Data for Poverty Measurement

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1. Introduction

Poverty alleviation is the first of the United Nation's 17 Sustainable Development Goals. However, the three decades of progress in poverty alleviation hit the COVID-19 pandemic wall (World Bank, 2022). This was further exacerbated by longstanding macroeconomic mismanagement in countries such as Sri Lanka. Counting the poor is the first step in poverty alleviation (The Economist, 2023). Deaton (2016), for example, notes that recording details of how people live, their consumption patterns, and their expenditure has long served as a tool, sometimes a political one, that aimed to bring the living conditions of the impoverished to the attention of those in authority, to evoke shock, and to advocate for reform. However, defining and measuring poverty is a complex and multifaceted task that requires careful examination of various indicators and methodologies. A clear definition of poverty is crucial as that it guides the determination of indicators for it, which leads to identifying individuals suffering from it, and eventually helps formulate effective policies to alleviate the same (Laderchi et al.,2003).

This paper first draws on the literature to discuss various conceptualizations of poverty and their relative merits. This step is intended to guide policy practitioners on which types of poverty they are trying to alleviate through various social protection programmes. It then provides several examples of types of data sources can be drawn on for poverty measurement – this includes relatively new sources such as call detail records and geospatial data, which have not been addressed in previous discussions on data sources. Thereafter it discusses the suitability of the different data sources for measuring types of poverty, and different considerations for policymakers and policymakers when picking the suitable data source.

2. Defining poverty

Boltvinik (1999) notes that the term poverty "in its daily use, implies a comparison between the conditions of a person, family or human group, and the perception of the one who speaks or writes, about what is necessary to sustain life." and implies "a comparison between an observed and a normative (standard) condition. However, even within Boltvinik's broad conceptualization, poverty can be defined, used, and viewed heterogeneously.

Lok-Dessallien (1999) presents several key concepts based on which poverty can be viewed. One such concept is that poverty can be approached from an objective lens, as well as a subjective one. Another is how poverty can be viewed as absolute or relative. Absolute poverty "refers to subsistence below minimum, socially acceptable living conditions, usually established based on nutritional requirements and other essential good". Relative poverty, on the other hand, "compares

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the lowest segments of a population with upper segments, usually measured in income quintiles or deciles", and may also be considered a measure of inequality.

Box 1: Poverty lines
With some exceptions, poverty lines are often associated with absolute poverty. Absolute poverty lines are mostly anchored on food – a feature that is prominently used in measures that aim to inform welfare enhancing policy (Deaton, 2016). Methods such as cost of basic needs (CBN), food energy intake (), and food share are used to form absolute poverty lines – the latter is based on Engle's law (1857) which states that poorer households spend a greater proportion of their income on food. Poverty lines can help identify the number of people living in poverty through indicators such as the poverty headcount ratio, and the depth of poverty through indicators such as the poverty gap index and monthly shortfall. However, this is not necessary, particularly when dealing with indicators relevant to inequality. Poverty lines embody the feature of being 'arbitrary but intelligible' (Bowley in Atkinson, 1987) due to different views in forming them. As such, they can be objective, subjective or a hybrid form of both (Ravallion, 2016).

Additionally, Hulme et al (2001) indicate that the duration of poverty is a key consideration. For example, chronic poverty, which builds on duration, multidimensionality, and severity of poverty, differs greatly from the transient or temporary poor. (Boltvinik, 1999).

Laderchi et al. (2003) presents an alternative framework, with four conceptualizations of poverty in the form of the monetary approach, capabilities approach, social exclusion approach and the participatory approach. There are other approaches to understanding and measuring poverty such as Ravallion's 'opportunities approach' (Ravallion, 2016) which are closely related to one or more of the above-mentioned approaches. Thereby, this paper anchors its discussions on the four conceptualizations of poverty used by Laderchi et al (2003), while drawing on additional concepts such as absolute and relative poverty, and subjective and objective perspectives, within this framework. (Aiken et al., 2022).

2.1 Monetary Approach

Booth and Rowntree, in their seminal work pioneered the use a monetary approach to poverty measurement. This approach uses a 'money-metric of utility' to understand poverty Ravallion, 2016. That is, income, expenditure (or consumption) or wealth can be used as a proxy to identify individuals' utility maximization (Kumar, 2018)(Kumar, 2018))(Kumar, 2018). Laderchi et al (2003) posits that the centrality of the assumption utility maximizing behaviour in economics makes the approach appealing to economists, but notes that this indicator is often used not because monetary resources are seen as measuring utility, but because it is assumed to approximate other elements of poverty because the data is more readily available and accessible. However, as we highlight in Section 3, data on monetary indicators are often not readily accessible nor verifiable in many developing country contexts. Many argue monetary poverty is not an 'adequate' measure of poverty, however.

As highlighted in Kumar (2018), the monetary poverty can be used to refer to conceptualizations based on wealth, income, and expenditure. But these should not be viewed uniformly. Wealth draws on a stock concept, while income and expenditure draw on a flow concept. Income and wealth are both more explicit measures of financial security than expenditure. Atkinson (1987) justifies the use of income on a rights-based approach, stating that a minimum income can be seen as a basic right. However, Haughton and Khandker (2009) illustrate how income is more volatile than expenditure throughout a lifecycle. This hints that expenditure may be a better indicator of chronic poverty than income.

2.2 Capabilities Approach

Amartya Sen stressed on an approach that broadens the scope of poverty assessment into 'functionings and 'capabilities' beyond incomes and commodity holdings where capabilities are a set of functionings that an individual can achieve (Alkire et al., 2015; Sen, 1985). This extends into aspects of social justice including 'rights, opportunities, …and social bases of self-respect' (Sen, 1997_ The capabilities approach views 'well-being' as the freedom individuals have to lead meaningful lives that align with their values, and which helps them fulfill their potential. As opposed to an approach based on assumptions of utilitarianism, this implies that an individual can be satisfied in a deprived state even while their desires are only within the scope of what they know to be possible to achieve (Laderchi et al, 2003).

The focus on the outcomes that reflect individuals' quality of life is a departure from relying only on monetary indicators (Laderchi et al.,2003). There exists no formal one-size-fits-all full list of capabilities as it is intended to be highly context specific and chosen with methods such as 'general social discussion' and 'public reasoning', with the aim of expanding the freedoms of a particular population. Alkire (2007) a framework to achieve this, while others like Nussbaum (2000) attempted to provide a general list of human rights and 'dignities' centered 'human capabilities' that could be the object of 'overlapping consensus'. Moser & Satterthwaite (2008) indicate that vulnerability is linked to a lack of assets – thereby, it identifies five types of assets that serve to reduce vulnerability, namely, physical capital, financial capital, human capital, social capital and natural capital/ Although this approach broadens the scope of what poverty could mean, ambiguities of definition may play a limiting role when measuring poverty according to it. Unless frameworks are built and adopted internationally, it will not be comparable – especially when features that signal to poverty differ across geographies. Although this approach broadens the scope of what poverty could mean, ambiguities of definition may play a limiting role when measuring poverty according to it. Unless frameworks are built and adopted internationally, it will not be comparable – especially when features that signal to poverty differ across geographies.

2.3 Social Exclusion Approach

Social exclusion as a concept emerges in literature in connection to Lenoir's 1974 work on 'the excluded', or the people in the fringes of society with no access to the welfare state such as persons with disability, single parents, and asocial persons (Kumar, 2018; Peleah M et al., 2012; Sen, 2000). Although this approach has shaped European policymaking in the poverty and inequality space for many years, there exists little consensus on the definition of the concept - hence it ranges from 'material poverty to multidimensional poverty to systematic discrimination to social isolation'. (United Nations Economic Commission for Europe Task Force on the Measurement of Social Exclusion, 2022). Social exclusion (as the name suggests) is socially defined and oftentimes places more emphasis on collectively owned resources rather than what each individual owns(Kumar, 2018; Townsend, 1979; United Nations Economic Commission for Europe Task Force in the Measurement of Social Exclusion, 2022) essentially linking people to their environment to assesses the marginalized status of individuals or groups within a society, and how it may prevent their participation in key socioeconomic activities. (Burchardt et al., 2002). This marginalization could happen due to historical, social, ethical, gender-specific, or racial reasons within economic, political, and cultural dimensions due to systemic barriers, limited access to resources and opportunities, and cultural deterioration (United Nations Economic Commission for Europe Task Force on the Measurement of Social Exclusion, 2022).

Hence, it can be used as a basis to provide greater access by combatting discrimination and even justifying affirmative action, or other types of positive discrimination (Kumar, 2018; Laderchi et al., 2003) warns using categorical targeting methods to pronounce specific groups as 'socially excluded' or 'marginalized' may be at the danger of further stigmatizing those groups and of running the risk of undermining or missing some of the underlying causal factors that are implied by the selection of the groups in question. warns, using categorical targeting methods to pronounce specific groups as 'socially excluded' or 'marginalized' may be at the danger of further stigmatizing those groups and of running the risk of undermining or missing some of the underlying causal factors that are implied by the selection of the groups in question.

2.4 The Participatory Approach

The participatory approach is subjective and follows a qualitative and context-specific approach to defining poverty as per input given by people themselves themselves (Kakwani & Silber, 2007). A commonly used qualitative approach to poverty assessment is the PPA (Participatory Poverty Assessment) (Kakwani & Silber, 2007; Kamanou et al., 2005). Asking the minimum income question, economic ladder question and income evaluation question can also be employed for this purpose. It is believed that this may lead to the identification of more wholesome findings (Deaton et al., 2010; Kakwani & Silber, 2007)

3. Types of data sources

The conceptual elements of defining poverty, and the practical elements of measuring poverty should go hand in hand. There are a variety of different data sources that one could draw on to measure the various conceptualizations of poverty. UNDP & OPHI (2019) highlight three different types of data sources in their handbook on creating an MPI – census data, household survey data, and administrative data. We expand this list, adding several new data sources that have gained prominence in recent empirical and academic work. As such, we study four types of data sources: (i) survey data (ii) government administrative records (iii) call detail records (iv) and geospatial data While we understand that this may not be comprehensive (particularly as it relies largely on structured, quantitative insights). However, we expect it to give a broader glimpse into the types of data that can be used for poverty assessment. We discuss the rationales of using these data sources, with an emphasis on its usefulness and challenges in developing countries.

3.1. Survey data

Surveys, are a close examination of an area of interest and can be carried out in multiple forms. They constitute individuals answering a well-defined set of questions, in many cases, with structured responses. At one end of the spectrum, we have censuses, which capture data from the entire population. It can allow for the most granular level of data collection, which in turn is expected to create the most comprehensive database for poverty assessment, with no sampling error. Censuses are often implemented by governments, rather infrequently (often once a decade in developing countries) due to it being costly in terms of both data collection and data cleaning.

Sample surveys which look at a subset of the population are more common (Annex 1 highlights how several countries utilize surveys). It can yield various levels of precision based on research design, including but not limited to sample size, sampling methods and data collection techniques. These too, incur a sizable cost and may be susceptible to sampling and non-sampling errors. While sample surveys are generally thought to be held more frequently than a census, this is not always the case.

For example, the household income and expenditure survey (KIHBS) conducted by the Kenya National Bureau of Statistics had a ten-year gap between the last two surveys conducted (KIHBS 2005/06 and KIHBS 2015/16), creating a data-gap between these years for poverty analysis (Kenya Statistics Bureau, 2023).

In addition to the two types of commonly discussed survey types, we also examine surveys administered to a target population – for example, those who register for social assistance programmes. While this accounts for less external validity beyond the specific purpose for which the data was collected, it can be particularly useful for identifying poverty of the more limited group.

3.2. Government administrative data

Administrative records, such those owned by government, could form a strong evidence base for poverty assessment. In this case, we define government administrative data as supply side data that is purposively collected with the knowledge of the data subject, moving beyond survey data for social registries identified in section 3.1.1, which relies on information declared by individuals for poverty assessments. This data could include data that is not collected specifically for poverty assessment, but to complete a process that could (among other reasons) be a part of receiving goods or services from a government authority, records maintained for the purpose of regulating an industry or activity from vehicle registration to emigration records, legal requirements to record certain events like births or deaths, and records held for the administration of public institutions (ADB, 2010). An example is Vietnam's National Statistical Indicator System (NSIS), which is made up of over 250 socioeconomic indicators across 24 categories. Here, the data collection responsibilities are entrusted to various government agencies, forming the foundation for statistical analysis to take place

As such, using administrative records of the government is a convenient data source that also imposes relatively less transaction costs. The records obtained are 'actuals' as opposed to survey responses which may be over or underestimated by respondents (Alatas et al., 2022). Further, as (Alatas et al., 2022) points out, this method can reduce 'recall bias' of respondents in surveys that measure outcomes after a certain period of time by providing a continuous stream of timely information. Certain types of these records which are legal requirements have wide coverage and completeness and can be disaggregated at very granular levels (ADB, 2010).

However, the data sourced through government records may suffer from deliberate or non-deliberate incorrect reporting and hence be of poor quality (ADB, 2010). They may also be unsuitable for statistical analysis. As ADB (2010) highlights, robust data sharing agreements and coordination between parties are required to increase their usability in socioeconomic assessment. Further, there is also a scarcity of data affects the use of administrative data for poverty measurement in developing countries. Further, even when such data are available there may be practical limitations when using them due to concerns on quality or completeness. Excessive and inefficient bureaucratic processes present in many developing countries could further hamper timely access to available data.

3.3 Call detail records

There is a growing body of literature of call detail records (CDRs) being used for poverty assessment. Like administrative data, this constitutes of supply side data, though it could be owned by government or private entities. However, while the data subject may or may not be aware of that the data is being collected as it requires less administrative filings. Further, call detail records are updated more frequently than the administrative data, which in turn means that the data subject is even more unlikely to be cognisant of impacts on poverty assessment each time a call is made.

According to Blumenstock (2015), call data records can be used as an indicator of wealth or poverty, especially in developing countries where other big data sources are scarce. Historical patterns of phone use can capture information on an individual's social network, patterns of travel and location choice, as well as histories of consumption and expenditure and therefore act as a proxy for a mobile phone subscriber's wealth.

3.4 Geospatial data

Geospatial data obtained through remote sensing too can aid in poverty assessment. Data sources can include satellite imagery and aerial imagery. Unlike in the sources highlighted above, the data subject will have nearly no knowledge of data collection but can allow for high frequency estimates (or in the case of remote sensing, actuals) to be made for large areas. Yeh (2020) states that while majority of African households are not captured in household well-being surveys, their location 'appears on average at least weekly in cloud free imagery from multiple satellite-based sensors'.

Satellite imagery and remote sensing can capture geospatial data that translates to 'physical living conditions' such as housing material, environmental characteristics, and access to resources in real time, which can be fed into socioeconomic indexes which can in turn be used to identify poverty at fairly granular levels (Dias, 2020). Jean (2016) found that utilizing hi-res satellite imagery could accurately estimate household expenditure and asset ownership. Further, Head (2017) used these methods to infer a set of human development indicators and found that some indicators like wealth and education can be predicted reasonably well with these data while others such as health and arthrometric indices (except for female BMI) were more difficult to predict across countries.

4. Data sources for poverty measurement

The data sources identified above can play a key role in identifying different types of poverty. We first highlight the suitability of the four data sources discussed in Section for the four types of poverty discussed in Laderchi et al (2003) (Section 2). Thereafter, we discuss other considerations when choosing the appropriate data source.

4.1 Data sources for measuring four types of poverty

Table 1 provides insights on the different types of data that can directly be gathered from the different types of data sources. Thereafter, we discuss several practical considerations when using these data sources for specific types of poverty measurement, as well as examples of how other types of poverty can be imputed/predicted from the data gathered.

Table 1: Data sources used for measuring four types of poverty identified in Laderchi et al (2003)

Data source		Monetary	Capabilities	Social exclusion	Participatory
Survey data	Census	√	√	√	
	Sample survey	√	√	√	
	Targeted[2]	√	√	√	√
Government administrative records		√	√	√	
Call detail records		√	√	√	
Geospatial data		√	√	√	

Survey data is a commonly used method that can be tailored to understand each of the four different types of poverty that we have discussed. A census could include questions on income and expenditure to understand monetary poverty. However, they generally do not identify comprehensive income and expenditure (consumption) data (Tarozzi, 2008) at the same level of depth as a household income and expenditure sample survey due to its scale and resource constraints that imposes. A census may also provide data on livelihoods, education attainment, dependency, and disabilities among others. Through such data, a census could be useful to understand poverty in the capabilities and social exclusion lens. Sample surveys of households too are used to collect much of the same data that censuses collect, and therefore, captures many of the same types of poverty (See Annex 2 highlighting how different types of poverty can be calculated in Sri Lanka using household data). However, in practice in developing countries, they are more likely to include questions on income and expenditure than censuses are – therefore, they are a more commonly used measure of monetary poverty. Further, targeted surveys such that are administered to self-registrants to receive welfare payments also allow a more participatory approach to understanding poverty.

Government administrative records can provide a wide range of insights given that many types of such records exist. This data naturally feeds into different ways of understanding poverty. Income information obtained from tax records could point to monetary poverty, a database offering public utilities could provide information on access to resources, and civil registries may identify whether an individual belongs to a group of people who are more vulnerable to experience social exclusion. Similarly, income data may be available in countries with a large direct tax base; however, this is not the case in many developing countries with high levels of informality; seasonal variations (Fergusen, 2003; Deaton, 1997) in income sources for those employed in sectors such as agriculture, fisheries, and tourism, add further complexity.

CDRs do not directly and/or independently determine the types of poverty highlighted by Laderchi (2003). However, it can be used to generate highly granular, real-time maps on individuals' socioeconomic characteristics including consumption expenditure, social networks and mobility, and access to resources like electricity (Blumenstock, 2015, Steele, 2021, Soto, 2011). The predictions generated could hence point to monetary poverty, social exclusion, and capabilities poverty respectively.

Similarly, geospatial data can be used to predict monetary poverty and capabilities poverty via estimates on household wealth and access to resources (Jean, 2016, Head, 2017). By design, it also allows to examine elements of social exclusion, such as geographical exclusion. Geospatial data, unlike CDRs, does not lend itself well to identifying individuals living in poverty, rather, units such as households.

[2] We base this analysis on the factors examined in Sri Lanka's Aswesuma programme.

In sum, many data sources can be used to measure the capabilities approach and the social exclusion approach. Monetary poverty is more difficult to measure in developing countries. The specific examples don't lend itself well to a more participatory approach, but is used in practice, particularly for determining eligibility for social assistance programmes.

4.2 Additional considerations when selecting data sources

Selecting a data source for measuring poverty is a complex, multifaceted one – there are many factors that one should consider. As highlighted in section 3, is it crucial to determine what type of poverty one is trying to measure before selecting the data source. However, in addition, there are several other factors that one should consider when selecting a data source. We discuss some key considerations in this section.

- Identifiability of individuals

Different datasets will be able to give insights on specific individuals, while others will be able to give more aggregate insights. A sample survey, for example, will only be able to give insights on the types of groups that are in living in poverty which could be useful in programme design and evaluation, but not target specific individuals. Census data and government administrative data are more likely to be able to identify specific individuals – however, whether it is often used for this purpose is unclear. Purpose collected data, may it be quantitative and qualitative, could help identify specific individuals for benefits.

- Frequency of data updates/availability

Some datasets, such as call detail records and sat are updated frequently. Provided that data access is not a concern, frequent data updates could be obtained for poverty measurement. However, survey data, may be updated less frequently, even being one-off in some cases. Census data is often collected once a decade. There may be a lag between when the data is made available to the public, however. This may also be the cases such as satellite imagery, where data may be updated frequently but not be available to the public.

- Cost of data acquisition/analysis

Carrying out primary data collection is costly. In turn, it can influence the number of individuals from which data can be collected as well as the frequency of data collection. Collecting data from a census is therefore more costly than a sample survey, though the size of the differential will depend of the specific methods used. Meanwhile, if secondary data (e.g.: CDRs) must be purchased, this will have to compared vis-à-vis data collection costs.

- Data sharing/licensing conditions

There may instances where the data owner may be different to the party undertaking poverty measurement. In such cases, the data licensing/sharing conditions of the data owner will be of importance. This will be relevant to data sharing between and within government and non-government data sources. If individuals are identifiable when datasets are shared, then it is important to ensure that it is done in a rights protecting way (e.g.: in compliance with the local personal data protection laws).

All data sources, despite their relative merits, are subject to bias and inaccuracy. Ideally, data users should be able cross reference and verify the accuracy of poverty measurements.

5. Conclusion

This paper highlights that poverty can be conceptualized in many ways, and that the type of poverty that one is trying to solve for should be a focal point in the design, implementation, and monitoring stages of social protection programmes. Access to and use of accurate, updated data is a necessary condition for policy and programme level decision-making. However, not all data sources are created equal. There are many different practical considerations when selecting a data source. First, whether it collects the type of data that is important for decision-making relevant to the specific type of poverty one is trying to alleviate. Second, how factors such as time, cost and data ownership play into decision-making. Overall, both conceptual and practical considerations are important complements in poverty measurement.

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Annex 1: Data sources for poverty measurement in developing countries

Table 2: Data sources from developing countries

Country	Data source	Poverty measurement modality
Kenya	Household Survey	Uses data sourced from household surveys. The Kenya Integrated household Budget Survey (KIHBS) collects comprehensive data on household income and expenditure. However, data collection intervals vary as there was a ten-year period between the last two surveys conducted that were KIHBS 2015/16 and KIHBS 2005/06. Data from these surveys were used to measure consumption-based poverty. The Quarterly Kenya Continuous Household Survey (KCHS) was established in 2019 to bridge this gap. The data from these surveys are used to measure poverty, monitor the SDGS and for various development initiatives.
Uganda	Household Survey	Uganda conducts household surveys out of which the largest is the Uganda national household Survey (UNHS) to derive poverty indicators. UNHS 2019/20 collected information on household consumption, education attainment, labour market outcomes, physical features of household and other areas of social and material wellbeing. This data was used to construct monetary poverty indicators. Later, they were used to construct Uganda's multidimensional poverty index.
Vietnam	Household Survey	Vietnam has been conducting the household living standards survey (VHLSS) at regular periods to capture some basic demographic characteristics related to living standards, education, health and health care, employment, income and expenditure, asset ownership, Access to housing, electricity, water, sanitation, participation in poverty elimination programs, among others.
Columbia	Household Survey	Columbia conducts annual Gran Encuesta Integrada de Hogares to collect income data, on which their official poverty statistics are based.
Sri Lanka	Household Survey	Poverty data in 1980 to 1990 came from various surveys (family budget survey, labour force and socio-economic survey). In 1990, a dedicated Household Income and Expenditure Survey conducted every three years to obtain poverty estimates began. Official poverty lines, poverty statistics by administrative units and multidimensional poverty (among others) are generated using the data collected through this source.

Sources: Kenya National Bureau of Statistics, Uganda Bureau of Statistics, General Statistics Office Vietnam, Departmento Administrativo Nacional De Estadistica (DADA) Columbia, Department of census and statistics Sri Lanka,

Annex 2: Defining and measuring poverty in Sri Lanka

Many developing countries use consumption expenditure as a basis for determining poverty (Greeley, 1994; Kamanou et al., 2005).. Sri Lanka is no exception, using consumption expenditure per capita to determine absolute poverty through its national poverty line. It uses a cost of basic needs approach to determine its poverty line linking to a nutritional anchor of 2030 kcal per capita per day, though the government has not disclosed the exact subcomponents that have been used for this purpose (Department of Census and Statistics, 2022). Table 3 highlights that in 2019, when the national poverty line stood at LKR 6,966, 14.3% of the population (3 million people) were considered poor by this poverty classification. This 14.3% of people on average were short of LKR 1,374 each month for subsistence. The poverty gap of 2.8 shows the depth of poverty as an average of the ratio of shortfall from the poverty line over both the poor and non-poor, assuming no shortfall for the non-poor. The gini coefficient of 0.46 signals a high level of income inequality.[3] This is echoed the share of expenditure per decile, which shows that the 10% of households with the highest monthly expenditure spends over 13 times that of the 10% households with the lowest monthly expenditure.

The economic crisis that prevailed in Sri Lanka owing to the COVID-19 pandemic and the longstanding economic mismanagement led to high inflationary environment. The national poverty line was adjusted accordingly (last updated to LKR 13,977 in December 2022). This impact is echoed in the poverty headcount. LIRNEasia's 2023 survey showed that the population living below the poverty line increased from 14.3% (3 million people) to 31% (7 million people). The monthly shortfall for people too, increased. However, while absolute poverty increased, relative poverty reduced – evidenced by a fall in the gini coefficient and the share of expenditure at higher expenditure deciles.

In Sri Lanka, we have identified that such excluded groups can include the estate population, the elderly, PWDs, single parent families, and daily wage earners that lack a guaranteed income source. The estate sector is one group that is disproportionately disadvantaged. Made up of 'residential workers' who were brought down from South India to work on the estates under the management of the plantation, the sector is 'socially, economically, and politically isolated from the rest of the society due to historical, cultural, geographical, and other reasons' (Jayawardena, 2014). The geographic isolation of the estate sector as a key driver of the exclusion experienced by the estate population, as it holds back the investment and growth that is experienced elsewhere – especially in the Western Province's liberalized macroeconomic environment (Gunatilaka et al., 2009). At a household level, geographical isolation limits their networks outside of their localities and may also frequently expose some to natural disasters such as landslides and droughts with inadequate cushioning or protection.

PWDs are another of such groups. PWDs have high barriers to or may not be able to participate in key socioeconomic activities as those without disabilities. According to (Gunatilaka et al., 2009) employment is lower for the disabled than the non-disabled, ranging from 7% for psychiatric disabilities and 26% for mobility disabilities – while even most of the employed live below the poverty line.

Like the cases in other countries, this is also true for the elderly and the other groups. Further, (Gunatilaka et al., 2009) found that informal employment such as daily wage-earning jobs make

[3] Gini coefficient < 0.2 is perfect income equality, 0.2-0.3 is relative income equality, 0.3-04 is adequate equality, 0.4-0.5 is significant inequality, >0.5 is the critical inequality ranges and 1 is perfect inequality.

individuals more excluded from a set of economic and social activities due to work in geographically isolated locations and/or insufficient income to be able to participate in society effectively.

Table 3: Indicators measuring three types of poverty based on household surveys

Approach	Metric		2019	2023
Monetary approach	Poverty headcount ratio[4]		14%	31%
	Poverty gap index		3%	8%
	Monthly shortfall		Rs. 1,374	Rs. 3,706
	Gini coefficient		0.46	0.36
	Share of household expenditure per expenditure decile	Decile 1 (poorest)	3%	3%
		Decile 2	4%	4%
		Decile 3	5%	5%
		Decile 4	6%	6%
		Decile 5	7%	7%
		Decile 6	8%	8%
		Decile 7	10%	10%
		Decile 8	12%	12%
		Decile 9	15%	15%
		Decile 10 (richest)	31%	29%
Capabilities Approach	Lack of access to education (school attendance of 5–16-year-olds in household)		5%	6%
	Lack to adequate toilet facilities		2%	7%
	Lack of drinking water		8%	7%
	Lack of vehicle ownership		45%	46%
Social Exclusion Approach	Estate population		5%	5%
	Households with PWDs		14%	29%*[5]
	Single parent households		3%	4%
	Households with at least one daily wage earner		n/a	64%

Source: (Department of Census and Statistics, 2022; Department of Census and Statistics & Ministry of Economic Policies and Plan Implementation, 2019; World Bank, 2023), LIRNEasia (2023)

[4] The poverty headcount ratio is determined as a percentage of the population. The same estimates at a household level are as such: 12% of households were living below the poverty line in 2019; this number was 27% in 2023.

[5] This change was due to the method in which the question was framed, as opposed to an increase in the proportion of households with PWDs. Whereas in the 2019 HIES the question 'does this member have difficulty walking a short distance or walking up and down 12 steps due to some difficulty/issue' was answered with the 4 codes 'no difficulty', 'some difficulty', 'a lot of difficulty', and 'unable to do'; LIRNEasia's 2023 study answered the same question with a binary code – 'yes' or 'no' leading to some overestimation of the criteria.