)			(0.707)
Constant	-0.444	-0.421	-2.231	-2.165***	-1.620***	-23.852*
	(0.351)	(0.323)	(8.213)	(0.437)	(0.570)	(12.644)
Adj. R-sq.						
Observations	2192	2164	2117	1811	1798	1767

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The dependent variables are binary variables that take a value of 1 when a poverty estimate is available in a given country/year, and 0 otherwise. All regressions include country and year fixed effects.