Food and Agriculture Organization of the United Nations

RURAL POVERTY ANALYSIS

From measuring poverty to profiling and targeting the poor in rural areas

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FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS
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CONTENTS

FIGURES

TABLES

BOXES

FOREWORD

This publication will help us measure rural poverty and profile the rural poor to better target them, thus guiding and helping to scale up FAO's work over the coming years to reduce rural poverty and foster inclusive rural development. Rural poverty reduction is one of FAO's three main goals, along with hunger eradication and the sustainable management of natural resources, and it will continue to be a key priority in FAO's new Strategic Framework 2022–30 where issues of inclusivity will take centre stage.

The launching of this publication is very timely as unprecedented events caused by the COVID-19 pandemic severely challenge the world, increasing the number of the poor in the world for the first time in a generation, reversing recent gains in global poverty reduction and hampering the prospects of achieving Sustainable Development Goal (SDG) 1. In addition, climate change continues to create new and significant challenges to global efforts to eliminate rural poverty and achieve zero hunger.

Poverty remains an overwhelmingly rural phenomenon. Four out of every five people living in extreme poverty in the world live in rural areas. The incidence of poverty in rural areas is four times that of urban areas. In this context, FAO must further strengthen its capacity to reach and support the poor and the extremely poor in rural areas, analysing their needs and aspirations and providing effective guidance for the design of policies and investments that foster inclusive and sustainable development.

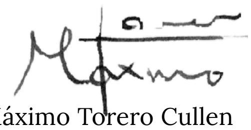
Recognizing this, FAO established the Corporate Framework on Rural Extreme Poverty to orient the work of the Organization towards reaching Target 1.1 of the SDGs: Eradicate extreme poverty. As part of the implementation of the Framework, FAO has committed to increasing its own capacity to reach the extremely poor by undertaking poverty analysis and integrating it into the formulation and implementation of its projects, programmes and policies, including Country Programming Frameworks (CPF), Common Country Assessments (CCA) and the United Nations Development Assistance Framework (UNDAF).

More recently, FAO is introducing a new cross-cutting theme in its Strategic Framework 2022–30: inclusivity. Inclusivity should be mainstreamed throughout FAO's programmatic work so that its activities produce deeper and more sustained impacts, improving lives and livelihoods by ensuring food security and nutrition, promoting social and economic inclusion, fostering environmentally sustainable and resilient livelihoods, and preventing and protecting against risks and shocks for poor, vulnerable and marginalized people. The extremely poor, who are represented in all three of these categories, require specific and targeted interventions.

This publication provides key information to measure poverty, characterize rural populations and identify their constraints so as to target them more accurately – an essential first step to developing programmes and projects that are inclusive as well as effective. The guide also provides an overview of targeting techniques that can enable more effective solutions and partnerships on the ground, so that no one is left behind.

The tools and methods provided herein will help accelerate the implementation of the newly-instituted FAO Framework on Rural Extreme Poverty and will support other key initiatives, including the Hand-in-Hand Initiative, the United Nations Decade of Family Farming, the Food Systems Summit, and others that will arise.

We encourage all FAO staff, from every discipline and role, to use poverty analysis in their work and to join us in our commitment to enhance our capacity to better understand the needs of the rural poor and extremely poor. This will enable us to more effectively respond to those needs and contribute to achieving the 2030 Sustainable Development Agenda.



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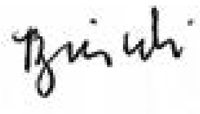

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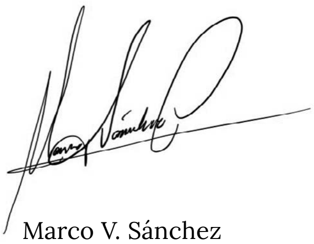

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Combating rural poverty is at the heart of the mandate of the Food and Agriculture Organization of the United Nations (FAO) and of the first Sustainable Development Goal (SDG 1): No poverty. During 2018–19, in working to realize FAO's Strategic Objective 3 (SO3), "Reduce Rural Poverty", and implement the FAO Framework on Rural Extreme Poverty, the Strategic Programme for Reducing Rural Poverty (SP3) identified the urgent need to mainstream rural poverty analysis in FAO's work. It also determined that guidance was needed to carry out such mainstreaming and a platform was needed to help implement it – neither of which were available at the time.

To bridge this gap, the SP3 established a collaboration with the Agrifood Economics Division (ESA). This collaboration resulted in the creation of the Technical Network on Poverty Analysis (THINK-PA) in 2020 and in this publication. Under the overall technical supervision and guidance of Marco V. Sanchez, Deputy-Director of ESA, this publication was prepared by Leopoldo Tornarolli (ESA), Lorenzo Moncada (ESA) and Ana Paula de la O Campos (ESA), coordinators of the THINK-PA.

Benjamin K. Davis, former leader of the SP3 and current Director of the Inclusive Rural Transformation and Gender Equality Division (ESP), and other former members of the SP3 team, provided significant inputs and guidance. Raul Andrés Castañeda Aguilar (World Bank) and John Maluccio (Middlebury College) provided an external review that significantly contributed to improving the final product.

Dianne Berest copyedited this publication and Daniela Verona (ESA) provided design support and publishing coordination.

Saado sorts and cleans seeds in Hargeisa, Somalia.

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ABBREVIATIONS AND ACRONYMS

AAD	Action Against Desertification
AF	Alkire-Foster (approach)
BGM	Bayesian geostatistical models
CBN	cost of basic needs (method)
CBT	community-based targeting
CCA	common country assessments
CI	concentration index
COSOP	Country Strategic Opportunities Programmes
COVID-19	novel coronavirus disease
CPF	country programming frameworks
CPI	consumer price index
CCT	conditional cash transfers
DAP	*Declaração de Aptidão ao Pronaf* (Statement of Qualification)
DHS	demographic and health surveys
EB	empirical best/Bayes (method)
ELL	Elbers, Lanjouw and Lanjouw (method)
EU	European Union
FAO	Food and Agriculture Organization of the United Nations
FEI	food-energy intake (method)
FGT	Foster-Greer-Thorbecke
FH	Fay-Herriot (model)
FIES	food insecurity experience scale
FISP	Farm Input Subsidy Program
GCF	Green Climate Fund
GDP	gross domestic product
GEF	Global Environmental Facility
GGW	Great Green Wall
GIS	geographic information systems

GWR	geographically weighted regression
HIH	Hand-in-Hand Initiative
ICA	Integrated Country Approach (programme)
IFAD	International Fund for Agricultural Development
IHS3	Third Integrated Household Survey
INE	*Instituto Nacional de Estadística*
INEC	*Instituto Nacional de Estadística y Censos*
INEI	*Instituto Nacional de Estadística e Informática*
LASSO	least absolute shrinkage and selection operator
LISA	local indicators of spatial association
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
MAAIF	Ministry of Agriculture, Animal Industry and Fisheries
MCA	multiple correspondence analysis
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
MICS	Multiple Indicator Cluster Surveys Programme
MIQ	minimum income question
MPI	multidimensional poverty index
MT	means testing
NGO	non-governmental organization
OLS	ordinary least squares
OPHI	Oxford Poverty and Human Development Initiative
PCA	principal component analysis
PL	poverty line
PMT	proxy means testing
PPI	Poverty Probability Index
PPP	purchasing power parity
PROEZA	*Pobreza, Reforestación, Energía y Cambio Climático* (Poverty, Reforestation, Energy and Climate Change)
R-MPI	rural multidimensional poverty index
RAFC	rural agriculture and fishery census
SAE	small area estimation
SCTP	social cash transfer programme
SDG	Sustainable Development Goal
SISBEN	*Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales* (System for the identification of potential beneficiaries of social programmes)

SME	small and medium-sized enterprises
SSPL	social subjective poverty line
TD	targeting differential
UN	United Nations
UNDAF	United Nations Development Assistance Framework
UNDP	United Nations Development Programme
UNICEF	United Nations Children's Fund
UN-REDD	United Nations Collaborative Programme on Reducing Emissions from Deforestation and forest Degradation
UNU	United Nations University
USAID	United States Agency for International Development
USD	United States dollar
VIF	variance inflation factor
WHO	World Health Organization
YIYA	Youth Inspiring Youth in Agriculture Initiative

Women carrying pumpkins and kitchen utensils on their way back home following harvesting crops at Nkhwazi Village, Malawi.

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1 INTRODUCTION

This publication guides us through the process of poverty analysis in rural areas. Its purpose is to assist FAO's endeavour to mainstream rural poverty analysis in its work in order to properly identify, profile and reach the poor with adequate targeting and programme and project design.[1] The sections that follow explain what to expect from this document and how to navigate its chapters in order to reach the final destination of this poverty-analysis journey, which will become the starting point of new avenues in rural poverty reduction.

1.1 STRUCTURE, CONTENT AND USE OF THE GUIDE

This guide follows a programming sequence: from understanding how poverty is measured, to characterizing or profiling who the poor are (focusing on rural areas), to using this information to define a targeting strategy. Figure 1 provides an overview of this sequence. Following the introduction provided in Chapter 1, Chapter 2 discusses how poverty is measured, focusing on the different indicators that can be used, depending on the context, specific circumstances, data availability and policy objectives. Chapter 3 provides guidance on how to build a poverty profile and produce poverty maps to understand who the poor are and where they located. Chapter 4 focuses on the targeting process, on various targeting techniques and on how to choose one over another to ensure that programmes and projects effectively combat poverty, particularly in rural areas. Finally, Chapter 5 sets the next steps for the development of further analytical guides. The glossary provided at the end of this document defines essential concepts in poverty analysis.

These three chapters provide an overview of both widely used and emerging techniques in poverty analysis, focusing on quantitative methods. (Links are provided to resources on qualitative techniques, but bear in mind that a qualitative description of the context will, in any case, always have to inform any poverty analysis.) The poverty analysis techniques described focus on the challenges posed by operating in rural areas and give constant attention to FAO's areas of work.

[1] In this document the words "project" and "intervention" refer to any set of time-bound activities that are put in place to create a
well-identified set of results that contribute to the development objectives of FAO or other development partners.

▶ FIGURE 1

Overview of the guide

Chapter 2: Measuring rural poverty

- What is poverty?
- What are the different ways of measuring poverty?
- How can I measure poverty with a focus on rural areas?
- Which sources of data can I use?

Chapter 3: Characterizing the rural poor and the extremely poor

- What is a poverty profile? How is it structured?
- What should I include in a rural poverty profile?
- What is a poverty map? How can I interpret it?
- What are the different techniques for creating a poverty map?
- Which sources of data can I use to build a poverty profile or poverty map?

Chapter 4: Targeting for rural poverty reduction interventions

- What is targeting?
- When should I use targeting?
- What are the most common targeting mechanisms and what are their advantages and disadvantages?
- How can I choose a combination of targeting mechanisms for a poverty reduction intervention?

Source: FAO.

The emphasis on the rural poor is due to the fact that information on poverty is often not disaggregated by urban and rural location, and the resulting lack of information on the extent, depth and characteristics of poverty in rural areas limits the Organization's ability to effectively target and design its rural poverty reduction programmes. FAO recognizes the distinctions between the rural poor, the urban poor and the non-poor across different dimensions. For example, the incomes of the rural poor largely depend on agricultural activities, which can be quite varied (crop, livestock, fisheries, aquaculture and so forth). Their livelihoods rely on natural resources, making them highly vulnerable to climatic shocks and weather events. The rural poor also diversify their sources of income through non-agricultural activities, often providing services across the agrifood chain or working in construction or other sectors. The profitability of these activities is often constrained by numerous factors such as insufficient access to basic infrastructure, markets and public services. Seasonal migration, either within rural areas or from rural to urban areas, is often a livelihood strategy for rural populations, including for the rural poor. Within rural areas, there are also different levels of poverty, with the poorest people often concentrated in marginal areas such as high mountains, arid lands, rainforest jungles, and small islands with low population densities, poor agroecological endowments, limited access to markets and few sources of employment. Overall, the rural poor engage in different livelihood strategies, have less access to resources, often have distinct cultures and social arrangements, and are often isolated from economic development and policy support. Therefore, in order to be effective, rural poverty reduction strategies, programmes and projects must consider the specific contexts and needs of the different rural populations. These particular conditions, as well as other aspects, are considered in the poverty analysis strategies covered in this guide.

Is there a poverty measure that is more suitable for rural areas? Which type of analysis can be used to better characterize the livelihoods of rural populations and the rural poor? Which targeting mechanisms are more appropriate for the work of FAO and other development partners engaged in agricultural, nutritional, environmental and related interventions? The answers to these and similar questions are provided in the next three chapters.

The guide is designed so that users can go through the material at their own pace and according to their own interests and learning objectives, studying all its content or using it as a reference, without direct guidance or facilitation. Each chapter can be used as a stand-alone resource. Like other FAO guides, it can be also adapted for training workshops with a dedicated facilitator to respond to specific country demands or contexts. An additional resource which may be useful are the online courses on rural poverty reduction available at the FAO e-learning Academy website (FAO, 2021).

1.2 INTENDED USERS AND OBJECTIVES

This guide is intended for use by all staff from FAO and its development partners who seek to enhance their capacity to integrate poverty analysis in their work. For those with less experience in poverty analysis, the chapters will provide an overview of the information that is needed when commissioning poverty analyses and targeting exercises for poverty-reduction interventions. For users with more experience in applied poverty analysis, the chapters will provide a point of departure before delving into more advanced guidance.

As indicated previously, this guide aims to support the mainstreaming of rural poverty analysis throughout FAO's technical units and decentralized offices and among its partners, at three levels: technical, programming and project.

At the technical level, guidance is provided to:

- use existing monetary and multidimensional poverty measures and carry out analytical work on rural poverty and the characterization of rural livelihoods;
- support efforts to better identify, characterize and target the rural poor; and
- enhance existing methodologies, and, where necessary, develop new methodologies and tools to support policy and programme assistance in FAO's technical areas, and to characterize and reach the rural extreme poor.

At the programming level, the guidance provided can:

- enhance the use of global and country poverty data by programme formulators to better focus FAO's work at the country level;
- increase FAO's capacity to integrate poverty analysis and pro-poor targeting to support UNDAF CCA and CPF formulation, and to guide national and regional initiatives; and
- improve the monitoring of the contribution of FAO's strategic objectives to SDG 1.

At the project level, the guidance provided can promote the use and development of:

- poverty analysis and targeting by project formulators to develop sound theories of change in the project design, increase their poverty-reduction potential and monitor outcomes;
- poverty analysis by project formulators for the development of sound social safeguard mechanisms, particularly for the FAO Emergency programme and projects developed for the Global Environmental Facility (GEF), the Green Climate Fund (GCF) and the Investment Centre; and
- rigorous evidence, including impact evaluation on poverty-related outcomes.

Female farmers experimenting with new farming practices in Nepal.

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2

MEASURING RURAL POVERTY

We cannot manage what we cannot measure. Reducing rural poverty is at the centre of FAO's programmatic work and at the heart of SDG 1. Proper management and delivery of this programmatic work demands proper measurement of the problem. This chapter aims to provide a clear understanding of the methodological implications for constructing a poverty measure, including monetary and multidimensionally based measures. While only a few users of this guide will be required to create a new, or revised, national poverty measure, it is important that those using poverty measures master the concepts behind such measures and understand the differences between them in order to use them adequately when providing technical support, contributing to project design and performing similar tasks.

For those users involved in data collection, including for informing project design or evaluation, this chapter also provides guidance on which measure of poverty is most suitable, according to the different objectives and contexts where the project is situated. Finally, for the advance user, the chapter provides further information on the characteristics and validity offered by the different measures so as to better inform their selection. The annexes provide more information on procedures to build income and consumption aggregates from household survey microdata and on different methodological alternatives that can be used to set a poverty line.

2.1 INTRODUCTION

The measurement of poverty is preceded by a longstanding tradition in empirical economics. It is not surprising that a wealth of well-developed economic literature on poverty measurement exists. Despite this, there is still no widespread agreement among researchers on the best methodology for measuring poverty, and the characteristics of rural settings make measuring rural poverty challenging. This is largely due to a lack of agreement on the definition of welfare,[2] which should underpin the measurement of poverty. Nevertheless, the steps involved in the empirical implementation of the different poverty measurement approaches are very similar. In a nutshell: the poor are identified by comparing, for all individuals of a given population, an indicator capturing household or individual welfare to a threshold representing a certain minimum level of welfare, and those whose welfare indicator falls below the minimum are aggregated into an overall poverty measure that separates them from the non-poor population.

Deciding on the best approach to measure poverty is even more complicated when the measurement exercise is implemented in rural populations (see Box 1 on the definition of rurality). Most empirical approaches to poverty measurement were primarily developed to measure poverty in urban settings, and they are not necessarily useful or relevant for measuring poverty in rural areas. Conceptually, there are clear differences between rural and urban livelihoods, and urban-based definitions of welfare do not capture the diversity of rural lifestyles. As stated by Conconi *et al.* (2019):

> Rural poverty is characterized by a myriad of intertwined challenges that make it distinct from urban poverty [...] Rural people live differently, derive their income differently; may live in remote and sparsely populated areas, such as forests and savannahs, and depend on agricultural income and on the management of natural resources [...]. Rural people may be exposed to covariate shocks differently, such as crop or livestock losses due to natural disasters, poor rainfall or specific crop and animal diseases, and suffer exclusion from social services due to their remoteness and political exclusion [...] Thus, the nature of rural livelihoods and the constraints that the rural poor face may require a better conceptualization of what constitutes the rural and the rural poor's wellbeing [...]

[2] In this document, the terms welfare and well-being are used interchangeably.

▶ **BOX 1**
Definition of rurality

An aspect that should be considered when measuring rural poverty is that, unfortunately, there is no universal definition of what constitutes a rural area. For this reason, countries use their own criteria when identifying urban and rural areas at the national level. In most cases, countries use population density and distance from densely populated areas as defining factors of rurality. Some countries use definitions of rurality based on other factors, such as administrative classifications generated in the past or the share of agricultural employment in total employment. Therefore, it is not surprising that there is a wide diversity among areas categorized as rural in different countries, with differences in size, population density, distance from densely populated centres and employment structures. Given this lack of international consensus on the definition of "rural", most assessments of rural poverty simply rely on the definitions used by the different countries.

Another aspect that should be considered in measuring rural poverty is that, as countries go through processes of structural transformation, the characteristics that make an area "rural" change over time. Urbanization is a prominent phenomenon in most countries and the majority of the world's population now resides in urban areas. In addition, areas that were traditionally considered rural have gradually acquired urban and peri-urban characteristics with the irruption of different technological advances. Likewise, the size and demographic composition of rural areas tend to change with the migration from rural to urban areas that often accompanies structural transformation processes.

All these aspects pose important challenges in the measurement of rural poverty, particularly when attempting to quantify its evolution over time. Given the changes in the size, composition and density of the rural population; in the supply of goods and services; and in the degree of connectivity; it is not easy to determine whether changes in rural poverty are due to changes in the well-being of the rural population itself or whether the results can be explained by the fact that the populations being compared are not strictly comparable.

Finally, another aspect to keep in mind is that urban and rural areas tend to be classified dichotomously in household surveys, the main source of data for poverty measurement. However, in reality, the population is distributed along a continuum of rural–urban contexts. Although it is advisable to consider this aspect when analysing rural poverty, this is normally neglected in most analyses. This is because of the lack of sufficient information to properly identify this continuum and the lack of an accepted methodology for incorporating this factor into the analysis.

Source: Based on Conconi *et al*. (2019).

The United Nations recognized the lack of agreement on poverty measurement at the time of defining the SDGs (see Box 2). In fact, the first SDG makes explicit in its text, targets and indicators that there are different useful and valid ways in which poverty can be conceptualized and measured. However, the adoption of different methodologies for measuring poverty does not change this fundamental fact: the identification of the rural poor and the measurement of rural poverty are particularly challenging tasks, both conceptually and in terms of what can be measured in practice.

BOX 2

The measurement of poverty in the Sustainable Development Goals (SDGs)

The commitment to eradicate poverty is at the heart of the SDGs. This commitment is expressed in **SDG 1**: End poverty in all its forms and everywhere.
Two of the targets associated with SDG 1 explicitly mention different ways of measuring poverty:

- **Target 1.1**, "By 2030, eradicate extreme poverty for all people everywhere, currently* measured as people living on less than USD 1.25 a day", refers to the measurement of monetary poverty using the international extreme poverty line.**
- **Target 1.2**, "By 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions", refers to the measurement of poverty using national definitions. In turn, Target 1.2 provides for measuring poverty using two different approaches:
  - **Indicator 1.2.1**, "Proportion of population living below the national poverty line, by sex and age", is monitored using national monetary poverty lines.
  - **Indicator 1.2.2**, "Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions", is monitored using multidimensional poverty measures, as defined by national methodologies.

* The SDGs were established in September 2015. At that moment, the international extreme poverty line defined and used by the World Bank was USD 1.25 a day. Currently (May 2021), the value of the international extreme poverty line is set at USD 1.90 a day.

** The values of the international monetary poverty lines are periodically updated by the World Bank. They are defined to guarantee comparability between countries – to represent the same standard of living across them. Currently, the World Bank monitors global poverty using three international lines. The international extreme poverty line of USD 1.90 a day reflects the minimum level of welfare that is deemed necessary not to be considered poor in the poorest countries of the world. The international poverty lines of USD 3.20 and USD 5.50 a day reflect the typical standards of living of lower-middle-income and upper-middle-income countries, respectively. The comparability between countries is achieved by converting the USD values of the different lines to local currencies through purchasing power parity (PPP) indices. PPP indices represent the number of units of a country's currency required to buy the same amounts of goods and services in the domestic market as USD would buy in the United States. Hence, even though not specified throughout this document, international poverty lines should always be understood as expressed at PPP.

In line with the SDG target indicators, the FAO Framework on Rural Extreme Poverty (FAO, 2019a) recommends the use of different approaches for measuring rural poverty. Specifically, for cross-country comparisons and analysis, the Framework recommends using the World Bank's extreme monetary poverty measure based on the international extreme poverty line of USD 1.90 a day, as well as different multidimensional indices, such as the Global Multidimensional Poverty Index (MPI), developed by the Oxford Poverty and Human Development Initiative (OPHI) and reported in the Human Development Report of the United Nations Development Programme (UNDP); and FAO's recently developed Rural Multidimensional Poverty Index (R-MPI).

For programming and policy support at country level, the Framework recommends using the countries' own definitions and measures of rural extreme poverty, both monetary-based and multidimensional, when available.

This chapter provides detailed descriptions of the two main methodologies employed for poverty measurement: the monetary approach and the multidimensional approach. Although these are general methodologies, the descriptions unfold with a rural lens, in the sense that the aforementioned specificities of rural livelihoods are taken into account – with all their implications. This chapter is organized as follows: Section 2.2 discusses some conceptual and general aspects involved in measuring poverty. Section 2.3 describes and analyses in detail the monetary approach for poverty measurement, with a special focus on its use in poverty analysis in rural areas. Similarly, Section 2.4 is devoted to describing and discussing the multidimensional approach to poverty measurement, paying particular attention to how that methodology can be adapted to rural settings. Section 2.5 contains a short review of the main sources of data used for poverty measurement. Finally, Section 2.6 discusses tracking the evolution of poverty over time.

2.2 POVERTY MEASUREMENT

2.2.1 Welfare and poverty measurement

Traditionally, the measurement of welfare in applied economics has been rooted in concepts such as income and consumption (Deaton, 1980). In other words, economic analysis associates household and individual welfare with variables that denote the ability of households and individuals to purchase goods and services considered essential for well-being, such as food, clothing, housing and so on.

Poverty measurement is thought of as a special case of welfare measurement: the situation of poverty of a household is determined by comparing its total income or consumption with a monetary threshold (the poverty line) representing the minimum amount needed to purchase goods and services that are considered essential for well-being. The main limitation of this method of measuring welfare and poverty is obvious: not all aspects of welfare can be accounted for through a monetary measure (e.g. safety and clean air). Although this implies that the monetary measurement provides only a partial picture of overall well-being, it is still the dominant approach for welfare measurement in economic analysis.

In the last few decades, other approaches to welfare (and poverty) measurement have been developed and implemented. Amartya Sen's capability approach is probably the most widely recognized alternative to the monetary measurement of welfare. Sen (1992) argued that the definition of well-being should be made in terms of the "functionings" and "capabilities" that people enjoy. He defined functionings as the "beings and doings" that people value. For example, elementary functionings include "being well nourished" and "avoiding premature mortality" while more sophisticated functionings include "having self-respect" and "being able to take part in the life of community". Regarding "capabilities", they are defined as "the various combinations of functionings (…) that a person can achieve". Instead of measuring welfare in terms of monetary resources, as is done in the traditional approach, Sen's approach establishes that welfare should be measured in terms of capabilities. Analogously, Sen argued that poverty should be thought of as *capability deprivation*. This definition has a clear implication for poverty measurement: given that there are multiple functionings and capabilities, a multidimensional approach is required.

2.2.2 Monetary and multidimensional poverty measurement

The previous section points to the different conceptual approaches to measuring welfare and poverty. Although the monetary approach is the most common methodology used, most researchers and policy-makers agree on the multidimensionality of poverty: a condition in which households and individuals face multiple challenges and disadvantages.

This multidimensional character of poverty is perfectly illustrated in the summary of the Voices of the Poor study (Narayan *et al.*, 2000). The authors highlight six dimensions that feature prominently in the definition of poverty provided by the poor themselves: 1) poverty involves several interlocked dimensions, with hunger or lack of food being the deprivation most commonly mentioned by the poor; 2) lack of power and voice, dependency, shame and humiliation are all important psychological dimensions of poverty; 3) lack of access to basic infrastructure and roads (particularly in rural areas), transportation and clean water characterize the living conditions of the poor; 4) schooling is important for the poor, but it should be accompanied by improvements in the quality of education and the general economic environment; 5) poor health and illness are seen as two important sources of destitution; and 6) lack of income (cash) does not seem to be the most urgent problem for the poor; rather, lack of access to assets (physical, human, social and environmental) constitutes an important barrier to cope with vulnerability and risk.

This evidence supported the view of Sen and other social theorists that the measurement of welfare and poverty should be approached from a multidimensional perspective. The Millennium Development Goals (precursors of the SDGs) embraced this view and, consequently, many researchers began developing tools to study multidimensional poverty. Today, complementary monetary and multidimensional poverty measures are available to measure poverty at the global level and for most developing countries.

2.2.3 Common aspects to all poverty measurement exercises

As remarked long ago by Sen (1979), regardless of the conceptual definition of poverty, there are some aspects that are common to every poverty measurement exercise. Sen (1979) stated that measuring poverty always consists of two distinct operations: identifying who the poor are (identification), and combining some information regarding those identified as poor in an overall poverty measure or index (aggregation). Before discussing the particularities of monetary poverty measurement and multidimensional poverty measurement (in Sections 2.3 and 2.4), the following paragraphs describe the most important aspects involved in the processes of identification and aggregation of the poor.

Identification of the poor

The process of identifying the poor requires defining and comparing two basic elements: the measure or indicator of welfare and the minimum level of welfare that must be met to be classified as not poor. In the monetary approach, income and consumption are the two most commonly used welfare indicators, whereas in the multidimensional approach, multiple indicators are used to represent the welfare situation of the unit of identification, as further defined below.

Regarding the minimum level of welfare, in the monetary approach, its value is represented by the monetary poverty line,3 while in most methods used to measure multidimensional poverty a deprivation cut-off is established to assess the overall situation of deprivation of each unit of

[3] In most cases, the monetary approach is implemented using two alternative and complementary poverty lines: an extreme poverty line and a total (also called moderate) poverty line. The extreme line, commonly referred to as the food poverty line, represents the cost of a food basket providing the minimum daily energy requirement, while the total poverty line includes both the extreme poverty line and an additional amount representing the cost of acquiring some basic non-food items.

identification. The various concepts mentioned here will be presented and analysed in much more detail in Section 2.3 for the case of monetary poverty measurement, and in Section 2.4 for the case of multidimensional poverty measurement.

The household, instead of the individual, is the unit of identification most widely used in monetary and multidimensional poverty measurement exercises.[4] The unit of identification is the entity that is identified as poor or non-poor. There are both conceptual and practical reasons behind the use of the household as the unit of identification in poverty measurement. From a conceptual point of view, the main argument is that some individual resources are shared among members of the household.[5] From a practical perspective, data constraints usually make it impossible to use the individual as the unit of identification: household surveys, the most common data source for poverty measurement, rarely collect information at the individual level for the indicators used to measure poverty (e.g. income, consumption or the multiplicity of indicators used to measure multidimensional poverty).[6]

The use of the household as the unit of identification implies that the indicator(s) of welfare will be defined at the household level, by combining the information of all household members. As a result, all of them will be classified with the same poverty condition: either all members will be identified as poor and will be considered as experiencing the same degree of poverty, or none of them will be identified as poor. In other words, it is assumed that all resources, or at least those used to represent household welfare for poverty measurement purposes, are shared evenly within the household. This assumption has been highly contested, given that it ignores potential inequality in the distribution of resources within the household, as a result of power imbalances, and has important implications for measuring poverty (see Box 3 for a more detailed discussion on this topic).

Even if the household is the unit of identification for poverty measurement, it is very common that the individual is used as the unit of analysis for reporting purposes. As mentioned in the previous paragraph, all the members of any given household will share the same poverty condition (poor or non-poor). In that sense, once a household has been identified as poor (or non-poor), all its members will be considered poor (or non-poor) for purposes of analysis and reporting. In this way, although the identification of the monetary or multidimensional poor is not performed at individual level, it is possible to report the percentage of people living in monetary or multidimensional poverty, and the incidence of monetary or multidimensional poverty by gender, age, educational level, ethnicity, occupation and other individual characteristics.

[4] Following this practice, the household will be the unit of identification for poverty measurement in this document, unless specified otherwise.

[5] In the case of monetary poverty, it is assumed that the individual monetary resources of all the members of the household are shared and that every member has access to those common resources. A similar reasoning applies to aspects related to multidimensional poverty. For example, if a household member suffers a severe health condition, it is likely that the welfare level of other household members will be negatively affected by that situation. Similarly, illiterate household members can be benefited by the presence of educated household members.

[6] In the case of monetary poverty, almost all the information used to estimate consumption is normally collected at household level. In the case of income, there are some variables collected at individual level (e.g. labour income and pensions) that are easy to aggregate to generate income streams at household level, whereas others are directly collected at household level (e.g. transfers from the government and remittances). Regarding multidimensional poverty, some of the indicators usually selected to construct a multidimensional poverty index are collected at individual level (e.g. health condition of each member and school attendance), while others are collected at household level (e.g. access to safe water and ownership of some durable goods).

▶ **BOX 3**

Intrahousehold inequality

The methodologies of poverty measurement that use the household as the unit of identification assume that all resources are equally shared within it, such that all household members reach the same level of welfare; however, this assertion has no empirical underpinning. Unfortunately, the information needed to analyse the potential existence of intrahousehold inequalities is scarce, not least because collecting detailed information at the individual level can be relatively expensive. Even with this data limitation, a growing body of literature suggests that most resources are not equally allocated within households, for example:

- Dunbar, Lewbel and Pendakur (2013) derive intrahousehold resource allocation data by looking at the fraction of certain household expenditures that can be linked to each member. When applying their methodology to Malawi, they find that poverty rates for children (95 percent) are significantly higher than those for adult women (85 percent) and adult men (60 percent).
- Brown, Ravallion and van de Walle (2017), using data from several sub-Saharan African countries, find that underweight women and undernourished children "are spread widely across the household wealth and consumption distribution". Although there could be other factors contributing to this result, the authors conclude that the finding is consistent with unequal distribution of resources within households.
- De Vreyer and Lambert (2020), using a survey that collects consumption information at the individual level in Senegal, discover that intrahousehold inequality in consumption explains 14 percent of consumption inequality in the country. They also find that some poor individuals belong to non-poor households.

The existence of intrahousehold inequality has a clear implication for poverty measurement methodologies that use the household as the unit of identification: It means that the poverty condition of different household members likely differs, and thus, assuming the opposite will introduce a bias in poverty estimations, given that some individuals will be classified as poor when they are not in reality – or vice versa. This could result in information that misguides policy-making for poverty reduction and the targeting of poverty reduction programmes.

Aggregation of the poor

The process of aggregating the poor consists of using the information of those units identified as poor to generate an index that summarizes the level of poverty in a given society. One of the most common uses of aggregate poverty measures is to monitor socio-economic conditions and to provide a benchmark against which socio-economic progress is assessed. In this case, poverty indices are instruments to evaluate how a country, region or area is doing and to identify and qualify the results of socio-economic projects, programmes and policies. Another important use of poverty measures is to inform the design of socio-economic policies, including those related to agriculture. For example, through the use of aggregate poverty measures, different population subgroups can be ranked according to their poverty levels and this information can be used to more effectively target cash transfers, livelihoods interventions, agricultural extension and advisory services and other interventions.

Poverty measures are also used to summarize complex socio-economic information, and are useful inputs for discussing and setting policy priorities. Consequently, selecting the index, or group of indices, that will be used to report poverty results, should follow a rigorous and transparent process, and the advantages and limitations of the different aggregate poverty indices must be clearly understood by the different stakeholders. Section 2.3.2 (covering monetary poverty measurement) and Section 2.4.2 (covering multidimensional poverty measurement) provide detailed descriptions of the characteristics of the poverty indices most frequently used in empirical exercises.

2.3 MEASURING MONETARY POVERTY

The monetary approach is the most widespread method of poverty measurement in quantitative assessments of poverty. It has a long tradition in economics, and was the method chosen by Booth (1887, 1888) and Rowntree (1901) in the first scientific attempts to measure poverty. Interestingly, the methodology employed by Rowntree[7] more than a century ago, which was partially inspired in Booth's previous work, is essentially the same as the methodology currently used to measure monetary poverty.

As in all poverty measurement exercises (see Section 2.2.3), measuring monetary poverty requires solving the problems of identification and aggregation of the poor. In the monetary approach, the poor are identified by comparing the monetary value of a proxy variable representing the welfare level of the household (typically household income or consumption), to a monetary poverty line representing the minimum level of welfare a household should meet to be identified as not poor. As to aggregation, the most commonly used monetary poverty indices aggregate using the Foster-Greer-Thorbecke (FGT) family of poverty measures. The rest of this section discusses in detail the technical aspects involved in identifying and aggregating the poor, in the context of measuring monetary poverty.

2.3.1 Identifying the monetary poor: the poverty line approach

The method used to identify the monetary poor is sometimes referred to as the poverty line approach. Accordingly, households are identified as poor (or extremely poor) when their total income or consumption is below a certain monetary threshold established as the poverty line (or the food poverty line). Therefore, identifying the monetary poor requires choosing a variable representing the welfare level of each household and determining the monetary value of the poverty line before a comparison can be made. This section analyses the different aspects related to choosing the welfare indicator and determining the value of the poverty line and the food poverty line.

The welfare indicator: household income vs household consumption

The monetary approach uses either household income or household consumption as the welfare indicator. Although experts have not reached a consensus regarding the most appropriate indicator to measure welfare, and there are legitimate conceptual and empirical points in favour of both alternatives, consumption is usually viewed as the preferred welfare indicator for poverty measurement. There are three main reasons for that preference, two of which are particularly relevant in terms of measuring poverty in rural areas of developing countries:

[7] Rowntree proposed two definitions of poverty, primary and secondary. Poor families living in primary poverty were those whose earnings were insufficient to maintain "merely physical efficiency". Families living in secondary poverty were those whose earnings would be sufficient to maintain "merely physical efficiency" if they did not divert part of their earnings to other kinds of expenditures.

1. **Theoretically, consumption is considered a better proxy of household well-being than income.** When measuring poverty, most researchers and practitioners consider that well-being depends mostly on the present satisfaction of basic needs. In that case, current consumption is a good proxy for measuring the true level of household well-being. Current income, on the contrary, could overestimate or underestimate well-being. For example, overestimation of well-being may occur when a household does not spend all its income to satisfy current basic needs, but rather saves a part of it. On the other hand, underestimation may occur when the household increases current consumption by using accumulated savings or resorts to borrowing.
   However, it is not universally accepted that household welfare is solely determined by the satisfaction of basic needs at present. If household welfare is also understood as the ability to satisfy basic needs in the future, income could be a better proxy indicator for household well-being than consumption, given that current income includes not only current consumption, but also savings, which could eventually be used to satisfy basic needs in the future. In other words, income measures the consumption potential of the household, irrespective of how the household allocates its income between satisfying present basic needs and savings.
2. **Empirically, it has been observed that consumption is a more stable measure of household well-being than current income.** Evidence suggests that most households are at least partially able to maintain their consumption levels over time (known as consumption smoothing), even if income shows significant short-term fluctuations. For example, when income is unusually high, households do not increase their consumption at the same level, but rather save or pay off debts. When income is unusually low, households avoid significantly reducing their consumption level, when possible, by using their savings or borrowing from family, friends or formal and informal credit channels. Box 4 discusses an example in which the use of consumption smoothing strategies greatly affects the measurement of rural poverty.
   The influence of consumption smoothing strategies in poverty estimations is more important when poverty is measured over short time periods. As explained by Deaton and Grosh (2000) and Deaton and Zaidi (2002), from a lifetime perspective, and taking into account bequests and inheritances, the choice between consumption and income becomes irrelevant, given that the average level of consumption must be equal to the average level of income. However, the common practice is to measure poverty over shorter time periods, ranging between a month and a year, and in this case, the choice of the welfare indicator can significantly affect poverty measurement. Using consumption instead of income will produce more stable poverty estimates in cases where incomes fluctuate greatly over time, and households are able to smooth consumption. This is particularly relevant for rural households in developing countries, who derive a large share of their income from agriculture, a highly seasonal activity.
3. **In practice, survey respondents are more willing to share information on consumption than on income.**[8] **In addition, information on consumption tends to be more accurately reported than information on income.** Deaton and Grosh (2000) explain that the share of households refusing to respond to at least one question of a survey instrument tends to be much higher when questions refer to income rather than consumption. Underreporting also tends to be higher for income compared to consumption.
   Even when respondents are willing to share their income information, collecting accurate information on income can be complex. The rural poor in developing countries earn their

[8] The main reason households are more reluctant to report income is that income is taxable in most countries, and it is not easy to persuade households that their income information will not be shared with tax authorities.

livelihoods primarily in informal sectors and in seasonal activities. Incomes from these sectors and activities can fluctuate widely during the year. Lengthening the period of reference over which income is captured in surveys is the usual practice used to mitigate the influence of these short-term variations. While this practice can reduce income fluctuations, it increases the potential for recall errors.[9]
Furthermore, obtaining an accurate measure of income for (informal) self-employed workers is very cumbersome. Capturing net income of such workers requires considering not only the revenues, but also the quantity and cost of the inputs and production factors used in the production process. This is particularly complicated in the case of the rural self-employed, given that the costs associated to the use of capital and land are difficult to gauge.

In spite of these limitations, using income as the welfare indicator has also some practical advantages. The main one is that **collecting data on income tends to be relatively cheaper than collecting data on consumption**. This difference is explained by the simple fact that the number of potential income sources is significantly lower than the number of potential consumption sources. In other words, collecting information on consumption requires designing longer household questionnaires.

In practice, consumption is the preferred welfare indicator for poverty measurement in most developing countries. According to PovcalNet (World Bank, 2021a),[10] all low-income countries (31 out of 31) and almost all lower-middle-income countries (41 out of 45) use household consumption as the welfare indicator, while only one low-income country[11] and five lower-middle-income countries[12] use household income as the welfare indicator. The share of upper-middle-income countries using consumption as the welfare indicator in poverty estimates is also high (29 out of 48),[13] while almost all (40 out of 43)[14] high-income countries use income as the welfare indicator in monetary poverty measurement.

9 Recall errors occur when respondents forget the information needed to answer a question or provide an erroneous answer because the period of reference of the question is too long or the type of information requested is too detailed.
10 PovcalNet is an interactive computational tool for global monetary poverty monitoring, developed by the World Bank.
11 Haiti stands out as the only low-income country where monetary poverty estimates can be alternatively obtained by using consumption or income.
12 Bolivia, El Salvador, Honduras and Nicaragua are the middle-income countries where the estimates of monetary poverty are only obtained using income, while the Philippines monetary poverty can be estimated using either consumption or income.
13 Most of these are countries of Latin America and the Caribbean.
14 Poland is the only high-income country that uses consumption as its welfare measure.

FIGURE 2
Welfare indicator used for official poverty measurement by countries' level of income

Note: The classification of countries by level of income is that used in PovcalNet in July 2021 and might not reflect the latest World Bank classification.

Source: World Bank, 2021a.

▶ BOX 4
Consumption smoothing and rural poverty measurement

The use of strategies to smooth consumption seems to be particularly relevant for the poorest rural households, and this can influence poverty measurement in rural areas. Table 1, which shows the percentage of Peruvians identified as poor in 2018, using different welfare indicators and poverty lines, illustrates this. The first two columns show the percentage of individuals considered poor when the total poverty line is alternatively compared with household per capita consumption and income. The last two columns present a similar exercise, but in this case comparing the food poverty line (or extreme poverty line) with household per capita consumption and income.
The choice of the welfare indicator does not create significant differences in the estimation of total poverty, but it markedly affects that of extreme or food poverty. In the case of total poverty, the share of individuals considered poor is practically the same whether consumption or income is used as the welfare indicator. This result holds at national, urban and rural levels. However, in the case of food poverty, the share of individuals identified as poor is clearly higher when the welfare indicator is income. Food poverty at the national level is 2.8 percent when the welfare indicator is consumption, and 5.3 percent when it is income. Although a similar result is observed in urban areas, the most important difference is found for rural areas: the share of rural poor moves from 10.0 percent to 17.2 percent when using the consumption and income welfare indicator respectively.

▶ TABLE 1
Monetary poverty rates in Peru, 2018

	TOTAL POVERTY		FOOD POVERTY	
	CONSUMPTION	INCOME	CONSUMPTION	INCOME
National	20.5%	19.7%	2.8%	5.3%
Urban	14.4%	13.5%	0.8%	2.0%
Rural	42.1%	42.1%	10.0%	17.2%

Sources: Authors´ calculations based on data from INEI (2018).

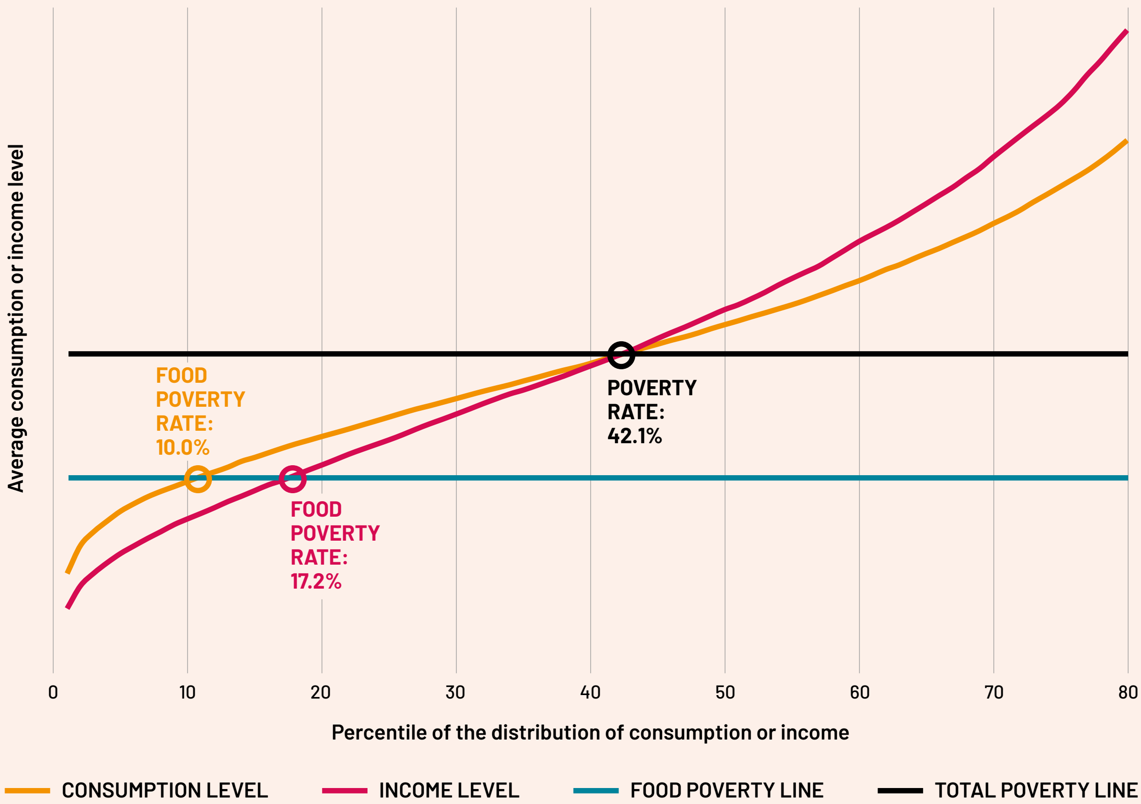
Table 1 shows that, in rural areas, total poverty is similar for both welfare indicators (42.1 percent), which implies that income and consumption levels are similar for households located around the 42nd percentile of the distributions of income and consumption in rural areas. In the case of food poverty, however, it is significantly lower when the welfare indicator is consumption (10.0 percent vs 17.2 percent), suggesting that the level of consumption is higher than the level of income for households located between the 10th and the 20th percentiles of the distributions of income and consumption in rural areas. ▼

▶ BOX 4 (CONT.)

The assertion in the last sentence is confirmed by Figure 3, which shows that, in rural areas of Peru, the average level of consumption (orange line) is higher than the average level of income (pink line) for all percentiles belonging to the bottom 40 percent of the respective distribution. This means that, on average, households belonging to the poorest 40 percent of the distribution are able to sustain consumption levels that are higher than their current income level. Although the difference could be partially explained by measurement errors, this clearly indicates that consumption smoothing is a common practice among poorer rural households.

▶ FIGURE 3

Income and consumption levels in rural areas of Peru, 2018



Note: For illustrative purposes, the figure only shows the bottom 80 percent of both income and consumption distributions.

Source: Authors' calculations based on data from INEI (2018).

PRACTICAL TIPS: SELECTING THE WELFARE INDICATOR FOR MEASURING POVERTY IN RURAL AREAS

The balancing act in favour of using income or consumption as the welfare variable for measuring poverty in rural areas mainly depends on the circumstances in which the exercise is performed. In most cases, contextual factors are far more relevant than theoretical arguments. The choice will depend on the availability of data. In any case, once a welfare indicator is selected, poverty comparisons between regions or areas or over time should be always made using the exact same welfare indicator. The remainder of this section provides practical tips for selecting a welfare indicator for measuring rural poverty.

CASE 1. Poverty is estimated using microdata[15] from an existing household survey

Most of the time, household surveys collect information to define only one welfare indicator.

- Sometimes microdata made available for public use contains a constructed variable representing the welfare indicator captured in the survey (such as total household consumption or total household income). In that case, it is best to use that welfare indicator.
- When microdata does not include a constructed welfare measure but contains all the disaggregated information needed to define it, then the welfare measure can be constructed using that disaggregated information. Annex 1 explains how to define a consumption-based welfare measure, while Annex 2 discuss how to define an income-based welfare measure.

Sometimes, household surveys provide information on both welfare indicators.

- If microdata contains constructed variables capturing both indicators, the welfare indicator used by the country for its official poverty estimates should be prioritized.
- If the country does not have an official poverty measure, analyse which welfare indicator is more accurately captured by the survey. In determining that, it is important to consider the period over which the indicators are captured, and the level of detail of both the income and consumption modules of the survey.
- If both welfare indicators are provided by the survey data on hand, it is possible to estimate poverty using both indicators. This will provide complementary information, such as whether poor households use consumption smoothing strategies (see Box 4). Using both indicators will also facilitate assessing the robustness of the estimates.[16]
- If microdata does not contain constructed variables capturing total household income or consumption, but provides all the data required to construct one or the other, a poverty measure could be constructed using the disaggregated information. As mentioned before, Annexes 1 and 2 discuss how to do this.

[15] Microdata is unit-level data obtained from surveys, censuses or administrative data. It includes information on individuals or entities such as households, farms, firms or communities. In official statistics, microdata is used to produce aggregate information, such as the poverty rate in a country.

[16] Poverty measurement, like other empirical analyses, depends on the use of assumptions and arbitrary decisions. Let us consider the case in which a practitioner, based on the information discussed in this section, chooses consumption as the welfare indicator for monetary poverty measurement in the rural areas of a given country. As a result of her analysis, the practitioner finds that the incidence of poverty decreased in the last five years. However, the practitioner is unsure about how robust the result is and would like to check whether her results would change if she used income, instead of consumption, as the welfare indicator. In that sense, checking poverty estimates using alternative welfare indicators is a common robustness exercise, used to validate the results obtained with the welfare indicator originally chosen by the practitioner.

- Once the welfare indicator is constructed at the household level (i.e. total household income or consumption), it is necessary to convert it from a household basis to an individual basis. While the most common practice is dividing total household income or consumption by the number of members of the household, this practice is not without its problems. In addition to the assumption of equal intrahousehold allocation (see Box 3), this procedure assumes that every household member has the same needs and that there are not economies of scale within the household. These aspects, and the alternatives to the per capita procedure, are presented in detail in Box 5.

CASE 2. An ad hoc household survey is carried out and used for measuring poverty

If an ad hoc household survey is being carried out, in the context of a project for example, and assuming that resources are scarce, it is advisable to focus on capturing only one welfare indicator. The choice of one or the other should be guided by the purpose for which poverty is being measured. For example, if the purpose is to evaluate the impact on household welfare of a project designed to improve food security and nutrition, consumption should be the preferred welfare indicator. Alternatively, if the purpose is to evaluate the impact on household welfare of a project aimed at increasing smallholders' productivity, or the economic inclusion of rural women or migrant populations, income should be the preferred indicator.

As discussed previously, the characteristics of rural areas in developing countries, particularly those related to livelihoods, favour the use of household consumption as the welfare indicator for measuring monetary poverty. The arguments behind this proposition are the following:

- **Consumption is a more stable measure of welfare than income. This is particularly true for rural households in developing countries.** Agriculture, which is highly seasonal and exposed to climate events, is the main source of livelihoods for most rural inhabitants in developing countries (Castañeda *et al.*, 2018). Consequently, the income of these rural households is very volatile. Consumption also has seasonal fluctuations, but they tend to be of smaller magnitude than fluctuations in income, as households implement strategies to smooth consumption.
- **Reducing volatility in the income indicator is possible, but at a high cost.** There are some alternatives to mitigate the influence of income volatility in poverty measurement, but all of them have associated costs. Lengthening the period of reference over which income is reported in the survey will reduce volatility, but at the cost of increasing recall errors and diminishing the quality of the data collected. Similarly, visiting households multiple times to capture income across different seasons can greatly improve the quality of the income data, but it can significantly increase the cost of the survey.
- **The concept of income is not easy to define and measure for the rural self-employed, the main labour category in rural areas of developing countries.** A correct measurement of net income requires that all the revenues of the activity be included and all the costs (such as the inputs used for production) be excluded. Furthermore, in some cases, it is very complicated to disentangle business revenues and expenses from personal revenues and expenses. Similarly, the costs associated to the use of capital and land are difficult to gauge. In that sense, consumption could be a better indicator of the welfare derived from self-employment in agricultural activities.

Although these are strong reasons to recommend the use of consumption as the welfare indicator to measure monetary poverty in rural areas, it is worth mentioning that collecting information on consumption usually implies longer and more detailed survey modules than collecting information on incomes. This means that the cost per household of collecting consumption information through a survey is higher than the cost of collecting income information. For that reason, when the budget allocated to the survey is limited, as is the case in many projects, a relatively short income module might be preferred over a long, detailed consumption module.

▶ BOX 5

Equivalence scales and adjustments for economies of scale in consumption

Once a welfare indicator is constructed at the household level, additional adjustment is required to correctly infer well-being at the level of the individual. This adjustment is needed as the well-being of individuals belonging to households of different size and composition will differ even when the household welfare indicator (i.e. total household income or consumption) takes the same value for all households. Thus, a procedure is needed to convert the welfare indicator from the household to the individual level.

The most straightforward method to perform this adjustment is to simply divide the household welfare indicator by the number of household members. In this way, the welfare indicator is expressed in per capita terms, and it is assigned to each household member. While this per capita procedure is the most commonly used solution, it only takes into account that households differ in size. It fails to acknowledge, however, two other important aspects that should be considered in the adjustment.

The first aspect that is not properly considered in the per capita procedure is that **different household members have different needs**. For instance, adults typically need more food than children. The second aspect is that family members living together benefit from **economies of scale**, at least in certain consumption items. That is, although the needs of a household increase with each additional household member, certain household goods can be shared among household members and do not need to be acquired in proportion to the household size. For example, while a household composed of only one member will need to purchase a fridge, this same fridge will likely satisfy the needs of a household of two, three or four members.

If these issues are not properly addressed, one might underestimate or overestimate the level of poverty of certain demographic groups, especially children. The most obvious solution to these problems is to use a system of weights to adjust the number of household members according to household size and demographic composition.

The first aspect, the different needs of each household member, is usually solved using an equivalence scale to express the size of the household in terms of adult (male) equivalents.

In this method, each household member counts as a fraction of an adult male, with that fraction depending on age and gender, and household size is re-expressed as the sum of these fractions (i.e. the number of adult male equivalents). The second aspect, adjustment for economies of scale in consumption, is handled by converting the number of adult equivalents into "effective adult equivalents". This procedure usually involves raising the total number of household members to a power lower than 1. ▼

▶ **BOX 5 (CONT.)**

In practice, although there is no full consensus on the most accurate equivalence scales and adjustments for economies of scale, most researchers consider that using an imperfect equivalence scale and/or an imperfect adjustment for economies of scale is better than simply relying on the per capita procedure. For this reason, it is recommended that practitioners choose one of the available scales and check for robustness by applying one or more alternative scales and comparing the results (see Atkinson, Rainwater & Smeeding [1995] for a review on this topic). Different studies show that using equivalence scales and adjustments for economies of scale in consumption generally results in downward adjustments of child poverty and child-adult poverty gaps.

The monetary poverty line

Defining the poverty line[17] is one of the most important and complex steps in measuring monetary poverty. Fortunately, in most cases, poverty lines are already defined by national statistical offices. Still, when using monetary poverty lines it is important for practitioners to understand how they were established. This section describes how absolute monetary poverty lines – the poverty lines that are more relevant for rural areas of developing countries – are defined.

The monetary poverty line is thought of as the monetary cost of attaining a certain minimum level of welfare in a given place and time.[18] In most empirical exercises, two complementary poverty lines are used together: the **extreme poverty line** and the **total poverty line**. There are three main approaches to setting these two poverty lines: the **absolute**, the **relative** and the **subjective** approaches. These approaches differ according to the basic needs that are considered in defining the poverty line and how those basic needs are valued in monetary terms. In the **absolute** approach, the poverty line is equal to the amount of money households need to meet some absolute basic needs. Under the **relative** approach, the poverty line is defined relative to the distribution of income or consumption in society. In the **subjective** approach, the poverty line is set in accordance with people's subjective perceptions of what constitutes poverty in a given society and at a given time.

As is explained in greater detail in Box 6, the use of absolute poverty lines is recommended for purposes of informing poverty reduction policies. In addition, absolute poverty lines tend to be most widely used for monetary poverty measurement in rural areas of developing countries, where guaranteeing minimum standards of living for a majority of the population is still one of the most important policy objectives. For this reason, the remainder of this section describes how absolute poverty lines are set. The interested reader is referred to Annexes 4 and 5, which provide supplemental information on how to set monetary poverty lines using the relative and the subjective approaches, respectively.

[17] Ravallion (2016) provides a comprehensive discussion of the issues involved in defining poverty lines in developing countries. This section closely follows the structure of that discussion, focusing on the aspects related to rural areas.
[18] It is important to note that, in a typical poverty measurement exercise, the poverty line is utilized to identify which households have the monetary capability to meet certain basic needs, which is not the same as identifying which households actually meet those basic needs.

Setting absolute poverty lines

Absolute poverty lines are set with reference to a fixed absolute standard of what households should get access to in order to meet their basic needs. In general, all the methods used to define absolute poverty lines anchor them to a non-monetary welfare indicator. In most cases, this indicator is the food–energy requirement for maintaining a required body weight and sustaining a certain level of physical activity. The food–energy requirement is defined by nutritionists, who take into consideration the composition and certain socio-economic characteristics of the population, such as age, gender, type of economic and daily activity, and area of residence.

FAO, the World Health Organization (WHO) and the United Nations University (UNU) (FAO, WHO and UNU, 2004) define energy requirement as "the amount of food energy needed to balance energy expenditure in order to maintain body size, body composition and a level of necessary and desirable physical activity consistent with long-term good health…". Their interagency report (*Human energy requirements: Report of a Joint FAO/WHO/UNU Expert Consultation*) provides a detailed analysis of food–energy requirements and allowances for populations with lifestyles involving different levels of habitual physical activity (FAO, WHO and UNU, 2004). That information should be taken into consideration when defining specific poverty lines for urban and rural areas. In general, because of the difference in the predominant economic activities between rural and urban areas, the amount of food energy required by a typical rural inhabitant is higher than that required by a typical urban inhabitant.[19]

Once the food–energy requirement is set, there are different methods to define the monetary value of the absolute poverty line. The method more commonly used is known as the **cost of basic needs (CBN) method**. Through this method, absolute poverty lines are generated whose value is expressed in real terms across areas or regions and over time (providing consistency). At the same time, these values are locally meaningful (providing specificity). The next section details the implementation of this method. For the interested reader, Annex 3 describes an alternative method to define absolute monetary poverty lines: the **food-energy intake method**.

The cost of basic needs (CBN) method

Once the food–energy intake required to maintain body weight and sustain certain normal levels of activity is established, the monetary value of the food poverty line and the total poverty line can be obtained using the CBN method, which is described below.

STEP 1: Defining the composition of the food bundle and estimating its monetary cost (the food, or extreme, poverty line). Initially, a food bundle must be chosen among the alternative bundles that meet the food–energy requirement defined by nutritionists. A **first alternative** is to find a combination of food items that minimizes the cost of meeting the food–energy requirement at a given set of prices. This approach, however, ignores the food habits of the population and, thus, will have little meaning for policy analysis as its cost will be significantly less than the cost of a bundle that is defined according to the food habits of the population of interest. A **second alternative** is to use a normative food bundle, selected by a group of nutrition experts. This type of bundle, also called a balanced nutritional food bundle, tends to have a much higher cost than that of the food bundle normally consumed by the population of interest.

The **third (and, in general, better) alternative**, is to define the composition of the food bundle according to the prevailing food habits of the population of interest. In most cases, the composition of the bundle is based on the consumption patterns of a reference group, typically comprised of

[19] Working in agriculture and in other rural activities tends to be more arduous and physically demanding than working in most urban jobs. For this reason, rural activities tend to entail higher food-energy requirements than urban activities.

households with relatively low levels of income or consumption.[20] Given that the consumption habits and the relative prices of goods and services may vary between regions within a country and, particularly, between urban and rural areas, it is advisable to set specific bundles for each region/area.

Once the composition of the food bundle is defined, the monetary cost of that bundle represents the value of the monetary food poverty line. If specific bundles for different regions/areas are set, their costs should be estimated using local prices.

STEP 2: Going from the food poverty line to the total poverty line. The total poverty line is obtained after adding an allowance for some basic non-food items to the food poverty line. Considering some non-food items as basic needs is justified both by theoretical and empirical reasons. Theoretically, attaining a minimum standard of living requires acquiring some non-food items such as basic clothing, housing and healthcare. Empirically, it is observed that even those households with income or consumption levels below the food poverty line allocate part of their budget to some essential non-food items.

The method more commonly used to estimate the allowance for non-food items is the one proposed by Orshansky (1965). This method does not identify an explicit bundle of non-food goods, but directly estimates the allowance for non-food items based on the consumption behaviour of the same reference group used to define the food bundle. According to Orshansky, it is not possible to define an explicit bundle of non-food items because "there is no generally accepted standard of adequacy for essentials of living except food". Following an empirical regularity that she observed in her work, Orshansky considered that the relation between the food poverty line and the total poverty line could be similar to the relation between the expenditure in food and the total expenditure for an average family. For example, if the food share in total expenditure for an average family were 25 percent (i.e. 1 out of 4 dollars spent by the family goes to food items), then the poverty line would be four times the food poverty line. In this way, the relation between the food and non-food allowances in the poverty line will be the same as the relation between food and non-food consumption expenditures for the reference group (i.e. the average family, according to Orshansky).

In general, the share of food in total expenditure decreases as total expenditure increases (Engel's law), and this implies that the value of the **Orshansky multiplier**, the ratio between the poverty line and the food poverty line, positively depends on the level of income or consumption of the reference group. When the reference groups for different population subgroups, such as urban and rural areas, are determined independently of each other, this method can introduce artificial differences in the value of the resulting poverty lines. For example, if real income is significantly higher in urban areas than in rural areas, then the food share will be much lower and the poverty line will be much higher in urban than in rural areas. A way to avoid this problem is to select a single national reference group and define the multiplier for each area according to the consumption patterns of the households of each area within the national reference group.

[20] There is not a fully specified standard method for selecting the reference group that it is used to define the composition of the food bundle. The most common method is the iterative process proposed by Pradhan *et al*. (2001). With this method, the authors identify a reference group centered on the poverty line. For more details, see Pradhan *et al*. (2001).

▶ BOX 6

Setting a monetary poverty line for rural areas

Desirable properties of poverty lines. Whatever the approach followed to set poverty lines, the resulting lines should satisfy two desirable properties: consistency and specificity. Consistency demands that poverty lines represent a fixed purchasing power across space and time. Specificity calls for poverty lines that are relevant to each local space-time domain. In some cases, the two desirable properties can be in conflict with each other. For example, selecting the same food bundle across space and time would be an easy way to ensure consistency. However, if relative prices (or tastes) vary across space and time, consumption patterns will also vary. For this reason, selecting the same food bundle across space and time violates specificity. At the same time, and given that individual preferences are not observable, selecting different food bundles across space and time will satisfy specificity, but could violate consistency.

Absolute, relative or subjective? In addition to ensuring purchasing power comparability across space and time (consistency) and choosing food bundles in accordance with social norms and local circumstances (specificity), poverty lines must be consistent with the objectives of measurement. Ravallion (1998) argues that poverty lines should always be absolute for purposes of informing poverty reduction policies or allocating resources among regions or areas of a country using poverty comparisons.

In rural areas of developing countries, where attaining minimum standards of living for a majority of the population still is one of the main policy objectives, **the measurement of monetary poverty should be performed using absolute poverty lines**. This will guarantee that poverty rates will decrease when income or consumption grows for all members of society, which is not necessarily the case when using relative or subjective poverty lines (see Annexes 4 and 5 for more details).

PRACTICAL TIPS: DEFINING THE POVERTY LINE FOR MEASURING POVERTY IN RURAL AREAS

As mentioned above, most countries – through their national statistical offices – define their own national poverty lines. This simplifies considerably the work of most practitioners. However, practitioners and researchers could face some problems when using those poverty lines for rural poverty measurement: the available poverty lines could be outdated (e.g. the poverty lines were defined for 2010, but the available household survey is from 2015), or the poverty lines could have been defined only with reference to urban areas. This section presents some recommendations on how to deal with those problems, as well as how to define absolute poverty lines when no official poverty lines have been defined by the country.

CASE 1. National poverty lines have been defined by the country

Most developing countries set their own official absolute poverty lines using the CBN method described previously. When available, these lines should be the point of departure of a rural poverty analysis. The following aspects should be considered carefully:

- **Check that the available national poverty lines and microdata correspond to the same period.** If this is not the case, the value of the poverty lines should be updated according to the evolution of prices over time.
  - Ideally, one should first update the value of the food poverty line by updating the prices of each food item included in the food bundle and, after that, update the value of the total poverty line multiplying the food poverty line using the Orshansky multiplier.
  - However, in most cases, information on the exact composition of the food bundle (on the specific food items included in the bundle and the quantity of each of them) and on the evolution of the prices of the different food items is not available. In this case, the value of the food poverty line can be updated using the subindex *Food* of the Consumer Price Index (CPI),[21] while the value of the total poverty line can be updated using the overall CPI.
  - If the poverty lines are region-area- or area-specific, if possible, they should be updated using regional/area prices (although most countries do not collect detailed prices for each region/area).
- **If possible, use region-area- or area-specific poverty lines.** In some cases, countries define specific poverty lines for rural and urban areas of each region (region-area-specific). In others, they only define specific poverty lines for rural and urban areas at the national level (area-specific). Using these lines in rural poverty analysis is superior to using a single national poverty line.
- **In the event the country only defines a single national poverty line, evaluate whether this line satisfies the property of consistency (i.e. representing the same purchasing power in urban and rural areas).** To do this, analyse the documentation explaining how the poverty line was defined. If the line violates consistency (e.g. the food bundle was selected only based on the consumption patterns of urban households or its monetary value was estimated using only prices collected in urban areas), it is best to avoid using it to draw poverty comparisons between rural and urban areas. If possible, the value of the poverty line would at least need to be adjusted to take into consideration spatial (urban/rural) differences in cost of living. Information on price differences between urban and rural areas will be needed to implement this adjustment.

CASE 2. The country does not define its own national poverty lines

In the absence of an official absolute poverty line defined by the country, the international poverty lines are the resource at our disposal, since defining a new absolute poverty line from scratch is a challenging task and beyond the scope of most projects. In this situation, practitioners should use the "dollar-a-day" international poverty lines set by the World Bank: USD 1.90, USD 3.20 and USD 5.50 a day per person, at purchasing power parity (PPP). (The USD 1.90, USD 3.20 and USD 5.50 lines are particularly relevant for low-income countries, lower-middle-income countries and upper-middle-income countries, respectively.)

[21] The Consumer Price Index (CPI) measures the price change between the current and reference periods of an average basket of goods and services purchased by households. CPI series for multiple countries can be consulted at the website of the International Monetary Fund.

For example, the monthly value of the USD 1.90 a day poverty line (PL) in local currency can be obtained using the following formula:[22]

$$PL_{1.90}^{m\text{-}lcu} = (1.90 * ppp) * \frac{cpi^{sy}}{cpi^{py}} * \left(\frac{365}{12}\right)$$

Where:
$PL_{1.90}^{m\text{-}lcu}$: monthly PL USD 1.90 a day in local currency.
ppp: PPP factor for consumption between the country and the United States of America (see the International Comparison Program to find the value of the PPP factor for each country).
cpi^{sy}: Consumer Price Index for the period of reference (month and/or year) of the data on the welfare indicator (income or consumption).
cpi^{py}: Consumer Price Index for the year in which the PPP factor was estimated.[23]

The international poverty lines are defined to guarantee comparability between countries, but they do not necessarily guarantee comparability among regions or areas of the same country. Ideally, the value of these lines should be adjusted using local PPP factors, capturing differences in purchasing power within a country, particularly between urban and rural areas. However, most countries do not produce these local PPP factors.

2.3.2 Aggregating the monetary poor: the FGT family of poverty measures

Once the monetary poor are identified by having compared a monetary indicator representing their welfare level and a monetary poverty line, the final step of a poverty measurement exercise consists of combining some information of those identified as poor in an aggregate poverty measure.

The poverty measures most predominantly used in empirical exercises of monetary poverty measurement are those of the FGT family. Among them, the **headcount ratio** (or **poverty rate**) is, by far, the most frequently used poverty measure. The **poverty gap index** is also commonly included in empirical analyses, while the **severity of poverty index** is often used to complement the information provided by the other two indices. Box 7 presents the formal definition of the FGT class of poverty measures, and the next sections analyse and discuss the characteristics and information provided by these three poverty indices.

[22] The value of the poverty line should be expressed using the same period of reference used in the construction of the welfare measure (e.g. monthly or annual).
[23] At the time of writing (January 2021) World Bank poverty estimates are obtained using the PPP factors of 2011.

BOX 7
The Foster-Greer-Thorbecke (FGT) family of poverty measures

The **headcount ratio**, the **poverty gap** and the **severity of poverty** indices belong to the FGT family of poverty measures and can be derived from the same general formula:

$$FGT_{\alpha} = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{z-y_i}{z}\right)^{\alpha}$$

Where:
z is the poverty line; y_i is the income/consumption level of each individual/household;
N is the number of individuals/households in the total population; H is the number of poor individuals/households (those with $y_i<z$); and α is a parameter capturing the differential weight placed on the situation of the poorest individuals/households.
When $\alpha = 0$, the formula becomes the share of the population (**headcount ratio**) with an income or consumption level lower than the poverty line:

$$FGT_0 = \frac{H}{N}$$

When $\alpha = 1$, the formula becomes the **poverty gap** index:

$$FGT_1 = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{z-y_i}{z}\right)$$

Finally, when $\alpha = 2$, the formula becomes the **severity of poverty** index:

$$FGT_2 = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{z-y_i}{z}\right)^2$$

MORE IN DETAIL According to the axiomatic approach to poverty measurement, first proposed by Sen (1976), a "good" poverty measure should satisfy certain desirable properties, which practitioners can consider in choosing an appropriate poverty index among the different available indices. Building on the work of Sen, Ravallion and Chen (2001) argue that there are three axioms that are essential to any good measure of poverty, namely the focus axiom, the monotonicity axiom and the transfer axiom.

1. **Focus axiom.** The focus axiom establishes that a good poverty measure should be independent of the non-poor population. It should only reflect the conditions of those identified as poor, and any change among those identified as non-poor should not affect the measure. For example, if a monetary transfer was made to non-poor people only, the poverty measure should not change.

2. **Monotonicity axiom.** The monotonicity axiom states that, holding all else constant, when there is a reduction (or an increase) in the income or consumption of a poor household, a good poverty index should show an increase (or a decrease) in its value, reflecting an increase (or decrease) in poverty. For example, if a group of people who are already poor is hit by an adverse event that further reduces their welfare, this should be reflected in an increase in the poverty measure.
3. **Transfer axiom.** The transfer axiom indicates that, holding all else constant, when there is a regressive (or progressive) transfer between two poor persons, a good poverty measure should show an increase (or a decrease) in poverty. With this axiom, Sen introduced the idea that a good poverty measure should be sensitive to the degree of inequality among the poor. For example, if a new tax shifts resources from people who live in moderate poverty to people who live in extreme poverty, this should be reflected in a decrease in the poverty measure.

Although all these axioms seem to be reasonable criteria for assessing the quality of a monetary poverty measure, not all commonly used poverty indices satisfy them, as will be shown later in this chapter. Moreover, several authors mention two additional desirable characteristics of monetary poverty measures: scale invariance and subgroup decomposition. **Scale invariance** is met when poverty remains unchanged as a result of scaling up/down the welfare variable and the poverty line for all households by the same factor. For example, if the income of all households in a country increases by 10 percent and the poverty line is adjusted accordingly (i.e. it is increased by 10 percent as well), then the poverty measure should not change. **Subgroup decomposition** implies that the poverty measure can be decomposed by different population subgroups, provided that each member of the population belongs to one and only one subgroup. Examples of subgroups could be people living in rural areas vs people living in urban areas or people engaged in agriculture vs people not engaged in agriculture.

Headcount ratio or poverty rate

The headcount ratio simply gauges the share of the population whose income/consumption is below the poverty line, in other words, the share of the population identified as poor. In that sense, it provides the answer to the most basic question about poverty: "How many (or what percentage of) people are living in poverty conditions?" Two characteristics of this index explain why it is by far the most frequently used poverty measure: It is relatively simple to calculate, and it is extremely easy to understand, interpret and communicate.

However, the headcount ratio does not consider other interesting pieces of information about households and individuals identified as poor. First, it does not reveal how poor the poor are (i.e. it does not provide any information regarding the depth of the poverty condition of households and individuals living in poverty). As such, this index will not capture the positive effect of an intervention that, although it does not lift the poor out of poverty, improves their levels of income or consumption. Second, the index provides no information on the distribution of welfare (e.g. income or consumption) among the poor. As such, other things being equal, the index will not differentiate between interventions helping the poorest of the poor and those helping poor individuals and households that are relatively better off or closer to the poverty line.

For these reasons, the headcount ratio should be considered a rather partial measure of poverty, and it should not be used as the sole measure of poverty in designing and evaluating policies to reduce poverty. Adopting the poverty rate as the sole criterion in the design and evaluation of such policies can be problematic, as it may encourage policy-makers to target the "richest of the poor" through their interventions so as to maximize their poverty reduction impact. In other words, if the main objective of an intervention is to maximize the reduction in the poverty rate, without considering the deprivation situation of those who remain in poverty after the intervention, then the most efficient way to achieve the objective would be to concentrate the resources of the intervention on the "richest of the poor".

While the previous paragraph describes an extreme case, many poverty reduction interventions focus on poor households with more resources. Focusing on these households increases the chances of demonstrating the success of a given intervention, for example in terms of increased production, economic inclusion and poverty reduction. In these cases, by using only the headcount ratio in the evaluation of such schemes, observed impacts could hide relatively small effects in the welfare condition of the poorest participants. This is particularly problematic when evaluating interventions that are explicitly designed to improve the welfare situation of the "poorest of the poor", such as cash transfer programmes. Using only the headcount ratio might fail to identify the positive effects of such programmes among the poorest of the participants.

MORE IN DETAIL The limitations of the headcount ratio can be expressed in terms of the axiomatic approach to poverty measurement presented in the previous section: The headcount ratio satisfies the focus axiom as it concentrates its attention on those below the poverty line, but it fails to satisfy both the monotonicity and the transfer axioms. More specifically, **it violates the monotonicity axiom** because any changes in the income/consumption of the poor that do not move an individual or household beyond the poverty line will not be captured by the headcount ratio. **It violates the transfer axiom** because it is completely insensitive to the distribution of income/consumption among the poor: a transfer from a poor person to another poor (but wealthier) person does not increase the poverty level as measured by this index.

Poverty gap index

The poverty gap index provides information on one of the aspects that is not considered by the headcount ratio: the depth of the poverty condition of households living in poverty. More specifically, it reflects the average distance between the income/consumption of each household and the poverty line. It is obtained by adding all the income/consumption shortfalls of poor households (assuming that the income/consumption shortfall of the non-poor households is zero) and dividing it by the total number of households.

With the information provided by this measure, it is possible to estimate the total amount of monetary resources necessary to bring all the poor to the income/consumption level of the poverty line. In other words, the poverty gap provides an indication of the minimum amount of resources needed to eradicate poverty – monetarily speaking – assuming that it is possible (and costless) to transfer to each poor person the amount required to lift her/him out of poverty. This is a useful indicator for project design and investment if a project is seriously considering generating sufficient economic development and support to move its targeted populations out of poverty.

Although the poverty gap informs on the depth of the poverty condition of those households living in poverty (i.e. how poor the poor are), it neglects an important aspect of poverty: the distribution of income or consumption among the poor. Even with this limitation, the poverty gap is a very useful index for designing and evaluating different poverty reduction policies, particularly when it is used in combination with other poverty measures.

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MORE IN DETAIL In terms of the axiomatic approach to poverty measurement, the poverty gap satisfies the focus and the monotonicity axioms, but **it violates the transfer axiom**. That is, this index is able to reflect situations whereby the welfare level of some or all the poor improves, even if none of them escapes from poverty. However, the index is not able to capture situations in which the welfare situation of two poor households changes as a consequence of a regressive transfer (from the poorer to the richer household) between them. That is, it is insensitive to the distribution of income or consumption among the poor.

Severity of poverty index

In addition to considering the distance that separates the poor from the poverty line, the severity of poverty index also gauges the degree of inequality among the poor. In this index, also known as the squared poverty gap, the weight attached to the poverty gap of each poor household increases with the depth of the poverty condition of the household.

Although the information provided by this index is not necessarily intuitive, when used in combination with the headcount ratio and the poverty gap, the severity of poverty index is very useful for designing and evaluating poverty reduction interventions. For example, in the case of interventions that are strongly targeted towards the very poor (e.g. a social protection intervention targeted to the rural extreme poor), it is possible to find that the poverty rate does not change much after the implementation of the intervention. However, the information provided by the poverty gap and the severity of poverty indices could indicate that the intervention was very effective in reducing both the depth of the poverty condition of rural extreme poor and the degree of inequality among rural poor households, which would indicate that the living conditions of the poorest rural households improved after the intervention. This poverty index satisfies the three basic axioms of poverty measurement: focus, monotonicity, and transfers.

Using the FGT measures: a practical example

As shown in Table 2, the official poverty report from the *Instituto Nacional de Estadística y Censos* (National Statistics and Census Institute) of Costa Rica (INEC, 2020) provides a comprehensive picture of monetary poverty in the country using the three main poverty measures of the FGT family: the headcount ratio, the poverty gap index and the severity of poverty index. These indices, as discussed in this section, provide different pieces of information and are very useful to describe both the level and the evolution of poverty in a certain geographic area and during a certain period. For example, the headcount ratio shows that the percentage of households living in poverty in Costa Rica remained virtually unchanged between 2018 and 2019, showing only a slight drop from 21.1 percent in 2018 to 21.0 percent in 2019. The headcount ratio also shows, however, that the percentage of poor households jumped to 26.2 percent during 2020 as a direct consequence of the COVID-19 pandemic.

The poverty gap index also shows that poverty remained stable between 2018 and 2019 but worsened significantly during 2020. While in 2018 and 2019 the average percentage shortfall in income from the poverty line for the entire Costa Rican population was approximately 8.0 percent (assuming that the shortfall in income from the poverty line is zero percent for the non-poor population), this percentage grew to 10.1 percent in 2020.

The severity of poverty index confirms the results of the other two poverty measures. While the poverty situation did not change much between 2018 and 2019, the evolution of the severity of poverty index between 2019 and 2020 reveals that there was an important increase in inequality among the poor as a result of the economic recession provoked by the pandemic.

Taken together, the results of the three poverty measures of the FGT family provide a detailed characterization of the evolution of poverty in Costa Rica between 2018 and 2020. Summarizing, these indexes inform that the number of poor households increased (headcount ratio), the poor became poorer (poverty gap), and inequality among the poor also increased (severity of poverty).

TABLE 2

FGT poverty measures for Costa Rica, 2018–2020

	NATIONAL	URBAN	RURAL
Headcount ratio - FGT(0)			
2018	21.1%	19.5%	25.1%
2019	21.0%	19.8%	24.2%
2020	26.2%	26.4%	25.5%
Poverty gap - FGT(1)			
2018	8.3%	7.7%	9.9%
2019	8.0%	7.6%	9.0%
2020	10.1%	10.2%	9.8%
Severity of poverty - FGT(2)			
2018	4.8%	4.4%	5.8%
2019	4.4%	4.2%	4.9%
2020	5.7%	5.8%	5.5%

Sources: INEC, 2020.

2.4 MEASURING MULTIDIMENSIONAL POVERTY

Multidimensional poverty measurement is a field that has developed rapidly in recent years. Among the different approaches that have been proposed to measure multidimensional poverty,[24] the Alkire-Foster (AF) approach (Alkire and Foster, 2011) has attracted the attention of most

[24] Chapter 3 of Alkire *et al.* (2015) provides a detailed discussion of the major existing methods for measuring multidimensional poverty.

researchers and policy-makers. Counting measures, such as the AF approach, are based on deprivation profiles[25] for a particular unit of identification (i.e. the individual or the household) and the deprivation profiles are used to create a deprivation score for each unit of identification (Alkire *et al.*, 2015). That score is obtained as the weighted sum of all the deprivations that a unit of identification is found to experience at a particular time.

The AF approach can be thought of as a multidimensional extension of the FGT methodology, and it satisfies all the desirable properties for a multidimensional poverty measure (see Section 2.4.2 for a detailed discussion on this topic). In particular, the poverty indices obtained through the AF approach can be decomposed by population subgroups and broken down by dimensions and indicators. These properties are very useful for designing interventions aimed at addressing the situation of the poor that use criteria that go beyond the monetary realm. It is because of these characteristics of the AF approach that this approach is used to estimate the Global Multidimensional Poverty Index (MPI) and the Rural Multidimensional Poverty Index (R-MPI) of FAO, as well as various national multidimensional poverty measures that are emerging in several developing countries.

The AF approach uses several steps to solve the problems of identifying and aggregating the poor. The next sections describe these steps. The experience of FAO in developing its R-MPI will be used to illustrate some of the aspects discussed below.

2.4.1 Identifying the multidimensionally poor: the counting approach

Although it requires following several sequential steps, the identification of the multidimensionally poor under the AF counting approach is a relatively intuitive and structured process. Alkire *et al.* (2015) summarize how that process of identification unfolds through the following steps:

1. defining the unit of identification and the unit of analysis;
2. defining relevant dimensions and indicators;
3. defining a threshold of satisfaction (or deprivation cut-off) for each indicator;
4. creating binary deprivation scores for each unit of identification in each indicator;
5. assigning a weight (or deprivation value) to each indicator;
6. generating a deprivation score for each unit of identification, by taking the weighted sum of deprivations;
7. setting a threshold score of poverty (or poverty cut-off) such that if the unit of identification has a deprivation score at or above the threshold, it is considered multidimensionally poor.

The most important aspects of each of these steps are introduced in the next seven sections.

Defining the unit of identification and the unit of analysis

As mentioned in Section 2.2.3, in almost all multidimensional poverty measurement exercises, including FAO's R-MPI and OPHI's Global MPI, the household is the unit of identification. Although using the individual as the unit of identification is possible and would have some clear advantages (e.g. it makes it possible to decompose the poverty index by individual characteristics and to analyse differences within households in terms of incidence of multidimensional poverty), in most cases it is not feasible because the information required is not available.[26] Regarding the

[25] Once the indicators used in the multidimensional measurement of poverty are selected, a deprivation profile for each unit of identification is constructed by identifying the deprivation status (e.g. deprived or non-deprived) of each unit of identification in each indicator.

[26] There have been some global efforts to apply the AF method at the individual level. The Women's Empowerment in Agriculture Index (WEAI) of USAID and IFRPI is an example in which indicators required for the index are derived from individual-level data of both men and women living in the same household.

unit of analysis, the unit used to report results, both the household and the individual, are used in most empirical applications.

The use of the household as the unit of identification implies that all household members will share the same deprivation condition (deprived or non-deprived) in each indicator, even if individual information indicates that some of the household members do not share that condition. For example, if the dimension "Education" includes an indicator on school attendance, and the deprivation cut-off is "at least one household member at school age not attending school", all the members of a household will be considered deprived in that indicator if one child at school age in the household does not attend school. If there are other children in the household who do attend school, they will also be considered deprived. This would not be the case if the unit of analysis were the individual. As noted, however, in most cases, it is not possible to have the individual as the unit of analysis.

PRACTICAL TIPS: UNIT OF IDENTIFICATION AND UNIT OF ANALYSIS

- The definition of household-level indicators using information on individual-level achievements, as in the case of the previous paragraph, can introduce biases according to household size and composition (e.g. a household without school-age members will never be deprived in an indicator of school attendance).* In that sense, not all indicators are comparable across the population. For example, comparisons in school attendance indicators should be restricted to school-aged individuals, comparisons in health indicators should be done controlling by age, etc.
- The choice of the unit of analysis should be guided by the type of indicator under analysis. For some indicators it is better to perform the analysis at the household level (e.g. indicators related to housing and infrastructure), while for others the individual level is more useful (e.g. educational and health related indicators).

* Those biases can be checked and assessed (see Alkire and Santos [2014]).

Defining relevant dimensions and indicators

The structure of a multidimensional poverty index is made up of dimensions and indicators. Indicators are the variables used to define the deprivation scores and to measure poverty, while dimensions are the conceptual categories used to group the indicators. In that sense, the indicators provide the basis upon which a multidimensional poverty index is built, and grouping them into dimensions is just a very helpful way to interpret and communicate the results of the estimates, given that there will be fewer dimensions than indicators and these dimensions represent more general and intuitive categories of deprivation.

The choice of the relevant dimensions and indicators is the key step for measuring multidimensional poverty. There is no consensus on the dimensions and indicators that matter most in multidimensional poverty measurement, not even in terms of the criteria for selecting them. In general, the **selection of the relevant dimensions** is a highly normative process in which different criteria, or different combinations of criteria, are applied. In some cases, the choice is driven by the objectives established in national development plans. In others, it follows international conventions (such as the SDGs). In still other cases, the choice is made through participatory processes and public consultations or is based on theoretical arguments.

Regarding the **selection of the relevant indicators for each dimension**, this procedure must be as rigorous as possible, given that the quality of the poverty index is highly dependent on the quality and accuracy of the indicators upon which it is built. For this reason, this selection tends to be a more technical and empirical exercise, although, even in this case, value judgements will be necessary at some point of the process. In this stage, the information included in the data source is a key constraint in determining what indicators can be estimated in practice and, thus, can be selected. With this constraint in mind, indicators can be selected also following deliberative processes, political priorities, statistical exercises or theoretical considerations. Once the indicators are selected, different statistical techniques can be used to assess their reliability, validity, redundancy, robustness and so forth, helping in this way to justify their selection (see Box 8 for more details).

Despite the lack of consensus on the criteria to select dimensions and indicators, most countries with national MPIs tend to select similar ones, adapting them to their national contexts and objectives. For instance, there seems to be agreement on including **education, health and living conditions as the core dimensions** in the measurement of multidimensional poverty. On the other hand, the most frequently included indicators in national MPIs are school attendance, access to health services, access to safe drinking water, access to adequate sanitation and other indicators related to housing and basic services.

The structure of the dimensions and indicators in FAO's R-MPI is based on the experience of the Global MPI.[27] As shown in Table 3, the R-MPI includes the three dimensions of the Global MPI: "Health" (renamed as "Food security and nutrition"), "Education" and "Living standards". In addition, the R-MPI includes two dimensions aimed at capturing specific conditions of deprivation suffered by rural inhabitants: "Rural livelihood and resources" and "Risk".

The R-MPI includes a total of 18 indicators, while the Global MPI is composed of 10 indicators. In the dimensions included in both indices, the indicators are practically the same, the only difference being that the "Food security and nutrition" dimension of the R-MPI includes an indicator on "Food insecurity", based on the Food Insecurity Experience Scale (FIES) of FAO,[28] while the "Health" dimension of the Global MPI includes an indicator on "Nutrition", based on a measure of undernourishment.

The two dimensions specific to the R-MPI are represented by eight indicators. In the case of the "Rural livelihood and resources" dimension, these are "Agricultural assets adequacy", "Low pay rate", "Social protection", "Child labour" and "Extension services"; while in the case of the "Risk" dimension, the indicators are "Credit denial", "Risk exposure and coping strategies" and "Risk of climate shocks".

[27] The global Multidimensional Poverty Index (MPI) is an international measure of multidimensional poverty covering more than 100 developing countries. It measures poverty by capturing simultaneous deprivations in three dimensions: health, education and living standards. The global MPI was developed by the Oxford Poverty and Human Development Initiative (OPHI) with the UN Development Programme (UNDP) for inclusion in the UNDP's Human Development Report in 2010. Since then, it has been published annually by OPHI and UNDP in the Human Development Report.

[28] For a detailed explanation of the Food Insecurity Experience Scale see the FAO's Voices of the Hungry webpage (available at www.fao.org/in-action/voices-of-the-hungry) (FAO, 2018).

TABLE 3

Dimensions and indicators in the Rural Multidimensional Poverty Index (R-MPI)

DIMENSIONS	INDICATORS	WEIGHTS
Food security and nutrition	Food insecurity	(1/10)
	Child malnutrition	(1/10)
Education	Years of schooling	(1/10)
	School attendance	(1/10)
Living standards	Cooking fuel	(1/30)
	Improved sanitation	(1/30)
	Drinking water	(1/30)
	Electricity	(1/30)
	Housing	(1/30)
	Assets	(1/30)
Rural livelihood and resources	Agricultural assets adequacy	(1/25)
	Low pay rate	(1/25)
	Social protection	(1/25)
	Child labour	(1/25)
	Extension services	(1/25)
Risk	Credit denial	(1/20)
	Risk exposure and coping strategies	(3/40)
	Risk of climate shocks	(3/40)

Sources: Author´s elaboration based on FAO and OPHI, 2021.

PRACTICAL TIPS: SELECTING DIMENSIONS AND INDICATORS

- The selection of the relevant dimensions and indicators is usually constrained by the availability of data and depends on normative and policy considerations. **A key first step is to create a list of all the relevant indicators which available microdata would allow to construct.** The most appropriate dimensions and indicators for the objective of measuring poverty should be selected according to the analyst's expertise and taking into consideration the information collected from other sources (e.g. interviews with qualified informants and literature review). ▼

- **It is strongly recommended to include indicators capturing the "core dimensions"** included in both the Global MPI and the R-MPI: "Education", "Nutrition and health" and "Living standards".
- **Specific dimensions and indicators aimed at capturing poverty conditions in rural settings should be included**. An example to follow is the R-MPI, which includes two specific dimensions for rural areas: "Rural livelihood and resources" and "Risks".
- If a new survey will be conducted to collect data on poverty in a specific rural sector in order to add such rural dimensions, the questionnaire should be designed having already decided, through a rigorous process of analysis, which are the most relevant poverty dimensions and indicators for the sector.
- Not all indicators are relevant (or collected) for all population groups. Some specific indicators, such as school attendance, are only relevant for some groups (households with school-age children), while surveys only collect some indicators (such as anthropometric measures) for some specific population groups (i.e. children aged six or less). In those cases, the normal procedure is to consider households without relevant populations as non-deprived in the respective indicator.
- Atkinson and Marlier (2010) and Maggino and Zumbo (2012) provide detailed guidance on how to select appropriate indicators for different objectives.

Defining the deprivation cut-offs for each indicator

After selecting the dimensions and the relevant indicators for each one, the next step is to define deprivation cut-offs for each indicator. These are thresholds indicating the minimum level that a unit of identification needs to reach in order to be considered non-deprived in that particular indicator. The definition of the deprivation cut-offs is a normative exercise, which can be guided by different criteria:

- national legislation (e.g. indicators related to education can be set in accordance with legislation on compulsory schooling);
- international conventions (e.g. the SDGs, health recommendations from WHO);
- goals of an existing national development plan; and,
- participatory and consultative exercises.

Usually, when the household is the unit of identification, there will be some indicators (e.g. educational indicators) for which the deprivation cut-offs will be defined by combining individual information for some or all household members. For example, four alternative ways of setting the deprivation cut-off of the indicator "years of education for members aged 15 and above" would be that a household is deemed to be deprived if:

- no member aged 15 and above has completed at least X years of education;
- at least one member aged 15 and above has not completed at least X years of education;
- the household head has not completed at least X years of education; or,
- on average, members aged 15 and above have not completed at least X years of education.

In some cases, the deprivation cut-offs for each indicator are modified through an iterative process: once the index is estimated and the contribution of the different indicators to the final result is evaluated, it can be decided that a certain cut-off needs to be adjusted because it is too strict or too lenient in the context of the area, region or country in which the poverty measurement exercise is performed.

PRACTICAL TIPS: SETTING DEPRIVATION CUT-OFFS FOR EACH INDICATOR

- **The deprivation cut-offs should be set in the least arbitrary way possible.** National legislation, international conventions and the objectives established in national development plans can guide the decision on the deprivation cut-offs. Also, participatory and consultative exercises can be used to guide the definition of the cut-offs.
- **It is critical to understand how cut-offs are set across indicators in different countries.** For example, in almost all cases, the cut-off for school attendance is to consider a household as deprived if "at least one member at school age is not attending", whereas the cut-off for social protection is to consider a household as deprived when "no member is covered by any social protection programme".
- **When an indicator is defined on the basis of two or more variables, the deprivation cut-off can be defined using different combinations of these variables.** For example, for an indicator on the quality of housing construction materials, the cut-off could be that the household is deprived if the dwelling has low-quality materials in the construction of at least two of its main component parts (roof, floors and walls).
- **Once the deprivation cut-offs are defined, it is important to validate them empirically.** In particular, it should be analysed if the deprivation cut-offs are too lenient (when a very small percentage of households is identified as deprived in a particular indicator) or too strict (when almost all households are identified as deprived in a particular indicator). In addition, the sensitivity of the headcount ratio (the proportion of individuals/households deprived) to small changes in the deprivation cut-off of each indicator should be studied. These kinds of robustness checks will help to increase the legitimacy and acceptance of the index (see Box 8 for more details).

Establishing the deprivation status of each indicator for each unit of identification

After selecting the indicators and defining the cut-offs, these thresholds are used to construct dichotomous/binary deprivation scores (0=non-deprived, 1=deprived) for each unit of identification in each indicator. In other words, if the value of a certain indicator for a given unit of identification is lower than the deprivation threshold, then that unit of identification is considered deprived in that indicator (and non-deprived if the value of the indicator is not less than the deprivation threshold). This information will be then used to produce an overall deprivation score for each unit of identification.

Selecting the weights for each indicator

Going from the binary variables of deprivation in each indicator to an overall deprivation score for each unit of identification requires assigning a weight to each of those binary indicators and, after that, obtaining the weighted sum for all of them. These weights represent the relative importance that is assigned to the deprivations in each dimension/indicator within the multidimensional index.

In most cases, countries use a nested weight structure in their national MPIs. Normally, under this type of weight structure, each dimension receives the same weight (e.g. if there are five dimensions, each of them receives a weight of 20 percent). In turn, each indicator is equally weighted within each dimension. If the number of indicators included in each dimension is the same, the nested weight structure is equivalent to using equal weights for all indicators (e.g. if each of the five dimensions is composed by two indicators, each indicator receives a weight of 10 percent). However, if not all the dimensions have the same number of indicators, then not all indicators will receive the same weight.

In some cases, countries use equal weights for all indicators, even if this implies different weights for each dimension (when the number of indicators is not the same across all dimensions). In other cases, the dimensions receive the same weights, but some indicators within dimensions receive different weights (e.g. as shown in Table 3, in the R-MPI, the indicator of “Credit denial” receives a weight that is lower than the weights of the other two indicators in the “Risk” dimension). Finally, Chile uses four dimensions (Education, Health, Labour and social security, and Housing and local environment) with the same weights, and a fifth one (Networks and social cohesion) with a lower weight.

In general, the final decision on the weight structure arises from the combination of normative arguments[29] with exercises of empirical validation (using statistical methods). The importance that different stakeholders place on each indicator of deprivation can guide the selection of the weights. However, regardless of the normative criteria used to develop the weight structure, the resulting structure must be empirically tested, analysing to what extent the selection of a particular weight structure influences the estimates of the MPI and, through those results, policy recommendations and decisions. In general, “good” weight structures are considered to be those in which small changes in the selected weights do not have significant effects on the estimates of the MPI.

Once the decision on a certain weight structure has been made and the structure has been empirically validated and clearly documented, it is recommended that this same structure of weights be used for a given period of time, to facilitate the comparison of results across years. This increases the credibility and sustainability of a multidimensional poverty index.

PRACTICAL TIPS: SELECTING THE WEIGHTS FOR EACH DIMENSION/INDICATOR

- **If there is no strong reason to prefer a particular weight structure, one may opt for the most common solution**: a nested structure with equally weighted dimensions and equally weighted indicators within dimensions; or a structure with equally weighted indicators, but unequally weighted dimensions.
- **Ideally, both weight structures can be used, and the results obtained under both structures can be compared**. This robustness exercise provides information about the sensitivity of the results to the selection of the weight structure. Establishing the robustness of results is particularly important when elaborating policy recommendations that are grounded in the multidimensional index.
- **In some particular cases, different dimensions and/or indicators can be unequally weighted**. In that case, the reasons behind that choice should be clearly stated and documented.
- In cases where it is important to identify changes in multidimensional poverty across time, **the weight structure should be fixed for the period of comparison**.
- Decancq and Lugo (2009) and UNDP and OPHI (2019) provide detailed guidance regarding the selection of weight structures.

[29] As in other aspects, the decision on the weight structure can be informed by participatory processes; the opinions of experts, authorities and policy-makers; analysis of survey data; etc.

Establishing the deprivation score for each unit of identification

Once the binary variables reflecting the situation of deprivation in each indicator and the weights attached to each indicator are defined, the overall deprivation score for each unit of identification is easy to estimate. This score is defined as the sum of the weighted deprivations suffered by the unit of identification. When all the indicators are equally weighted, the deprivation score is obtained as the number of deprivations experience by the unit of identification.

Selecting the (multidimensional) poverty cut-off

This section presented the steps used to define an overall deprivation score for each unit of identification in multidimensional poverty measurement. That score is analogous to the welfare (i.e. income or consumption) indicator used in the monetary measurement of poverty. Regarding the multidimensional poverty cut-off, it plays the same role that the poverty line plays in the monetary context. The value selected for the poverty cut-off (k) indicates the minimum level of deprivation a unit of identification must be suffering to be identified as multidimensionally poor.

The selection of the cut-off is a normative exercise, reflecting the level of deprivations that a given society considers acceptable or unacceptable. In that sense, there are different ways to define that threshold of acceptability. It can be established through a participatory process, based on subjective poverty assessments, or it can be chosen using qualitative studies. In some cases, development priorities and policy goals can guide the selection of the poverty cut-off.

There are two extreme approaches to the problem of selecting the poverty cut-off: the union approach and the intersection approach.

- The **union approach** identifies as multidimensionally poor all units of identification that experience deprivation in at least one of the selected indicators. This approach tends to overestimate the number and the percentage of people/households who are multidimensionally poor.
- The **intersection approach** identifies as multidimensionally poor those units of identification that are deprived in all the indicators at the same time. Unlike the previous case, this approach tends to underestimate the number and the percentage of people/households who are multidimensionally poor.

Normally, counting approaches, such as the AF method, use an **intermediate poverty cut-off**. In the AF method, the value of the poverty cut-off indicates what combined share of weighted deprivation identifies a unit of identification as multidimensionally poor. This can range between the value of the lowest weight attached to any indicator (the union approach) and 1 (the intersection approach). While the cut-off can be set at any level within that range, **it is recommended that the value selected be one that is easy to communicate**.

For example, if the index includes ten equally weighted indicators of deprivation, then the poverty cut-off could be set at 20 percent, 30 percent or 40 percent, indicating that the units of identification should be deprived in at least two, three or four indicators, respectively, to be considered multidimensionally poor. No matter the selected cut-off, the multidimensional poverty index should be estimated for a range of poverty cut-offs (robustness exercise).

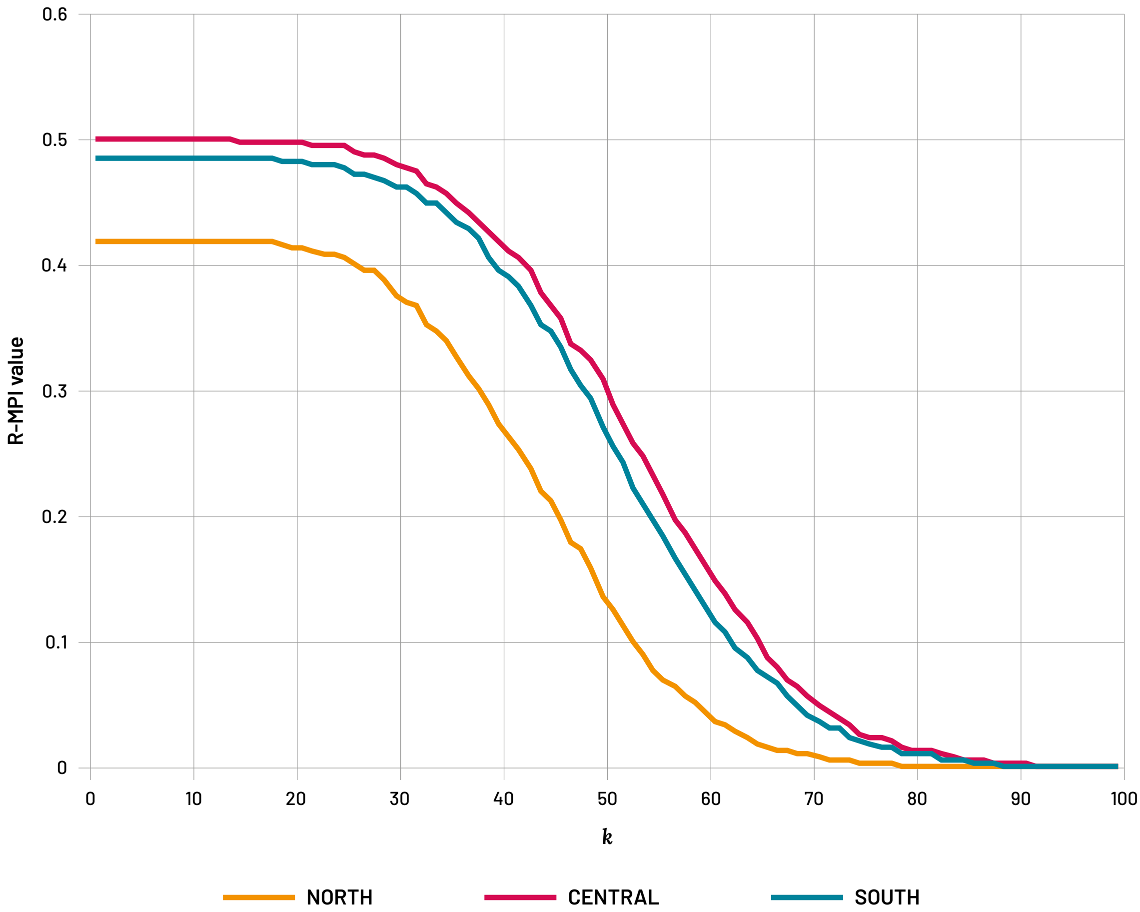
Once the deprivation score for each unit of identification has been calculated (as the weighted sum of deprivations of a unit of identification) and the poverty cut-off (k) has been set, the problem of identification can be solved: those units of identification with a deprivation score equal to or higher than the poverty cut-off are identified as multidimensionally poor. The next section discusses how to aggregate information of those identified as multidimensionally poor in a multidimensional poverty index.

PRACTICAL TIPS: SELECTING THE MULTIDIMENSIONAL POVERTY CUT-OFF

- **It is better to use an intermediate approach to set the poverty cut-off.** Most of the time, the results obtained using the union approach or the intersection approach are uninteresting or uninformative.
- **It is very important to run robustness exercises** in order to establish that small changes in the poverty cut-off will not significantly affect the results and, in turn, the policy recommendations derived from those results. In addition to the estimation obtained with the selected poverty cut-off, the results obtained with alternative intermediate values of the cut-off should be presented. FAO and OPHI (2021) provide an example of the use of a robustness test to assess the effect of the selected poverty cut-off on poverty estimates. They show that the value of the poverty cut-off does not modify the poverty ranking among regions in Malawi (Figure 4).

FIGURE 4

Sub-national R-MPI estimates for different values of the poverty cut-off (*k*) (Malawi, 2017)



Source: FAO and OPHI, 2021.

2.4.2 Aggregation: the AF methodology

Following the steps detailed in Section 2.4.1, it is possible to identify the multidimensionally poor such that, subsequently, th**e problem of aggregation ca**n be solved. The simplest way to aggregate the information of the multidimensionally poor is by counting the percentage of units of identification (households or individuals) in this condition. This index, known as the multidimensional **headcount ratio (H)**, describes the incidence of multidimensional poverty in a given population, and it is analogous to the headcount ratio usually employed in monetary poverty measurement.

However, the percentage of people or households living in multidimensional poverty is not the only interesting result one can estimate. As indicated previously, not all the multidimensionally poor face the same degree of deprivation. In fact, the deprivation score of each multidimensionally poor person/household indicates the number of (weighted) deprivations suffered by this person/household. The average number of (weighted) deprivations suffered by the multidimensionally poor can be reported in a separate index, known as **intensity of poverty (A)**.

The AF method proposes the definition of an additional index, known as the **adjusted headcount ratio (M0)**, which combines the information contained in the previous two indices: **M0 = (H x A)**. This last index, also known as the multidimensional poverty index (MPI), is the one used in global comparisons of multidimensional poverty.

Measuring multidimensional poverty: a practical example

Costa Rica has developed a multidimensional poverty index based on the AF methodology (in addition to monetary poverty estimates). The Costa Rican MPI includes five dimensions (education, housing and internet access, health, employment and social protection) and 19 indicators. It is important to note that this index is estimated for both urban and rural areas, without including any modification to capture the particularities of rural areas.

The estimates for the period 2018–2020 of the three multidimensional indexes proposed by Alkire and Foster are presented in Table 4. It is very interesting to compare these results with the monetary poverty results, shown in Table 2.

The monetary poverty estimates for Costa Rica indicate that the poverty situation remained virtually unchanged between 2018 and 2019 but worsened significantly in 2020. In particular, the results in Table 2 point out that the percentage of monetary poor households increased significantly between 2019 and 2020, and that poor households became poorer in 2020.

According to the multidimensional poverty estimates, however, the percentage of households living in multidimensional poverty (H) decreased markedly between 2018 and 2019 (particularly in rural areas) but remained mostly unchanged between 2019 and 2020. Regarding the intensity of poverty (the average number of deprivations suffered by those households identified as multidimensionally poor), the results in Table 4 show that this index (A) did not change much during the period under analysis. As a consequence, the observed decrease in the MPI (M0) between 2018 and 2020 is mostly driven by the reduction in the percentage of households identified as multidimensionally poor.

While the significantly different results obtained through both methodologies of poverty measurement could be seen as contradictory, they are in fact complementary. The monetary methodology is best suited for capturing the short-term but strong impacts produced by the COVID-19 pandemic. For this reason, the monetary measures show a significant increase in poverty. The multidimensional methodology, on the other hand, is best suited for capturing medium- and long-term changes in living conditions and, in most cases, is not affected by short-term phenomena. For this reason, the multidimensional measures presented in Table 4 indicate that the poverty situation of Costa Rica tends to improve gradually as the country makes progress in different socio-economic dimensions.

▶ TABLE 4

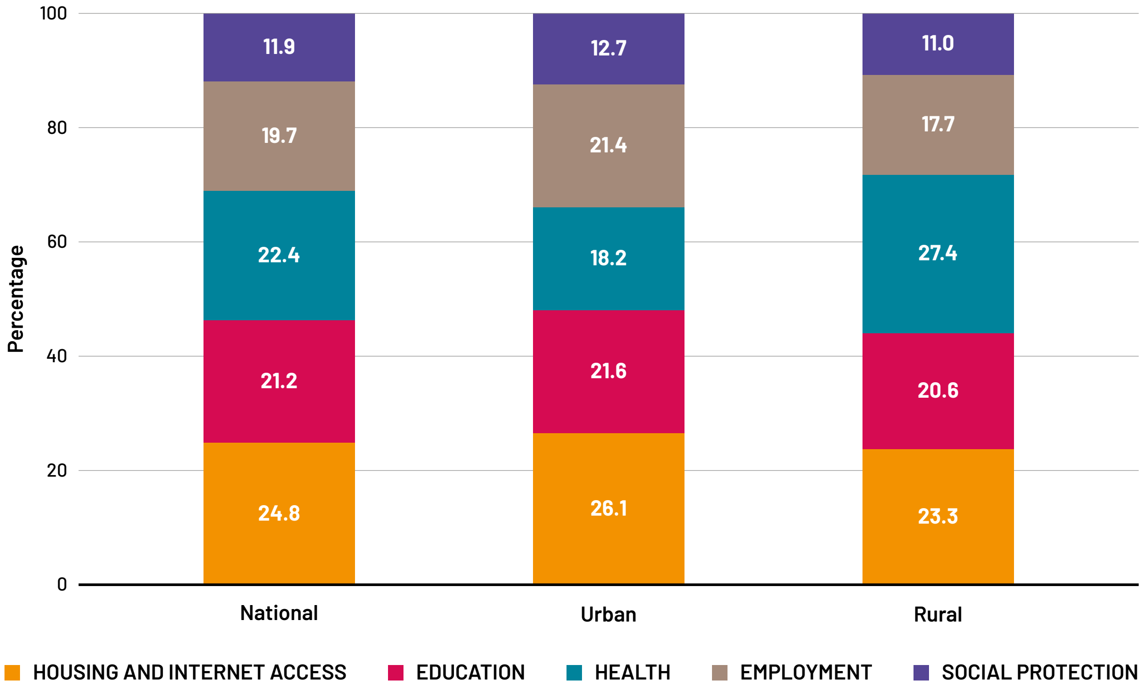
Multidimensional poverty measures for Costa Rica, 2018–2020

	NATIONAL	URBAN	RURAL
Multidimensional headcount ratio - H			
2018	19.1%	14.5%	31.3%
2019	16.6%	12.9%	26.2%
2020	16.1%	12.2%	26.3%
Intensity of poverty - A			
2018	26.7	26.1	27.3
2019	26.8	26.0	27.7
2020	26.3	25.8	26.9
Multidimensional poverty index - M0			
2018	5.1	3.8	8.5
2019	4.4	3.4	7.3
2020	4.2	3.1	7.1

Sources: INEC, 2020.

In addition to the monetary and the multidimensional poverty estimates, Costa Rica's official poverty report also includes information on how the different dimensions included in the multidimensional poverty index contribute to the results. The results, presented in Figure 5, illustrate a fact that was explained at the beginning of this chapter: the way in which poverty is experienced differs between urban and rural areas. In the case of Costa Rica, the results indicate that the relative contribution to multidimensional poverty of the "Health" dimension is significantly higher in rural than in urban areas, while the opposite is true for the remaining dimensions. This result reflects that rural households in Costa Rica are relatively more deprived than urban households in terms of the different indicators included in the "Health" dimension of the national MPI: access to health insurance, availability of drinking water in the dwelling, availability of sanitation services and availability of garbage-collection service.

FIGURE 5
Contributions of the dimensions to the multidimensional poverty index in Costa Rica, 2020



Source: INEC, 2020.

BOX 8
Redundancy and robustness checks

As has been noted repeatedly, measuring multidimensional poverty involves utilizing several normative arguments. Given that this is a field in continuous progress, it is expected that different conventions and standards will be developed in the short run, and this will facilitate the selection of indicators, deprivation cut-offs, weights and poverty cut-offs. However, the measurement of multidimensional poverty will always require the use of some value judgements. In that sense, it is recommended to employ empirical and statistical tools to explore the redundancy of indicators and to analyse if the results are robust to a range of reasonable parameter choices. In cases where small adjustments in those parameters imply significant changes in the results, the process of selection of the parameters should be carefully reviewed.

Redundancy exercises are useful to understand the interaction between indicators. They provide information to support the inclusion or exclusion of different indicators, or to combine the information of two or more indicators, in cases where indicators are highly redundant. The final decision on dropping or keeping a potentially redundant indicator is still a normative decision. ▼

▶ BOX 8 (CONT.)

For instance, maybe the indicator should be retained for its relevance to policy implications.
The traditional tools used to assess relationships between indicators are principal component analysis (PCA), multiple correspondence analysis (MCA), factor analysis (FA), cluster analysis and confirmatory structural equation models, as well as simple cross-tabulations and correlations. Details on the use of these techniques are provided in Chapter 7 of Alkire *et al*. (2015). The authors also propose an additional measure of overlap or redundancy (R0), which is particularly useful in implementing the AF method.
Regarding robustness checks, as previously noted, the measurement of multidimensional poverty involves the selection of a set of parameters (e.g. indicator cut-offs, weights and poverty cut-offs) and there are no universal criteria for selecting the parameters. In that sense, poverty estimates and comparisons could be performed using different sets of parameters, with variations within a plausible range. Chapter 8 of Alkire *et al*. (2015) contains a detailed explanation on how to apply dominance and rank robustness tests to assess comparisons as poverty cut-offs and other parameters change.

2.5 SOURCES OF INFORMATION FOR RURAL POVERTY MEASUREMENT

2.5.1 Main sources of data for rural poverty measurement

Since the implementation of the World Bank's Living Standards Measurement Study (LSMS) programme at the beginning of the 1980s, national household surveys have become the main source of information for measuring monetary poverty and inequality. Almost all countries conduct regular household surveys and use the information contained in those surveys to produce their official poverty estimates, while international organizations, such as the World Bank, use the information to produce comparative poverty and inequality estimates. The Rural Livelihoods Information System (RuLIS) has harmonized some of the household surveys collected by the LSMS programme as well as some household surveys collected by different national statistical offices. In that sense, RuLIS provides FAO users with comparable microdata on rural incomes, livelihoods and rural development across countries and over time. This source of data is readily available and can be utilized in different types of monetary poverty analysis in rural areas.

Regarding multidimensional poverty, the Global MPI for most countries is estimated employing surveys carried out within the Demographic and Health Surveys (DHS) Program of the United States Agency for International Development (USAID) or within UNICEF's Multiple Indicator Cluster Surveys (MICS) Programme. In the last few years, however, most **national household surveys** have begun collecting all the necessary information to estimate multidimensional poverty. Nowadays, most national household surveys include information on a variety of topics, such as household income or consumption expenditure, demographic characteristics, housing and infrastructure, health, education, employment and ownership of different kind of assets, which can be used for poverty measurement. In the near future, microdata harmonized by the RuLIS will also include the variables needed to estimate a specific multidimensional poverty index: the Rural Multidimensional Poverty Index (R-MPI).

2.5.2 Household surveys in rural areas

Household surveys collect information for a sample of households in a given population. In a typical survey, the interviewed households are randomly selected from a list of households representing the whole population. The selection of households is usually performed using some stratified multistage sampling technique. For example, in the first stage the population is divided into several groups or strata (e.g. urban–rural, regions, provinces). In the second stage, primary sampling units (e.g. villages, neighbourhoods) are selected within each stratum. Finally, in the last stage, some households are randomly selected from each primary sampling unit. Given that poverty measures obtained with information from household surveys are sample estimates, it is important to report them together with their **standard error** estimates and **confidence intervals**.[30] This practice is particularly recommended when estimates are used for policy purposes (e.g. monitoring, evaluation or policy redesign).

Although the quality of the information captured by household surveys tends to increase over time, household surveys do have some inherent problems: **sampling errors** and **non-sampling errors** (or measurement errors). Sampling errors derive from the fact that surveys do not cover the entire population of interest, but rather only a small sample of the population. Adequate use of stratified sampling techniques and population weights can help reduce potential sampling errors. Non-sampling errors include both random errors (usually cancelled out with a large sample size) and systematic errors. Examples of systematic errors are those deriving from questionnaire design and data collection issues (e.g. complex questions and surveyor bias, respectively) or data processing mistakes.

Household surveys are normally designed to be representative of the whole population of a country at national and, sometimes, regional level and by urban/rural areas. In that sense, the estimation of poverty at disaggregated levels (e.g. by geographical areas or sector of activity) is normally constrained by the relatively small sample size of household surveys. This problem is particularly acute when trying to estimate poverty among households that engage in primary activities other than agriculture. Activities such as pastoralism, forestry and fisheries, and remote populations, such as people living in mountainous places, are normally not adequately represented in national household surveys as they are often concentrated in specific geographical areas and involve only a small part of the population. In addition, the typical household survey might contain questions that are not sufficiently relevant and detailed to capture the living conditions of this type of households.

2.5.3 Other sources of data for rural poverty measurement

Although the most common source of data for poverty analysis are the household surveys collected by the national statistical offices of the different countries, there are some alternative data sources that could be used for poverty analysis in the context of a particular programme or project. The following paragraphs discuss those alternatives.

A first alternative are surveys carried out at the local level by FAO or its partners to design or evaluate a specific intervention or project. Depending on the degree of detail of a given survey, that information might be used to produce a measure of poverty at the local level and evaluate the

[30] Standard errors and confidence intervals are measures that indicate the uncertainty associated with estimates obtained from sample data. In technical terms, a standard error is the standard deviation of the sampling distribution of a statistic, while a confidence interval is an interval that contains the true value in the population with a known probability (e.g. 90, 95, or 99 percent). In practice, the larger the standard error and confidence interval associated with an estimate (e.g. the poverty headcount in a given country), the lower the precision with which the estimate approximates the true value in the population (e.g. the poverty headcount that would result from observing all households in a country with a census).

impacts of the intervention or project in terms of poverty reduction. The methodology of poverty measurement (i.e. monetary or multidimensional) that should be used with ad hoc surveys will depend on the information that has already been captured in the survey. In general, all surveys try to capture some information on living standards, and that information can be used to estimate poverty.

A second and more ambitious alternative is considering an adequate poverty measure at the stage of designing the ad hoc survey (often referred as **quantitative baseline** by FAO project evaluators). Conducting a household survey in the area of the intervention to collect information relevant to the project, but also on household income or consumption, or on all the indicators that compose a multidimensional poverty index, would help build evidence on FAO's role in poverty reduction, particularly in rural areas. However, depending on the sample size needed and the methodology of data collection that is chosen, as well as the specific context, conducting that type of household survey can be both complex and expensive. Therefore, ad hoc surveys are suggested in the context of large-scale projects and investments or, in the case of smaller projects, when there is interest by governments to scale-up a project after a pilot phase.

A third alternative, particularly useful when there are budget constraints, is using a rapid poverty assessment tool, such as the Poverty Probability Index (PPI) (IPA, 2021). In general, r**apid poverty assessment tools** use proxy means testing (PMT) to identify poor households. PMT, covered more in detail in Chapter 4, is based on a formula that estimates the probability that a household is poor. It is developed using data from a nationally representative household survey and entails a few steps: 1) selection of a (relatively small) set of variables that are highly correlated to poverty from the national household survey; 2) estimation of a model that predicts household poverty condition using those variables; and 3) translation of the results of the model into a scorecard.

The main advantage of this methodology is that it significantly limits the costs of data collection. As mentioned, the small set of variables included in the PMT should be correlated with poverty and easy to collect. Some examples of those variables are household size, school attendance of the children in the household, educational attainment of the household head, materials of roof/floor/walls, type of cooking fuel, ownership of different durable assets, etc. The PPI website provides detailed information on how to implement this method, and Skoufias *et al.* (2020) provides a critical review and useful advice on how to apply it to estimate poverty at the subnational level.

A fourth alternative, particularly appropriate for community-based interventions, is using a **participatory poverty assessment method**.[31] One example of this type of method is the **wealth ranking tool**, which is used to identify the main socio-economic groups in a community, as well as their livelihood characteristics. In this method, the information is obtained through community meetings with key informants. In the meetings, and using the livelihood assets framework (i.e. human, natural, physical, financial and social capital), informants are asked to describe the different socio-economic groups in the community, and the criteria that they use to distinguish between the different groups are identified (e.g. land, livestock, labour, household composition, ability to send children to school or buy medicine). Then, informants are asked to determine the distribution of the households in the community across the different socio-economic categories (e.g. rich, middle, poor, very poor). This distribution can be used as a quick estimate of the poverty level in the community, and it can be verified using direct interviews with different households in the community.

[31] For a guide on conducting qualitative and participatory poverty analyses, see the FAO toolkit on social analysis (FAO, 2011).

2.6 TRACKING THE EVOLUTION OF POVERTY OVER TIME

2.6.1 Estimating poverty trends

The most common way in which the time dimension is included in the analysis of poverty is through the estimation of poverty trends. A first example of this practice are the estimates of (monetary) poverty and extreme poverty rates at the global level, published each year by the World Bank in the PovcalNet website (World Bank, 2021a). Another well-known example is the Global MPI report, which is published annually by OPHI and UNDP. Both publications take advantage of newly released national household survey databases to produce estimates of the poverty and extreme poverty rates at national, regional and global levels that are comparable with similar estimates released in previous years.

At the country level, a common practice in estimating poverty trends is the following: every year or every few years, national statistical offices produce estimates of monetary and/or multidimensional poverty and extreme poverty rates, that are comparable with previously published estimates, and that information is used to track the evolution of poverty over time at different aggregate levels.

The estimation of poverty trends is normally performed using **cross-sectional surveys**. That is, estimating a poverty trend involves the comparison of poverty (or extreme poverty) rates estimated from household survey data collected in, ideally, several different years. For these comparisons to be meaningful, certain requisites must be met:

- **The poverty lines (monetary approach) or the poverty cut-offs (multidimensional approach) used to estimate poverty in each year should represent the same welfare level.** In the case of monetary poverty, this requisite implies that the poverty line must be adjusted to correctly take into account the increase in prices occurred between the years that are being compared. In the case of multidimensional poverty, this requisite is usually interpreted as using fixed structure of indicator and poverty cut-offs for all the years under analysis.
- **The definition of the welfare variable used for poverty measurement should remain mostly unchanged over time.** In the case of monetary poverty, this requisite implies that the income or consumption variable chosen as the welfare indicator must be constructed including the same items over time (some flexibility is allowed to include new sources of income, such as a new government transfer, or new goods and services that households incorporate in their consumption periodically). In the case of multidimensional poverty, this requisite implies that both the indicators used to define the deprivation profile of each household, and the structure of weights used to aggregate the deprivation profiles must be the same for all the years under analysis.
- **The household surveys providing the information to estimate poverty should be comparable in their most important aspects.** A first aspect that should be comparable between surveys is the design of the questionnaires of the different surveys. A requisite to define similar welfare indicators from the information collected by the different surveys is that the questions and the recall period used to capture the welfare variables be the same. A second aspect that should be similar between surveys to increase comparability of poverty estimates, and which is particularly important for rural areas, is the timing of the fieldwork. This is a requisite to avoid problems of comparability derived from the fact that some variables, such as income derived from farm production, vary seasonally. Finally, two other aspects that should also be comparable between the surveys used to estimate poverty trends are the sampling frame (i.e. the list of households from which a sample is drawn) and the geographical coverage of the surveys.

2.6.2 Assessing poverty dynamics

As can be easily deduced from the previous paragraphs, comparing poverty trends at some level of aggregation (e.g. national, regional or by urban/rural area) does not say anything about the poverty situation of specific individuals or households. In other words, this kind of poverty analysis is not enough to identify which individuals or households are persistently poor, and which individuals or households typically show movements in and out of poverty over time.

Ideally, a more comprehensive analysis of poverty dynamics should be able to identify the following four groups:

1. the **chronic poor** are those households or individuals whose average welfare indicator over time is below the poverty line or poverty cut-off;
2. the **persistent poor** are those chronic poor who never escape from poverty, not even in a single period;
3. the **transient poor** are those who are poor in some periods, but who are not poor on average (e.g. they might be able to avoid spells of poverty with a better welfare smoothing strategy); and
4. the **never poor** are those who never fall into poverty.

The analysis of poverty dynamics and the identification of the individuals and households belonging to the groups described above are important from a policy perspective. They help design better and more efficient policies to support the different groups to escape from poverty through differentiated strategies. As is apparent, combating transient and chronic poverty requires different policy instruments, and using one-size-fits-all approaches is not recommended.

Policies intended to deal with *transient* poverty tend to focus on short-term interventions designed to stabilize incomes and consumption for the transient poor. The implementation of safety nets and social assistance programmes to prevent vulnerable non-poor households from falling into poverty is an example of an intervention tailored to the needs of the transient poor.

On the other hand, policies intended to deal with *chronic* and *persistent* poverty tend to concentrate on structural and long-run interventions, such as human capital development and building infrastructure, given that the chronic poor usually lack the skills needed to be successful in the labour market and tend to reside in distant or isolated locations.

Identifying the dynamics of poverty is a much more complex and data-demanding exercise than estimating poverty trends. In an ideal scenario, the study of poverty dynamics requires **panel data** (i.e. data in which the same households are observed at different points in time). Unfortunately, this kind of data source, which is more expensive and complex to collect than a cross-sectional survey, is not available in most developing countries. (An exception are the African countries covered by the LSMS-ISA programme.) This is an important barrier to understanding the dynamics of poverty and an enormous disadvantage at the time of designing poverty reduction policies.

When panel data is available, it is possible to observe how households move into and out of poverty and classify them in the different groups mentioned above. In this way, it is possible to estimate gross movements in and out of poverty. This is much more informative than analysis conducted using cross-sectional data, which only makes it possible to compute net movements in and out of poverty (the difference between those entering and those escaping from poverty between two periods).

Livestock herder
in Mongolia.

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Purevragchaa

3

CHARACTERIZING THE RURAL POOR

Once poverty has been measured through the different approaches introduced in the previous chapter, a subsequent step in poverty analysis is to identify where the poor live and explore their socio-economic characteristics. This chapter gives an overview of some of the most common uses of poverty estimates: poverty profiles and poverty maps. First, the chapter provides guidance on how to create poverty profiles, including how to organize data to best portray the socio-economic characteristics of the poor. The chapter provides a comprehensive list of indicators to best characterize the poor in general, and the rural poor in particular. The second part of the chapter presents an overview of poverty mapping techniques, including those that are most widely utilized, as well as new poverty mapping approaches based on non-traditional sources of data.

3.1 INTRODUCTION

As seen in Chapter 2, poverty measurement is a complex task. It involves a number of delicate methodological choices that include selecting a welfare measure, setting monetary poverty lines or cut-offs and choosing an appropriate poverty index. Yet, measuring poverty is a worthy exercise, not only to generate indicators and provide numbers (e.g. the incidence of poverty in a country in a given year), but also to make poverty comparisons – over time, across different groups of individuals/households, or across countries. These poverty comparisons are useful for several applications, including designing, targeting and evaluating projects and programmes. In fact, “poverty comparisons [...] often matter far more to policy choices than do aggregate poverty measures” (Ravallion and Bidani, 1994).

This section focuses on poverty comparisons across geographic areas (mostly rural and urban) and across population groups within countries. Representing the different level and manifestations of poverty in rural and urban areas can be considered the starting point to prioritize, target and design rural poverty reduction policies.

Let us consider a situation in which a government aims to reduce poverty in a country. The objective is likely to maximize the poverty reduction impact of its policies under a budget constraint. The government will then face the question: which regions should be prioritized to achieve the highest returns in terms of poverty reduction using the limited budget? A comparison of the levels of poverty across rural and urban areas could be an important starting point in the quest to answer this question. The government may already know that the prevalence of poverty (i.e. the share of the population that is poor) in rural areas is higher than in urban areas, but may not know exactly by how much. It might also do not know where the majority of poor people live – which may be dynamically changing with urbanization. In the face of these unknowns, a poverty comparison between rural and urban areas might highlight the extent to which poverty is mainly concentrated in the rural areas of the country. On the basis of this finding, the government might decide to set up a national strategy for rural poverty reduction and dedicate a greater share of its budget for anti-poverty policies to rural areas.

A next step would be to identify the poorest areas within the rural sector to further focus the strategy. Identifying the rural areas with the highest incidence of poverty or the highest number of poor people would help the government allocate its anti-poverty budget more efficiently. However, this would not be enough to fully design a successful rural poverty-reduction strategy. Even if the government identified, say, the three poorest rural areas and decided to allocate most of its budget to reduce their poverty levels, other relevant questions would still have to be confronted: What are the characteristics of the rural poor? Which assets and services do they lack? Which environmental factors, if any, drive poverty? Investigating the diversity behind aggregate rural poverty figures represents the basis for identifying appropriate policy options.

This chapter presents poverty profiles (Section 3.2) and poverty maps (Section 3.3), which are simple, yet very useful tools to target and design rural poverty reduction strategies. A poverty profile provides information about the characteristics of the poor, including a first approximation to where they are located. A poverty map, on the other hand, helps identify more accurately where the poor are geographically located. Both will certainly help a government answer the hypothetical questions posed above.

3.2
POVERTY PROFILES: GOING BEYOND COUNTING THE POOR

A poverty profile is an analysis that sets out the major facts on poverty in a given context and helps examine patterns of poverty to see its variation by geography (e.g. mountain or plain areas), community characteristics (e.g. communities with and without a school), and household characteristics (e.g. main occupation of household head). A poverty profile serves as a special type of poverty comparison, showing how poverty varies across the subgroups of a society (Ravallion, 1992). It is a mostly descriptive document, containing a number of tables and graphs, that serves as the basis for analysing poverty in a particular context. Poverty profiles can be extremely useful to understand poverty in a given context and design poverty reduction interventions accordingly.

A **rural poverty profile** is a profile more specifically designed for rural settings. It systematically addresses issues related to rural areas, exploring the particular features that characterize the rural poor. For example, in order to understand the features of the rural poor, a rural poverty profile must investigate access to (and sometimes the rights over) productive assets that are necessary to carry out primary livelihood activities such as crop agriculture, livestock, fisheries and forestry. The elements that are usually employed to characterize the poor in a rural poverty profile are discussed in Section 3.2.2.

Most poverty profiles provide a disaggregation between rural and urban areas. Comparing the results obtained for rural areas with those obtained for urban areas helps identify the distinctive characteristics of the rural poor. However, when sufficient data are available, it is desirable that rural poverty profiles go beyond a binary rural–urban relationship (see Box 1). This might involve observing how poverty varies across a wider spectrum of rural–urban typologies (e.g. semi-urban and semi-rural spaces) or analysing poverty across agro-ecological typologies that have a primary importance for the livelihoods of the rural people (e.g. forested, arid, coastal or fertile areas).

As explained in Box 1, the definition of "rural areas" is not straightforward and may vary from country to country.[32] A number of intermediate geographical typologies exists between markedly urban and rural environments. In addition, evidence shows that poverty and the characteristics of the poor might vary considerably within rural and urban areas. For example, Zimbalist (2017) highlights substantial differences in household composition, access to services and assets that are likely to make households located in particular geographical areas of South Africa more vulnerable to poverty, and that, although on average rural areas are poorer than urban areas, "formal rural areas" are far less poor than "informal urban areas".[33]

3.2.1 The structure of a poverty profile

In most cases, a poverty profile has two main parts. In the first part, Part A, the sample is split into two or more groups according to some characteristic (e.g. region or area of residence) and different measures of poverty are estimated for each group. For example, Part A of a profile would point us to areas of a country where poverty is highest.

In the second part, Part B, the sample is split into different groups according to their poverty status (e.g. extremely poor, moderately poor and non-poor) and those groups are described and analysed in terms of different aspects such as demographic, educational and labour characteristics; housing conditions; access to services and dependency on agriculture. For example, Part B of a profile would indicate how the average size of agricultural land owned differs among poor and non-poor households.

Let us consider a situation in which a government wants to implement a cash transfer programme for the rural poor, but cannot identify which households are poor. It may decide to benefit only those living in certain rural areas. In this case, the government would need to know which rural areas have the highest level of poverty in order to maximize the poverty reduction impact of the programme. Part A of a poverty profile would provide this information. However, if the government wanted to further refine the eligibility criteria to increase the impact of the programme, it would need to know the characteristics of the extremely poor living in the selected rural areas. This information would be found in Part B of a poverty profile.

Part B can also inform the design of poverty reduction interventions. For example, Part B often reports various characteristics of living standards across poverty groups. In this way, the profile indicates the dimensions in which the poor present the most severe deprivations. Let us imagine that a profile highlights that the rural extreme poor of certain regions present particularly low access to piped water and electricity services. The policy implication is straightforward in this case: there is a need to improve access to these services in rural areas of those regions.

[32] See Wineman, Alia and Anderson (2020) for an empirical illustration of the implications that using different definitions of rural areas has on measuring poverty and other indicators of rural development.

[33] According to Zimbalist (2017) geographical divisions in South Africa reflect its apartheid history. Rural areas can be divided into "formal areas", corresponding to white commercial farming areas, and "tribal authority areas", which fall under the leadership of traditional or tribal authorities and correspond to homelands where the black population was confined during apartheid. Urban areas, on the other hand, can be classified into formal and informal areas, reflecting the division between black townships with poor basic infrastructure and white suburbs with significantly greater resources.

Table 5 presents an example of what Part A of a poverty profile for Bolivia (Plurinational State of) in 2018 would look like. This poverty profile is based on monetary poverty. The table shows the three main indicators of the FGT family (i.e. the headcount ratio or poverty rate, the poverty gap and the severity of poverty – see Section 2.3.2 and Box 7 in Chapter 2) for two poverty lines (the food or extreme poverty line and the total or moderate poverty line). The table disaggregates the information by departments and urban–rural areas.

At the national level, in 2018, 34.5 percent of the population was living in moderate poverty, while 15.2 percent of the population was living in extreme poverty. The departments of Chuquisaca and Potosi had the highest headcount ratios for moderate and extreme poverty (47.4 percent and 26.1 percent for Chuquisaca and 52.0 percent and 31.7 percent for Potosi, respectively), while the departments of Santa Cruz and Tarija had the lowest incidence of moderate and extreme poverty (26.1 percent and 7.3 percent for Santa Cruz and 28.7 percent and 8.5 percent for Tarija, respectively).

The results indicate that the probability of being poor is significantly higher for an average rural inhabitant compared to an average urban inhabitant. Rural inhabitants are twice as likely to live in total or moderate poverty than urban inhabitants (53.9 percent vs 26.1 percent). As to extreme poverty, rural inhabitants are almost five times more likely to suffer from extreme poverty than urban inhabitants (33.4 percent vs 7.2 percent).

The results obtained with the poverty gap and the severity of poverty indices lead to similar conclusions: the departments of Chuquisaca and Potosi have the highest levels of extreme and moderate poverty, while the departments of Santa Cruz and Tarija have the lowest levels of extreme and moderate poverty. The use of complementary poverty measures also confirms that there are clear differences in the level of extreme and moderate poverty between urban and rural areas, with the latter showing significantly higher levels of poverty than the former.

TABLE 5

Part A of a poverty profile – Bolivia (Plurinational State of) 2018

	EXTREME POVERTY			MODERATE POVERTY		
	Headcount ratio FGT(0)	Poverty gap FGT(1)	Severity of poverty FGT(2)	Headcount ratio FGT(0)	Poverty gap FGT(1)	Severity of poverty FGT(2)
National	15.2%	6.1%	3.6%	34.6%	14.1%	8.2%
Department (province)						
Chuquisaca	26.1%	11.6%	6.9%	47.4%	22.7%	14.4%
La Paz	19.1%	7.1%	4.2%	37.6%	15.8%	9.2%
Cochabamba	12.8%	4.7%	2.5%	32.9%	12.9%	7.1%
Oruro	15.4%	5.6%	3.0%	33.8%	13.5%	7.5%
Potosi	31.7%	15.5%	9.9%	52.0%	27.0%	17.9%
Tarija	8.5%	2.7%	1.3%	28.7%	9.3%	4.6%

▶ TABLE 5 (CONT.)

	EXTREME POVERTY			MODERATE POVERTY		
	Headcount ratio FGT(0)	Poverty gap FGT(1)	Severity of poverty FGT(2)	Headcount ratio FGT(0)	Poverty gap FGT(1)	Severity of poverty FGT(2)
Santa Cruz	7.3%	2.9%	1.8%	26.1%	8.8%	4.7%
Beni	19.3%	7.6%	4.6%	39.9%	17.7%	10.6%
Pando	9.9%	3.9%	2.0%	32.1%	11.1%	5.7%
Area						
Rural	33.4%	14.9%	9.1%	53.9%	27.1%	17.6%
Urban	7.2%	2.2%	1.2%	26.1%	8.4%	4.1%

Sources: Authors' own calculations based on INE (2019).

PRACTICAL TIPS: PART A OF A POVERTY PROFILE

- Which type of poverty measure should be used? Irrespective of whether one uses monetary or multidimensional poverty measures, as a general principle, **it is much easier to make poverty comparisons using a poverty measure that satisfies the property of subgroup decomposability**, whereas poverty in different mutually exclusive groups (e.g. areas) can be added up easily to get the overall poverty rate. The FGT poverty measures (for monetary poverty) and the poverty measures of the AF approach (for multidimensional poverty) satisfy this property, as explained in Chapter 2.
- **If possible, it is better to show different poverty measures.** Poverty measures provide complementary information. This will give a greater and more nuanced understanding of how poverty varies among population subgroups. If the profile is built using monetary poverty, a typical option is to present food (or extreme) and total (or moderate) poverty rates. In addition, all the FGT poverty measures (i.e. headcount ratio, poverty gap and severity of poverty) can be presented. If the profile is built using multidimensional poverty, it can include information on the different poverty measures of the AF method: the headcount ratio, the intensity of poverty and the adjusted headcount ratio.
- To convey a stronger message through the profile, **poverty measures can be interpreted as the relative risk of being poor for different subgroups**. For example, if the incidence of poverty in a country is 60 percent in rural areas and 30 percent in urban areas, then rural households can be considered twice as likely to be poor as urban households.

Table 6 presents an example of what Part B of a monetary poverty profile would look like for Bolivia (Plurinational State of) in 2018. In this case, the population is split into three groups: the extreme poor, the moderate poor (excluding the extreme poor)[34] and the non-poor. In turn, the information on demographic characteristics, characteristics of the household head, and housing and infrastructure characteristics for the three groups is reported at the national level and disaggregated by rural and urban areas.

TABLE 6

Part B of a poverty profile – Bolivia (Plurinational State of) 2018

	NATIONAL			RURAL AREAS			URBAN AREAS		
	Extreme poor	Moderate poor	Non-poor	Extreme poor	Moderate poor	Non-poor	Extreme poor	Moderate poor	Non-poor
Demographic characteristics									
Age	27.0	27.4	31.9	28.7	35.7	34.0	23.7	23.4	31.3
Women	51.4%	52.2%	50.4%	50.3%	51.7%	49.1%	53.7%	52.5%	50.8%
Total members	5.1	4.7	3.9	5.0	4.3	3.8	5.1	4.9	3.9
Number of children (14 years old and younger)	2.4	2.0	1.1	2.3	1.8	1.3	2.4	2.1	1.1
Indigenous or Afro-Bolivian	43.8%	25.2%	20.4%	54.8%	43.8%	35.1%	21.4%	16.3%	16.4%
Characteristics of the household head									
Age	48.5	47.8	47.3	50.5	57.0	50.9	44.3	41.8	46.1
Women	25.7%	28.5%	28.6%	19.8%	26.2%	22.8%	38.4%	29.9%	30.4%
Years of education	6.2	7.4	10.2	5.2	4.5	6.9	8.4	9.2	11.2
Employed	85.3%	84.2%	85.2%	92.8%	89.6%	92.3%	69.1%	80.7%	83.1%
Unemployed	5.3%	3.2%	1.8%	1.7%	0.9%	1.1%	14.2%	4.8%	2.0%
Inactive	10.0%	13.0%	13.2%	5.5%	9.6%	6.7%	19.4%	15.3%	15.2%
Housing and infrastructure characteristics									
Walls: low-quality materials	59.2%	37.3%	21.4%	78.8%	67.9%	50.3%	17.4%	17.3%	12.5%
Floor: low-quality materials	54.0%	30.7%	14.7%	73.6%	62.9%	45.6%	12.2%	9.6%	5.1%

[34] In this table, the moderate poor do not include the extreme poor. In other words, this group only includes households and individuals whose income/consumption is higher than the extreme poverty line, but lower than the total poverty line.

▶ TABLE 6 (CONT.)

	NATIONAL			RURAL AREAS			URBAN AREAS		
	Extreme poor	Moderate poor	Non-poor	Extreme poor	Moderate poor	Non-poor	Extreme poor	Moderate poor	Non-poor
Safe water in the dwelling	68.4%	77.5%	88.3%	57.5%	56.7%	68.0%	91.7%	91.0%	94.6%
Adequate sanitation in the dwelling	33.2%	51.1%	72.9%	13.4%	14.8%	26.3%	75.6%	74.8%	87.3%
Electricity in the dwelling	83.0%	90.8%	94.9%	75.6%	77.4%	79.9%	98.7%	99.6%	99.6%
Livelihood characteristics									
Self-employed agriculture	34.0%	24.2%	10.4%	39.7%	47.0%	36.1%	8.4%	4.1%	1.6%
Self-employed non-agriculture	13.6%	30.2%	36.0%	4.5%	9.1%	17.7%	55.0%	48.8%	42.2%
Wage worker agriculture	0.7%	1.2%	1.7%	0.5%	1.3%	4.2%	1.5%	1.1%	0.8%
Wage worker non-agriculture	3.3%	22.3%	41.6%	0.8%	4.6%	17.9%	14.5%	37.9%	49.7%
Family worker agriculture	44.8%	18.2%	5.7%	53.7%	37.3%	21.3%	4.5%	1.3%	0.4%
Family worker non-agriculture	3.7%	3.9%	4.6%	0.9%	0.8%	2.7%	16.2%	6.7%	5.2%

Sources: Authors' own calculations based on INE (2019).

The results show important differences between the extreme poor, the moderate poor and the non-poor. Interestingly, there are also significant differences between the extreme poor and the moderate poor living in rural areas and their urban counterparts. The next paragraphs describe some of the main differences, focusing on rural areas.

Demographic characteristics. On average, the rural extreme poor are younger than the rural non-poor, but older than the urban extreme poor. At the same time, the percentage of persons belonging to an indigenous or Afro-Bolivian ethnic group is much higher among the rural poor than among the rural non-poor. This gap is even higher if the comparison is between rural and urban areas.

Characteristics of the household head. Household heads of all groups tend to be older and less educated in rural than in urban areas. Also, the proportion of women household heads is lower in rural areas than in urban areas. In rural areas, the only clear difference between poor and non-poor households is the level of education of the household head, which is relatively lower for the former.

Housing and infrastructure characteristics. These characteristics clearly reflect the differences between poor and non-poor households in rural areas and between the rural poor and the urban poor. Housing conditions and access to basic infrastructure services are significantly worse for the rural poor than for the rural non-poor and for rural households in general in comparison to urban households. For example, while 78.8 percent of rural households living in extreme poverty reside in dwellings with walls built with low-quality materials, that number drops to 50.3 percent among non-poor rural households. The difference is even more notable when the comparison is made relative to households living in extreme poverty in urban areas: only 17.4 percent of them live in households with walls with low-quality materials. Similar patterns are observed in the proportion of households with low-quality floors and with access to safe water, adequate sanitation and electricity.

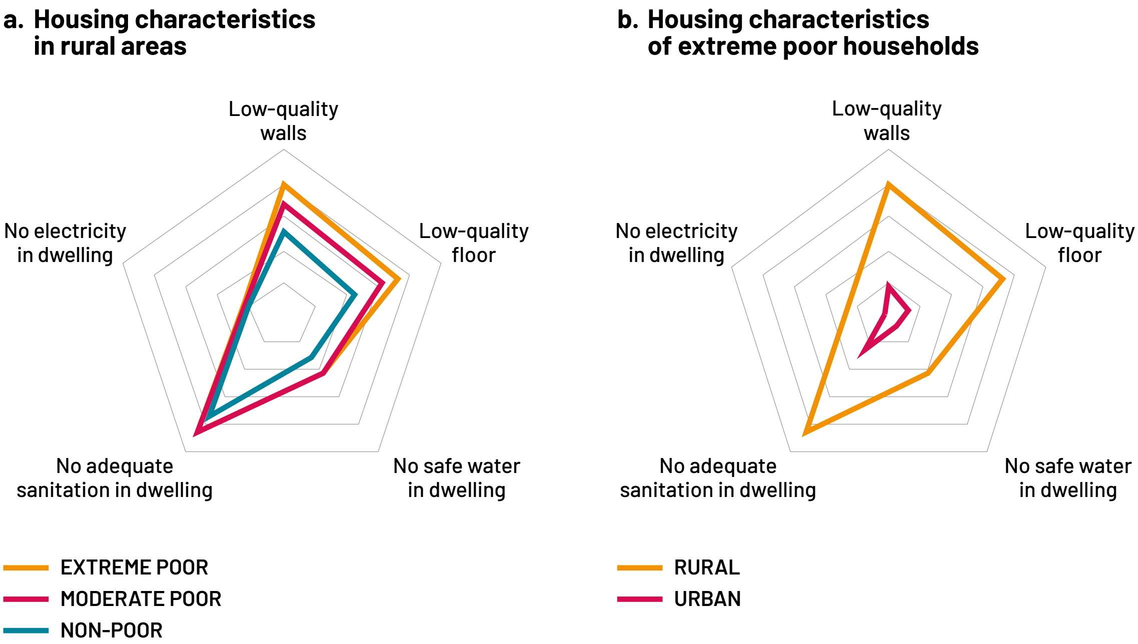
Livelihood characteristics. In rural areas, the extreme poor are much more likely to work as family labourers in agriculture than the moderate poor and, especially, the non-poor. Among the moderate poor, self-employment in agriculture is the most common form of employment. Finally, the extreme poor and the moderate poor have very limited access to non-agricultural economic activities (both as self-employed and wage workers) compared to the non-poor. Interestingly, while self-employment in non-agriculture appears as a distinctive feature of the rural non-poor, it is also the main source of employment for the urban extreme poor.

PRACTICAL TIPS: PART B OF A POVERTY PROFILE

- Although tables are typically used in poverty profiles, **poverty profiles can also be communicated through graphs or charts**. When the number of variables under analysis is not too large, graphs can be used to make comparisons and differences across groups more evident. For example, radar charts can be used to communicate the differences in housing characteristics shown in Table 6 across poverty status categories and place of residence (Figure 6).
- Compared to profiles based on a monetary measure of poverty alone, those using a multidimensional measure have additional layers of information. In addition to showing the characteristics of the poor, **multidimensional poverty profiles further show which dimensions and indicators of poverty are more relevant for different groups and areas of interest**, which can be an important policy input. For example, the country briefs produced by OPHI often show how the indicators of the different dimensions contribute to the MPI across rural and urban areas. Figure 7 shows an example from Nigeria, in which it can be seen (left panel) that nutrition, child mortality and cooking fuel contribute relatively more to the MPI in rural areas than in urban areas, while years of schooling, school attendance and housing are relatively more important in rural areas. However, in rural areas, each indicator contributes to a higher absolute value of the MPI (right panel), denoting that people in rural areas suffer greater deprivations in all indicators. A similar example showing how the different indicators and dimensions of a multidimensional poverty index contribute to its overall value across rural and urban areas is shown for Costa Rica in Figure 5.

FIGURE 6

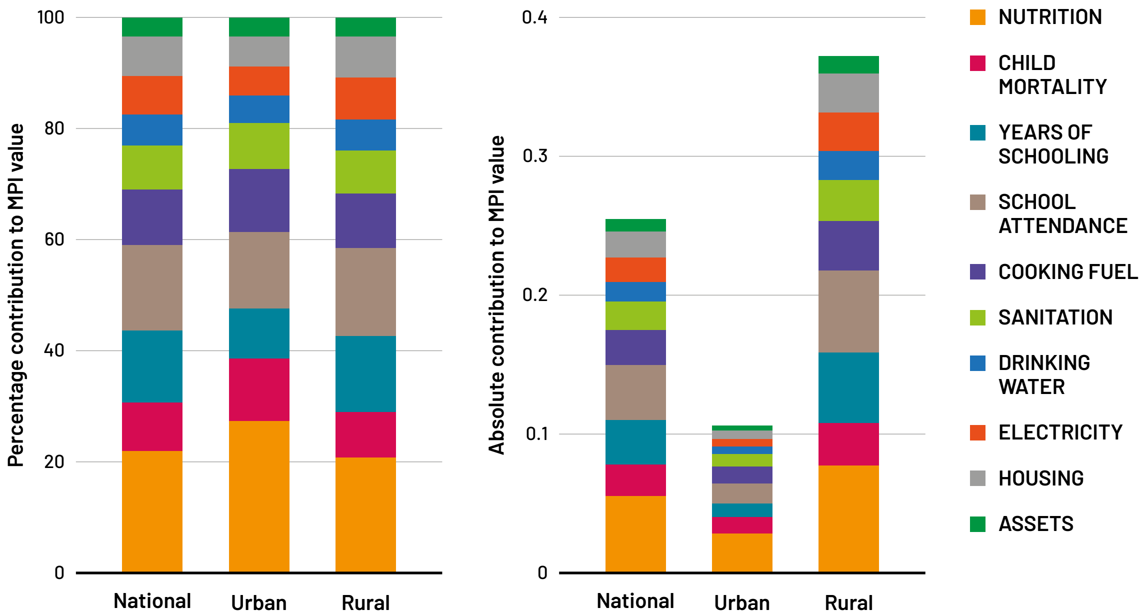
Housing characteristics across monetary poverty status and place of residence in Bolivia (Plurinational State of), 2018



Source: Authors' elaboration based on INE (2019).

FIGURE 7

Relative and absolute contribution of indicators to MPI by place of residence in Nigeria, 2018



Source: OPHI, 2020.

3.2.2 Exploring the characteristics of the rural poor

As noted, Part A of a poverty profile helps identify where and among which population subgroups poverty is highest (or lowest), whereas Part B focuses on characterizing those who have been identified as poor. Characterizing the poor is done by presenting various elements that describe, in a broad sense, who the poor are, which is valuable to inform the policies and programmes intended to reach them. These elements include individual, household and community characteristics as well as geographical aspects. The level of detail of a poverty profile will depend on data availability. In principle, all the variables that correlate with poverty and are relevant for the policies under consideration should be included.

Aspects such as income-generating activities, access to and ownership of (when applicable) assets, access to services and infrastructure are all of potential interest. Importantly, a rural poverty profile should incorporate the aspects that are relevant to the livelihoods of rural people (e.g. their agricultural activities and assets – including those of people involved in forestry and fishery activities, and access to markets, productive services, etc.). Section 3.2.2 presents different characteristics and aspects that can be included in a rural poverty profile.

Who are the poor? (Demographic and educational characteristics)

All poverty profiles should include information on basic demographic and educational characteristics. Examples of typical variables include gender, age, years of education, ethnic characteristics, household size, number of children and dependency ratio. In some cases, these variables are reported at the individual level by taking averages over all individuals (e.g. age and gender) or over a restricted group (e.g. years of education for individuals aged 18 and above). In other cases, the information is reported at the household level (e.g. household size, number of children or household composition). Finally, some poverty profiles report the averages of the same individual variables twice: for the total population (or some specific group, such as the adult population) and for those identified by the household as “the household head”.[35]

Examples of demographic variables that might be included in the poverty profile are the following:

- average age (individual level);
- percentage of women/men (individual level);
- percentage of individuals belonging to ethnic minorities (individual level);
- average years of education (individual level, adult population);
- percentage of children attending school (individual level, children);
- percentage of women-headed households or percentage of households with only one female adult (household level);
- percentage of single-parent households, by gender of the parent (household level);
- average household size (household level);
- average number of children (i.e. members of the household younger than 15) (household level);
- average number of elderly (i.e. members of the household aged 65 and above) (household level);
- dependency ratio (number of non-working-age members/number of working-age members) (household level).

[35] Identifying a “household head” often reinforces gender roles, wrongly supporting the idea that the decision-making and income generation of one adult in the household is more important than that of other adults in the household. This practice is becoming contested as other ways of categorizing households are becoming more common in household economic analysis. For example, instead of classifying women-headed or men-headed households, these could be classified as “households with only female adults” or households with high dependency ratios to identify potential social vulnerabilities.

Where do they live? (Environmental characteristics and natural resources)

As explained before, Part A of a poverty profile helps to identify where poverty is highest. This is usually done by looking at rural and urban areas and comparing poverty measures across the main administrative divisions of a country. In turn, Part B can help dig deeper into the characteristics of the environments in which the various categories of poor live.

Several aspects regarding the environments, or context, of rural poverty are worth exploring. These include agro-ecological typologies (e.g. the percentage of the extreme poor who live in arid or coastal areas, in comparison to the non-poor) and finer classifications of the rural-urban spectrum (e.g. semi-urban and semi-rural spaces, based on criteria such as population size, density or distance from urban spaces). In addition, it might be relevant to observe how natural resource endowments vary among the poverty subgroups (e.g. the percentage of the poor and extreme-poor who live in areas with good soil quality and precipitation and how this compares to the non-poor). Finally, this part of a profile might include indicators representing risks related to the environment (e.g. the percentage of the poor and extreme-poor who live in flood-prone or storm-prone areas and how this compares to the non-poor). These indicators are usually obtained from different sources of data than the surveys used to measure poverty (for more details see Section 3.2.3). All these variables should be reported at the household level.

Examples of variables that might be included in poverty profiles are the following:

- percentage living in rural/semi-rural/semi-urban/urban areas;
- percentage living in mountainous/plain/humid/arid/coastal areas, depending on the country under analysis;
- percentage with access to forest resources;
- average soil quality in the area of residence;
- average level and standard deviation of precipitation in the area of residence;
- average level and standard deviation of temperature in the area of residence.

What are their living conditions? (Housing, infrastructure and basic services)

Aspects related to housing (e.g. ownership of domestic assets, dwelling size, quality of construction materials, access to safe water and adequate sanitation, connection to the electrical grid) and basic services (e.g. health facilities, schools, banks) can be seen as important determinants of poverty (for monetary poverty), or can represent some of the dimensions and indicators used to identify the poor (for multidimensional poverty).

Many variables related to the living conditions of the poor can be used in poverty profiles, depending on the context and the availability of data, bearing in mind that when the profile is built using multidimensional poverty, it should not include the same indicators used in the poverty index. For example, if a multidimensional poverty index includes an indicator regarding access to safe water, the profile should not report the percentage of poor people who do have access to safe water.[36] All these variables should be reported at the household level.

Examples of variables that might be included in the poverty profile are the following:

- percentage of households (legally) owning the dwelling where they live;
- average dwelling size (number of rooms or square meters);
- percentage of households living in a dwelling built with good-quality materials (walls, floor, roof);

[36] This does not mean that multidimensional poverty indexes should not be disaggregated. Indeed, it is advisable to analyse how the various indicators contribute to the index, which can be seen as a sort of poverty profile (see Figure 7). The main point here is that, in a poverty profile using a multidimensional measure of poverty, it is not advisable to compare directly the indicators used to compute the poverty measure to those that are not.

- percentage of households with access to safe water/adequate sanitation/electricity;
- percentage of households with washing machine/fridge;
- percentage of households with computer/phone/internet;
- percentage of households owning a car/motorcycle;
- percentage of households with access to road/clinic/school/public transportation within 5 km;
- percentage of households with a bank account;
- percentage of households with access to credit.

What are their sources of income? (Income and employment)

Household income can be derived from both labour and non-labour sources. In turn, these can be classified with different levels of detail. For example, labour sources can be described based on employment status (e.g. self-employment vs wage earning), sector (e.g. agriculture vs non-agriculture), or the specific products and services that people sell (e.g. cereals vs fruits and vegetables). Poor rural households often diversify into multiple sources of income to reduce their level of vulnerability, or simply because the types of employment they engage in provide low levels of income. For these reasons, rural poverty profiles must report information on income derived from various farm and non-farm activities, including the production of the main crops. At the same time, non-labour sources of income might be classified into general categories (e.g. transfers vs rental income, public vs private transfers) or more detailed categories (e.g. transfers from various public programmes). The more specific these aspects are, the more they will depend on the context of the analysis. In general, employment variables should be reported at the individual level, while income variables should be reported at the household level.

Examples of variables that might be included in the poverty profile are the following:

- percentage working in agricultural/non-agricultural activities (individual level, adult population);
- percentage working as salaried workers/self-employed (individual level, adult population);
- percentage of working children (individual level, children);
- percentage unemployed (individual level, adult population);
- percentage inactive (i.e. those who are not working and are not looking for work, nor are available to work) (individual level, adult population);
- percentage with diversified income sources (e.g. no income source is >75 percent)[37] (household level);
- percentage whose income share in agriculture/non-agriculture is >75 percent (household level);
- average share of income from own crop agriculture/fisheries/forestry (household level);
- average share of income from agricultural/non-agricultural wage (household level);
- percentage receiving public transfers (e.g. subsidies and social protection) (household level);
- percentage receiving private transfers (e.g. gifts and remittances from family and friends) (household level);
- average share of income from public/private transfers (household level).

What agriculture-specific assets and services they can count on?

The rural poor rely on heterogeneous asset portfolios and services. As highlighted by de Janvry and Sadoulet (2000), rural households are highly heterogeneous in terms of their control of productive assets (including land, natural resources, machinery and equipment) and their access to finance, insurance, extension services, membership in producer organizations, etc. Showing how

[37] This cut-off is consistent with FAO's Rural Income Generating Activities (RIGA) project, and with the classifications of the Rural Livelihoods Information System (RuLIS).

these characteristics vary among the extremely poor, the poor and the non-poor in rural areas, provides key insights for the design of rural poverty reduction interventions, identifying the main gaps in access to assets and services between the poor and the non-poor. It is important to keep in mind that this part of the profile will apply only to the subset of households that are engaged in agricultural activities. All these variables should be reported at the household level.

Examples of variables that might be included in the poverty profile are:

- percentage of households with land rights;[38]
- average size of land owned or cultivated;
- average share of owned or cultivated land that is irrigated;
- average quantity of livestock owned (various types, usually measured in livestock tropical units);
- percentage of households with mechanical equipment for production;
- percentage of households that use fertilizer/pesticides/improved seeds;
- percentage of households that receive extension/advisory services;
- percentage of households that are part of a producer organization or other economic group (including self-help and saving/microcredit groups);
- percentage of households that have agricultural insurance;
- percentage of households with access to agricultural credit;

Table 7 presents an example of a rural poverty profile covering some of the aspects mentioned above regarding income and employment and agricultural assets and services. The profile shows that, in Malawi, access to agricultural assets and services as well as alternative livelihood strategies vary considerably among rural households engaged in crop farming, depending on their poverty status. For example, extremely poor households are substantially less likely to use inorganic fertilizer and mechanized equipment and to receive credit than moderately poor households, and the difference is even greater when comparing them to non-poor households. At the same time, extremely poor households are much more likely to participate in agricultural wage labour, while they are less likely to keep livestock, engage in non-agricultural wage labour and receive private transfers.

▶ TABLE 7

Rural poverty profile: access to agricultural assets and services and alternative sources of income and employment of rural households engaged in crop farming (Malawi, 2017)

	EXTREME POOR	MODERATE POOR	NON-POOR
Agricultural assets			
Agricultural land	0.51 ha	0.57 ha	0.63 ha
Irrigation	3.4%	6.7%	7.8%
Plant chemicals	3.4%	4.0%	7.5%
Improved seeds	22.5%	24.0%	31.9%

[38] Land rights can be granted through individual property rights or tenure rights allocated by the state, but more often, for rural areas, rights over land are determined by customary laws and often influenced by religious law and cultural beliefs. Selecting a set of rights associated with land ownership or land rights should be based on the country's tenure system.

▶ TABLE 7 (CONT.)

	EXTREME POOR	MODERATE POOR	NON-POOR
Inorganic fertilizer	51.2%	61.6%	74.4%
Mechanized equipment	6.5%	10.0%	15.9%
Extension and training	66.3%	70.9%	68.8%
Credit (last 12 months)	16.2%	19.9%	26.2%
Alternative livelihood strategies			
Livestock	27.8%	35.3%	45.6%
Agricultural wage labour	84.1%	75.2%	55.8%
Non-agricultural wage labour	4.2%	7.2%	12.1%
Non-agricultural income	53.9%	61.8%	69.7%
Private transfers (domestic)	37.1%	43.8%	48.9%
International remittances	2.1%	4.2%	6.3%

Sources: Authors' calculations based on World Bank (2021c), harmonized using the RuLIS methodology.

3.2.3 Data requirements for poverty profiles

As explained in Chapter 2, the measurement of monetary poverty is usually carried out using information from national household income and expenditure surveys, such as those implemented under the World Bank's LSMS programme (World Bank, 2021b), while multidimensional poverty is mostly measured employing information from the national household surveys carried out within the Demographic and Health Surveys (DHS) Program (USAID, 2021) or within the Multiple Indicator Cluster Surveys (MICS) Programme (UNICEF, 2021).

As seen in Section 3.2.2, preparing a rural poverty profile implies reporting various characteristics related to rural livelihoods across groups, based on their poverty status. This is best accomplished by **using household surveys that include information needed to accurately calculate poverty as well as detailed information regarding agricultural and other primary activities**. However, household surveys used to measure poverty often do not include detailed information on activities related to rural livelihoods. Conversely, surveys aimed at characterizing primary activities usually do not collect socio-economic information on households and individuals, including the information necessary to measure poverty. An exception is the LSMS-Integrated Surveys on Agriculture (LSMS-ISA) Programme (World Bank, 2021b), which develops household surveys (often panel surveys) with a strong focus on both agricultural activities and poverty in eight African countries.[39] LSMS-ISA surveys provide the information required to produce rural poverty profiles like that shown in Table 7.

[39] Those countries are Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Uganda and United Republic of Tanzania (the).

If a survey with the information needed to estimate monetary or multidimensional poverty as well as detailed agricultural information is not available, it might be possible to pool different data sources. For example, it might be useful to characterize the environments in which the rural poor live. This can be done by adding area-level information (i.e. variables that refer to certain geographic areas rather than specific households and individuals) to a household survey. Examples include data on variables influencing the results of agricultural activities, such as information on temperature, precipitation and weather shocks.[40]

As previously mentioned, **most household surveys are not statistically representative of (or do not contain sufficient relevant information about) population groups engaged in certain primary activities, such as pastoralism, forestry and fisheries**. Thus, characterizing the poor working in those sectors is a particularly challenging exercise. For this reason, poverty profiles that seek to dig deeper into the characteristics of poor households engaged in such activities are usually based on ad hoc surveys.[41] However, in recent years, the World Bank's LSMS, FAO and other partners have undertaken efforts to establish tools to improve the representation of these rural subsectors in national household surveys (see FAO *et al.* [2016], Béné *et al.* [2012]; Zezza *et al.* [2016]). These have already been applied to some countries, but barriers to further uptake by governments remain. The main barrier is probably the cost of oversampling specific groups, in particular for the fisheries and forestry sectors, in countries in which these activities are carried out by only a small proportion of the population.

More in general, household surveys are not designed to be statistically representative of poverty situations at local levels (e.g. villages, municipalities, counties and, in general, any administrative or geographical area below the main national subdivisions), which often is what is needed for targeting and designing local projects. In this case, different solutions might be considered:

- **Conducting a local household survey.** However, this usually presents a high financial and time cost. Using a poverty measure with relatively low data requirements such as a rapid poverty assessment tool instead of a monetary or a proper multidimensional measure (see Section 2.5.3 in Chapter 2 for more details) may be a way to lower the cost. Donors often demand that a "baseline" be conducted in the design phase of a project. This represents an opportunity to collect the necessary information on poverty and the characteristics of poor households, including those related to rural and agricultural livelihoods.
- **Using census data.** By its nature, census data is representative of local areas. However, censuses are conducted only every 10 years in most countries and the associated microdata are often not disclosed due to privacy concerns. In addition, when the microdata is made available it includes less detailed information that it is sometimes insufficient to measure poverty satisfactorily. The use of census data is discussed in more detail in Sections 3.3.2 and 3.3.3.
- **Using qualitative participatory techniques** to develop a local poverty profile based on local definitions of poverty.[42] Qualitative research can also help inform future design of surveys that intend to collect information on poverty and the characteristics of poor households.

[40] Possible sources of this type of data are the websites of the US National Oceanic and Atmospheric Administration Climate Prediction Center (NOAA-CPC, 2021) and NASA (NASA, 2021).
[41] For guides to conducting socio-economic surveys on fisheries see Gee *et al*. (2017) and Pinello *et al*. (2017). For an example of a poverty profile of forest-adjacent communities based on an ad hoc survey see Dokken and Angelsen (2015).
[42] See FAO's toolkit on social analysis for more effective agriculture and rural development investments (FAO, 2011).

3.2.4 Reliability of poverty profiles

The reliability of a poverty profile depends on two main factors: the quality and the representativeness of the data that underpins it. Regarding the quality of the data, if the questions of a survey are not well designed or those in charge of administering a survey to households (i.e. the enumerators) are not properly trained (among many other potential data collection problems), the data could contain substantial measurement error, which would negatively affect the reliability of the profile built on the survey. This can be considered an upstream problem about which little can be done, other than using an alternative data source or identifying specific elements of the survey that present problems of data quality and refraining from reporting statistics generated from them.

However, unreliable poverty profiles are not always the result of low quality data. Sometimes analysts who generate profiles do not use the data properly. Poverty profiles are often based on household surveys and these are normally designed to be representative of the whole population of a country at national, rural/urban and, sometimes, regional level. This poses a potential problem of reliability for a profile.

For instance, let us consider the necessity of analysing the characteristics of extremely poor farmers who engage in coffee production in a specific geographical area of a country. Confronted with such a task, an analyst will likely find a very small subsample with data not representative of the population of interest. In other words, the analyst risks that, if a different household survey was conducted (under exactly the same conditions but drawing another sample of households) and he/she were to perform the same analysis, he/she would obtain different results. Similarly, using such data to compare the characteristics of the extremely poor coffee farmers in that region over time, would imply the risk of highlighting misleading trends.

This by no means suggests that analysts should avoid conducting disaggregated analyses in poverty profiles. Rather, they should be aware of the potential problem and assess "how far they can go" when using the existing data – keeping in mind that the profile is based on sample data and can thus only represent the true characteristics of the entire population of interest with some degree of uncertainty. For this reason, it is important that when analysts use a dataset to produce a poverty profile, they read the accompanying technical documentation to ensure that the data is representative of the population subgroup to which the poverty profile should refer. In addition, the figures reported as part of a poverty profile should be accompanied by the associated standard errors and confidence intervals. Knowing the degree of uncertainty around what is reported in poverty profiles is important in all cases, but even more so if the ultimate use of the profile is to allocate public resources for poverty reduction.

3.2.5 Robustness of poverty profiles

As seen in Section 3.2.2, poverty profiles can be built using different poverty measures and indicators. The figures in these profiles are not exempted from some uncertainty. For example, if one generates a poverty profile for a country based on the monetary measurement approach, one would not know exactly what the poverty profile of that country would look like if this were instead generated based on the multidimensional measurement approach. This problem refers to the robustness of a poverty profile; that is, how sensitive it is to certain choices of the analyst. Issues of robustness might emerge in relation to:

- the choice between using the monetary approach vs the multidimensional approach to poverty measurement;
- the choice of the welfare measure (e.g. income or consumption in the case of monetary poverty, or the choice of dimensions and indicators in the case of a multidimensional poverty index);

- the choice of the poverty line (for monetary poverty);
- the choice of cut-off values and weights (for multidimensional poverty).

Robustness to the choice of the measurement approach: monetary vs multidimensional. As explained in Chapter 2, monetary and multidimensional poverty approaches capture related, yet different, phenomena. As different phenomena are usually associated with different groups of a population, a poverty profile might present substantial differences depending on whether it is built using the monetary or the multidimensional approach to poverty measurement. In other words, different types of poverty measures might classify different groups of people as poor or non-poor.

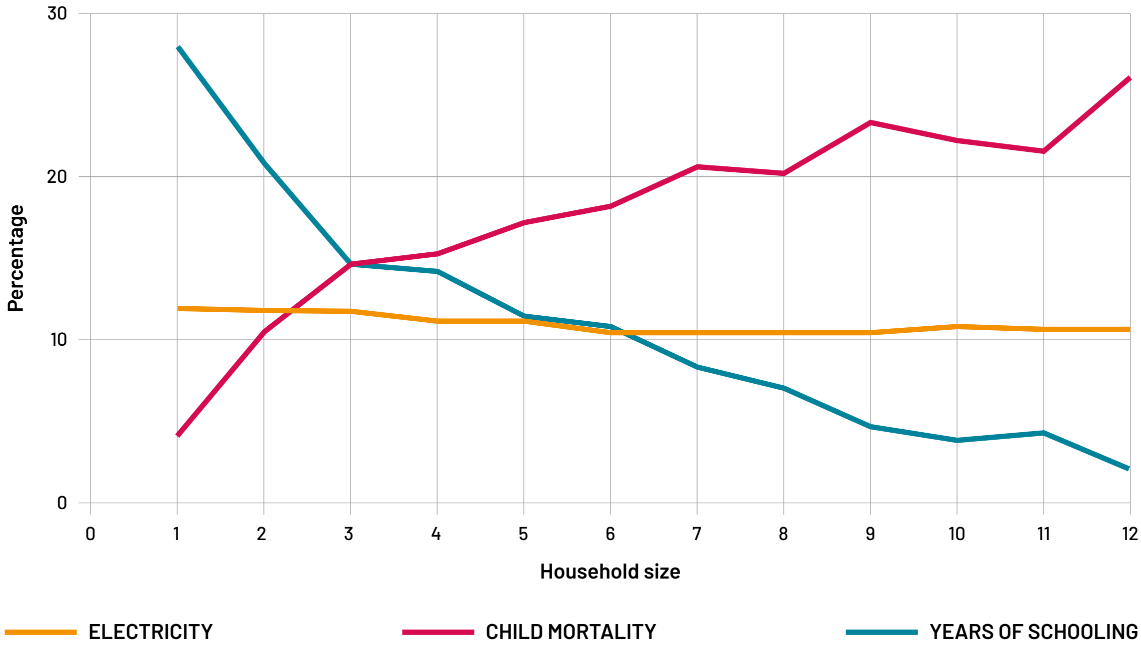
At the global level, the overall characteristics of the multidimensionally poor (identified with the Global MPI) are similar to those of the monetary poor (identified with the international extreme poverty line of USD 1.90 a day) (Robles Aguilar and Sumner, 2020). However, there might be substantial differences in these characteristics at the regional and national levels. For example, Bader *et al.* (2016) find that, in Laos, monetary poverty does not capture the multiple deprivations of ethnic minorities, who are only identified as poor when using a multidimensional poverty measure. These differences tend to be more pronounced where there are discrepancies between economic opportunities (more associated to monetary poverty) and public expenditure and service provision (more associated to multidimensional deprivations).

Robustness to the choice of the welfare measure. Even within the monetary or the multidimensional approaches to poverty measurement, different choices regarding the underlying welfare measures might result in differences in a poverty profile. For example, household size and household composition are typical issues related to welfare measures used in the measurement of monetary poverty. As explained in Box 5, the existence of different consumption needs among the members of a household and the presence of potential economies of scale, not only affect the relationship between household size and poverty, but also potentially affect the relationship between poverty and all the variables of the profile that are associated with household size (White and Masset, 2003). For example, given that rural households are typically larger than urban households, a measure of welfare that does not adjust for household size risks overstating the poverty level of rural versus urban areas. While there is no agreement on the best method to be used to generate equivalence scales and economies of scale parameters, White and Masset (2003) advise that “it is better to work with arbitrary, but reasonable, values of these parameters, than to leave unreasonable ones implicit in the analysis”.

The problem of household size is also important for profiles built using multidimensional poverty measures. For example, the MPI includes a mix of indicators that are measured both at the individual level and at the household level. For the latter, multidimensional poverty status is assigned to individual household members based on the experience of the household as a whole, which in turn may depend on the experience of just one member. Consequently, some of these indicators are directly correlated with household size. Years of schooling is an example: the more members a household has, the higher the likelihood that at least one of its members has completed five years of schooling. The concept is well illustrated by Levine *et al.* (2014), who, in the context of a multidimensional poverty profile of Uganda, show how the relative contribution of some indicators to the MPI varies across a range of household sizes (Figure 8). While the contribution of the “electricity” indicator remains essentially unchanged with increasing household size, the contribution of the “child mortality” indicator increases and that of the “years of schooling” indicator decreases. Apart from this specific example, it is important to keep in mind that a poverty profile can be affected by the way in which the indicators of a multidimensional poverty index are defined.

FIGURE 8

Relative contribution of selected indicators to the MPI by household size (Uganda, 2005/2006)



Source: Levine *et al.*, 2014.

Within the multidimensional poverty approach, the profile might also change depending on which dimensions and indicators are included in a poverty index. In fact, different subgroups of a population are often exposed to certain deprivations in a different way. For example, Robles Aguilar and Sumner (2020) found that, at the global level, poverty in rural areas tends to be characterized by deprivations in education and living conditions (water, sanitation, electricity and housing), while child mortality and malnutrition are more frequently observed in the context of urban poverty.

Robustness to the choice of the poverty lines. In the context of monetary poverty, the way in which poverty lines are defined can also have a substantial impact on poverty profiles. For example, Ravallion and Bidani (1994) show that, in Indonesia, a poverty line set with the cost of basic needs (CBN) method (see Section 2.3.1) finds greater poverty incidence, depth and severity in rural areas, while the opposite is true using the food energy intake (FEI) method (see Annex 3). Tarp *et al.* (2002) take a further step and show how rural and urban poverty, as well as the characteristics of the poor in different regions, change using different variants of the FEI and CBN methods.

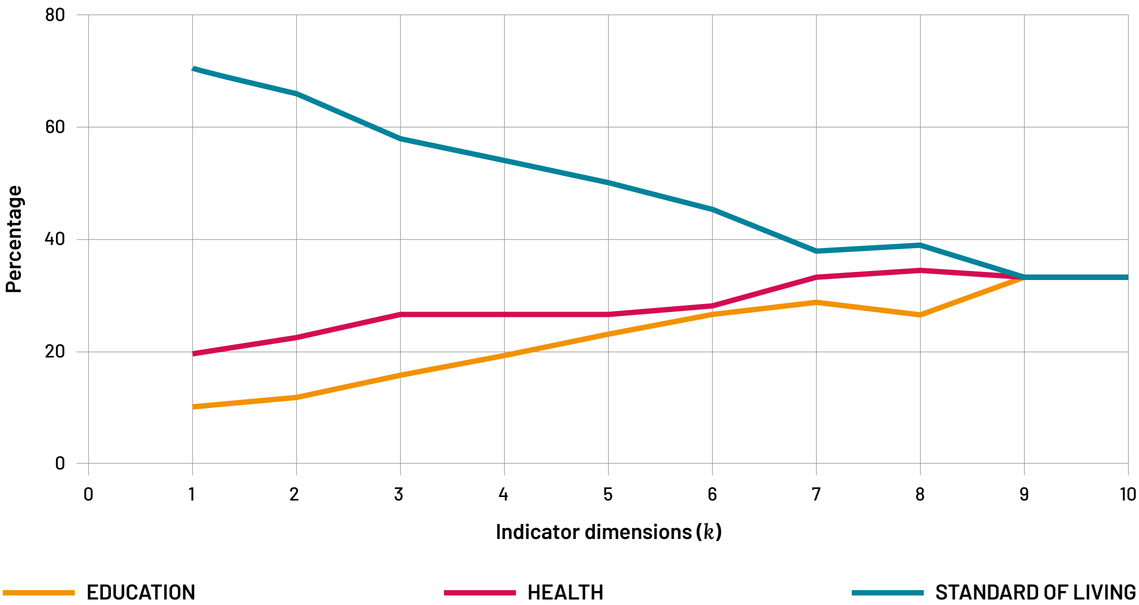
In general, multiple factors determine how different poverty lines can affect a profile, particularly the comparisons between rural and urban areas and rural and urban poor. These include the method used to estimate the lines (e.g. FEI, CBN, international poverty line, relative poverty line) and the extent to which they are adjusted to the condition of different geographical areas (e.g. the composition and prices of goods consumed in rural vs urban areas).

Robustness to the choice of cut-offs and weights. In the context of multidimensional poverty, the choice of the number of deprivations that a person must suffer in order to be classified as poor presents another issue of robustness for profiles. Focusing on Uganda, Levine *et al.* (2014) show that the relative contribution of the various dimensions to the MPI substantially changes as different cut-offs (k) are used (Figure 9). In general, a higher (or lower) cut-off will change the poverty profile in a way that it reflects more the characteristics of the population subgroups that are more (or less) affected by simultaneous multiple forms of deprivation.

Analogous considerations can be made in relation to the choice of weights. Increasing the weight of a certain dimension or indicator will tend to alter a poverty profile toward the characteristics of the population subgroups that are relatively more exposed to deprivations in that dimension or indicator.

FIGURE 9

Contribution of dimensions to MPI by cut-off (Uganda, 2005/2006)



Source: Levine *et al.*, 2014.

Checking for robustness

Thus far, we have discussed that using monetary or multidimensional poverty, different underlying welfare measures, and different parameters (poverty lines, cut-offs and weights) will inevitably produce a change in the figures of a poverty profile. However, this is not the main issue. For public policies, what matters the most are poverty comparisons between areas or population subgroups (i.e. relative rankings). For example, if we were to target an area for anti-poverty public transfers or investments, we would like to be confident that this is the place where the level of poverty is highest or where the greatest number of poor people are concentrated.

In general, the more reranking in terms of poverty levels among the areas or subgroups of interest, the more one should pay close attention to the choice of the methodological aspects mentioned above. Hence, when analysing the robustness of a poverty profile, one should focus on checking for potential reranking among subgroups that might be used to target rural poverty reduction policies. This is particularly important for Part A of a profile, where population subgroups are compared in terms of their incidence or other measure of poverty. In the fictitious example provided in Table 8, the profile is not robust to the choice of the approach to poverty measurement. In fact, using the monetary approach, rural areas appear poorer compared to urban areas; while the opposite is true using a multidimensional poverty measure.

TABLE 8

Robustness of a poverty profile to different poverty measurement approaches, Part A

	HEADCOUNT RATIO BY PLACE OF RESIDENCE	
	MONETARY	MULTIDIMENSIONAL
Rural	30.0%	32.0%
Urban	22.0%	36.0%

Sources: Authors' own elaboration.

The concept applies to Part B as well, which describes the poor in terms of their characteristics. In this case, one should check carefully whether characteristics that were predominant among the poor become more predominant among the non-poor using a different measure of poverty. In the fictitious example in Table 9, the profile is not robust because, using a monetary measure of poverty it appears that the majority of the poor engage in agriculture while, with a multidimensional measure, the majority of the poor engage in non-agricultural activities.

TABLE 9

Robustness of a poverty profile to different poverty measurement approaches, Part B

	SHARE OF THE POOR ENGAGING IN DIFFERENT SECTORS OF EMPLOYMENT	
	MONETARY	MULTIDIMENSIONAL
Agriculture	58.0%	47.0%
Non-agriculture	42.0%	53.0%

Sources: Authors' own elaboration.

The most straightforward way to check the robustness of a poverty profile is to produce and compare results under various circumstances of interest.[43] In general, a profile can be considered robust if the ranking among population subgroups of interest remains consistent under various circumstances (e.g. changing welfare measures and poverty lines). Specific attention should be given to the aspects that are determinant for the targeting, design and monitoring of poverty reduction interventions. In a rural poverty profile, it will be particularly important to check for potential reranking between rural and urban areas, and between different subgroups associated to particular rural livelihoods. For more details on how to assess the robustness of a poverty profile, see Box 9.

[43] For example, in a poverty assessment of Bosnia and Herzegovina, the World Bank (2003) examines the changes that different equivalence scales, poverty lines and alternative definitions of well-being have on the poverty figures in respect to location, displacement status, education of household head, employment status and household size.

▶ BOX 9

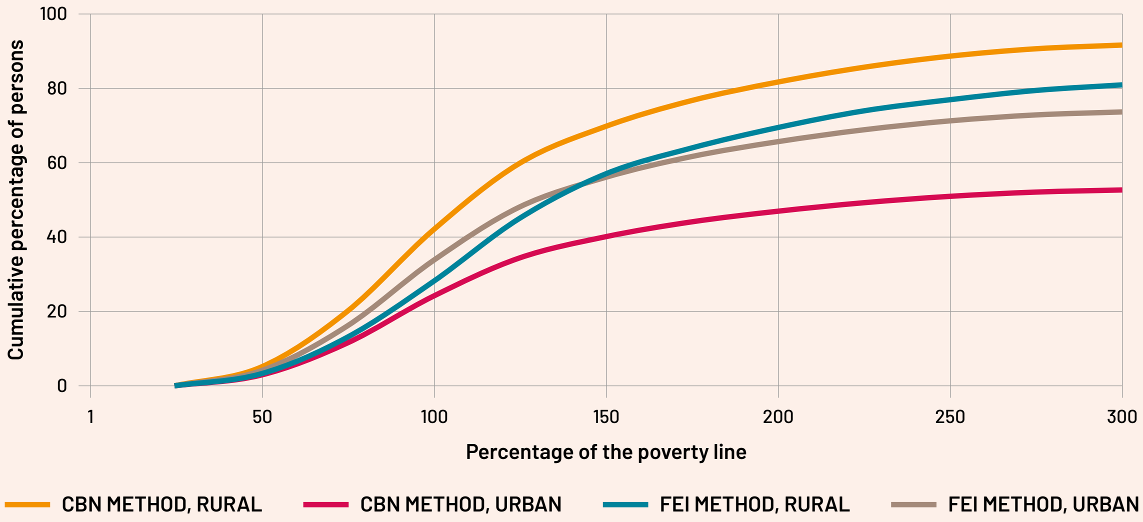
Stochastic dominance and other approaches to check the robustness of profiles

Stochastic dominance can be used to check the robustness of Part A of a poverty profile (i.e. where subgroups of the population are compared in terms of their poverty level). The approach was first applied to poverty measures by Atkinson (1987) and then to poverty profiles by Ravallion and Bidani (1994). It is based on comparing well-being distributions of different groups (e.g. rural vs urban inhabitants) to test whether one presents a higher level of poverty than the others under different poverty measures or lines. Stochastic dominance determines whether the poverty ranking between distributions depends on the choice of the poverty measure or line. Let us assume that one wants to compare poverty incidence among rural and urban people. In practice, one needs to plot the cumulative density functions of, say, per capita expenditure for the two subgroups and observe whether they cross. If they do, it means that over a certain range of poverty lines rural people will turn out to be poorer than urban people while, over a different range, the opposite will be true. In practice, what matters is that the distributions not cross over a set of relevant poverty lines (i.e. poverty lines that are commonly used). Otherwise, the profile will not be robust.

This example from Ravallion and Bidani (1994) illustrates stochastic dominance for rural and urban areas, using two different methods to determine the poverty line (Figure 10). The incidence of poverty is shown as a function of the poverty line. Using the CBN method, for any given poverty line, poverty is unequivocally higher in rural areas than in urban areas. Using the FEI method, however, the poverty incidence curves intersect. Up to about 150 percent of the poverty line, poverty is higher in urban areas, while, at higher lines, poverty is higher in rural areas.

▶ FIGURE 10

Illustration of stochastic dominance: incidence of monetary poverty in rural and urban areas using different poverty lines



Source: Ravallion and Bidani, 1994.

▶ BOX 9 (CONT.)

Stochastic dominance can be tested also with multidimensional poverty, although this is technically more challenging. For an overview see Garcia-Gómez *et al*. (2019) and Yalonetzky (2013).

Other methods. There are milder forms of robustness checks that can be applied, for example by counting the percentage of pairwise comparisons that are robust to the change in the parameters of a poverty measure (Alkire *et al*., 2015). Let us consider a comparison of poverty in ten districts of a country for which robustness to two poverty lines needs to be checked. The first step would be to compare the poverty level of each pair of districts with one of the poverty lines. Then, the same procedure is applied using the alternative line. Finally, the percentage of pairs for which the relative ranking changed using the alternative poverty line should be counted (e.g. those where poverty was higher in A than in B using the first poverty line, but then was higher in B than A using the second line). If, for example, the poverty ranking changed in 50 percent of the pairs, this shows a lack of robustness.

Another way to test robustness is to calculate a rank correlation coefficient between the original and the alternative rankings (Alkire *et al*., 2015). A rank correlation coefficient (e.g. Spearman's rho) measures the degree of similarity between two groups of rankings. Using the above example, the coefficient would compare the similarity between the poverty rankings of the ten districts obtained using the first poverty line with the rankings obtained using the second line. If the rankings are weakly correlated (i.e. they differ substantially), this means that using an alternative poverty line substantially "reshuffled" the poverty ranking of the ten districts. In this case, again, it is likely there is a problem of robustness. Alternatively, Wodon (1999) proposes a method based on a decomposition of the Gini coefficient.

3.2.6 Conditional poverty profiles: understanding the determinants of rural poverty

The poverty profiles presented so far are based on descriptive data. These profiles are very useful in their own right – as a first approximation to the determinants of rural poverty. However, **they do not identify the causal mechanisms behind rural poverty**. For example, if a poverty profile shows that the poor farmers, on average, own less tractors than the non-poor farmers, that does not imply that poor farmers are poor because of that observation. It might well be the opposite: that is to say, the poor might own less tractors because they cannot afford them. The explanation could also be that poor farmers use less tractors because they tend to operate smaller and more fragmented land plots or cultivate crops that do not allow the use of mechanized equipment. **When making policy recommendations based on a poverty profile, one should always be aware of this limitation.**

To mitigate this limitation, at least partially, poverty profiles are often complemented by **econometric analyses that show the conditional association (i.e. holding all other factors constant) of relevant variables on poverty**. This can provide more precise insights for policy design, indicating what factors contribute to rural poverty reduction and to what extent. Consider two farmers with very similar characteristics in terms of age, sex, education and land size, but only one of whom has access to irrigation. This type of analysis can reveal if the farmer with no access to irrigation is more likely to be poor. These techniques can be particularly useful to investigate the strength of the association between different variables capturing rural livelihoods and poverty.

Let us note two main types of analysis that typically integrate poverty profiles (Haughton and Khandker, 2009):

- **Linear regressions** attempt to explain expenditure or income using a set of explanatory variables. These variables may refer to the individual, household, community and geographic characteristics discussed in Section 3.2.2.
- **Logit or probit regressions** attempt to explain the probability of households to be poor given a set of explanatory variables, as above. In this case, the dependent variable is binary, taking the value of 1 if a household is poor and 0 otherwise.

Table 10 provides an example of results from a logit regression showing some potential determinants of poverty in rural Malawi. The table shows average marginal effects, meaning that coefficients can be interpreted as the effect that a marginal change in a given household characteristic has on the probability of being moderately poor. For factor categorical variables (i.e. non-numerical variables such as gender or place of residence), coefficients are to be interpreted with respect to the base level. For example, the “HH head is a woman” coefficient represents the difference in the probability of being poor between a woman-headed and a man-headed household. For continuous variables (i.e. numerical variables), margins should be interpreted as the change in the probability of being poor due to a unit change in the independent variable (e.g. the effect of an additional member on a household’s probability to be poor). Among other things, the table shows that, in rural Malawi, women-headed and larger households are more likely to be poor, while households with an older and more educated head are less likely to be poor. Households in the central and southern regions of the country are less likely to be poor than those in the north. Finally, households that engage in crop farming and receive social assistance are more likely to be poor, while those engaged in wage labour, livestock or fishing and that receive remittances are less likely to be poor.

▶ TABLE 10

Average marginal effects of household characteristics on the probability to be moderately poor (monetary definition) in rural Malawi, 2016/2017 (logit model)

VARIABLES	COEFFICIENT	STANDARD ERROR	P-VALUE
Demographic characteristics			
Household (HH) head is a woman	0.025	(0.013)	0.051*
Age of HH head	-0.003	(0.000)	0.000***
Years of education of HH head	-0.026	(0.002)	0.000***
HH size	0.089	(0.003)	0.000***
Share of HH members of non-working age	0.210	(0.022)	0.000***
Place of residence			
Central region	-0.143	(0.014)	0.000***
Southern region	-0.038	(0.014)	0.006***

▶ TABLE 10 (CONT.)

VARIABLES	COEFFICIENT	STANDARD ERROR	P-VALUE
Livelihood characteristics			
HH head is employed	-0.009	(0.015)	0.533
At least one member has a wage job	-0.150	(0.020)	0.000***
HH engages in crop farming	0.042	(0.019)	0.025**
HH engages in livestock	-0.143	(0.011)	0.000***
HH engages in fishing	-0.099	(0.034)	0.003***
HH receives international remittances	-0.124	(0.023)	0.000***
HH receives internal remittances	-0.038	(0.011)	0.001***
HH receives social assistance	0.041	(0.011)	0.000***
Observations	10 174		
Pseudo R2	0.192		

Notes: * significant at 10 percent level, ** significant at 5 percent level, *** significant at 1 percent level.
Sources: Authors' own calculation based on World Bank (2012c).

Very often the econometric analyses that accompany poverty profiles are used to presumably reveal the causes of poverty. Although this is very appealing from a policy point of view, identifying the causes of poverty in practice would require using exogenous (explanatory) variables (i.e. variables that are not affected by poverty). Nevertheless, this is rarely the case, as poverty is a complex phenomenon with interconnections with most of the variables typically used in poverty profiles. For example, Table 10 indicates that households that receive social assistance are more likely to be poor. Interpreting this as a causal relationship (i.e. social assistance leads to more poverty) is likely misleading. In fact, the likely explanation is simply that the poor have a greater probability to receive social assistance because it is targeted to those who need it most. This does not mean that econometric analyses are not useful. When interpreted as correlations, they can indicate whether the patterns observed in the descriptive profile hold after controlling for multiple variables (Castañeda *et al.*, 2018).

3.3 POVERTY MAPS

3.3.1 Definition and use of poverty maps

Poverty is not distributed evenly across geographies. In fact, the level and manifestations of poverty can be substantially different in different geographical spaces within a country. Additionally, the poor tend to be clustered in specific areas. Aggregate national-level indicators can thus mask this spatial variability and give a false sense of homogeneity within a country (Henninger and Snel, 2002). Poverty profiles may help show part of this variability, but they are still insufficient to fully capture and communicate the geographical heterogeneity in the incidence of poverty.

Poverty maps provide detailed descriptions of the geographical distribution of poverty within a territory. Although the primary purpose of poverty mapping is the spatial identification of the poor, the term is also used to refer to the spatial analysis of poverty in a broader sense (Davis, 2003). In other words, poverty mapping can also include the analysis of the relationship between poverty and various geographical aspects (e.g. agro-ecological characteristics or the infrastructure network of a region).

Poverty maps can represent poverty at various levels and according to different criteria. Maps can show poverty at the global, regional, national and subnational levels, by administrative, agro-ecological or land-use units. The choice of the disaggregation level is critical as alternative aggregations of data might lead to different and even conflicting results (Davis, 2003). The higher its resolution (i.e. the level of disaggregation), the more a poverty map captures the heterogeneity behind aggregated poverty figures.

Maps not only summarize large volumes of data in a clear way, but also enhance interpretation by preserving the spatial relationships among different areas, which is impossible in a tabular data format (e.g. a poverty profile). For that reason, maps are "powerful tools for presenting information in a way that is easily comprehensible by a non-specialist audience" (Deichmann, 1999). This can help increase awareness on poverty issues within a country and engage local stakeholders, especially in more remote areas, in the political debate on poverty (Bedi *et al.*, 2007).

From a policy perspective, the most direct benefit of poverty maps is that if governments and other development actors can identify where the poor are, they will be able to allocate their resources more effectively. They will also be able to design rural poverty reduction interventions taking into account the geographical characteristics of the spaces where the rural poor live. For example, poverty maps can support subnational planning by determining formulas to adjust funding based on various poverty levels of administrative units (instead of, say, determining funding based on an eligible/not-eligible basis).

Another benefit of knowing where the poor are located is the ability to investigate how the spatial heterogeneity of poverty is linked to geographical factors. This can reveal patterns that might otherwise be hard to detect and shift the dialogue on poverty towards new approaches and strategies (Bedi *et al.*, 2007). Even further, detailed poverty maps can be used to generate, as a by-product, explanatory spatial variables for use in multivariate analysis (Davis, 2003), especially combining disaggregated poverty estimates with geographical information (e.g. measures of distance and accessibilities to markets, services and infrastructure) through geographic information systems (GIS) (Hyman *et al.*, 2005).

This chapter focuses on poverty mapping applications based on quantitative data. These include: (i) mapping exercises that involve descriptive and inferential statistics directly relying on survey and census data; (ii) mapping applications based on the estimation of disaggregated poverty measures through econometric models, using survey, census and other data sources; and

(iii) poverty mapping approaches not based on traditional survey and census data. The chapter places more emphasis on the first two poverty mapping applications (Sections 3.3.2 and 3.3.3), and provides a brief overview of recent developments regarding the third application (see Box 12). There are other approaches for mapping rural poverty that are not covered in this document. These include livelihood assessments, combinations of qualitative and secondary data and participatory methods. For an overview of these approaches, see Davis (2003).

3.3.2 Direct mapping with survey and census data

Mapping both monetary and multidimensional poverty using data from a household survey might look like a straightforward approach. Nevertheless, as mentioned before, **household surveys usually have a reduced number of observations and can only be disaggregated at a relatively low spatial resolution** (e.g. the main regions within a country, or rural vs urban spaces). While this could be satisfactory for some applications, this disaggregation level is often insufficient for mapping exercises that are aimed at informing a more granular targeting and design of rural poverty reduction interventions. This issue should not be ignored: the use of household survey data to map poverty at a finer spatial level than the survey was designed for will produce imprecise and unstable estimates. For example, an area (e.g. a municipality) that appeared poor in a period of time, might appear rich in a subsequent period of time when the next round of the survey is conducted, even if no actual change in the poverty level occurred.

An alternative worth exploring is to produce disaggregated poverty maps using census data. Some countries collect information on income in population censuses. Soares *et al.* (2016) offer an example of direct poverty mapping using income data from the Brazilian population census, which traditionally administers a more detailed questionnaire, including questions on income, to a subsample of households (drawn to be representative of municipalities). Figure 11 illustrates the results on poverty for municipalities of Brazil. Given that municipalities include different types of households, the authors present their results differentiating between agricultural, pluriactive, non-agricultural rural and non-agricultural urban households.

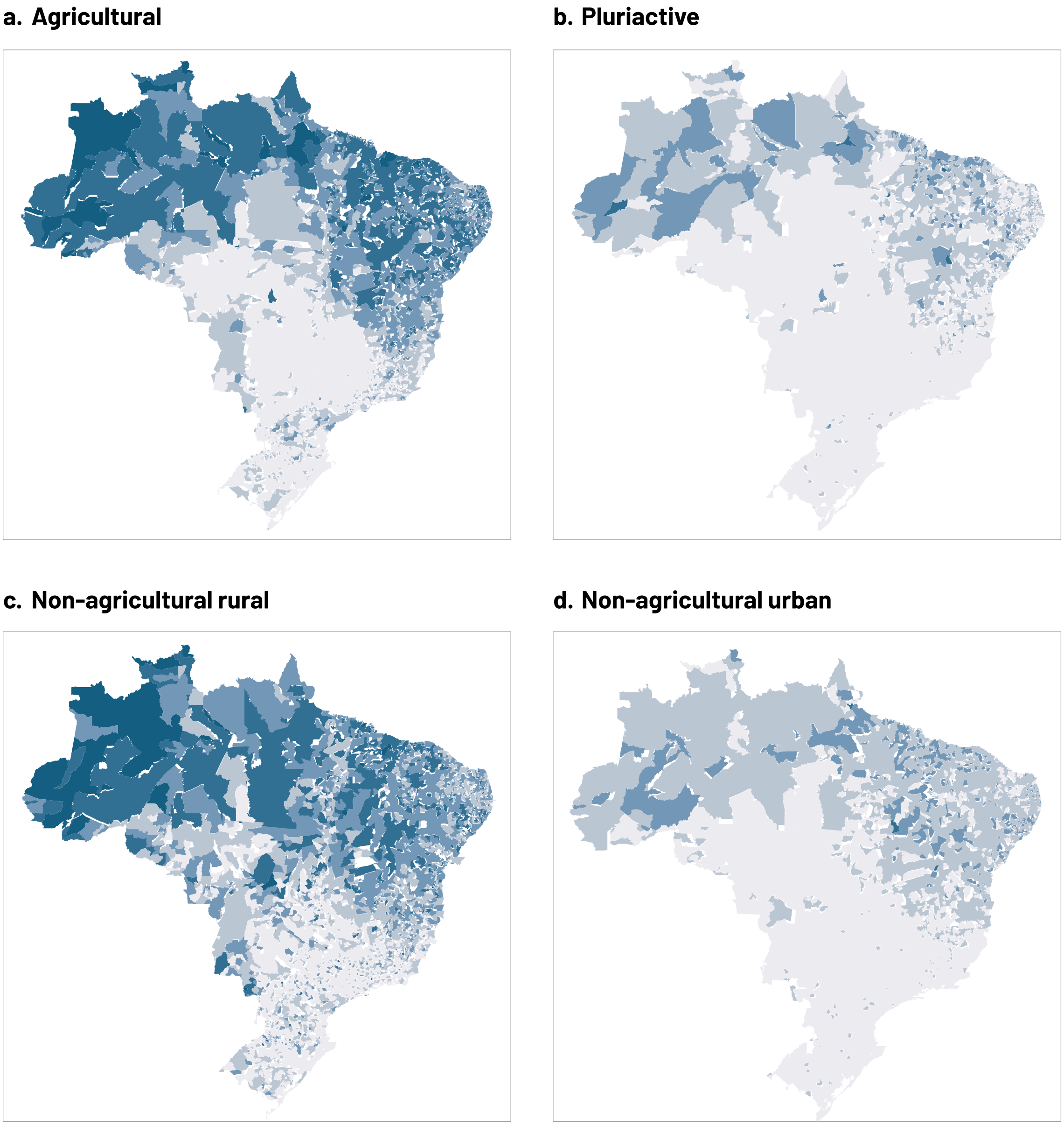
It should be born in mind, however, that, in most cases, the income information collected in censuses refers to cash income and it is captured using only one or few questions. Consequently, income data derived from censuses are systematically biased, as they underrepresent the well-being of rural households with a higher share of non-cash income. For this reason, **disaggregated monetary poverty maps produced directly from censuses are not recommended for developing countries with large agricultural sectors characterized by informality and non-cash income** (Davis, 2003).

In general, **multidimensional measures of poverty offer more possibilities for direct mapping with census data**. Although censuses often do not have enough information to produce standard multidimensional poverty measures (e.g. the Global MPI cannot be estimated with most censuses because they usually do not collect nutrition data [Alkire and Robles Aguilar, 2015]), most of them include enough variables to construct and compute basic needs and ad hoc multidimensional poverty indices. Davis (2003) presents different methods to produce multidimensional poverty maps with census data, including weighting techniques based on econometrics methods, such as principal component analysis and factor analysis.

Irrespective of the source of data and the technique used, there are a number of good practices that can be followed to create a poverty map. These are summarized in the reminder of this section, and Box 10 provides advice regarding the communication of poverty maps.

▶ **FIGURE 11**

Incidence of extreme monetary poverty in Brazilian municipalities by demographic group, 2010



PREVALENCE OF EXTREME POVERTY ■ 0–20 ■ 20–40 ■ 40–80 ■ 60–80 ■ OVER 80

Source: Soares *et al.*, 2016.

▶ BOX 10

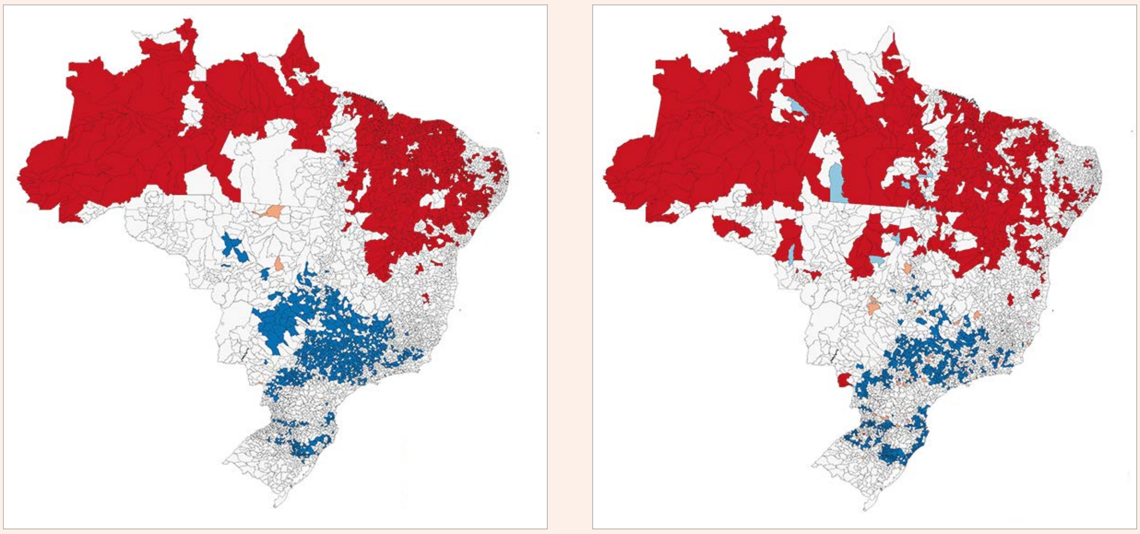
Improving the communication of maps with cluster analysis

To be policy relevant, poverty maps must be presented in a simple and meaningful manner. In fact, maps presenting rural poverty levels across hundreds of spatial units can be informative but also disorienting for policy-makers. The identification of spatial clusters of poverty can simplify disaggregated poverty maps and help identify local determinants of poverty and opportunities for policy interventions beyond predefined areas (e.g. administrative units). Local indicators of spatial association (LISA) are tools that identify and statistically test the associations of poverty levels between a spatial unit and its neighbouring units and classify them into high-high, low-low, high-low and low-high categories. They bring together statistical rigor and simplicity (Azevedo, 2018). Figure 12 shows an example from Soares *et al*. (2016). In this figure, red areas indicate clusters of high extreme poverty, while blue areas indicate clusters with low poverty levels.

▶ FIGURE 12

Extreme monetary poverty among agricultural or pluriactive households and non-agricultural rural households – patterns of association in municipalities with significant LISAs (Brazil, 2010)

a. Agricultural or pluriactive **b. Non-agricultural rural**



EXTREME MONETARY POVERTY ■ HIGH-HIGH ■ HIGH-LOW □ NON SIGNIFICANT ■ LOW-HIGH ■ LOW-LOW

Source: Soares *et al.*, 2016.

PRACTICAL TIPS: SOME DOS AND DON'TS OF POVERTY MAPS

- Do report measures of uncertainty such as standard error or confidence intervals if the poverty figures that are being mapped are estimates.
- Do report poverty indicators other than the poverty rate, such as the poverty gap and the severity of poverty, and possibly integrate poverty maps with maps of inequality.
- Do present both the prevalence and the density of poverty. Often, it might be the case that more densely populated areas of a country have more poor people than more scarcely populated areas with a higher prevalence of poverty.
- If possible, generate poverty maps using different measures of welfare (e.g. food security) and compare them. This will make it possible to check the robustness of a map.
- When comparing a poverty map with maps depicting geographical factors, do not interpret visual correlations as causal relations. Although comparing maps can be a useful exploratory analysis, establishing causal relationships between poverty and other variables requires rigorous statistical analysis. Interpreting causal relationships from visual associations could mislead policy.
- If the main goal of the poverty mapping exercise is to identify where the poor live and what are the poorest areas, do not try to update poverty maps too often, unless there is a large-scale event that affected a region in particular (e.g. an earthquake, tsunami or conflict). Although poverty levels change over time, the spatial distribution of poverty tends to be persistent. "Poverty maps have a longer shelf life than what is perceived by policy makers" (Azevedo, 2018).

3.3.3 Mapping with imputed data: small area estimation (SAE)

As mentioned, producing poverty maps for small geographic units can be very useful, but it typically faces a data challenge. While household surveys are the traditional data source to generate poverty measures, they are not statistically representative at the small-area level. At the same time, censuses usually do not collect reliable income or consumption information or do not include enough variables to calculate standard multidimensional poverty indices. This data challenge can be overcome using **SAE**, a family of statistical techniques that combine survey and census data to create detailed poverty maps.

SAE refers to various statistical techniques for producing more precise estimates for small geographical areas with small or zero sample sizes in household surveys (Tzavidis, 2010). In most applications, SAE consists of imputing a variable for the various observation units of a large database (usually a census) based on an econometric model estimated through a smaller database (usually a household survey). It can be thought of as a survey-to-census geographical imputation (Dang, 2018). Imagine a very simple case in which a household survey includes data on age, sex, education and income of households. A census, on the other hand, collects data on age, sex and education, but excludes income. SAE uses the survey data to determine the relationship between income and the other variables. Once this relationship is estimated, an income variable can be simulated for each observation unit of the census based on their sex, age and education.

The literature on SAE is rapidly evolving, with researchers in various fields, such as economics, statistics, geography and computational sciences, making constant refinements to the available techniques. A first categorization of SAE methods is between **household-level** and **area-level** methods. The first category predicts well-being for each household unit of a census and then aggregates this information into poverty estimates for small areas, just like the two-step identification-aggregation procedure introduced in Chapter 2. The second category predicts poverty directly for each small area in the census based on area-level variables. In general, household-level methods are preferred to area-level methods because they produce more precise estimates (Minot and Baulch, 2002; Anjoy *et al.*, 2019; Nozaki *et al.*, 2019). Area-level methods are used when household-level methods cannot be applied due to the lack of unit-level data (often national statistical offices publish census microdata only at some level of aggregation). Beyond the relatively greater availability of area-level data compared to household-level data, area-level methods have the advantage of being less data-intensive, simpler and less sensitive to outliers (Nozaki *et al.*, 2019).

While there are different SAE techniques, **the general procedure to produce a map in the context of poverty mapping can be summarized in the following four steps** (Tzavidis, 2010; Coulombe and Wodon, 2007):

1. A household survey is used to estimate an econometric model that links a welfare measure to a set of covariates (i.e. explanatory variables) that are common to both the survey and the census.
2. The estimated parameters are applied to the covariates in the census to predict the values of the welfare variable for each observation unit.
3. The predicted welfare variable is used to estimate poverty indicators for small areas.
4. The estimates are depicted in a map.

The Fay-Herriot (FH) model is the most common area-level method, often used in official statistics (Guadarrama *et al.*, 2015). Within household-level methods, the most common is that of Elbers, Lanjouw and Lanjouw (2003) often referred to as the ELL method, which the World Bank has traditionally used to produce its poverty maps.[44] In addition to ELL, there are newer (and more sophisticated) methods for household-level SAE. These include the Empirical Best/Bayes (EB) method (Molina and Rao, 2010), the M-quantile approach (Tzavidis *et al.*, 2008), and the Hierarchical Bayes method (Molina *et al.*, 2014). For a more comprehensive picture of the different SAE methods, see Rao and Molina (2015). Here we focus on ELL, given its wide application for developing countries and institutional support from the World Bank.[45]

The **ELL method** was the first household-level model-based SAE technique to be developed. It is based on a mixed-linear model in which household welfare (consumption or income) is predicted based on a set of household-specific and area-specific variables and in which the error term is decomposed in a household component and an area component. Even though it is still the most popular method for producing poverty maps with SAE, it is not exempt from complications. Tarozzi and Deaton (2009) showed that the method relies on two assumptions that often do not hold in practice, with the consequence of overestimating the precision of poverty measures. The two assumption are:

- **The variables that are common to the survey and the census (i.e. those used to predict welfare in the census based on the model estimated through the survey) must be defined and measured in the same way.** Often, seemingly similar variables are measured differently in different surveys. For example, a household survey and a census might use different definitions

[44] The World Bank has recently introduced a Stata command for small area estimation, which it is aiming to expand and refine further (Nguyen *et al.*, 2018). It also has a dedicated software than can be used to produce poverty maps (see www.worldbank.org/en/research/brief/software-for-poverty-mapping [World Bank, 2015]).

[45] ELL models are usually based on monetary poverty and, for convenience, this section will focus on that. However, SAE techniques can be applied to multidimensional measures of poverty as well. For example, Nájera Catalán *et al.* (2019) estimate multidimensional poverty in Tonga down to the block level using a hierarchical Bayesian estimator.

of household or economic activity. It is important that the analyst ensure that the variables actually measure the same thing. This can be done by comparing the average value of variables in the census and the survey for geographical areas for which the survey is designed. For example, estimating the average household size in a given administrative region of a country with both the survey and the census should give similar results.

- **The relationship between the welfare variable (e.g. income or consumption) and the independent variables (e.g. demographic or employment characteristics) must be homogeneous across geographic areas in the survey and the census.** In other words, the coefficients of the independent variables should be the same in all areas of a country. For example, the overall effect of household engagement in agriculture on poverty that emerges from a survey might be generally negative, but it might be positive in some areas of a country with particular agro-ecological conditions. If the coefficients of the independent variables vary in different areas of the country, **there are strategies to mitigate the negative effects of such potentially biased estimation**:
  - First, area-level variables from external sources (e.g. the Hand-in-Hand GIS Platform), such as soil quality or precipitation, may be included in both the survey and the census. This can help control for local effects and reduce area-related error. Using the previous example, controlling for variables such us soil quality and precipitation can help avoid engagement in agriculture being negatively associated with welfare in some areas but positively in other areas.
  - Second, instead of estimating the relationship between the welfare variable and the covariates using the full household survey, one may fit a model for each region for which the survey is representative (Haughton and Khandker, 2009) and use these models to predict welfare in the census. For example, a model can be estimated using only the survey observations in the north of a country, such that the coefficients obtained are used to predict the welfare variable only for the census observation units that live in the same region.

The more distant in time the survey and the census are, the less likely the two key assumptions described above will hold.[46] For this reason, it is advisable that the survey and the census be as close as possible with regard to time of implementation. **A rule of thumb is to avoid using censuses and surveys conducted more than 3 to 5 years apart**.

What does the quality of the estimates (i.e. the level of poverty estimated for small areas based on the survey-to-census imputation of welfare) depend on? On the one hand, the precision of the estimates depends on the degree of geographical disaggregation sought. **The more disaggregation, the less precision, meaning that there might be a trade-off between precision and policy needs, as policy-making generally requires more disaggregated poverty maps**. For example, when using the ELL procedure, poverty estimates obtained for villages will inevitably be less precise than estimates at, say, district level. On the other hand, the precision will depend on the explanatory power of the econometric model developed in the first of the four steps outlined above (Davis, 2003). In fact, ELL requires extensive data mining and model searching effort. The analysis involves substantial analytical skills and time (Nozaki *et al.*, 2019). See Box 11 for more details.

[46] This can be said for any imputation technique. For a review of these techniques in the context of poverty analysis see Dang (2018).

BOX 11

ELL in practice – step-by-step procedure for variable selection

The first step of the ELL method requires estimating a model of welfare using a household survey. For this, the analyst will need to select a set of independent variables (covariates). Nozaki *et al*. (2019) have recently completed a poverty mapping exercise in Georgia using SAE. Here is a summary of the main steps they followed to select the variables to be included in the econometric model:

1. Identify potential covariates included both in the survey and the census, including ancillary area-level variables generated from census and external sources. If possible, differentiate area-level variables into rural and urban.
2. Make sure that variables that are common to the survey and the census actually measure the same thing by computing the mean at the more disaggregate representative level in the survey.
3. Select a subsect of covariates using least absolute shrinkage and selection operator (LASSO) regression to minimize prediction error. Exclude from the model variables with a regression coefficient equal to zero after the shrinkage process.
4. Run a linear regression and drop the covariates with high variance inflation factor (VIF) to reduce the variance to the model estimate. Drop also explanatory variables that are highly insignificant.
5. Use the prediction of the linear regression to identify and drop outliers to increase the overall precision of the model estimates.
6. Run the ELL model with the remaining variables and drop those that are highly insignificant.

Nozaki *et al*. began with an initial list of 307 candidate variables covering aspects such as demographic characteristics of the household, income-earning characteristics, dwelling type and asset ownership, access to services and geographic characteristics. The final ELL model used 32 of the initial 307 variables.

Because true poverty rates at the small-area level can never be observed and quantified, estimates should be evaluated against different references by, for example:

- checking that poverty estimates from the census are comparable to those obtained from the household survey at the geographic level in which the latter is representative (e.g. region or state);
- checking the correlation of poverty estimates with other non-monetary welfare measures that are available at the small-area level (e.g. MPI constructed using census); and
- discussing the small-area poverty estimates with local experts and comparing with the perceptions of local stakeholders.

The SAE methods presented so far do not focus specifically on rural poverty. Indeed, although these techniques have been developed mainly as an application for monetary poverty mapping, they can be applied to any human development indicator of interest (e.g. child malnutrition).

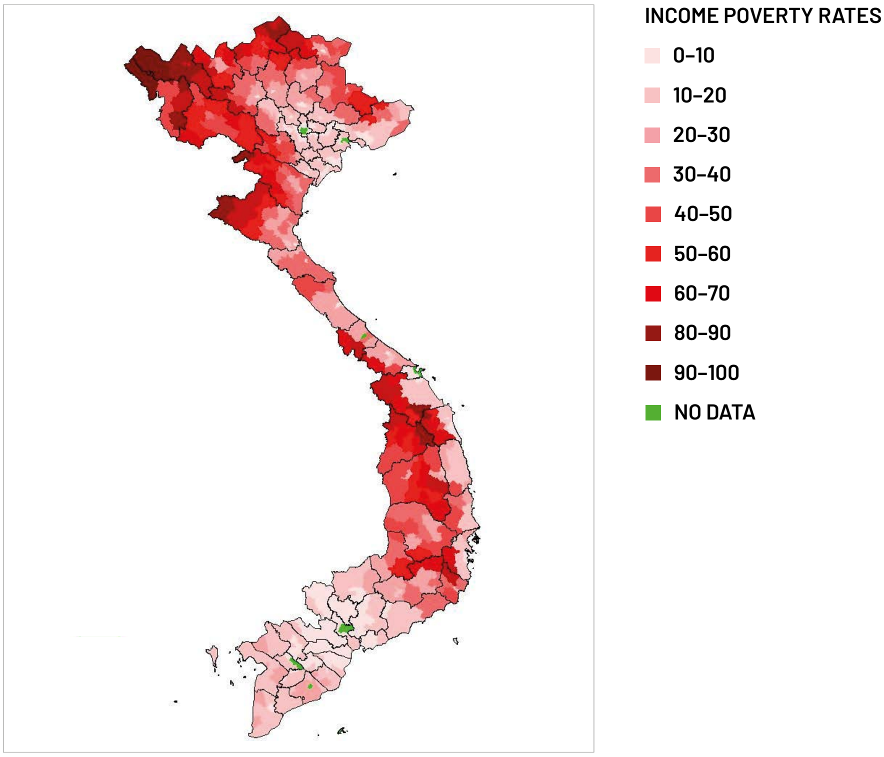
To build a map that focuses specifically on rural poverty, a first (and straightforward) approach is to map poverty separately for geographic areas that are classified as rural. Another approach is to map poverty separately for subsets of the population such as agricultural households.

See, for example, Figure 11 – the poverty map of Brazil developed by Soares *et al.* (2016). In both approaches, SAE offers the possibility of building a model that predicts poverty on the basis of aspects that are particularly relevant to the livelihoods of the rural poor. One way to do this is to use an agricultural census instead of a general population census.

Nguyen *et al.* (2009) built a rural poverty map for Viet Nam by combining a household survey (the 2006 Viet Nam Household Living Standard Survey) and an agricultural census (the 2006 Rural Agriculture and Fishery Census, or RAFC) (Figure 13). The RAFC included all households in rural areas and variables specific to rural livelihoods. As the first step of the ELL procedure, the authors integrated in the household survey a set of both commune-level variables derived from the census (e.g. number of irrigation units, extension staff and markets per 1 000 households) and district-level data from external GIS databases (e.g. elevation, temperature and rainfall), so as to estimate a consumption/income model. In this way, the fine-grained estimates of rural poverty could better reflect the conditions of the rural poor.

FIGURE 13

Incidence of rural monetary poverty in Viet Nam's districts, 2009



Source: Nguyen *et al.*, 2009.

All the methods for SAE presented so far rely on population or agricultural censuses. Their main limitation is that censuses are repeated with low frequency and not all countries can afford to conduct them. This means that it is often not possible to generate detailed poverty maps for years and countries (or regions of countries) that are not covered by census data. Promising new methods that combine traditional household survey data and non-traditional data sources are creating opportunities to map poverty at a higher resolution. Some examples are provided in Box 12.

BOX 12

Poverty mapping with imputed data derived from non-traditional data sources

New methods use traditional household survey data in combination with non-traditional data sources such as mobile phone data, satellite data and text data (e.g. text from Wikipedia articles or social media) to produce high-resolution poverty maps, even in the absence of a census (Rodríguez Castelán *et al.*, 2019). These methods are developing rapidly in the academic literature and are being adopted by international development agencies (see ADB, 2020; Engstrom & Newhouse, 2017; Hersh *et al.*, 2020; Masaki *et al.*, 2020; Pokhriyal *et al.*, 2020). The methods that have emerged so far can be classified in two broad categories: those that use a structural econometric model to predict poverty based on covariates derived from geospatial, phone and other data; and those that rely on machine learning techniques to predict poverty directly based on satellite imagery.

Steele *et al.* (2017) provide an example of the first approach, in which they explore the integration of environmental and mobile phone data for high-resolution poverty mapping. These types of data are complementary as they capture different aspects of human living conditions and behaviour and are generated at different spatial scales. The spatial resolution of mobile phone indicators is determined by tower coverage, which is larger in rural areas and fine-scaled in urban areas. By contrast, remote sensing data can be relatively coarse in urban areas and only capture physical properties of the land. The authors used overlapping sources of remote sensing, mobile phone and georeferenced household survey data from Bangladesh to accurately estimate three different measures of poverty. The estimation was performed through hierarchical Bayesian geostatistical models (BGMs). In the study, estimates were disaggregated by urban and rural regions, which further highlighted the importance of different data in different contexts. Night-time lights, transport time to the closest town, and elevation were important variables in models both at national and rural levels. Climate variables were also important in rural areas. Distances to roads and waterways were significant in both urban and rural strata. The mobile phone data produced accurate estimates in urban areas, which would not have been possible using remote sensing data alone.

Other examples of the econometric approach are found in Pokhriyal and Jacques (2017) and Njuguna and McSharry (2017). Unlike the previous studies, these studies relied on census data to obtain the MPI for small areas. Then the authors estimated different econometric models to predict the MPI based on geospatial and phone data. The main purpose of these applications was to generate high-resolution poverty maps for the periods between surveys.

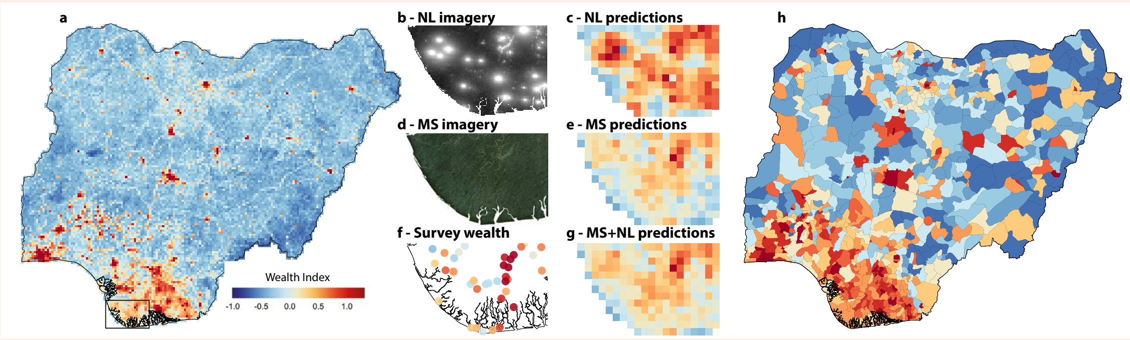
Yeh *et al.* (2020) offer an example of the approaches relying on machine learning. The authors use a machine learning model to predict an index of wealth across about 20 000 African villages from publicly available nightlight and daytime satellite imagery (see Figure 14 showing an example for Nigeria). In practice, a model is trained to predict village-level wealth from geolocalized DHS surveys based on daytime and nightlight satellite images. On average, the model explains 70 percent of the variation in ground-based wealth measurements in held-out country-years (i.e. countries and years that were not used to train the model). This means that the model is successful at predicting wealth at very high spatial resolution, even for countries for which neither survey nor census data is available. A similar exercise is presented in Lee and Braithwaite (2020), who produce a high-resolution poverty map of sub-Saharan Africa (excluding small island states).

▶ BOX 12 (CONT.)

Finally, some applications combine the two main approaches, using machine learning techniques to extract salient features from satellite images, which are then employed as covariates in structural econometric models. Examples of this approach are Ayush *et al*. (2020) and Pokhriyal *et al*. (2020).

▶ **FIGURE 14**

High-resolution map of wealth in Nigeria produced using satellite images and machine learning



Notes: **a** Satellite-based wealth estimates across Nigeria at pixel level. **b**, **d** Imagery inputs to model over region in Southern Nigeria depicted in box in **a**. **f** Ground truth input to model over the same region. **c**, **e**, **g** Model predictions with just nightlights (NL) as input, just multispectral (MS) imagery as input, and the concatenated NL and MS features as input. In this region, the model appears to rely more heavily on MS than NL inputs, ignoring light blooms from gas flares visible in **b**. **h** Deciles of satellite-based wealth index across Nigeria, population weighted using Global Human Settlement Layer population raster, and aggregated to Local Government Area level from the Database of Global Administrative Areas.

Source: Yeh *et al*., 2020.

3.3.4 Mapping the spatial patterns and determinants of poverty

As mentioned, poverty mapping can be used as a by-product to analyse various spatial patterns of poverty. In other words, identifying poverty across relatively fine spatial units makes it possible to conduct a number of analyses that can enhance the understanding of poverty and provide useful indications for rural poverty reduction interventions. The remainder of this section presents some possible approaches.

Identifying the geographical determinants of poverty through econometric analysis

This is the most straightforward application that is made possible by mapping poverty at finer geographical levels. Once a dataset of small areas with their associated poverty measures is constructed, various georeferenced variables can be used to estimate models through simple econometric techniques such as regressions. For example, GIS-based measures of travel time to markets and facilities have often proved to be important factors associated with poverty and food security outcomes at the small-area level (Hyman *et al*., 2005). If a poverty map was generated through an SAE method like ELL, it is important that the variables not be the same ones that were used for the imputation of poverty from the survey to the census. For example, if a variable representing soil quality is used (among other variables) to estimate poverty for small areas through the ELL technique, then it should not be used as explanatory variable in a model of the geographical determinants of poverty in which the poverty level estimated through ELL is used as dependent variable.

Exploring the geographical variation of the determinants of poverty: mapping explanatory variables

In addition to identifying geographical determinants of poverty, it is possible to complement the analysis by observing how these vary across different geographical spaces. A straightforward application is to generate maps of the covariates used in an econometric model and compare them with poverty maps. For example, Kristjanson *et al.* (2005) identified and mapped critical spatial factors grouped into natural, human, social, financial and physical capital assets for 120 sub-locations in a district of Kenya. In practice, they chose indicators based on the sustainable livelihoods framework, collated GIS-layers, generated covariates at sub-location level, conducted a regression analysis and finally mapped the average values of the covariates across the 120 locations. Erenstein *et al.* (2010) used a similar approach for the Indo-Gangetic Plain of India.

Exploring the geographical variation of the determinants of poverty: mapping the differential effects of explanatory variables

The effect of a certain factor on poverty, be it space-related or not, might be different across different geographic spaces. For example, in a region with unfavourable agroclimatic conditions, agricultural specialization could affect poverty negatively, while in a more favourable area, the opposite might be true. Geographically weighted regression (GWR) is a tool that can help observe these patterns. It is a technique used to develop local models and thus estimate local regression coefficients (with the associated measure of error) for each spatial unit considered in the analysis. Box 13 provides examples of studies using GWR.

Spatial autocorrelation and clusters of poverty

The level of welfare in a given geographic space does not depend only on its geographic characteristics and the features of its inhabitants. High levels of welfare in a given area usually have spillover effects in surrounding areas. This occurs, in part, through the diffusion of innovations, social capital, trade and economies of scale. At the same time, poor areas tend to be surrounded by areas that are also poor. This phenomenon, defined as spatial autocorrelation,[47] can be analysed by treating location as a variable in econometric analysis. Broadly speaking, these analyses are concerned with determining the degree to which poverty outcomes in a spatial unit are associated with having high or low levels of poverty in neighbouring units (Hyman *et al.*, 2005). An example is provided in Amarasinghe *et al.* (2005) where the authors investigate the extent and the factors associated with spatial clustering of poverty across small areas in Sri Lanka.

[47] Spatial autocorrelation is one of the main complexities of SAE (Coulombe and Wodon, 2007) which, if not properly controlled for, can substantially decrease precision. Recently, specific techniques have been developed to better control spatial autocorrelation in SAE. For example, see Pratesi (2015).

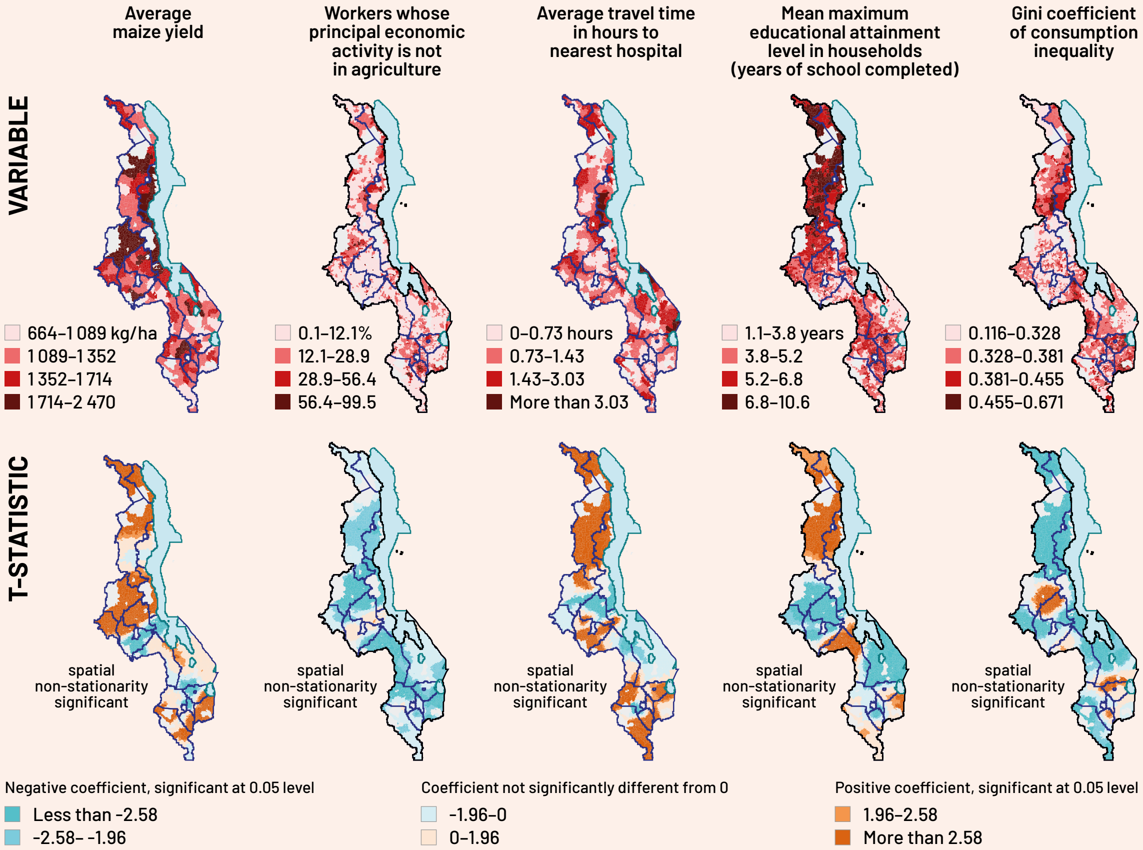
▶ BOX 13

Geographically weighted regression (GWR)

Benson *et al.* (2005) used this technique to estimate the differential effects that a number of variables related to agro-ecological conditions, natural hazards, agricultural characteristics, access to services and demography have on poverty across 3 004 rural enumeration areas in Malawi. (Poverty was estimated in an earlier step using ELL.) Upon mapping the sign and statistical significance of the local coefficients (lower part of Figure 15), they obtained some counterintuitive results. For example, in some areas of the country, education has a positive and significant correlation with poverty. Overall, their analysis shows that the determinants of poverty vary in their effects across rural Malawi. The approach represents an opportunity to tailor the design of rural poverty reduction interventions to local circumstances. For a similar exercise in Bangladesh see Kam *et al.* (2005).

▶ FIGURE 15

Maps of selected independent variables and associated t-statistics from geographically weighted regression



Source: Benson *et al.*, 2005.

Farmers after the cabbage harvest in in Northen Sierra Leone.

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4

TARGETING FOR RURAL POVERTY-REDUCTION INTERVENTIONS

The ultimate goal of poverty analysis is to facilitate policies and programmes that effectively reach those who need them the most. Once poverty profiling has been conducted on the basis of one or more poverty measures, targeting is a natural third step in the poverty-analysis process. This third step is critical to ensure that key stakeholders in the poverty-reduction quest, such as programme designers or policy-makers, can effectively identify the poor and reach them. This chapter discusses narrow targeting mechanisms, which are most useful for interventions on the ground. It describes: (i) the advantages and disadvantages of targeted interventions vs universal interventions; (ii) the characteristics of several targeting mechanisms; and (iii) the different steps of the targeting process in the context of programmes and projects. As in the previous chapters, the discussion pays particular attention to the specificities of operating in rural areas and gives constant attention to development interventions in the areas of food, agriculture and rural development.

4.1 INTRODUCTION

Targeting seeks to ensure that a development intervention reaches specific groups of a population in need of assistance. In the context of rural poverty reduction interventions, targeting can be thought of as the process of allocating the resources of a strategy, programme or project to the poor, through **broad targeting** or **narrow targeting** (Van De Walle, 1998). Broad targeting consists of concentrating resources in sectors that are more relevant to the poor. For example, investing in the agriculture sector might be considered, at least in the short run, more beneficial to the poor than investing in technologically advanced manufacturing sectors because, while a substantial share of the poor work in agriculture, relatively few poor people can access employment in technology-intensive economic activities. Narrow targeting, on the other hand, refers to allocating the benefits of an intervention directly to the poor. This chapter focuses on narrow targeting.

Targeting is implemented through **targeting mechanisms**: a set of rules to define the regions, areas, households or individuals that will be eligible to receive the benefits of a certain intervention. These rules are decided upon in the attempt to reach one or more **target groups** that have been previously identified. Poverty analysis plays an important role in defining target groups because these should be identified after measuring and characterizing poverty in a given context. Target groups can be identified across various dimensions, such as poverty status, sociodemographic characteristics and geography.

Let us consider a situation in which a government is committed to reducing rural poverty. After observing that the level of poverty in rural areas is very high, and given that resources are limited, the government decides to focus its strategy on the poorest of the poor. A poverty profile is developed to analyse the characteristics of the rural extreme poor. The results show that, although the rural extreme poor strongly rely on agriculture, they also present very low productivity. It is further observed that most of the extreme poor who engage in agriculture can be divided in two groups: those who live in arid areas and rely on a crop–livestock farming system, and those who live in plains areas vulnerable to floods and who focus on a single crop. Based on this information, the government decides to design a poverty reduction programme that seeks to boost productivity through the promotion of improved agricultural practices and to adapt the programme according to the needs of the two groups. After broadly defining the content of the programme (e.g. components and type of activities), the government will need to determine who will actually benefit from the intervention. To do this, a targeting mechanism will need to be established through which the abstract target groups identified through the profiling (extremely poor farmers living in arid areas and extremely poor farmers living in plains areas) will actually be identified on the ground.

Although targeting refers to identifying who should benefit from an intervention, programme implementers will not necessarily identify beneficiaries one by one. In fact, **targeting can occur at different levels of detail**. Common levels used for targeting are geography, communities, households and individuals. The more an intervention seeks to benefit individual beneficiaries, the finer the targeting. However, not all types of interventions can be targeted to the same level of detail. For some interventions, benefits can be allocated anywhere from the individual level through the level of geographic areas. For other interventions, this is not an option because it is not possible (or desirable) to exclude non-poor individuals and households from the benefits of the intervention. An example is the provision of rural roads. Moreover, interventions usually comprise different components and activities that can be targeted to different levels.

The extent and detail to which an intervention (or a component of an intervention) can be targeted mainly depends on whether it deals directly with individual beneficiaries and on the type of benefit that it delivers. Interventions that can be finely targeted include forms of social assistance (e.g. cash transfers, food distribution and public work programmes), distribution of agricultural inputs and assets, provision of agricultural advisory and extension services, microcredit, and various forms training. These types of interventions deliver private goods that can be allocated to specific individuals. Some interventions, however, that also provide private goods, offer them to all the individuals within an organization or institution for practical reasons. Examples of these are school feeding programmes and value chain interventions offering benefits to all the members of producer organizations (e.g. extension services or matching grants for purchasing machinery).

Some types of interventions can only be targeted at a lower level of detail. For example, infrastructure development (e.g. irrigation schemes or rural roads) and natural resource conservation interventions can target poor areas or communities, but hardly individuals. Finally, interventions that deliver public goods cannot be narrowly targeted. These include sectoral investments (e.g. agricultural technology innovations), institutional value chain interventions (e.g. the development of a new grading system for a certain commodity)[48] and public-institution strengthening. These types of interventions can be targeted broadly, selecting the sectors, products and institutions that are more relevant to the poor. For example, agricultural innovations (e.g. new crop varieties, farming techniques or water management technologies) can be developed responding to the needs and constraints of poor farmers.

This chapter is organized as follows: Section 4.2 presents an overview of the main challenges associated with targeting and a brief discussion of the advantages and disadvantages of targeted interventions vs universal interventions. Section 4.3 focuses on describing the characteristics and exemplifying the operation of several alternative targeting mechanisms. Section 4.4 closes the chapter with a discussion on the different aspects of the targeting process that should be taken into account at the time of choosing and implementing one or more targeting mechanisms.

4.2 THE CHALLENGES OF TARGETING

Where resources are limited, which is particularly the case in low- and middle-income countries, well-designed targeting can help maximize the poverty reducing impact of a given budget. In other words, **targeting helps do more with less**. Furthermore, targeting can also be seen as a matter of fairness. Where resources are scarce, it might be considered fair that those who are more in need receive more assistance.

Even though the argument for targeting is straightforward from a theoretical perspective, it presents multiple challenges in practice because of the **problem of insufficient information**. On the ground, those designing and implementing an intervention may not be able to accurately identify who is poor. As explained in Chapter 2, identifying the poor requires information that might not always be readily available. Even when information is available, it might be subject to errors of measurement. All these problems are particularly acute in rural areas, where insufficient information (due to underrepresentation of rural populations in surveys and administrative records) and weak administrative capacities are more common than in urban areas.

[48] According to FAO (1997), a grading system "accurately describes products in a uniform and meaningful manner [...] contributes to operational and pricing efficiency by providing buyers and sellers with a system of communicating price and product information."

The fact that the poor cannot be perfectly identified exposes the targeting process to two types of errors (Cornia and Stewart, 1993). In the context of an intervention that targets the poor, **exclusion errors** – omitting individuals or households that are poor and should have been reached by the intervention – translate into a problem of undercoverage. On the other hand, inclusion errors – selecting individuals or households who are not poor – result in leakage or wasting an intervention's resources. Both types of errors must be minimized to enhance the **accuracy of targeting**. In practice, though, there is a trade-off between the two (Lavallée *et al.*, 2010). In order to reduce exclusion errors, interventions can increase coverage. However, this usually comes at the expense of controlling leakage to the non-poor. Conversely, trying to minimize inclusion errors usually comes at the expense of accurately including all the poor.

Reducing targeting errors requires collecting more information. However, searching for information can be costly. In general, the finer the targeting approach and the more information needed, the higher the financial cost of targeting (Besley and Kanbur, 1991). Costs are both public and private. **Public costs** are those borne by the administrators of the intervention. These include the costs of surveying a population to determine who is eligible for a programme and the costs of verifying declarations made by applicants. Public costs are of great concern because they can reduce the share of an intervention's budget that actually reaches beneficiaries. On the other hand, **private costs** are those borne by the beneficiaries. These include, for example, the costs involved in obtaining documents to demonstrate eligibility or traveling to a public office to apply for a programme. These private costs are a concern as well as they might discourage eligible people from participating in an intervention and could reduce the net benefit of participating, thus reducing the poverty-reduction impact of the intervention (Coady and Parker, 2009).

Another inefficiency emerges when the eligibility criteria established for an intervention **incentivizes potential beneficiaries to change their behaviour** in order to meet that criteria. This is of particular concern if the selection criteria are based on the development outcome that an intervention aims to improve (e.g. consumption or income). For example, it is often hypothesized that making transfers to the poor might incentivize them to work less in order to be eligible for the programme.[49] In general, this issue is of greater concern in interventions that provide repeated benefits, in which beneficiaries' eligibility is assessed multiple times and people have the opportunity to learn and adapt their behaviour to an intervention's eligibility criteria.

Even though concentrating resources on those who are most in need might be conceived as fair in many societies, **choosing who should benefit from an intervention is never a neutral decision**. For example, governments that implement or finance interventions might be reluctant to exclude people from the interventions for fear of losing their support. In fact, targeting the poor might translate into losing the support of the majority (Lavallée *et al.*, 2010) and making an intervention **politically unsustainable**. This means that, in some cases, a certain level of inclusion errors might be necessary in order to gain support for a poverty reduction intervention (Pritchett, 2005).

Targeting decisions might also cause **negative consequences within communities**, such as deteriorating community cohesiveness and eroding informal support networks (Devereux et al., 2015). For example, Handa and Davis (2006) find that, in the context of the Mexican conditional cash transfer[50] programme, *Progresa*, narrow targeting in communities with high poverty levels can lead to social conflict. Another negative social consequence that is often mentioned in literature is the **stigmatization** of beneficiaries (Devereux *et al.*, 2015).

[49] However, evidence on this is ambivalent and points at the fact that concerns for labour-supply distortions of social assistance tend to be exaggerated (Gentilini *et al.*, 2019).
[50] Conditional cash transfers (CCT) are a type of cash transfer scheme whereby beneficiaries are required to complete particular actions or meet particular conditions (attending a training or adopting certain agricultural practices) before receiving their assigned cash transfer.

As a consequence of these challenges, interest has grown in recent years in the use of universal policies as a tool to reduce poverty, such as universal basic income proposals (see Gentilini *et al.*, 2019). Universalism refers to providing (or at least offering) benefits, in equal amounts, to the entire population (irrespective of the fact that some individuals may not take or demand them). Typical examples of universal policies are education and health services, which some countries offer all citizens free of charge.

Universalism is considered to solve, or at least alleviate, many of the problems related to targeting. By considering everyone eligible for a certain benefit, universal programmes, by definition, avoid inclusion and exclusion errors.[51] Universalism also minimizes the public and private costs needed to identify beneficiaries. By benefitting everyone, universalism might gain stronger political support, reduce the scope for patronage (i.e. directing benefits to certain groups for political interest), reduce conflicts in society, and avoid stigmatization effects. As universal programmes create legal obligations on the part of governments, beneficiaries do not have an incentive to alter their behaviour (e.g. work less) in order to receive the benefit, and might enjoy psychological benefits due to reduced uncertainty (Gentilini *et al.*, 2019).

Universal approaches are certainly attractive. Nevertheless, **under the assumption of a fixed budget, universal approaches cannot be as pro-poor as targeting approaches**. If the resources for an intervention are fixed, universalism means that a part of the budget that could have been given to the poor is given to the non-poor. Clearly, this lowers the poverty-reduction effect of the intervention. In order for a universal approach to achieve the same poverty-reduction effect as a targeted approach, the amount of benefits delivered to everyone would need to be increased, which is likely to be financially unsustainable in most low- and middle-income countries. For example, Gentilini et al. (2019) calculate that if a universal basic income was given in an amount sufficient to eradicate poverty, it would cost between 36 and 48 percent of the national gross domestic product (GDP) in Haiti, Mozambique and Nepal, all three of which are low-income countries. In addition, some countries might not be administratively capable of delivering a programme to everyone.

It is also worth noting that few interventions can be truly universal. An intervention can be considered universal to the extent that it benefits all the people who can technically benefit from it. For example, old-age pensions are universal to the extent that they cover all the elderly, irrespective of other characteristics. Agricultural input subsidies are universal if they cover all farmers, irrespective of the characteristics of their land and farming system. For this reason, universalism is a more useful concept if conceived from the point of view of a country's overall system of social policies, guaranteeing everyone a minimum level of welfare, through differentiated interventions (Gentilini *et al.*, 2019).

With respect to the types of interventions implemented by FAO and other development partners that work to foster rural development and reduce hunger, poverty and the unsustainable use of natural resources, whether to target or provide universal benefits is usually not a choice. These interventions tend to have a relatively limited scale and sectoral specialization, such that the real decision refers to the extent, level of detail and modalities of the targeting process. This decision will inevitably depend on the type of intervention and the context. Nevertheless, the choice between different targeting mechanisms might affect the extent to which an intervention of FAO or its partners will be able to reach its intended target group and achieve the desired poverty-reduction impact. When assessing different targeting options, it might be useful to consider that a continuum of solutions exists between pure universalism and the finest level of narrow

[51] From a poverty targeting perspective, however, this is equal to eliminating exclusion errors, while maximizing inclusion errors.

targeting (i.e. selecting beneficiaries one-by-one), and that the art of the decision lies in finding the optimal balance between the trade-offs presented by the two concepts. For example, Ravallion (2019) suggests that, in some settings, the costs of fine targeting might exceed its benefits and, therefore, less efforts at fine targeting might be more effective in reducing poverty.

4.3 TARGETING MECHANISMS

As mentioned before, a targeting mechanism refers to the set of criteria and rules used to define who is eligible to participate in or receive the benefits of an intervention. Choosing an appropriate targeting mechanism during the intervention's design and implementation phases is of crucial importance to maximize its poverty-reduction impact. In most cases, successful targeting involves combining two or more targeting mechanisms.

The next sections describe the characteristics of several alternative targeting mechanisms. All of them have advantages and disadvantages and can be more or less appropriate in relation to different circumstances. The advantages and disadvantages of each mechanism will be reviewed keeping in mind the challenges of targeting that were introduced in the previous section. These are:

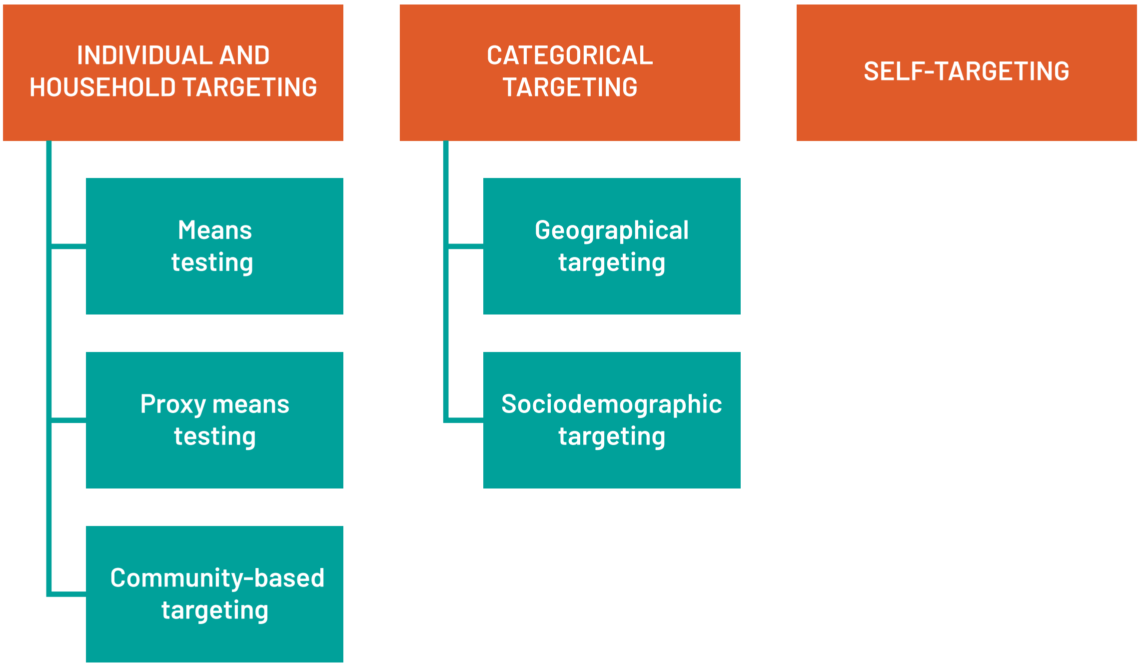
- effectiveness in terms of reaching the poor;
- administrative capacity, information requirements and administrative and private costs;
- potential distortions of incentives;
- political sustainability;
- social acceptance and psychological costs.

4.3.1 Classification of targeting methods and mechanisms

Targeting mechanisms fall into three main types (Coady *et al.*, 2004). In **individual and household targeting**, the project implementer verifies, unit by unit, if an individual or household complies with the eligibility criteria to participate in the intervention. In the context of a poverty reduction intervention, the main criterion to assess is the poverty status of the individual or household. Individual targeting can be done through three mechanisms: means testing, proxy means testing and community-based targeting. **Categorical targeting** refers to mechanisms in which all the individuals who belong to a certain category or population group, which should be easy to verify, are considered eligible. Categorical targeting includes geographical and sociodemographic targeting, in which all the individuals who live in a certain area or have certain demographic characteristics are considered eligible. Finally, **self-targeting** is a special method in which, theoretically, everyone is considered eligible even though the intervention is designed in such a way that only the target group will want to participate or benefit.

The following sections explain the targeting mechanisms of the first two methods as well as self-targeting, which is both a method and a targeting mechanism.

FIGURE 16
Targeting methods and mechanisms



Source: Adapted from Coady *et al.*, 2004.

4.3.2 Individual and household targeting

Means testing

Means testing is a mechanism in which a programme or project official directly assesses the eligibility of each individual or household for an intervention. There are different ways to implement this mechanism but, in all cases, an official collects information on household welfare and defines eligibility by comparing the value of welfare-related variables with eligibility thresholds for those variables. In the context of poverty-reduction interventions, and in particular those that offer social assistance, the threshold is typically set in terms of income. In this sense, means testing resembles the process of identifying the monetary poor, explained in Chapter 2. Means testing based on income is used mostly for cash transfer programmes (Coady *et al.*, 2004). However, thresholds can also be set in terms of other welfare variables, such as land size, the typical variable in agriculture-based poverty reduction interventions.[52]

As mentioned, there are different ways in which means testing can be implemented (Coady *et al.*, 2004). Officials might visit potential beneficiaries at their homes to collect the necessary information, or potential beneficiaries might visit a public office to provide the information. The information provided might have to be verified through third-party certifications (e.g. tax records or employee statements), by self-provided supporting documentation, or simply through an interview. These variations imply different targeting performance and costs.

[52] See Ravallion *et al.* (1994) for a critical review of land-based poverty targeting.

Effectiveness in terms of reaching the poor

Among targeting mechanisms, means testing has the highest potential for minimizing targeting errors. This is because poverty status can be directly used as the eligibility criterion and because a program/project official verifies the information provided by potential beneficiaries. Nevertheless, targeting effectiveness depends greatly on the specific way in which means testing is implemented and, in particular, the extent to which officials check the accuracy of potential beneficiaries' statements (Lavallée *et al.*, 2010). The more thorough the check, the lower the scope for inclusion errors. (Verification does not affect exclusion errors as potential beneficiaries are unlikely to overstate their welfare status.) However, despite its potential targeting efficiency, means testing has often proved to lead to high inclusion and exclusion errors in social transfer programmes (Devereux *et al.*, 2015). Exclusion errors can be due to the poor not applying because of the difficulties related to gathering the requested documentation. As explained by Coady *et al.* (2004), in low-income countries, requesting documents (not only income-related) might be an effective way to exclude the non-poor, but it is usually not an effective way to include the poor.

Administrative capacity, information requirements, and administrative and private costs

Consistent with the general idea that there is a trade-off between targeting accuracy and costs (Besley and Kanbur, 1991), means testing is regarded as the most expensive targeting mechanism (Devereux *et al.*, 2015). Again, the administrative requirements and the associated costs depend on the accuracy of the verification mechanism. Furthermore, means testing is demanding for programme administrators, who have to collect and process complex information, and for participants, who might need to produce documentation or proof of their statements. In the context of developing countries, especially in rural areas, verifying welfare information through documentation might be impossible due to the informality of the economy. Documentation aside, measuring income (or consumption) is, in its own right, a particularly challenging endeavour, as explained in Chapter 2. Covering multiple income sources and quantifying in-kind incomes requires qualified administrative personnel and a certain level of literacy among respondents. In addition, incentives to understate income are high.

Potential distortion of incentives

Apart from the risk of potential participants deliberately manipulating welfare declarations in order to meet eligibility requirements, means testing might incentivize participants to change their behaviour or intentionally alter their welfare conditions in order to meet such requirements, for example by working less or reducing their savings. This might undermine the effectiveness of a programme, especially when means testing involves eligibility criteria based on outcomes that the programme aims to improve (income or nutrition, for example). Conditioning programme benefits on certain behavioural requirements, such as actively looking for a job, taking care of children, etc. (as is the case with conditional cash transfer programmes), might mitigate the issue, although it imposes even more demanding monitoring requirements.

Political sustainability

Compared to the targeting mechanisms of the categorical targeting method, means testing, as well as the other individual and household targeting mechanisms presented in the reminder of this section (proxy means testing and community-based targeting), might generate more political resistance (Devereux *et al.*, 2015). This could be particularly the case when the government – rather than a non-governmental organization (NGO) or an international development institution – is financing and implementing the intervention. In general, it appears to be more politically acceptable to target groups such as children and the elderly, than to target the poor. This is partly because poverty is not a clearly observable characteristic, as are sex and age, and this creates scope for disagreement regarding who should be considered poor. In addition, there are often disagreements on the causes of poverty and on whether the poor deserve public assistance financed through the resources of the non-poor. From a different perspective, means testing could increase political support if the intervention is financed through local resources, given that a strict verification of eligibility criteria might be seen favourably by taxpayers, as it represents a way to prevent public resources leaking to the "undeserving".

Social acceptance and psychological costs

The social acceptance of mean testing is somewhat ambiguous (Coady *et al.*, 2004). From the point of view of potential beneficiaries, a thorough verification of eligibility criteria might represent an intrusion into someone's life. However, a clear eligibility criterion can help make beneficiary selection more acceptable within communities. From an individual point of view, means testing requires somebody to self-identify as poor. This might have more negative psychological consequences compared to categorical methods.

Box 14 provides an overview of the largest-scale application of means testing to a social programme in a developing country. It also illustrates how, thanks to social registries, the mechanism can be extended to target rural development programmes to the poor.

▶ **BOX 14**

Means testing for targeting social protection and productive inclusion programmes: the case of Brazil

Bolsa Família (Family Grant) is a conditional cash transfer programme focused on health and education, which benefits families whose self-reported income is below a certain threshold. This feature makes *Bolsa Família* the most known programme using means testing in a developing economy. Implemented by the government of Brazil since 2003, it benefits about 14 million families that have been targeted through means testing. The amount of the benefit varies based on whether households are classified as poor or extremely poor, and depending on the number of children, pregnant or lactating women, and youth.

In order to qualify for *Bolsa Família*, families must be enrolled in the Federal Government's Single Registry of Social Programmes. This registry, known as the *Cadastro Único*, collects information on low-income families and is used to target all federal programmes directed at the poor. Enrolment in the *Cadastro Único* occurs in three stages. First, potential households are identified. In most cases, households spontaneously report to a municipal office to register. However, the municipalities can also conduct active searches and visit potential households. In 2014, about 6 percent of the registrations were carried out in this way (Hellmann, 2015). In the second stage, a municipal official interviews the households. The information provided, including household income, is self-declared and the official is responsible for accepting it or not. Finally, the information is digitized in the *Cadastro Único* system. Municipalities are responsible for updating the record of each household every two years. ▼

▶ BOX 14 (CONT.)

Once a household is registered in the *Cadastro Único*, it qualifies for *Bolsa Família* if its per capita income is below a certain threshold. The selection of beneficiaries is an automated, impersonal process operated by federal authorities. Although income information is self-declared, some verification of the means-testing mechanism is conducted in the form of audits carried out by municipal and federal authorities to prevent improper receipt of benefits. The targeting performance of *Bolsa Família* is considered to be relatively good, compared to similar programmes in Brazil and other Latin American countries (Soares, Ribas and Soares, 2010). However, Barros *et al*. (2008) argue that most of the positive targeting performance of *Bolsa Família* is due to the self-selection implied by the registration process in the *Cadastro Único*, rather than by the means testing itself.

Since 2011, *Bolsa Família* was integrated in the plan *Brasil Sem Miséria* (Brazil Without Extreme Poverty), which was articulated along three dimensions: (1) an income guarantee, (2) access to public services, and (3) productive inclusion. Within the area of productive inclusion, the *Programa Fomento às Atividades Produtivas Rurais* (Promotion of Rural Productive Activities Programme) was targeted at extremely poor family farmers and Indigenous peoples. The programme aimed to expand agricultural and non-agricultural work opportunities for beneficiary households and to increase their skills, productivity and participation in rural organizations. The main actions of the programme consisted in providing extension services and grants for small productive projects.

The selection of extremely poor family farmers was made by crossing the income information from the *Cadastro Único* (hence relying on means testing) with a different registry, the *Declaração de Aptidão ao Pronaf* (Statement of Qualification), or DAP, which is used to qualify "family farmers" and "family rural entrepreneurs" in Brazil. The DAP collects detailed information regarding household and farm characteristics and is used to target a number of public programmes supporting rural family production units and their organizations. The conditions to qualify as family farmers include that: (i) the rural property not exceed a certain size; (ii) the labour used in the rural activities is predominantly family based; (iii) the share of family income that is generated by the activities linked to the rural property exceeds a certain threshold; and (iv) the activity is directly managed by the family.

This example shows that means testing can be successfully used to target poverty reduction programmes even without strong verification mechanisms. However, means testing for *Bolsa Família* still required a large and integrated information system that lower-income countries might not have the capacity to set up and manage. The example also shows that integrated information systems offer opportunities for extending poverty-based targeting mechanisms (such as means testing) from social protection to rural development interventions, as well as creating space for synergies between these two types of poverty-reduction programmes.

Sources: Barros *et al*., 2008; FAO and IFAD, 2017; Hellmann, 2015; MDS and MDA, 2011; Paes Herrera *et al*., 2017; Soares *et al*., 2010; Swensson, 2015.

Proxy means testing

Proxy means testing (PMT) was developed to overcome the challenges of collecting information on household income or consumption in developing countries (Coady *et al.*, 2004). With PMT each potential beneficiary has an associated welfare score, which is calculated based on certain observable characteristics of the beneficiary, using a formula. Eligibility is defined by comparing the welfare score with a cut-off value. As the main point of this targeting mechanisms is to simplify and lighten the administrative burden of means testing, a limited number of characteristics should be used to calculate the score. In addition, it is important that the characteristics be strongly correlated with poverty, easily observable (i.e. not requiring documentation to verify them), and hard to manipulate by potential beneficiaries (Coady *et al.*, 2004). Typical variables include quality of the dwelling, ownership of assets, sociodemographic characteristics and place of residence. There are different approaches to calculating the score. These can be divided into two broad categories: **multidimensional index-based approaches** and **monetary econometrics-based approaches**.

The **multidimensional index-based approaches** are related to the multidimensional approach to poverty measurement, introduced in Chapter 2. Essentially, a number of poverty-related characteristics are combined to produce an index or score using weights, which are fixed arbitrarily. An advantage of using this type of PMT approach is that the weights can be set to reflect the specific priorities of an intervention.[53]

Monetary econometrics-based approaches can be considered imputation techniques and, as such, resemble SAE, explained in Chapter 3. The first step of econometrics-based PMT approaches is to use an existing household survey (usually a nationally representative survey conducted by the national statistical office) to estimate the association between income or consumption and a number of "easy-to-observe" explanatory variables (e.g. quality of dwelling and place of residence). Subsequently, a brief household questionnaire is administered to potential beneficiaries to collect information on the explanatory variables. As is the case in means testing, for PMT, this can be done in a census fashion (with programme officials visiting all potential beneficiaries) or information can be collected only on applicants. Finally, for each potential beneficiary, the observed variables are multiplied by the coefficients estimated in the first step and added to obtain the PMT score.

Effectiveness in terms of reaching the poor

As with means testing, in theory, PMT can help minimize targeting errors and achieve higher poverty-reduction effects, compared to the targeting mechanisms in the categorical method. In practice, however, targeting performance can vary considerably depending on a number of factors.

First, it must be possible to identify variables that are good indicators or proxies of poverty and that are easy to observe on the ground, which is not always the case (Coady *et al.*, 2004; Brown *et al.*, 2018). Secondly, the appropriateness of the index (in multidimensional index-based approaches) or the quality of the model used to produce the formula (in monetary econometrics-based approaches) is essential to accurately identify who is poor. In the case of econometric approaches, standard linear regression (i.e. ordinary least squares, or OLS) does not predict well at the extremes of the income distribution. It tends to overestimate the income of the very poor and underestimate that of the better off. Thus, standard linear regression is not adequate for targeting the extreme

[53] For example, Azevedo and Robles (2013) simulate the targeting performance of Mexico's conditional cash transfer programme *Oportunidades* (Opportunities), using both an ad hoc multidimensional poverty index and an income-based PMT. They conclude that, beyond reducing inclusion and exclusion errors, the multidimensional method identifies a group of beneficiaries that is more relevant to the objectives of the programme, compared to the income-based approach.

poor.[54] In addition, even if it is possible to identify a model with high predictive power, the model might not be robust at predicting poverty (and thus at reducing targeting errors) everywhere and for every subgroup of the population.

The issue of possible lack of robustness in different locations and within different subgroups is basically a problem of out-of-sample validity, a concept that refers to whether a model estimated using a certain sample has the same prediction performance when applied to a different sample.[55] For example, at the national level, land size might be a good predictor of income. But this might not be the case in an arid area of the country where land is unproductive. For this reason, different PMT formulas should be developed for different areas of the country and, in particular, for rural and urban areas (Coady *et al.*, 2004; Skoufias *et al.*, 2020). Even more, if an intervention targets a specific subgroup of the population (e.g. farmers), the model should be calibrated on that subgroup. Although this terminology refers to econometrics-based approaches, the same logic can be extended to multidimensional index-based PMT approaches. The dimensions and indicators of a multidimensional poverty index that are relevant in a certain context might not be as relevant elsewhere. This is the rationality behind the development of the R-MPI introduced in Chapter 2.

Apart from the methodological aspects, misclassification of the poor (in monetary terms), and thus targeting errors, can also occur because the variables typically used in PMT indexes or formulas might not reflect short-term income changes. Variables such as dwelling type and asset ownership might be good proxies of past income flows, but not necessarily good indicators of present income levels (Brown *et al.*, 2018). For this reason, it has been argued that PMT should be used to identify chronic poor in the context of longer-term interventions, while it might not be adequate for programmes delivering short-term benefits such as postemergency relief or public work (Brown *et al.*, 2018). From a more operational perspective, the targeting performance of interventions that provide regular benefits (e.g. cash transfers, subsidies for basic services, and so forth) also depends on whether and how often beneficiary information is updated.

Administrative capacity, information requirements, and administrative and private costs

Compared to means testing, PMT requires a stronger administrative effort upstream, to develop the formula, but lower effort to collect information on the ground. Developing the formula requires substantial technical capacity but is an activity that can be easily outsourced. For monetary econometric-based approaches, cost will depend on whether a suitable household income and expenditure survey already exists. On the ground, costs will partly depend on the complexity of the scoring system. The more complex the scoring system, the more programme or project officials will need specific training (Coady *et al.*, 2004). As is also the case in means testing, administrative costs for PMT will depend on whether officials have to visit potential beneficiaries at home. In terms of private costs, PMT is generally considered less burdensome than means testing, although that depends on the amount of information requested from the beneficiaries and the extent to which the information must be demonstrated.

[54] Brown *et al.* (2018) advise using a more sophisticated "poverty-quintile regression" to increase the performance of PMT in terms of poverty impact. In general, the predicted welfare of a household is usually characterized by substantial uncertainty when using regression-based approaches. In these cases, it is advisable, therefore, to prioritize the avoidance of exclusion errors by deeming eligible those households that, although their level of predicted welfare is above the poverty line, have a substantial probability of being poor. For example, in the Nicaraguan programme *Red de Protección Social* (Social Protection Network), all households with a predicted probability of being extremely poor above 10 percent were considered eligible (Maluccio, 2009).

[55] McBride and Nichols (2016) stress the importance of prioritizing out-of-sample prediction when calibrating the PMT and propose two methods based on machine learning techniques.

Potential distortions of incentives

Compared to means testing, another advantage of PMT is that it offers less scope for negative behavioural responses, such as reducing work effort. As mentioned before, the variables used for the scoring system should be difficult to manipulate. However, it is still possible for individuals who are aware of the scoring system to try to qualify for an intervention by selling or concealing assets. This can happen when the index or formula is made public. These negative consequences can be reduced by keeping the index or formula confidential.

Political sustainability

Overall, PMT and means testing share the same political sustainability considerations. Targeting the poor directly might generate more political resistance than more universal or categorical approaches. However, thanks to its rigid quantitative approach, PMT might be less subject to political manipulation (patronage) at the local level. Risks of resources being diverted to the non-poor for political interest might occur when eligibility criteria are not well defined and local administrators can apply them more discretionarily. PMT helps reduce this risk (Devereux *et al.*, 2015).

Social acceptance and psychological costs

Although keeping the scoring system confidential presents some advantages, it also has an important drawback: it makes beneficiary selection less transparent, which might reduce an intervention's social acceptability and, in the worst case, induce conflict within communities (Adato, 2000; Handa and Davis, 2006). Kidd *et al.* (2017) mention qualitative evidence that, within communities, PMT mechanisms are often perceived as lotteries. The problem is particularly serious in settings where poverty is high and the mechanism produces large inclusion and exclusion errors (Kuhn, 2018). For excluded poor people, it will be hard to accept that non-poor people have been included on the basis of criteria they do not know or understand.

Box 15 provides an example of how PMT can be used in interventions with poverty-reduction and natural resource-management objectives.

BOX 15

Using PMT in a poverty-reduction programme with multiple objectives

Poverty, Reforestation, Energy and Climate Change (PROEZA) is a USD 90 million project developed by FAO and the Government of Paraguay and cofinanced with a USD 25 million grant from the Green Climate Fund (GCF). The objective of this 5-year project is to improve the resilience of about 17 000 poor households to climate change, through risk-informed social protection, while combating deforestation and mitigating greenhouse gas emissions. The project was approved in March 2018 and implementation began in January 2020.

The project is implemented in 64 municipal districts in eight departments of eastern Paraguay. The departments were selected due to their high environmental and social vulnerability.

The geographical targeting exercise was based on a background study conducted by the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation, or UN-REDD, (Walcott *et al.*, 2015) taking into account statistics regarding carbon density in biomass, poverty levels, risk of future deforestation and proximity to wood-consuming industries. Given that poor rural households in the project area are highly dependent on their natural environment for energy and food security, the first component of PROEZA (about 40 percent of the total budget) provides technical and financial support to establish agroforestry systems and forest plantations, or manage natural forest regeneration. To support beneficiary households in adopting new income diversification strategies, PROEZA also provides a cash top-up, complementing that of *Tekoporã*, a public conditional cash transfer scheme with health and education objectives, which is received by most households in the project area. The cash top-up is provided during the period required for agroforestry production to become financially sustainable. Payments are conditional on the successful establishment and care of the agroforestry production systems promoted by the project.

Poor and extremely poor beneficiaries of *Tekoporã* are identified through a roster generated by the *Ficha Social*, which is the official government database used for targeting social protection programmes. The data for this roster are collected door to door. The roster includes household information on a number of variables including demographic, education, dwelling, health, employment and agricultural production characteristics. Based on this data, a PMT determines whether a household is poor (or extremely poor). Households are eligible for *Tekoporã* if they are classified as poor according to the PMT and if they have children or youth (up to 18 years old), pregnant women, people with disabilities, or belong to indigenous communities.

Due to a relatively limited budget, but also to the technical features of the project, not all poor households can benefit from PROEZA. Several criteria are used to prioritize potential beneficiaries among those already receiving *Tekoporã* within the geographically targeted areas of the project. These include: (i) living in a zone at highest risk of deforestation and land degradation; (ii) being a women-headed and/or indigenous household; (iii) having at least 0.8 hectares of suitable land available; (iv) having occupied land peacefully and being interested in starting a titling process; and (v) having sufficient household labour and interest to participate in the training and cultivation activities.

▶ **BOX 15 (CONT.)**

The case of PROEZA shows that targeting the poor can also occur in projects with objectives other than poverty reduction (i.e. landscape restoration and reforestation) and that are primarily designed and targeted based on landscape features. The example also demonstrates that while it might not be cost effective to develop a PMT mechanism for targeting a single project, it might be possible to exploit synergies with already existing targeting information systems. In particular, this example highlights the crucial importance of integrated social registries (i.e. national databases that are used to target social programmes). The example also shows that, beyond "pure" cash transfer schemes, poverty status is rarely the only eligibility criterion for targeting a poverty reduction intervention. Finally, PROEZA exemplifies a typical case of combining multiple targeting mechanisms. In this case, PMT was used together with geographical targeting and sociodemographic targeting.

Sources: GCF, 2018; Secretaría Técnica de Planificación del Desarollo Económico y Social, 2018; Walcott *et al.*, 2015.

Community-based targeting

Community-based targeting (CBT) is a mechanism through which beneficiaries are selected by community leaders or by a group of community members (Coady *et al.*, 2004). It can also be used to validate the identification of beneficiaries made through other mechanisms. It is important to distinguish between **delegated community-based targeting**, whereby communities identify beneficiaries based on criteria predefined by administrators, and **devolved community-based targeting**, in which communities use their own criteria (Devereux *et al.*, 2015).

Effectiveness in terms of reaching the poor

The evidence on the targeting performance of CBT is mixed and often discussed in terms of a trade-off between the advantages of leveraging local information and the risks of local elite capture (Handa *et al.*, 2012).

On the one hand, CBT can improve targeting accuracy because community members have access to information that is typically not available to programme officials (Alderman, 2002). For example, community members might know if a household receives remittances from abroad or has just been hit by a negative event.

On the other hand, those in charge of selecting beneficiaries might use their power to appropriate resources or simply divert them away from the poor (Conning and Kevane, 2002). For example, in the context of an input subsidy programme in Kenya, Pan and Christiansen (2012) found that members of the local elite received 60 percent of the input vouchers distributed by the programme. Furthermore, given that those in charge of selecting beneficiaries normally do not work for the programme, they do not have a strong incentive to comply with its rules (Coady *et al.*, 2004). Indeed, they might have objectives that are different from those of the agency that finances the intervention. To reduce the risk of elite capture in the context of rural development projects, the International Fund for Agricultural Development, or IFAD (2019b), suggests providing leadership training, creating community grievance mechanisms, making information on eligibility criteria as transparent as possible, deferring payments for bigger investments (e.g. machinery) to a later phase of the project, and restricting eligibility to those who have completed other project activities (e.g. training).

Another factor that should be considered is that the definition of poverty within a community could be different from that of the funding agency. While governments typically define poverty in monetary terms, local communities may include other factors, such as a non-income dimensions of poverty and demographic factors (Alatas *et al.*, 2012). For delegated CBT, this might undermine targeting effectiveness because those selected by the community might not appear as poor according to the definition of the funding agency. In this case, the funding agency can reduce targeting errors by providing clear indications on eligibility criteria. However, for devolved CBT, the selection of beneficiaries according to a local definition of poverty represents an expected and desirable feature.

It has often been argued that the performance of CBT depends on a number of features of the community, including its level of inequality, social cohesiveness, spatial density and geographic setting (Handa *et al.*, 2012). Where inequalities are high, CBT might perpetuate patterns of exclusion (Conning and Kevane, 2002; Galasso and Ravallion, 2005; Pan and Christiaensen, 2012), although evidence is mixed on this point (Alatas *et al.*, 2012). In general, CBT seems to perform better in small and more cohesive communities (Devereux *et al.*, 2015). In fact, in larger settings community members might not be able to identify subtler characteristics of poverty (Handa *et al.*, 2012).

Administrative capacity, information requirements, and administrative and private costs

One of the most appealing aspects of CBT is its low administrative cost compared to other individual targeting approaches. As those who carry out the selection process are often non-paid community members, this might represent considerable savings for an intervention's budget (Coady *et al.*, 2004). This is particularly the case for interventions located in remote rural areas, where the cost of conducting means or proxy means testing might be high. The mechanism is also appealing because it does not necessarily require that new information be collected. However, private costs should not be underestimated. A thorough community involvement in identifying beneficiaries is time-consuming and resource intensive (Handa *et al.*, 2012). Different from other targeting methods, however, private costs are not necessarily borne by beneficiaries. (They may be borne by other members of their communities.)

Potential distortions of incentives

Under CBT, potential scope for negative behavioural responses depends on the criteria used to identify the poor. While the eventuality of prospective beneficiaries altering their behaviour (e.g. putting less effort into working) in order to signal neediness cannot be ruled out, under CBT there might be more limited scope for manipulating information. That is because households might be less inclined to hide their real standards of living to other members of their community and local authorities (Lavallée *et al.*, 2010).

Political sustainability

The advantages and disadvantages of CBT in terms of political sustainability are somehow unclear and the literature is scant. If an intervention is financed through local resources, on the one hand, problems of elite capturing and fund misappropriation might undermine its legitimacy. On the other hand, given that CBT might offer some space for inclusion errors, it might help secure the support of better-off members of the community.

Social acceptance and psychological costs

By transferring ownership of decision-making to communities, CBT helps improve the social acceptability and legitimacy of an intervention (Devereux *et al.*, 2015). This might be particularly true for devolved CBT, in which communities can apply their own definition of poverty to select beneficiaries. Alatas *et al.* (2012) conducted a randomized experiment to compare the performance of PMT and CBT in the context of a cash transfer programme in Indonesia. They found that, even though PMT performed slightly better in identifying the monetary poor, CBT resulted in higher satisfaction, greater legitimacy and easier disbursement of the funds. The authors conclude by highlighting that:

> ...given the relatively small differences in ultimate poverty outcomes between the alternative treatments [CBT and PMT], it is not evident that there is a strong enough case to overrule the community's preferences in favor of the traditional consumption metric of poverty, especially given the gain in satisfaction and legitimacy (Alatas *et al.*, 2012).

In addition, CBT promotes community mobilization, participation, and possibly, the empowerment of the target group, which all represent desirable outcomes in development interventions (Devereux *et al.*, 2015).

Nevertheless, these advantages should not be taken for granted. Depending on who is involved in the decision-making process, the poor might be empowered, or they might be marginalized. As mentioned before, under certain circumstances, CBT might perpetuate local power structures and exclude certain groups (Conning and Kevane, 2002). Finally, CBT might also lead to increased conflict within communities (Conning and Kevane, 2002). This might especially occur where most of the community's members are poor. In these settings, Coady *et al.* (2004) hypothesize that CBT would be less problematic if only a small fraction of community members was to be selected (5 to 10 percent). In this way, they argue, community members might adopt a more altruistic behaviour and allow the selection of the poorest.

Box 16 provides an example of how the performance of CBT can be analysed and a reflection on the use of targeting for poverty reduction programmes with multiple objectives.

▶ BOX 16

CBT performance in Malawi's Farm Input Subsidy Program (FISP)

Malawi's Farm Input Subsidy Programme (FISP) is one of the largest programmes of this kind in sub-Saharan Africa. Launched in 2005, the overall objective of the programme is to improve food security and increase the income of resource-poor farmers through enhanced maize and legume production. FISP distributes vouchers that allow farmers to buy seeds and chemical fertilizers at heavily subsidized prices.

In general, FISP is directed at resource-poor farmers. These are smallholder farmers who have the necessary land and labour to make use of the agricultural inputs but cannot afford the inputs at market prices. Since 2008, FISP relies on a community-based targeting mechanism to identify beneficiaries at the local level. CBT is the last of a three-step voucher allocation mechanism. First, the Ministry of Agriculture and Food Security allocates vouchers to districts based on the presence of farming households. Second, district authorities distribute the vouchers across villages. ▼

BOX 16 (CONT).

Finally, open forums of village members collectively decide which farmers within the community should receive the vouchers. Given that the number of potentially eligible households is greater than the number of vouchers, communities are encouraged to prioritize particularly vulnerable groups (e.g. women-headed households). However, no precise criteria are given at national level to define who is "resource poor".

In order to assess the performance of CBT in FISP, Kilic *et al*. (2015) analysed the Malawi's third Integrated Household Survey (IHS3) 2010/11, covering the 2009/10 agricultural season. (This survey is part of the LSMS-ISA Programme mentioned in Section 3.2.3.) The study assessed the targeting performance of FISP using two measures: one capturing the difference between coverage and leakage (known as the targeting differential) and the other representing the difference between the average value received by eligible vs non-eligible beneficiaries (a variant of the targeting differential).* Then both coefficients were decomposed into (i) interdistrict, (ii) intradistrict intercommunity, and (iii) intradistrict intracommunity components to identify the contribution of each of the three steps of the targeting process relative to the overall targeting performance.

Their analysis shows that the FISP is not poverty targeted and the programme reaches all socio-economic strata of rural Malawi. In fact, all the three steps of the voucher allocation process are nearly uniform in their failure to target the poor. Overall, the programme tends to reach people in the middle of the income distribution. They found that households that are relatively better off and are connected to community leadership are more likely to receive benefits. In particular, elite capture occurs more in communities that are more distant from rural towns and have more unequal land distribution.

The targeting of FISP has been often criticized for its limited pro-poorness, but also because it fails to concentrate input subsidies on those farmers who would use them more efficiently for producing more food. Various reforms have been suggested for it, such as centralizing the targeting mechanism to focus on farmers who would be more efficient in translating subsidized inputs into greater output (i.e. landowners specialized in agriculture, with middle wealth endowment, and living in semi-arid agro-ecological zones), while compensating excluded extremely poor farmers with alternative social protection programmes (Asfaw *et al*., 2017). Nevertheless, the decision is not straightforward.

An analysis of the interplay between FISP and Malawi's Social Cash Transfer Programme (SCTP), a social protection programme targeted at the poorest, found positive synergies between the two. The study found that, for households receiving both programmes, the impact in terms of increased expenditure, value of agricultural production, and improved food security was greater than the sum of the two programmes alone (Pace *et al*., 2018).

In a more general sense, the case of FISP shows that targeting the poorest is not necessarily the most desirable option for poverty reduction programmes, especially when they have multiple objectives (in the case of FISP, poverty reduction and greater food production). However, when this is the case, programme designers could take specific measures to improve inclusiveness and allow the extremely poor to benefit, for example by supporting extremely poor farmers with asset transfers that increase their potential to translate input subsidies into greater productivity.

Sources: Asfaw *et al*., 2017; Kilic, Whitney and Winters, 2015; Pace *et al*., 2018.

* Both measures of targeting performance are explained more in detail in Section 4.4.2.

4.3.3 Categorical targeting

Geographical targeting

Geographical targeting, a part of the categorical targeting method, uses place of residence as the main criterion to allocate the benefits of an intervention. In its simplest form, it consists of allocating benefits to all potential beneficiaries that reside in one or more selected geographic areas. In the context of narrowly targeted poverty reduction interventions, it is often used as a first step to allocate the resources of an intervention to areas that stand out due to their poverty level, before further detailing eligibility criteria. For this reason, poverty maps (Chapter 3) are essential tools for conducting geographical targeting in poverty-reduction interventions. More in general, geographical targeting is used to identify or prioritize regions/zones of intervention. In this sense, it can be particularly useful for interventions that cannot be targeted at individuals or households, such as infrastructure development.

Effectiveness in terms of reaching the poor

The effectiveness of geographical targeting mainly depends on whether poverty is geographically concentrated or not. In areas where the level of poverty is high, geographical targeting will imply relatively low inclusion and exclusion errors, and the benefits of using additional individual mechanisms will be limited (Handa and Davis, 2006). For example, FAO and IFAD (2016) report that an IFAD project to support pastoralists in four areas of Mongolia, after attempting to further target beneficiaries based on their poverty status (proxied by herd size) ended up including 90 percent of the population, meaning that it would have probably been better to avoid the costs associated with the targeting effort. However, if poverty is heterogeneous within a geographical area (e.g. a district that hosts both poor and rich villages), using geography as the only mechanism for targeting will not be efficient. If such a geographical area were considered poor as a whole and therefore selected to receive the intervention, a substantial part of the intervention's resources would go to non-poor people (inclusion error). If, conversely, the area was not selected, many poor people would not be included (exclusion error).

Moreover, the effectiveness of geographical targeting also depends on the granularity, or geographical disaggregation, with which the targeting mechanism can be implemented. In general, the smaller the areas to which geographical targeting is applied, the higher the accuracy of this targeting method. As explained in Chapter 3, national household surveys cannot be used to produce highly disaggregated poverty maps. Thus, it is usually necessary to conduct a small-area estimation exercise, which can be technically demanding. In addition, it is important to take into account that, while granularity will certainly improve the effectiveness of the geographical targeting mechanism, it does not ensure that effectiveness will be high in all circumstances. If poverty is heterogeneous even within small areas, using geography as the only mechanism for targeting will still produce high targeting errors. For example, Simler and Nhate (2005), after conducting a small-area estimation exercise, observed that only 20 percent of income inequality in Mozambique was explained by differences between small geographic areas. In other words, most of the variation in income (and thus poverty) occurred *within* small areas. This example clearly suggests that geographical targeting alone, even if based on granular data, does not guarantee great targeting accuracy.

Administrative capacity, information requirements, and administrative and private costs

Assuming that geographical targeting is performed using existing data, it is a relatively easy-to-administer and cheap targeting mechanism (Lavallée *et al.*, 2010). In particular, this targeting mechanism might be particularly convenient if a poverty-mapping exercise has already been conducted. Clearly, if data does not exist to build a poverty map, geographical targeting might still be used by relying on less formal mechanisms, such as qualitative assessments or expert consultations (Grosh, 1994). This might be especially the case when geographical targeting is implemented for a local project. Consider the case of a community-based natural resource conservation intervention, for which project implementers need to select the poorest communities living along a river. Unless a small-area estimation or a local household survey had already been conducted, implementers would have to select the communities mainly through consultation with local authorities, experts and other participatory processes.[56]

Potential distortions of incentives

In addition to its relatively low cost and limited administrative requirements, geographical targeting leaves little room for negative behavioural responses. Potential beneficiaries can hardly conceal or change their place of residence. Although it has been argued that concentrating interventions on specific areas might induce migratory flows, there isn't sufficient evidence to support this claim (Devereux *et al.*, 2015). On the other hand, using geographical targeting to allocate public resources to local administrations might create an incentive to manipulate and exaggerate poverty numbers. Castañeda (2005) presents anecdotal evidence of this phenomenon in the context of Colombia's SISBEN (*Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales*), a system to target social programmes to the poor.

Political sustainability

From a government point of view, the political tensions generated by selecting certain geographic areas can be high, since the excluded areas could feel that the system is unfair. This issue might be particularly delicate in a context characterized by ethnic or historical divisions. Let us consider the case of two districts, each inhabited by a different ethnic group. Selecting only one district for an intervention might cause tensions between the two ethnic groups. However, the issue could be addressed by targeting sparse communities, instead of concentrating resources on a few larger areas (Bigman and Fofack, 2000). Using the same example, this would entail including villages from both districts, instead of covering all the villages of one district only.

Social acceptance and psychological costs

Directing an intervention at all those who live in a certain area, irrespective of wealth (geographical targeting), presents relatively little issues of tensions within communities and stigmatization of beneficiaries.

Box 17 provides an overview of how FAO and IFAD use geographical targeting in their country-level strategies. Box 18 illustrates how geographical targeting does not necessarily mean working in the poorest areas, but it is often guided by the technical needs of projects. The box gives an example of how geographical targeting has to be adapted to the circumstances of a typical project in FAO's areas of work. Another example is provided by IFAD (2019a), which highlights the need to target clusters of both poor and better-off areas in order to ensure the effectiveness of value chain projects to link poor farmers with processors and markets.

[56] This is not to say that if a poverty map were available, consultations and participatory processes would not be needed. For local projects, it is always recommended that the results of a poverty mapping exercise be discussed and validated with local stakeholders before using them for targeting.

▶ BOX 17
Prioritizing geographic areas in rural poverty reduction strategies: IFAD and FAO approaches

Geographical targeting is a fundamental component of most country-level poverty reduction strategies. For development actors committed to reducing rural poverty, such as FAO and IFAD, prioritizing certain areas is not only a way to maximize the poverty-reducing impact of their interventions, but also a first step to design interventions in which poverty reduction objectives are aligned with other corporate priorities and areas of work in which the organizations have a competitive advantage.
In its *Revised Operational Guidelines on Targeting*, IFAD (2019c) establishes the criteria to perform geographical targeting in the context of its Country Strategic Opportunities Programmes (COSOPs). The criteria are based on the following principles:

- Incidence and intensity of poverty should have the highest priority in a given country, followed by food and nutrition insecurity.
- Environmental degradation and climate vulnerability, presence of Indigenous peoples, number of young people, and presence of specific marginalized groups should have medium priority.
- Finally, productive potential should have medium to low priority.

FAO's new **Hand-in-Hand Initiative (HIH)** takes a different approach (FAO, 2019b). The strategy, centred on the development of a comprehensive geospatial platform to perform multidimensional spatial analysis, seeks to identify highly impoverished areas with high potential for generating profits through agricultural investment. Areas prioritized by the HIH are targeted to achieve both poverty reduction and food security and nutrition outcomes trough agricultural transformation.

BOX 18

Geographical targeting of community-based natural resource management interventions: Action Against Desertification

Action Against Desertification (AAD) is an initiative of the African, Caribbean and Pacific Group of States, implemented by FAO and other partners, funded by the European Union. The initiative, launched in 2014, is a key partner of the Great Green Wall (GGW), Africa's flagship programme to combat climate change and desertification across North Africa, the Sahel and the Horn of Africa.

AAD is aimed at tackling the vicious circle between desertification and poverty. On the one hand, the degradation of the natural resources which the poor rely on reduces their productivity and makes them more vulnerable to adverse environmental events driven by climate change. On the other hand, poverty reduces their ability to cope and recover from these events. AAD's approach is helping communities and local institutions to restore degraded land, while stimulating economic growth through non timber forest products.

The initiative works at an ambitious scale. It was estimated that more than 150 million hectares of the GGW core area are in need of restoration. For this reason, AAD encourages the restoration of relatively large-scale communal lands in order to live up to this enormous challenge.

AAD is directed to communities in areas affected by land degradation whose livelihoods depend on natural resources. However, for technical and budget reasons, not all communities can participate. A selection of communities is conducted, which might be thought of as a form of geographical targeting.

Rather than being based on the poverty level, the selection of communities is led by technical considerations. These include aspects such as: (i) the availability of degraded land to be restored in the villages; (ii) the motivation and commitment of community members to take part in restoration activities, including in-kind contributions such as land and labour; (iii) the absence of unresolved land issues or community disputes; and (iv) the existence of community-based structures and organizations. The selection also depends on the availability of a suitable restoration site within the community. For example, sites should preferably have an area between 50 and 100 hectares, be suitable for cultivation, grazing or forestry, and be easily accessible by villagers.

AAD is an example of a poverty-reduction intervention that is not suitable for individual level targeting because of the type of benefits that it delivers. In addition, AAD shows that the primary criteria for targeting, even for interventions with a strong poverty-reduction emphasis, are often not poverty itself but rather technical considerations and the capacity of households to benefit from the project. In other words, in settings like those in which AAD operates, where poverty is generally very high, geographical targeting might be guided more by the potential to reduce poverty than by poverty itself.

Sources: Federal Republic of Nigeria Ministry of Environment, 2012; Sacande, Parfondry and Cicatiello, 2020.

Sociodemographic targeting

Sociodemographic targeting uses sociodemographic characteristics (e.g. gender, age, ethnicity, household composition, labour status) to identify the beneficiaries of an intervention. It is mainly used to identify beneficiaries at individual or household level, although it might also be used to target groups of people. For example, in the context of a value chain development project, producer organizations might be selected based on their members' demographic composition (e.g. establishing that a share of members should be below a certain age or should be women). The essence of this targeting mechanism is that the characteristics that determine eligibility should be easily verifiable and correlated with poverty. In other words, the sociodemographic group selected to benefit from an intervention should be poorer than the rest of the population on average. The information provided by poverty profiles (recall Chapter 3) can help identify the sociodemographic characteristics that are more strongly correlated with poverty, which increases the impact of poverty reduction in interventions targeted in this way.

Effectiveness in terms of reaching the poor

Assuming that an intervention is aimed at reaching the poor, this targeting mechanism, if used alone, is prone to large inclusion and exclusion errors. According to Devereux *et al.* (2015), the targeting errors produced with this mechanism are mainly **"errors by design"** as opposed to **"errors by implementation"** (see Box 19 for an explanation of these types of targeting errors). Given that the eligibility criteria are generally easy to verify and difficult to manipulate, sociodemographic mechanisms present low levels of errors by implementation. In general, the performance of sociodemographic targeting increases as the selected groups are poorer than the rest of the population and are relatively homogeneous (Lavallée *et al.*, 2010).

▶ **BOX 19**

Errors by design and by implementation when targeting the poor

Both inclusion and exclusion errors can be further classified into errors by design and errors by implementation (Devereux *et al.*, 2015). Errors by design occur when the poor (or non-poor) are excluded (or included) due to the eligibility criteria set for a programme. Errors by implementation occur when the eligibility criteria are not implemented correctly. The concepts can be illustrated with two simple examples.

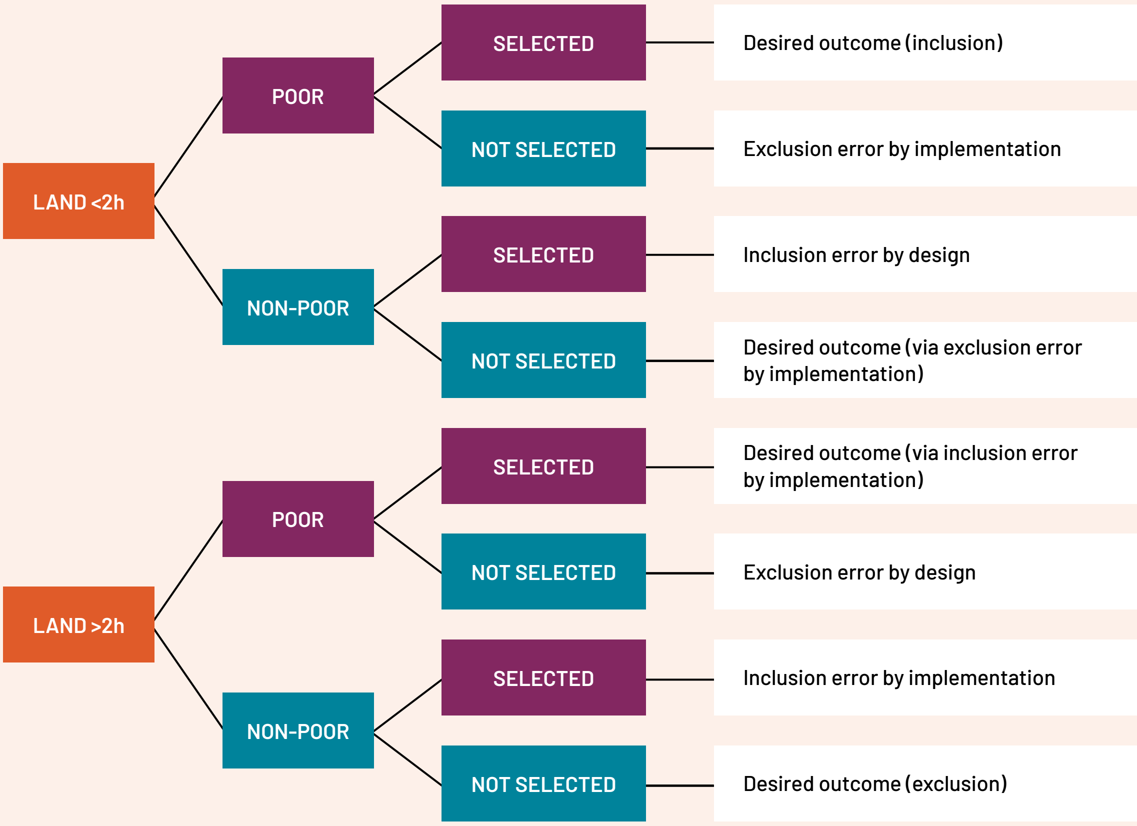
First, let us consider an unconditional cash transfer programme whose only eligibility criterion is monetary poverty status. Households whose income is below the national poverty line are entitled to the transfers, while other households are not. In this case, inclusion and exclusion errors by design are virtually zero because, if the eligibility criterion is applied correctly (and the programme has sufficient budget to cover the entire poor population), all the poor will receive the transfers while none of the non-poor will. However, things can go differently than planned. For example, applicants might understate their real income or might decide not to apply because of difficulties in obtaining the documentation requested to prove their earnings. This is when inclusion and exclusion errors by implementation occur. ▼

▶ BOX 19 (CONT.)

Second, let us consider an input subsidy programme that targets poor agricultural households, applying an eligibility criterion of holding less than two hectares of land (i.e. being a smallholder producer). Figure 17 illustrates this example. In this case, inclusion and exclusion errors by design occur simply because not all smallholders are poor and not all larger producers are non-poor. If land size is taken as a proxy for poverty, then inclusion errors by design refer to all smallholder producers who receive the subsidy despite not being poor. Conversely, exclusion errors by design refer to all agricultural households who are poor but do not receive the subsidy because the amount of land they own is greater than the established threshold. Targeting errors by implementation can occur in this case too. For example, a poor household with less than two hectares might not receive the subsidy because its land size is misreported or because it goes undetected given its remote location.

▶ FIGURE 17

Errors by design and implementation of an input subsidy programme targeted based on land size



Source: Authors' adaptation from Sabates-Wheeler *et al.* (2015).

When using sociodemographic targeting it is useful to keep in mind the typical living arrangements of the context in which the intervention will be implemented (Coady *et al.*, 2004). This can be done by looking at household composition data from censuses and national household surveys. For example, in a context where children often live with grandparents, targeting transfers to the elderly might produce additional benefits for children. More in general, sociodemographic targeting can help align multiple development objectives such as poverty reduction, food security and nutrition, and gender equality.

Administrative capacity, information requirements, and administrative and private costs

Similar to geographical targeting, sociodemographic targeting is considered to be a relatively easy-to-implement and cheap option for targeting, especially if a poverty profile has already been conducted. It is also considered to have low private costs for beneficiaries as, in theory, demonstrating eligibility based on sociodemographic criteria should be easy. Nevertheless, the private costs of sociodemographic targeting should not be underestimated (Coady *et al.*, 2004). Often, eligibility criteria such as age or disability should be demonstrated through documentation. However, in some low-income countries, obtaining documents might not be straightforward and might expose potential beneficiaries to high transaction costs. This is particularly the case for more vulnerable, dependent, and sometimes discriminated categories such as children, the elderly, Indigenous peoples and illiterate people.

Potential distortions of incentives

As in the case of geographical targeting, sociodemographic targeting presents a limited scope for negative behavioural responses in order to meet the eligibility criteria. Characteristics such as gender, age, disability and ethnicity are hard to manipulate. However, labour-related characteristics (e.g. employment status or sector of employment) offer a greater scope for negative behavioural responses. In addition, various studies have warned that targeting based on household structure characteristics (e.g. woman-headed household or elderly people living alone) might create perverse incentives for household restructuring, although empirical evidence for this is scarce (Devereux *et al.*, 2015).

Political sustainability, social acceptance and psychological costs

One of the main advantages of sociodemographic targeting is that it enjoys general political support and higher social acceptability. Concentrating resources on categories of people who are traditionally considered more vulnerable, such as children, the elderly, women or disabled people, is widely accepted and relatively uncontroversial (Coady *et al.*, 2004), while targeting people based on labour characteristics, such as sector of employment, might encounter more resistance. Finally, sociodemographic targeting presents limited stigmatization effects (Lavallée *et al.*, 2010).

Box 20 shows the example of an FAO rural poverty reduction project in which demographic targeting was used in an innovative way to reach the poor.

▶ BOX 20

Targeting the dynamic youth to boost decent jobs and reduce poverty: the youth champions approach under the Integrated Country Approach (ICA) programme

Rural areas suffer from less and lower-quality employment opportunities, one of the reasons they often present higher poverty levels than urban areas. The FAO programme "Integrated Country Approach for boosting decent jobs for youth in the agrifood system" (ICA programme) supports countries in adopting more youth-inclusive agrifood system development policies, strategies and programmes. Its ultimate objective is to reduce rural poverty and minimize the adverse drivers of migration among rural young people by reducing unemployment and underemployment. ICA has been implemented in three phases, all funded by the Swedish International Development Cooperation Agency. The programme is currently in its third phase (2019–2022) and is being implemented in Guatemala, Kenya, Senegal, Rwanda and Uganda.

The main direct beneficiaries and partners of the ICA programme are agricultural ministries and other public, private or civil society institutions involved in strategic planning for rural development. Through the ICA, these institutions are supported with capacity building, knowledge generation and dissemination, partnership creation and technical advice.

Beyond institutional interventions, the ICA is also piloting integrated models for creating employment for rural youth. Individual beneficiaries of ICA are usually vulnerable, informal, but market-oriented young producers or entrepreneurs involved in small-scale production, processing, input suppling and marketing. They are dynamic rural youth, with some skills, but who need support to stabilize their livelihoods, access decent jobs and contribute to the well-being of their communities. Some of them may indeed find themselves temporarily or permanently in a poverty situation, even though this is not explicitly assessed.

In Uganda for instance, the field activities during the second phase of ICA (2015–2017) focused on selecting and empowering rural youth champions across the country through the Youth Inspiring Youth in Agriculture Initiative (YIYA), implemented in partnership with the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF). The objective was to give visibility to the role of youth in the agrifood system, connect them to a network of service providers, and establish a network of local youth champions who could mentor other more vulnerable youth in their communities. One of the most important criteria for selecting youth champions was their experience, interest and ability to transfer entrepreneurship skills, agribusiness knowledge, and principles of decent work to poor youth in their communities. Requirements such as initial capital, legal registration, minimum years of activity and profitability were not used as selection criteria. In this way, even youth with very limited initial capital were among those selected to be youth champions.

In Uganda, the initiative showed positive results. Thanks to the youth champions, many local farmers were linked to the market. Interviews with communities revealed that the youth champions greatly influenced other young people, some of whom started their own agribusinesses. In addition, youth champions' agribusinesses created more employment opportunities in their communities, including for other young people. ▼

▶ BOX 20 (CONT.)

This example shows that, in the context of poverty reduction interventions, targeting a particular sociodemographic group (e.g. the youth) is not necessarily a straightforward operation. A particular sociodemographic group can be highly heterogeneous in terms of poverty and other characteristics. In this case, sociodemographic targeting can be the first step of a more stratified targeting strategy that relies on multiple mechanisms. In addition, the example shows that targeting a particular demographic group can be aligned with poverty reduction objectives (and inclusivity principles) even when the targeted group is not formed by the poorest in the society. However, when rural poverty reduction interventions use relatively more resource-endowed individuals (e.g. the youth champions) as a vehicle to reach the poor, it is important that the targeting strategy explicitly acknowledge the mechanisms through which this should occur and that concrete measures be taken to ensure the poor ultimately benefit from the intervention.

4.3.4 Self-targeting

Self-targeting, or self-selection, is a special approach to targeting in which the benefits of interventions are accessible to everyone but are designed in such a way that they are more attractive to the poor. In other words, the design of a self-targeted intervention is such that only those who are really in need choose to participate, whereby some characteristics of the design discourage the participation of the non-poor. The main elements that drive this mechanism are transaction costs of participation, stigma associated with the use of benefits provided, and preferences regarding quality.

In practice, most interventions rely, to some extent, on some form of self-selection (Coady *et al.*, 2004). Most programmes will require visiting an office, submitting an application or queuing. Similarly, matching grants (e.g. for small infrastructure or productive assets) in value chain development projects often require a certain percentage of co-financing from beneficiaries. Furthermore, trainings on low-input agricultural practices will naturally attract more smallholders than owners of larger mechanized farms. All these characteristics will encourage participation among those who have a higher interest in a programme. In an evaluation of its projects to promote smallholders' access to markets, IFAD (2016) noted that while most of its projects are explicitly targeted geographically, some self-targeting occurs simply because the projects cannot cover the entire population in the target area, so farmers who take greater interest in the project, who apply first or who are better informed are the ones who are included in the projects. However, it should be kept in mind that the specific characteristic of self-targeting interventions is that their incentives are explicitly designed in a way that take-up rates are much higher for the poor than for the non-poor.

The most common form of self-targeted interventions are public work programmes, which are particularly popular in rural areas (Lavallée *et al.*, 2010). These programmes use low-skilled labour for a number of development projects, including building rural roads, reforestation and land reclamation. The mechanism to exclude the non-poor is based on the fact that wages are low enough to attract only those who cannot find better work opportunities. In interventions that distribute food and basic social services, self-targeting occurs through a quality-differentiation mechanism. In the case of food, nutritional quality might not be lower, but the food item could simply be less prestigious. For example, distributing or subsidizing coarse vs fine flour will attract the poor more than the non-poor. Rural infrastructure interventions can also rely on self-targeting when a certain type of infrastructure will likely be used more by the poor than the non-poor. For example, community wells and standpipes are likely to be used more by those who do not have private access to water (IFAD, 2019b).

Effectiveness in terms of reaching the poor

The ability of self-targeting to include the poor and exclude the non-poor depends on the size of transaction costs, the level of stigma associated with participating in or benefitting from an intervention, and the extent to which the poor and the non-poor react to these factors (Coady *et al.*, 2004). In short, participating to the programme should be substantially costlier to the non-poor, in terms of time, forgone opportunities or social prestige, than to the poor. In public work programmes, the most important factor is the level of wage provided to participants compared to the wage commonly found in the labour market. The lower the wage, the more likely the programme will attract more poor people. For example, in Argentina's *Trabajar* (Work) programme, setting the wage at the level of the earnings of the poorest 10 percent of the population contributed to achieving strong progressivity in the programme, in other words, to the programme's effectiveness in allocating its resources to the most needy (Ravallion and Jalan, 1999). However, it is important to consider that lowering the wage reduces the benefit and, possibly, the poverty-reduction impact of the intervention (Coady *et al.*, 2004). For example, in the *Trabajar* programme, forgone earnings amounted to about half of the gross earnings received through the programme (Ravallion and Jalan, 1999).[57]

For any type of self-targeted intervention, one should always be aware of the magnitude of transaction costs. On the one hand, it is important that transaction and opportunity costs be high enough to discourage the non-poor and minimize inclusion errors. On the other hand, transaction costs should not be too high; otherwise, the take-up rate might be low and exclusion errors high. For example, public work programmes might be implemented in rural areas to provide employment outside of the agricultural season. Yet, it might be preferable to offer opportunities for short workdays so that beneficiaries can still perform some farm activities (Coady *et al.*, 2004). Similarly, if the stigmatization exploited by a self-targeting mechanism has a high social cost, the poor might choose not to participate.

Administrative capacity, information requirements, and administrative and private costs

Perhaps the most attractive feature of self-targeting mechanisms is that the information needed and the administrative effort required to identify participants are virtually zero, similarly to a universal intervention. For this reason, self-targeting is particularly popular in developing countries with limited administrative capacity (Lavallée *et al.*, 2010). As mentioned before, under self-targeting, the bulk of the costs of selecting the participants is born by the beneficiaries themselves. However, while beneficiary selection might be simple and cheap, these programmes can be difficult and expensive to manage. This is particularly the case for public work programmes in which the process of selecting and designing the works to be carried out, identifying the sites,

[57] Ravallion (2019) argues that in public work programmes, beneficiaries incur in welfare losses that are directly related to the heavy nature of the jobs provided. For example, Alik-Lagrange and Ravallion (2018) found that, once welfare loss due to participating in the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) (see Box 21) was taken into account, the programme performed worse, in terms of poverty reduction, than a hypothetical universal basic income scheme with the same budget.

procuring materials and hiring qualified workers represent challenging administrative tasks (Coady *et al.*, 2004) requiring a certain level of resources and technical capacity. For this reason, countries with limited administrative capacity may not be able to implement such programmes on a large scale and provide work to all those who are willing to participate (see Box 21).

Potential distortions of incentives

As participation is open in self-targeting interventions, potential beneficiaries do not have incentives to alter their behaviour in order to meet eligibility requirements. This represents an advantage of self-targeting. Yet, depending on how incentives are set, self-selection programmes might introduce distortions in labour and goods markets. For example, food subsidies might shift consumption toward less nutritious foods or negatively affect poor farmers (i.e. when the price of a subsidized commodity falls due to the subsidy).

Political sustainability

Self-selecting mechanisms tend to have low political costs (Coady *et al.*, 2004). Interventions such as food subsidies, even if designed to benefit the poor more than the non-poor, are used, to some extent, by a large share of the population. As already mentioned, some level of leakage can help secure larger political support (Pritchett, 2005). Furthermore, public work programmes tend to be popular, even if finely targeted at the poor, because non-participants consider that the poor "earn" the benefits of the intervention through their work (Coady *et al.*, 2004). Slater and Farrington (2009) report that public work programmes are particularly popular in Africa, especially when they complement other social programmes targeted at those who cannot work (i.e. children, the elderly and disabled people).

Social acceptance and psychological costs

Against this backdrop, one would expect that self-selection mechanisms have relatively high social acceptability. However, self-targeting can be particularly stigmatizing for the poor, although this can be largely influenced by the way in which an intervention is promoted (Coady *et al.*, 2004). As explained before, some interventions might leverage stigma in order to increase the effectiveness of a self-selection mechanism, for example by stressing that an intervention is meant for the poor. However, stigma should be considered carefully. In fact, in addition to increasing exclusion errors, it might reduce the self-esteem of participants, thus limiting the ability of development interventions to have a positive effect on their empowerment (Coady *et al.*, 2004).

BOX 21

The problem of rationing in self-targeting programmes: the case of India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA)

The Indian Parliament passed the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) in 2005. Under the Act, any adult from a rural area who is willing to perform unskilled manual labour for an established minimum wage has the legal right to be employed in public work programmes for at least 100 days per year. Since 2008, the act has been extended to the whole country, thus launching the largest public work programme in the world. Examples of works carried out include rural transportation, water conservation, irrigation and drought protection interventions. Like several public work schemes, MGNREGA is based on self-targeting. Anyone who lives in a rural area and is of adult age is entitled to request work. The request must be responded to within 15 days, otherwise the state should pay an unemployment allowance. Official government statistics report almost no cases of work requests being denied. Nevertheless, a large – albeit seemingly declining – share of unmet work requests emerges from the analysis of specific questions about participation in MGNREGA that are included in household surveys. The share was 44.4 percent and 23 percent in 2009–2010 and 2011–2012, respectively (Das, 2015).

This situation in which households are denied work despite their legal entitlement, can be referred to as rationing and can occur for different reasons. The most typical is lack of funds for projects that can employ people. However, even when funds are made available from the central government, work opportunities can still be insufficient to absorb all the requests due to limited local administrative capacity to identify and run work sites. In addition, local institutions might provide less opportunities for public work in order to minimize their cost (administrative costs increase with programme participation) and due to subtle incentive distortions caused by local corruption (for a detailed explanation see Ravallion [2019]). In the case of MGNREGA, poorer states of India receive more requests for work, which suggests that self-targeting works. However, actual participation is not higher than in richer states, meaning that rationing is higher in poorer states, where work is most needed (Ravallion, 2019). This probably reflects the fact that poorer states have lower institutional capacity to implement the programme, despite needing it the most. Rationing is concerning not only because it leads to many poor people not receiving support, but also because it undermines the safety net function of public work programmes (Dutta *et al.*, 2014). That is, if rationing is high, poor households cannot count on the programme in case of negative income shocks.

Rationing also means that local authorities will operate a de facto selection of applicants. Whether this will be pro-poor should not be taken for granted. In the case of MGNREGA, Das (2015) finds that, both in 2009–2010 and 2011–2012, poorer households were less likely to receive work after seeking it. In addition, in 2009–2010, among those who obtained work, poorer households worked less days than non-poor households. Similarly, Liu and Barrett (2013) find that administrative rationing favours those in the middle of the income distribution (i.e. around the national poverty line). However, they also find substantial variability between states: while in some states rationing is pro-poor, in others, it is markedly regressive.

▶ **BOX 21 (CONT.)**

Overall, the poor participate in and benefit from MGNREGA more than the non-poor (Das, 2015; Dutta *et al.*, 2014; Liu and Barrett, 2013) thanks to its functioning self-targeting mechanism. Nevertheless, the case of MGNREGA shows that rationing must be carefully considered in self-targeted interventions. While rationing reduces the poverty impact of an intervention because many poor do not receive (or receive a lower amount of) benefits, it might also produce selection mechanisms that undermine the pro-poorness of self-targeting.

4.3.5 Multiple targeting mechanisms

So far, targeting methods and their mechanisms have been presented separately to better understand their characteristics as well as their advantages and disadvantages. In practice, most interventions rely on a combination of two or more targeting mechanisms. Different targeting mechanisms can be implemented simultaneously, sequentially or in parallel. Coady *et al.* (2004) find that programmes using multiple mechanisms are associated with better targeting performance.

Mechanisms are used simultaneously when beneficiaries have to comply with multiple criteria at the same time (e.g. satisfy some sociodemographic characteristic and pass a means test). For example, Brazil's *Bolsa Família* (Family Grant) uses a combination of means testing and categorical targeting. Eligible households must have children up to 15 years old and/or a pregnant woman (see Box 14). In addition, their per capita income must be below a certain threshold. Mechanisms are used sequentially when, for example, the resources of the intervention are first distributed geographically (e.g. based on the level of poverty of administrative areas) and subsequently allocated to beneficiaries through other individual methods (e.g. means testing or community-based targeting). For instance, in Mexico's conditional cash-transfer programme, *Oportunidades* (Opportunities), first the poorest areas are selected. Then, households are selected through a proxy-means test (Azevedo and Robles, 2013). This is also the case of PROEZA (see Box 15), in which geographical targeting is followed by both sociodemographic targeting and PMT, and Malawi's FISP (Box 16), in which geographical targeting is followed by CBT. Finally, parallel mechanisms involve using different criteria to select different groups within the same intervention.

Using multiple methods is often both necessary and advantageous. For interventions that deliver benefits to individuals or households, poverty status can rarely be the only criterion of inclusion. As mentioned before, due to their very technical nature, most programmes will have to be directed to some subgroups of the population (e.g. farmers, fisher folks, families with young children). At the same time, most interventions need to rely on some geographical prioritization, with the exception of very few large-scale programmes with national coverage.

4.3.6 Summary of the strengths and weaknesses of targeting mechanisms

Table 11 provides a summary of the main strengths and weaknesses of each targeting mechanism with respect to the various targeting challenges. Green indicates that a given targeting mechanism performs generally better compared to other mechanisms with respect to a certain aspect. Red indicates a generally poor performance in a certain aspect. Finally, yellow indicates that the performance in a given aspect depends on the context and the modalities in which a mechanism is applied. As is clear from the description of each targeting mechanism in the sections above, this is the case most of the time. The implication is that it is impossible to identify a targeting mechanism that is generally better than the others. Instead, the appropriateness of each mechanism will have to be evaluated based on the context to which it should be applied. The remainder of this chapter provides guidance on how to make this analysis and choose an effective combination of targeting mechanisms.

TABLE 11

Overview of the strengths and weaknesses of different targeting mechanisms

MECHANISM	ERRORS BY DESIGN	ERRORS BY IMPLEMENTATION	INFORMATION REQUIREMENTS AND ADMINISTRATIVE CAPACITY	ADMINISTRATIVE COST	PRIVATE COST	POLITICAL SUSTAINABILITY	DISTORTION OF INCENTIVES	SOCIAL ACCEPTABILITY (AT LOCAL/COMMUNITY LEVEL)	PSYCHOLOGICAL COSTS
INDIVIDUAL AND HOUSEHOLD METHODS									
Means testing (MT)	Virtually zero because the (monetary) poor can be perfectly identified in theory.	Depends on accuracy of verification and if the poor exclude themselves due to difficulties in application process.	Requires collecting and processing individual information. Effort depends on degree of verification.	Depends on degree of verification.	Depends on documentation requested.	Relatively low if not coupled with socio-demographic targeting. More acceptable and less risk of political manipulation if verification is strong.	Potentially high when the eligibility criterion is directly related to the objective of the intervention (e.g. income or nutritional status).	Potentially low for participants because of intrusion in their lives.	Relatively high because people need to self-identify as poor.
Proxy means testing (PMT)	If poverty is multidimen-sional, and PMT uses the same variables, errors can be virtually zero. If poverty is monetary, depends on quality of model.	Depends on accuracy of verification and if applicants can manipulate information.	High technical skills required to develop the formula. Requires collecting and processing individual information. Can be easier than MT, but effort depends on complexity of formula.	Can be lower than MT, but depends on complexity of the formula.	Can be lower than MT, but depends on amount of information to be provided.	Same overall considerations of MT. Rigidity of the formula can reduce risk of political patronage.	Lower than MT because variables are hard to change. Even lower if formula is confidential.	Potentially low if formula is confidential or hard to understand.	Relatively high because people need to self-identify as poor.

▶ TABLE 11 (CONT.)

MECHANISM	ERRORS BY DESIGN	ERRORS BY IMPLEMENTATION	INFORMATION REQUIREMENTS AND ADMINISTRATIVE CAPACITY	ADMINISTRATIVE COST	PRIVATE COST	POLITICAL SUSTAINABILITY	DISTORTION OF INCENTIVES	SOCIAL ACCEPTABILITY (AT LOCAL/COMMUNITY LEVEL)	PSYCHOLOGICAL COSTS
Community-based targeting (CBT)	Virtually zero as in theory the poor can be perfectly identified.	Depends on whether incentives and definition of poverty of community members are aligned with funding agency (for delegated CBT). Depends on whether community members know each other.	No need to collect information on individuals.	Administrative costs are lowest. Costs of selection are passed on to community members.	Private cost of community members (not necessarily beneficiaries) can be high depending on complexity and degree of participation of selection process.	Unclear. Problems of elite capturing can undermine legitimacy. But given that CBT might allow inclusion errors it can increase support of better-off people.	Depends on definition of poverty. Community ties can reduce risk of hiding information and changing behaviour opportunistically.	Can increase legitimacy at local level but also generate conflicts within communities.	Depending on the process the poor can be empowered or further marginalized.
CATEGORICAL METHODS									
Geographical	Potentially high, depending on how poverty is concentrated and the granularity of targeting.	Low as it is easy to identify beneficiaries based on place of residence.	Technical skills needed upstream to build a poverty map but no need to collect (detailed) information on individuals.	Cheap, especially if poverty data already exists.	Lowest.	Potentially low from government perspective, especially with ethnic or historic divisions.	Low on the side of beneficiaries (but might induce local administrators to exaggerate poverty numbers).	Highest.	Lowest.
Socio-demographic	Potentially high, depending on how poverty is correlated with chosen eligibility criteria.	Low as it is easy to identify beneficiaries based on sociodemographic characteristics	Technical skills needed upstream to build a poverty profile but no need to collect (detailed) information on individuals.	Cheap, especially if poverty data already exists.	Relatively low but individuals might have to obtain documents to demonstrate sociodemographic characteristics.	High if selected categories are traditionally considered vulnerable.	Low.	High if selected categories are traditionally considered vulnerable.	Low.
SELF-TARGETING									
Self-targeting	Potentially high and hard to predict, as it depends on many factors.	N/A - no selection of participants is carried out.	Virtually zero.	Virtually zero.	High - private cost is used as part of the mechanism.	High.	Virtually zero.	High.	Potentially high - depending on how the intervention is framed. Stigma often used as part of the mechanism.

Source: Authors' own elaboration based on a review of existing evidence.

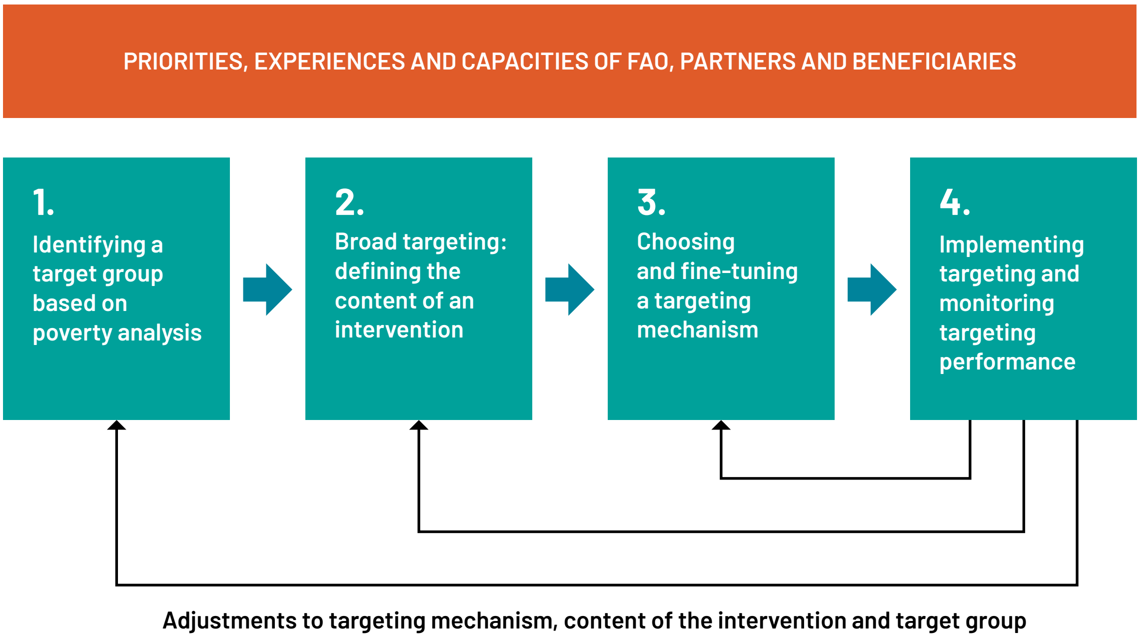
4.4
THE TARGETING PROCESS

4.4.1 Steps of the targeting process

Targeting is not only a matter of choosing a targeting mechanism. It is a complex process that involves various steps and occurs at various levels. If the targeting is carried out by an organization such as FAO, this process begins with defining a strategy at the corporate level and continues through operationalizing a project at the country level. In practice, the process of targeting can occur in different ways and it is ultimately driven by the specific context of an intervention (i.e. why, where, when, how and by whom it is carried out). However, the process generally involves four steps, illustrated in Figure 18.

▶ FIGURE 18

Steps of the targeting process



Source: Authors' own elaboration.

STEP 1 – IDENTIFYING A TARGET GROUP

This step is based on the application of the tools presented in Chapters 2 and 3. First, poverty is measured to understand the extent and magnitude of the poverty problem. This means understanding how many people are poor in a certain country or area and how severely they suffer from poverty. Poverty maps describe where the poor are more precisely and identify areas that could be prioritized for poverty-reduction interventions. Finally, poverty profiles reveal the characteristics of the poor. With this information, and based on corporate priorities as well as the objectives and capacities of international and local partners, it is possible to identify a target group. Examples of target groups might be poor youth engaged in fisheries, smallholder producers vulnerable to poverty, or extremely poor people living in the mountainous area of a country.

STEP 2 – DEFINING THE CONTENT OF AN INTERVENTION (BROAD TARGETING)

Once one or more target groups have been identified, a menu of actions that could be most effective at reducing poverty (and often achieve other complementary objectives) should be defined. To the greatest extent possible, this decision should be based on evidence regarding the characteristics of the target group (obtained from poverty profiles but also from qualitative fieldwork in the context of projects), their needs, and an analysis of the contextual drivers of poverty. For example, a poverty profile can tell whether poverty is more concentrated in crop agriculture vs the livestock sector, or whether poverty is more associated with lack of land or with limited access to markets.

Clearly, defining actions to tackle poverty for a given target group is not a purely analytical process. Here the priorities, experience and competitive advantage of an organization like FAO and its partners play a key role. Importantly, rural poverty reduction is not the primary objective of many interventions carried out or promoted by FAO and similar organizations. Other criteria also guide the choice. For example, interventions that aim to increase national food production will likely be directed at sectors and investments with high productive potential. Similarly, value chain development projects that aim to increase smallholders' access to markets could focus on relatively more competitive and better-off producers. Nevertheless, these interventions can also be made more pro-poor and inclusive if, among the range of technically viable options, a further prioritization is made based on poverty considerations.

Typical outputs of this step are a set of actions, a theory of change describing how these will lead to the desired objectives, an estimate of the number of beneficiaries, and an estimate of the resources required/dedicated to the intervention.

STEP 3 – CHOOSING AND FINE-TUNING A TARGETING MECHANISM

Once the objectives, target groups, content, prospective budget and the number of beneficiaries to be reached are outlined, it is possible to choose a combination of targeting mechanisms among those described in Section 4.3. This step is discussed in greater detail in the next section.

STEP 4 – IMPLEMENTING TARGETING AND MONITORING TARGETING PERFORMANCE

A correct implementation of the chosen targeting mechanism is key for the success of an intervention. As mentioned, targeting errors due to implementation can seriously undermine targeting and, consequently, an intervention's performance. The implementation phase can be more or less complex depending on the type of mechanism, the type of intervention and the local context. For example, selecting individual beneficiaries one by one for an input-subsidy programme clearly presents more challenges than targeting organizations or institutions to deliver capacity-building activities on ecosystem restoration practices.

It is important that the execution of targeting be well planned. First, roles and responsibilities must be clearly shared between FAO (or any organization pursuing the targeting) and its partners, including local public and private institutions. It is particularly important that those in charge of selecting beneficiaries understand the targeting mechanism and have the right incentives and appropriate resources to execute it correctly. At the same time, effective channels of communication must be established to make sure that potential beneficiaries are aware of the intervention and understand the eligibility criteria and the selection process. Stakeholder consultations may be a useful mechanism in this context. Finally, where applicable, mechanisms that allow feedback and complaints regarding the selection process must also be planned, together with a response system.

Monitoring targeting performance, both in terms of processes and outcomes, should be an integral part of an intervention's overall monitoring system. Monitoring targeting performance provides important feedback to adjust the adopted targeting strategy and, potentially, the selection of the target group and the activities planned by the intervention. A monitoring system should be able to capture whether those in charge of selecting beneficiaries are correctly applying eligibility rules and if potential beneficiaries are aware of the intervention and its selection process. In addition, it should capture whether inclusion and targeting errors are occurring. This can be done on an ongoing basis through field visits and re-assessment of the eligibility of beneficiaries. However, an accurate evaluation of targeting performance in terms of inclusion and exclusion errors can only be done through the analysis of a survey that is representative of the population of the interested area (both beneficiaries and non-beneficiaries). The next section examines how to calculate targeting performance.

4.4.2 How to choose a targeting mechanism

The aim of choosing a targeting mechanism is to reach the maximum number of beneficiaries in the target group under a certain budget constraint, while minimizing negative side effects (and maximizing positive side effects) on the objectives of the intervention, beneficiaries and local institutions. Finding the right targeting mechanism for a given circumstance involves screening potential mechanisms based on their feasibility, expected effectiveness and expected costs and secondary effects.

Importantly, this screening procedure does not involve only comparing different targeting mechanisms (e.g. proxy means testing vs sociodemographic targeting), but also comparing various ways in which a mechanism can be applied. For example, within sociodemographic targeting, one might need to compare the appropriateness of targeting rural households with children under 14 vs rural women-headed households. Or, within PMT, one might need to compare the adequacy of two different scoring systems.

Feasibility

Generally, given a certain type of intervention and the circumstances to which it should be applied, only a restricted set of targeting mechanisms can be taken into consideration for implementation. First, as indicated previously, not all types of interventions can be targeted to the same extent. Input subsidies, for example, can be allocated to selected beneficiaries while rural roads can only be targeted geographically. The diagram shown in Figure 19 can help perform this first screening.

Second, the different targeting mechanisms require certain conditions to be in place to be feasible in a given circumstance. Table 12 shows some of the critical conditions for each targeting mechanism, in addition to those related to the nature of the intervention.

FIGURE 19

Decision tree for assessing the feasibility of targeting mechanisms given the type of intervention

Source: Authors' own elaboration.

TABLE 12

Feasibility conditions of different targeting mechanisms

TARGETING MECHANISM	WHEN IS IT FEASIBLE?	CONSIDERATIONS FOR RURAL AREAS
Means testing (MT)	• When it is possible to collect individual information on the ground. • When the organization selecting the beneficiaries has strong administrative capacity to manage the selection process. • When the population has access to documents proving income or other welfare-related variables (if verification is needed).	• Reaching rural areas for conducting interviews or establishing offices where potential beneficiaries should apply can be expensive and challenging. • In rural areas it is more challenging to accurately measure income due to variability and informality of economic activities (see Chapter 2).
Proxy means testing (PMT)	• When it is possible to collect individual information on the ground. • When the organization selecting beneficiaries has strong administrative capacity to manage the selection process. • When there is enough analytical capacity to design an adequate scoring system or a system already exists that can be applied to the local context. • When the poverty situation is relatively stable in a certain context.	• Reaching rural areas for conducting interviews or establishing offices where potential beneficiaries should apply can be expensive and challenging. • Scoring systems might not adequately reflect the poverty status of rural people engaging in primary activities other than agriculture as they are typically underrepresented in national household surveys used to calibrate the scoring system.
Community-based targeting (CBT)	• When it is possible to identify a community. • When those in charge of selecting beneficiaries share the objectives of the government/funding agency (for delegated CBT).	• Particularly advantageous for remote rural areas where collecting information is more challenging. • Easier when rural settlements are organized in villages, harder when dwellings are sparse. • When CBT is devolved, easier to capture the poverty condition of specific groups of rural people and minorities.
Sociodemographic	• Documents must be readily available or easy to access for the population when needed (e.g. proof of marital status, age or medical condition). • When the organization selecting beneficiaries has the administrative capacity to manage the selection process (periodic enrolment of new beneficiaries and dropping those who are no longer eligible).	• In rural areas it might be more challenging to obtain documents when requested. • Administrative capacities tend to be lower in rural areas, even inexistent in remote rural areas.
Geographical	• When it is politically acceptable to allocate resources to a restricted number of areas.	• Disaggregated poverty maps are more easily available for rural than urban areas.
Self-targeting	• When the poor and the non-poor have different consumption and labour supply patterns.	• Particularly advantageous for remote rural areas where collecting data for beneficiary selection is not feasible.

Source: Authors' own elaboration.

Regardless of the type of intervention, the following checklist can help screen targeting mechanisms in terms of feasibility. These general questions can also be used to assess various ways in which the same mechanism could be applied. Particularly important aspects are whether programme personnel should actively look for potential beneficiaries or whether beneficiaries will have to reach out to offices to apply; whether and the extent to which applicants' information will be verified; and the frequency with which information on applicants will be gathered.

PRACTICAL TIPS: QUESTIONS FOR SCREENING TARGETING MECHANISMS IN TERMS OF FEASIBILITY

- Is this mechanism applicable to this specific intervention? For example, does the intervention deliver benefits to individual people/households or does it deliver benefits to groups of people?
- Is there enough information to implement this mechanism? If not, is it technically feasible to collect it?
- What does the mechanism imply in terms of logistic arrangements? Is it feasible on the ground?
- Is this targeting mechanism politically acceptable for the institution funding or delivering the intervention?

Effectiveness: how to measure targeting performance
The performance of a targeting mechanism can be understood through its ability to reach a given target group (e.g. the rural extreme poor). Consequently, for interventions specifically targeting the (rural) poor, targeting performance refers to a mechanism's ability to identify and select that specific population, minimizing exclusion and inclusion errors (although avoiding one or the other could be the priority, depending on the situation). Since inclusion and exclusion errors can occur both by design and by implementation, one should consider both sources of errors when assessing potential targeting mechanisms.

It is possible to measure the performance of mechanisms in the intervention design phase (i.e. *ex ante*) in terms of inclusion and exclusion errors by design, by using survey data with information on the poverty status of households. Ideally, the survey should be representative of the population in the area where the intervention takes place. However, if such a dataset is not available and new data cannot be collected, a survey that approximates reasonably well the characteristics of the local population can be used.

Approximating the performance of a targeting mechanism in terms of errors by design as described above is certainly useful. However, minimizing errors by design does not guarantee good targeting performance. In fact, implementation might not go according to plan and the targeting performance simulated *ex ante* might not materialize. Unfortunately, it is not possible to accurately measure the extent of inclusion and exclusion errors by implementation before the intervention. Yet, an accurate and participatory analysis of the local context and a thorough assessment of the risks implied by the targeting mechanisms under consideration might help anticipate potential errors by implementation. Important aspects to consider are whether implementing partners have the capacity to accurately apply a certain targeting mechanism and whether a targeting mechanism might excessively discourage programme participation (e.g. due to difficulties in providing requested information or stigma).

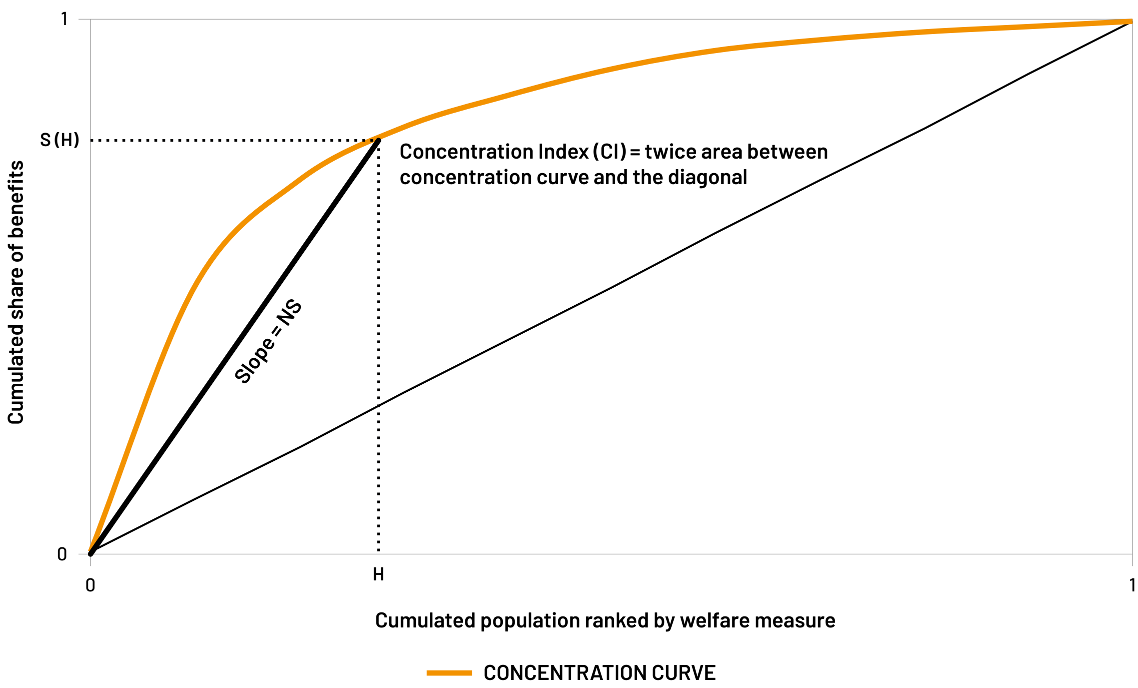
The most widely used **indicators of targeting performance** are those proposed by Coady *et al.* (2004). These measures quantify how a certain programme concentrates its benefits on the poor. According to Ravallion (2009), these measures of targeting performance are based on the concentration curve (see Figure 20), which indicates the percentage of transfers going to the poorest x percent of the population, ranked by a certain welfare measure (e.g. per capita income or consumption).

The measures based on the concentration curve are the following:

- **S(H): The share of benefits (S) going to the poorest H percent of a population.** The value of H can be set at different levels, such as the poorest 10/20/40 percent of a given population or, alternatively, as the percentage of people living below the poverty line (i.e. the value of H equals the poverty rate). For example, if H represents the poorest 40 percent of the population, and that population receives USD 500 000 out of a programme budget of USD 1 million, S(0.4) = 0.5. This measure is very popular because it is very easy to interpret and communicate.
- **NS: The normalized share of benefits going to the poorest H percent.** This indicator is obtained dividing S by H. Using the previous example, NS = S/H = 0.5/0.4 = 1.25. This measure can be interpreted as the performance of a targeting mechanism compared to "neutral targeting", a situation where every member of the population receives the same benefit from a given intervention. That is, if programme resources were distributed equally within the population, the poorest 40 percent would get 40 percent of the benefits (NS = S/H = 0.4/0.4 = 1). If NS is greater than 1, the targeting mechanism leads to pro-poor outcomes.

FIGURE 20

Targeting measures based on the concentration curve



Source: Ravallion, 2009.

Despite their popularity, these two measures of performance present some limitations, the most important of which is that they are insensitive to how benefits are distributed within the poor population. It could be the case that the poorest H percent receives more than H percent of the benefits, but with a very unequal distribution of benefits among them. Let us consider the case of H=40, representing the poorest 40 percent of a population. For example, in this case, all benefits S could go either to the richest among them (e.g. those between the poorest 30 and 40 percent of the distribution) or to the poorest among them (e.g. the poorest 10 percent of the distribution). Neither S(H), nor NS will be able to capture this difference, and both measures will show the same value in both circumstances.

- **CI: The concentration index.** CI is a generalization of the S(H) index. Instead of focusing on one particular point of the concentration curve (such as H), it considers the whole concentration curve, measuring its distance from the diagonal, which reflects a neutral distribution of benefits. This index ranges between -1 (the richest person receives all the benefits) and 1 (the poorest person receives all the benefits). Unlike the previous two measures, this index captures the distribution of benefits along the whole distribution of welfare, including the distribution among the poor.

The main disadvantage of these three measures is that they say nothing about the scale of the benefits. As is obvious, the poverty-reducing effect of an intervention depends not only on the share of benefits going to the poor, but on the size of the benefits received by the poor. For example, a large universal transfer of the same amount for everyone can have a larger impact in terms of poverty reduction than a perfectly targeted (to the poor) small transfer.

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MORE IN DETAIL An alternative measure is **Targeting Differential (TD)** (Galasso and Ravallion, 2005; Ravallion, 2009). This measure is the difference between the programme's participation rate for the poor (coverage rate) and that of the non-poor (leakage). TD ranges between -1 and 1. TD = 1 when only the poor and all the poor are covered by the programme, while TD = -1 when only the non-poor and all the non-poor are covered by the programme.

$$TD = \frac{n_{e,b}}{n_e} - \frac{n_{-e,b}}{n_{-e}}$$

$n_{e,b}$: number of poor individuals/households (eligible individuals/households) receiving the benefits of the intervention.
n_e: total number of poor individuals/households (eligible individuals/households) in the population.
$n_{-e,b}$: number of non-poor individuals/households (non-eligible individuals/households) receiving the benefits of the intervention.
n_{-e}: total number of non-poor individuals/households (non-eligible individuals/households) in the population.

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A particularly attractive feature of TD, compared to S(H) and NS, is its explicit and straightforward relationship with exclusion and inclusion errors. In fact, TD is equal to 1 minus the total proportions of exclusion and inclusion errors, which are given equal importance in determining targeting performance.

TD = Coverage - Leakage
Coverage = 1 - Exclusion
TD = 1 - Exclusion - Leakage

As expressed so far, TD assesses targeting performance based on the poverty status of the participants. This is very convenient because it makes it possible to measure the targeting performance for interventions that deliver benefits that are difficult to quantify in monetary terms, such as capacity development programmes on agricultural practices or business skills. However, when the amount of benefit can be quantified and is allowed to vary across beneficiaries (e.g. in a cash transfer in which the extremely poor receive a greater transfer than the moderately poor), targeting differential can also be expressed as the difference between the average value of benefits received by the poor (v_e) and the average value of benefits received by the non-poor (v_{-e}) (Stifel and Alderman, 2005):

$$TD = \left(\frac{1}{n_e}\sum_{i=1}^{n_e} v_{e,i}\right) - \left(\frac{1}{n_{-e}}\sum_{i=1}^{n_{-e}} v_{-e,i}\right)$$

As mentioned above, the type of *ex ante* targeting performance discussed here refers only to errors by design, and not to errors by implementation. For example, one might find that targeting a programme to small-scale women producers is more effective in terms of reaching the poor than using a PMT. However, if during the implementation of the programme those in charge of selecting beneficiaries allocate benefits to men with medium-sized landholdings, the final targeting outcome might well be different from that simulated *ex ante*. In that sense, this type of targeting performance analysis only allows measuring the *potential* targeting performance of the different mechanisms. Measuring the *actual* targeting performance of a targeting mechanism requires an *ex post* assessment. This will require gathering monitoring data and conducting follow-up surveys during and after the intervention.

Are these measures of targeting performance good predictors of success in poverty reduction interventions? The question is important because targeting performance is not a desirable characteristic in itself, but rather a means to achieving greater poverty reduction. Ravallion (2009) investigates how, in the context of the Dibao programme in China, one of the largest cash-transfer schemes in the world, different measures of targeting performance correlate with poverty reduction impact across 35 large cities. He found that only the Targeting Differential (TD) measure was positively and statistically significantly correlated with poverty reduction. Yet, correlation between targeting performance and poverty impact was generally weak, independent of the measure used. This is because "a number of factors cloud the relationship between targeting performance and total impact on poverty, including aspects of program design, implementation and the context in which a program operates" (Ravallion, 2009). These factors include the administrative, private and psychosocial costs of targeting discussed in this chapter.

The implication is that, when possible, it would be advisable to assess different targeting mechanisms directly based on their poverty-reduction impact. This means answering the question: given a certain budget, which targeting mechanism minimizes poverty? This exercise might be relatively straightforward for programmes that aim at reducing poverty directly, through monetary or easy-to-monetize benefits (e.g. cash transfers or food subsidies). However, for interventions that aim to reduce poverty through indirect or multiple channels (e.g. training, input subsidies, insurance schemes) assessing the poverty reduction effect of different targeting options will be a complex task. In these cases, measures of targeting performance based on beneficiaries' poverty status, such as targeting differential, will still be relevant.

PRACTICAL TIPS: QUESTIONS FOR SCREENING TARGETING MECHANISMS IN TERMS OF EFFECTIVENESS

- Using this targeting mechanism, by design, which proportion of beneficiaries will be in the target group (e.g. extremely poor producers)? Which proportion of people in the target group will not benefit?
- Once implemented, what are the chances that this targeting mechanism will select beneficiaries according to the eligibility rules?
  - Who will implement the selection process?
  - Does this agent have an incentive to select beneficiaries in the target group?
  - Does the agent have sufficient capacity?
  - Will the mechanism be easy to understand for those who will implement it?
- Is there a risk that, due to the features of the targeting mechanism, potential beneficiaries of the target group will not want to participate in the intervention?

Considering costs and other constraints

As explained in Section 4.2, planning and implementing a targeting system has costs, borne by both public and private actors. Ideally, one should choose the targeting mechanism with the best ratio between effectiveness and cost (i.e. the most efficient). Nevertheless, calculating the cost of targeting is a difficult exercise in practice, particularly during the planning phase of an intervention. One difficulty is that costs are shared between different actors, including international development organizations such as FAO, implementing partners (e.g. governments), and beneficiaries. Another difficulty is that targeting costs span throughout the multiple steps of the targeting process. Despite these difficulties, it is important to calculate an approximate estimate of how much the shortlisted mechanisms would cost for the programme administrator. Particularly important cost items to consider, both in terms of purchased services/materials and staff allocation, are:

- technical inputs to design the targeting tools needed (e.g. poverty maps, PMT formulas, training materials for implementers);
- outreach (e.g. advertising the programme and explaining its eligibility criteria);
- identification, screening and registration of beneficiaries (considering the frequency of enrolment);

- re-visits to beneficiaries to verify correct implementation;
- maintenance of a feedback and response mechanism;
- monitoring targeting processes and assessing their outcomes.

Calculating the costs borne by beneficiaries and other private actors is even more difficult because these costs are very variable, depending on the context, and are mainly opportunity costs (e.g. the cost of the time applicants need to register for programme). For interventions in rural areas, it is particularly important to consider that the time needed to obtain documents and travel to registration offices might be substantial. At the same time, the effort required by community-based targeting exercises should not be underestimated. Estimating private costs is best done through consultations with local stakeholders and groups of potential beneficiaries.

Finally, targeting mechanisms should also be assessed in terms of the other targeting challenges discussed throughout this chapter: potential distortion of incentives, social acceptability (at the local level), and psychological costs. Like private costs, these aspects are highly context-dependent and are best assessed based on previous experiences and consultations with local stakeholders.

PRACTICAL TIPS: QUESTIONS FOR SCREENING TARGETING MECHANISMS IN TERMS OF COST-EFFECTIVENESS AND POTENTIAL SECONDARY EFFECTS

Cost-effectiveness

- How expensive will it be to use this targeting mechanism? What percentage of the intervention's budget is likely to be needed to identify beneficiaries?
- Will the selection process impose a cost on beneficiaries? How does this compare to the amount of benefits received?

Potential negative secondary effects

- Is there a risk that the targeting mechanism will lead beneficiaries to adopt behaviours that undermine the poverty-reduction impact of the intervention? How substantial is this risk?
- Will the targeting mechanism be perceived as transparent and legitimate? Or does it risk generating distrust toward the institutions?
- Does the targeting mechanism risk deteriorating cohesiveness and producing tension or conflict in the communities or the overall society in which the intervention is implemented?
- Does the targeting mechanism risk generating stigma among beneficiaries? To what extent does this threaten the poverty-reduction impact of the intervention?

Potential positive secondary effects

- Will the targeting mechanism help strengthen the capacities of the institution in charge of implementing it?
- Will the targeting mechanism help sensitize local populations to the disadvantages and needs of the target group?
- Will the targeting mechanism help extend benefits of the intervention to groups other than the target group?

Making the final decision

After screening mechanisms based on their feasibility and assessing their expected effectiveness, costs and potential secondary effects, a decision should be made. Clearly, it is possible that no option will stand out as unequivocally better than the others. The most effective mechanism might be the most expensive. The one with the best expected performance by design might be the riskiest in terms of implementation. The cheapest option might have the highest risk of generating stigma and perpetuating exclusion. The trade-offs highlighted by the assessment of the various options will necessarily have to be solved considering the priorities of the main actors involved.

The final decision should be taken in a participatory way, weighting the advantages and disadvantages of the various options based on the priorities of development organizations and local stakeholders. There is no "best" overall targeting mechanism, and the options should always be assessed considering the local context, the specific characteristics of the intervention and the information available. Nevertheless, Table 13 highlights some of the circumstances under which the different mechanisms might be particularly appropriate. For simplicity, the mechanisms are shown separately, but it is important to remember that it is usually best to select a combination of mechanisms.

TABLE 13

Situations in which the different targeting mechanisms can be more appropriate

TARGETING MECHANISM	WHEN IS IT RECOMMENDED?	EXAMPLES OF POTENTIALLY SUITABLE INTERVENTIONS
Means testing (MT)	• Where the incidence of poverty is not very high, and poverty is not geographically concentrated or socially stratified. • When the intervention can rely on a national social registry. • When information regarding income can be easily obtained (from applicants) and verified (by public institutions). • When the intervention can count on substantial administrative capacity to collect and process individual information, including in rural areas. • Where benefits delivered are large enough to justify the cost and the potential negative socio-psychological consequences. • For long-term programmes.	• Cash transfers coupled with agricultural interventions. • Service, input, assets and food subsidies or distributions. • Payments for ecosystem services.

▶ TABLE 13 (CONT.)

TARGETING MECHANISM	WHEN IS IT RECOMMENDED?	EXAMPLES OF POTENTIALLY SUITABLE INTERVENTIONS
Proxy means testing (PMT)	• Where the incidence of poverty is not very high, and poverty is not geographically concentrated or socially stratified. • When the intervention is intended for the chronic poor (e.g. not for post-emergency rehabilitation). • When a scoring system is already available or there is technical capacity and data to develop a new one (but only if the intervention is large and long-term enough to justify the effort). • When those in charge of collecting information on the ground have enough technical capacity to handle the formula. • When the intervention uses a multidimensional definition of poverty or the intervention has additional objectives to reducing poverty.	• Cash transfers coupled with agricultural interventions. • Service, input, assets and food subsidies or distributions. • Payments for ecosystem services.
Community-based targeting (CBT)	• In communities where poverty is not too high and only a small fraction of community members is to be selected. • For remote rural communities where individual selection of beneficiaries by external actors would be too costly. • Where communities are relatively small and cohesive (e.g. in relatively ethnically uniform rural villages). • When the intervention prioritizes a definition of poverty more consistent with local perceptions. • Where poor are not marginalized by current power structures.	• Cash transfers coupled with agricultural interventions. • Service, input, assets and food subsidies or distributions. • Graduation packages or integrated livelihood programmes.
Sociodemographic	• When a method for selecting individual beneficiaries is needed but MT, PMT and CBT are not feasible or advisable. • When a certain population subgroup is particularly hit by poverty. • When a poverty profile is already available or can be easily produced. • When the selection of a certain demographic group is instrumental to achieving stronger impact in objectives of the intervention other than poverty (e.g. nutrition). • When selecting individual beneficiaries based on poverty status is socially unacceptable and politically complicated.	• Cash and food transfers. • Nutrition and health services. • Training or strengthening agrifood SMEs. • Extension or farmer field schools. • Graduation packages or integrated livelihood programmes.

▶ TABLE 13 (CONT.)

TARGETING MECHANISM	WHEN IS IT RECOMMENDED?	EXAMPLES OF POTENTIALLY SUITABLE INTERVENTIONS
Geographical	If coupled with other mechanisms… • When it is possible to identify geographic areas that are substantially poorer than others. • When the poverty reduction intervention is linked to aspects related to geography (e.g. agricultural productivity, climate change adaptation). If used as the only criterion (i.e. everyone in the area receives the intervention)… • When poverty is very high and concentrated in certain areas. • When a high-resolution poverty map is available. • When individual selection of beneficiaries is socially unacceptable and politically difficult.	Virtually any type of intervention, but particularly useful for… • rural infrastructure/irrigation; • community-based natural resource management; • strengthening cooperatives and private actors in value chains or promoting market linkages; • school feeding; • strengthening local institutions (e.g. local extension services, land rights systems).
Self-targeting	• When there is no administrative capacity or time to select beneficiaries. • Where avoiding exclusion errors takes great priority over inclusion errors. • When individual selection of beneficiaries is socially unacceptable and politically difficult.	Most interventions can use self-targeting to some extent, but few, such as the following, can rely only on self-targeting: • cash/food-for-work programmes; • food distribution; • basic public services; • emergency relief.

Source: Authors' own elaboration.

From defining the target group of a country strategy to choosing a targeting mechanism for a specific project

As mentioned at the beginning of this section, the process of targeting occurs at different corporate levels and involves various steps. Choosing and fine-tuning a targeting mechanism for an intervention is just the last (without considering implementation and monitoring) of a series of decisions and considerations that start with determining overall corporate objectives and pass through the definition of regional/country strategies and the design of programmes and projects.

Table 14 provides a stylized overview of the process described in this section, from identifying a strategy's target group (for example in the context of the Hand-in-Hand Initiative or Country Programming Framework) to choosing a targeting mechanism for a specific intervention, such as an operational or a technical cooperation project. The table shows the various steps of the process in two cases: when poverty is the main objective of a strategy and when it is not.

The scheme shown is clearly a simplification, as it does not show the complex dynamics that occur within development organizations like FAO and between these organizations and external stakeholders. Additionally, it shows a linear process while, in practice, targeting is characterized by a series of feedbacks and iterations. Still, the scheme helps to visualize the main decisions involved and the main entry points for applying some of the analyses presented in this guide.

▶ TABLE 14

Process of targeting of rural poverty reduction interventions

a. Is poverty reduction the main objective of the strategy? YES

STRATEGY DEFINITION	**Identifying the target group(s) (e.g. the extreme poor, poor smallholder farmers)**	Measure poverty. Find out where the poor live (maps). Classify them in subgroups and describe their main characteristics (profile). Investigate why they are poor.			
	Broad targeting of the strategy (which actions/investments/ sectors?)	Prepare a menu of actions that would be most effective for reducing poverty for one or more of these groups.			
	From strategy to interventions	Identify one or more interventions whose main objective is reducing poverty.			
INTERVENTION DEFINITION	**Assessing the feasibility of narrow targeting in relation to the type of intervention**	**Does the intervention provide benefits to individual beneficiaries?**			
		YES (e.g. livelihood projects, community-based natural resource management projects, productive components of value chain interventions, social protection schemes, emergency operations).			**NO** (e.g. policy advice, technical cooperation projects, institutional capacity building).
	Refining the target group for the intervention or broad targeting	Within the population that is technically eligible for the intervention, which subgroups are more at risk of poverty?			**Broad targeting**. Within the areas/sectors/products/ institutions that are technically eligible for the type of intervention, identify those that are more relevant to the poor.
	Considering the feasibility of different narrow targeting methods	**In this specific intervention (or component), will it be technically feasible to select individual beneficiaries one by one?**			**Process ends here.**
		YES		**NO**. For practical reasons the intervention will have to be delivered to groups of people (e.g. producer organizations, schools, communities).	
	Assessing the effectiveness, costs and secondary effects of different narrow targeting mechanisms	Weighting targeting performance in terms of reaching the poor against administrative, private, political and psycho-social costs – will it be worth identifying the poor one by one?		Use geographical targeting (meant as targeting producer organizations, schools, communities. etc.) and/or self-targeting.	
		YES	**NO**	**Process ends here.**	
	Selecting a specific targeting mechanism (or combination of mechanisms)	Choose one among MT, PMT or CBT or a combination of these. If it helps to increase targeting performance or reduce costs, use also categorical targeting and/or self-targeting.	Use self-targeting and/or categorical targeting.		

▶ TABLE 14 (CONT.)

b. Is poverty reduction the main objective of the strategy? NO

STRATEGY DEFINITION	**Identifying the target group(s) (e.g. the extreme poor, poor smallholder farmers)**	Find out which groups are most relevant to the main objective of the strategy. Among those groups, try to identify subgroups that are more at risk of poverty.			
	Broad targeting of the strategy (which actions/investments/ sectors?)	Identify a menu of actions that, while addressing the main objective, would also contribute to poverty reduction.			
	From strategy to interventions	Define one or more interventions with poverty reduction as a secondary objective.			
INTERVENTION DEFINITION	**Assessing the feasibility of narrow targeting in relation to the type of intervention**	**Does the intervention provide benefits to individual beneficiaries?**			
		YES (e.g. livelihood projects, community-based natural resource management projects, productive components of value chain interventions, social protection schemes, emergency operations).			**NO** (e.g. policy advice, technical cooperation projects, institutional capacity building).
	Refining the target group for the intervention or broad targeting	Within the population that is technically eligible for the intervention, which groups are more relevant to achieve the main objective? Within those, are there subgroups that are poorer?			**Broad targeting**. Within the areas/sectors/products/ institutions that are technically eligible for the type of intervention, identify those that are best suited to achieve the main objective. Among those, identify if there are any that might be more relevant for the poor.
	Considering the feasibility of different narrow targeting methods	**In this specific intervention (or component), will it be technically feasible to select individual beneficiaries one by one?**			**Process ends here.**
		YES		**NO**. For practical reasons the intervention will be delivered to groups of people (e.g. producer organizations, schools, communities).	
	Assessing the effectiveness, costs and secondary effects of different narrow targeting mechanisms	Weighting targeting performance in terms of reaching the target group against administrative, private, political, incentive and psycho-social costs – will it be worth identifying the poor one by one?		Use geographical targeting to benefit the communities, producer organizations, etc. that are more representative of the target group. Select the poorest among them.	
		YES	**NO**	**Process ends here.**	
	Selecting a specific targeting mechanism (or combination of mechanisms)	Choose one among MT, PMT or CBT or a combination of these. If it helps increase targeting performance or reduce costs, use also categorical targeting and/or self-targeting.	Use self-targeting and/or categorical targeting.		

Notes: MT = means testing, PMT = proxy means testing, CBT = community-based targeting.
Source: Authors' own elaboration.

Mohamed joins his father everyday to help him with his grapes farmer in Egypt.

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5

WHAT'S NEXT?

FAO is in a strategic position to help reduce poverty, particularly in rural areas. In the context of the United Nations system, it is a key partner to ensure the achievement of SDG 1, as poverty remains an overwhelmingly rural phenomenon. The Organization aims to improve the livelihoods of vulnerable rural populations, including small-scale producers, agricultural wage-labourers, migrants, refugees, indigenous peoples, rural women, children and youth. FAO is also strategically positioned to support countries in adopting inclusive and sustainable models of structural and rural transformation for poverty reduction, with an emphasis on agrifood systems.

As noted in the introduction, FAO has produced this document to guide the mainstreaming of poverty analysis in its work, with the support of the Technical Network on Poverty Analysis (THINK-PA) and to support FAO's positioning in rural poverty reduction efforts. In addition to being used for capacity development programmes and policy support in rural poverty reduction at the country level, this guide will shape the work of the THINK-PA in the coming years.

As the Organization continues to change in response to the needs of its Member Nations, the THINK-PA will adapt to respond to new challenges and priorities under FAO's new Strategic Framework and its respective programmes, in which poverty reduction and inclusivity principles will be mainstreamed.

First and foremost, FAO will need to respond to the ongoing COVID-19 pandemic and help accelerate post-pandemic economic recovery, along with poverty reduction. All current estimates point to the fact that the COVID-19 pandemic has pushed additional millions of people into extreme poverty. However, economic recovery that generates income and wealth that are not more equally distributed within countries' populations will not reduce poverty. Inequality, if left unaddressed, will undermine economic growth and the capacity of the economic system to reduce poverty.

Before the pandemic, income inequality was on the rise in the countries that accounted for the majority of the world's population (although in most other countries, income inequality had been decreasing). In general, human capital and well-being continue to be compromised not only by income inequality, but by inequalities in access to essential infrastructure, basic services, assets and access to decent employment and protection mechanisms. Reducing inequality is key to reducing poverty, and it is also a precondition for making agrifood systems both inclusive and environmentally sustainable.

The challenge ahead will be further exacerbated by climate change and, in some parts of the world, by conflict and violence. Because the poor are oftentimes the most vulnerable to these events, promoting equitable livelihoods should be a priority going forward.

The livelihoods of the rural poor depend on agrifood systems. In order to transform these systems, it will be necessary to place the rural poor at the centre of our efforts. Approximately 2.7 billion rural people depend on small-scale food production and, of those participating in agrifood systems, over 1.1 billion live in moderate to extreme poverty. Raising incomes, distributing risk, expanding economic inclusion and job creation and ensuring access to safe and nutritious food for all, will be some of the main mechanisms for reducing poverty and inequality through agrifood system development in the coming years. At the same time, policies aiming to achieve environmental objectives will directly impact those whose livelihoods depend directly on food systems.

Given FAO's new emphasis on post-COVID-19 recovery, environmentally sustainable and inclusive transformation of agrifood systems, and the reduction of inequality, the THINK-PA will continue to generate learning opportunities and tools that complement this FAO guide, focusing on the following areas:

- **Analysis of inequality**: generation of inequality indicators and profiles, with an emphasis on inequalities along the rural–urban continuum, agricultural labour and access to resources and markets.
- **Vulnerability to poverty**: expanding poverty analysis to identify those at risk of falling into poverty, to support risk-informed policy measures and resilience programmes.
- **Design of sampling methods for conducting ad hoc surveys, with an emphasis on small-scale family farmers**: in collaboration with the Statistics Division (ESS), enhancing the quality and capacity of the Organization to design surveys and develop sampling strategies, particularly in the context of FAO's projects. New ways of collecting data, including through less costly and more participatory methods, will also be included.
- **Evaluation of impact of agricultural and climate-related interventions on poverty and inequality**: in collaboration with FAO's Impact Evaluation Task Force, developing guidance for enhancing the quality and number of impact evaluations in FAO's technical fields related to agrifood systems.
- **Policy simulations on poverty-reduction outcomes**: micro-simulation methods to simulate the impacts of policy changes on poverty reduction and inequality, using household surveys.

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Food security intervention for people affected by the refugee crisis in Cox's Bazar, Bangladesh.

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ANNEXES

ANNEX 1
MEASURING HOUSEHOLD CONSUMPTION

Deaton and Grosh (2000) and Deaton and Zaidi (2002) are the two main references for those interested in how to collect household consumption information in household surveys and how to construct a consumption measure with the information provided by household surveys. The following list, based on these works, summarizes the most important aspects of constructing a measure of consumption using household survey microdata:

- The consumption measure used as welfare indicator for poverty measurement purposes should include *all* the goods and services contributing to the households' well-being.
- In measuring welfare, consumption is a better proxy variable than expenditure. In other words, household expenditure is just one of the components of household total consumption.
- A measure of household total consumption should include:
    - all reported expenditures on goods and services (goods and services obtained in the market);
    - the value of goods and services consumed that are produced or provided by the household itself;
    - the value of goods and services consumed that are received as in-kind transfers or gifts from other households, from the government and from other institutions;
    - the value of goods and services consumed that are received in-kind from employers;
    - the flow of services provided by durable goods and owner-occupied housing.

- The consumption measure may be decomposed into the following categories:[1]
    - food items
    - non-food items
    - durable goods
    - housing.

[1] In most household surveys that include information on consumption and expenditure there is information for these four categories. However, the disaggregation and detail of each category varies considerably between surveys.

- The food aggregate should include food consumption from all sources: food purchased in the market, food produced at home, food obtained from own-production as self-employed, food received as a transfer in-kind from the government or as a transfer/gift from other households, food received as payment from employers, food obtained from food banks or from school meal programmes, and food consumed outside the house (e.g. in restaurants or street-food markets).
- The non-food aggregate should *exclude* those expenditures that are not directly related to the satisfaction of household needs. Some examples are taxes, large expenditures that are not part of regular household consumption, transfers/gifts to other households, occasional expenditures (e.g. weddings and funerals), and payments of interest on consumer credit. The inclusion/exclusion of health expenditures should be carefully analysed, and it will probably depend on the objectives of the analysis.
- For most non-durable goods included in the food and in the non-food aggregate, consumption and expenditure are very similar over fairly short periods of time. However, in the case of major durable goods, or goods that can be stored for a long period of time, consumption and expenditure differ markedly in the short run. For durable goods, it is necessary to impute the consumption flow derived from their utilization. In general, the imputation strategy for durable goods is based on the following pieces of information: the stock of durable goods, their age, the original value/price and the current value/price of each durable good. With that information, it is possible to estimate a depreciation rate for each durable good, and the value of that depreciation rate should be added to the consumption measure.
- In the case of housing, the rental value of the owner-occupied dwelling can be obtained from the rental value of a similar dwelling in the market. If such a market does not exist or it is too limited, information on characteristics of the dwelling can be used to impute its rental value.

ANNEX 2
MEASURING HOUSEHOLD INCOME

The Handbook on Household Income Statistics of the Canberra Group (United Nations, 2011) constitutes the main reference for those interested in knowing specifically how to collect household income in household surveys and how to construct an income measure with the information provided by household surveys. The handbook provides the following definition of household income, which is broadly accepted by experts:

Household income consists of all receipts whether monetary or in kind (goods and services) that are received by the household or by individual members of the household at annual or more frequent intervals; but excludes windfall gains and other such irregular and typically one-time receipts.

Household income receipts are available for current consumption and do not reduce the net worth of the household through a reduction of its cash, the disposal of its other financial or non-financial assets or an increase in its liabilities.

Household income may be defined to cover: (i) income from employment (both paid and self-employment); (ii) property income; (iii) income from the production of household services for own consumption; and (iv) current transfers received.

Table A1 presents all the components that should be included in a comprehensive definition of household income. The two most important household income concepts in Table A1 are **total income** and **disposable income**. Total income includes income from employment (employee income + income from self-employment), property income (income from financial and non-financial assets, net of expenses + royalties), income from household production of services for own consumption (value of owner-occupied housing + value of unpaid domestic services + value of services from household consumer durables), and current transfers received (social security pensions + private pensions and other insurance benefits + social assistance benefits + transfers from non-profit institutions + transfers from other households/friends and family). Regarding disposable income, this is defined as total income less current transfers paid (direct taxes + compulsory fees and fines + interhousehold transfers paid + social insurance contributions + transfers to non-profit institutions).

TABLE A1
Household income components

1. Income from employment	**1.1. Employee income**	• Wages and salaries • Cash bonuses and gratuities • Commissions and tips • Directors' fees • Profit-sharing bonuses and other profit-related pay • Shares offered as part of employee remuneration • Free and subsidized goods and services from an employer • Severance and termination pay • Employers' social insurance contributions

TABLE A1 (CONT.)

	1.2. Income from self-employment	• Profit/loss from unincorporated enterprise • Goods and services produced for barter, less cost of inputs • Goods produced for own consumption, less cost of inputs
2. Property income	**2.1. Income from financial assets, net of expenses**	
	2.2. Income from non-financial assets, net of expenses	
	2.3. Royalties	
3. Income from household production of services for own consumption	**3.1. Net value of owner-occupied housing services**	
	3.2. Value of unpaid domestic services	
	3.3. Value of services from household consumer durables	
4. Current transfers received	**4.1. Social security pensions/schemes**	
	4.2. Pensions and other insurance benefits	
	4.3. Social assistance benefits (excluding social transfers in kind)	
	4.4. Current transfers from non-profit institutions	
	4.5. Current transfers from other households	
5. Income from production (sum of 1 and 3)		
6. Primary income (sum of 2 and 5)		
7. Total income (sum of 4 and 6)		
8. Current transfers paid	**8.1. Direct taxes (net of refunds)**	
	8.2. Compulsory fees and fines	
	8.3. Current interhousehold transfers paid	
	8.4. Employee and employers' social insurance contributions	
	8.5. Current transfers to non-profit institutions	
9. Disposable income (7 less 8)		
10. Social transfers in kind received		
11. Adjusted disposable income (sum of 9 and 10)		

Source: Author's own elaboration based on United Nations (2011).

The structure of household income provided by Table A1 should be considered the ideal case scenario. Most developing countries using household income as the welfare indicator for poverty measurement rely on a restricted version of this definition of household income. In general, developing countries include all the monetary sources of income (such as wages, self-employment income, received cash transfers, pensions, income obtained from the property of assets, child support payments and other forms of monetary income) plus some non-monetary income concepts (such as imputed rental value for owner-occupied dwellings). However, developing countries do not include taxes and other non-cash benefits received by households. In developing countries, where most poor do not pay direct taxes, the exclusion of taxes does not affect poverty estimations to a great extent. FAO has made specific recommendations to the computation of aggregate incomes for rural households. The full set of recommendations, as well as challenges encountered, can be found in Covarrubias *et al.* (2009).

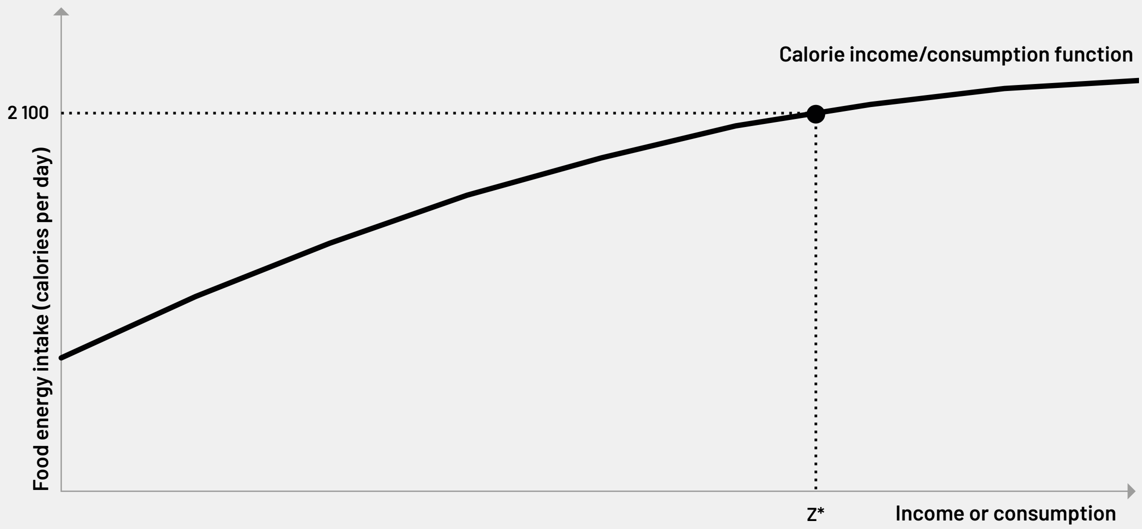
ANNEX 3
SETTING AN ABSOLUTE POVERTY LINE WITH THE FOOD-ENERGY INTAKE METHOD

The food-energy intake (FEI) method defines the (total) poverty line as the level of income or consumption expenditure at which an individual typically meets his/her food-energy requirements. Figure A1 provides a graphic description of how this method works. It presents a calorie income/consumption function, which relates the expected value of the food-energy intake (calories per day) at each level of income/consumption. The function shows that food-energy intake increases with income or consumption at a decreasing rate, as generally observed empirically. Once the energy requirement is established, the function identifies the income or consumption level (z*) at which the stipulated food-energy intake is typically attained. That income or consumption level is the value of the (total) poverty line in the FEI method.[2]

It should be stressed that the FEI method does not look at the relationship between the expected value of the food-energy intake and the level of income or consumption expenditure devoted to food items, but at the relationship between the expected value of the food-energy intake and the total level of income or consumption expenditure. For that reason, the method identifies the total level of income or consumption at which an individual typically meets the caloric requirement. This implies that the value of the poverty line defined by the FEI method already includes an allowance for non-food goods and services.

▶ FIGURE A1

The food-energy intake method



Source: Ravallion, 2016.

There are cases in which the FEI method fails to define poverty lines of same purchasing power for different population groups. This problem arises because the relation between food-energy intake and income or consumption is mediated by several other factors that differ between

[2] In empirical works, the poverty line is often estimated from a regression of calories per day on income or consumption (and other control variables).

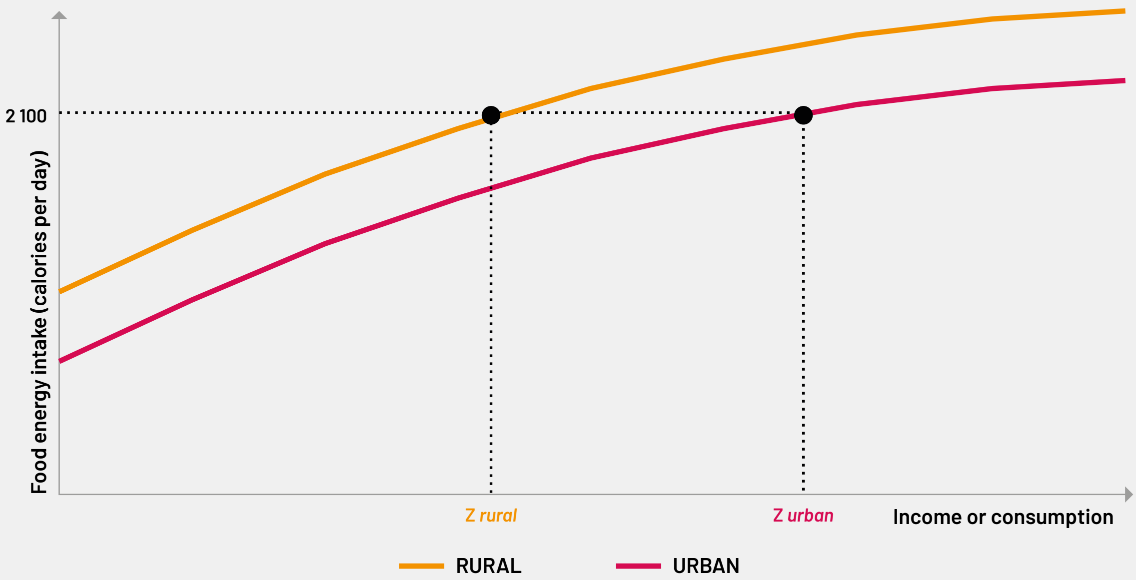
population groups (e.g. activity levels, tastes, availability of public goods, relative prices between different types of food and between food and non-food items).[3] These other factors can influence poverty comparisons through their effect in the poverty line.

Figure A2 illustrates the problem by means of a comparison between urban and rural areas. The empirical evidence indicates that food-energy intake tends to be relatively higher in rural areas, at any level of income or consumption.[4] There are two main reasons for this urban-rural gap: the cost of living tends to be lower in rural areas (e.g. food prices in urban areas tend to be higher, because of food transportation costs), and tastes differ between people residing in urban and rural areas. (For instance, urban inhabitants tend to be more willing to consume more expensive food and to allocate a higher share of their budget to non-food goods and services.) Consequently, urban individuals spend more money for each consumed calorie, and this translates into an urban-rural gap in the poverty line: the value of the poverty line obtained with the FEI method will be lower for rural than for urban areas, at any given caloric requirement.

If the difference between rural and urban poverty lines were only explained by cost-of-living differentials, this would not be a problem. However, as previously explained, the urban-rural gap reflected in the poverty lines obtained with the FEI method could exceed the difference in cost of living, capturing the influence of other factors, such as taste differences. The work of Ravallion and Bidani (1994) shows that this effect can be large enough to generate a rank reversal in the poverty rate between urban and rural areas: the estimated poverty rate for urban areas becoming higher than the poverty rate estimated for rural areas, even in contexts where standards of living are clearly higher in the urban sector.

FIGURE A2

The food-energy intake method by urban/rural areas



Source: Ravallion, 2016.

[3] In Figure A1 those other factors are kept constant along each calorie income/consumption function. When some of them change, there is a shift in the location of the curve.

[4] In Figure A2 it is assumed that the food-energy requirement is the same in urban and rural areas. However, the FEI method can be easily adapted to define the poverty lines using different food-energy requirements for each area.

A similar problem can arise when the FEI method is used for comparisons over time. The evidence indicates that the relationship between food-energy intake and income or consumption changes over time, as consumers gradually shift away from food to non-food consumption (i.e. consumers devote more resources to non-food items and less resources to food items at any level of income or consumption).[5]

When this shift happens between two periods, the expected value of the food-energy intake at any given level of income or consumption expenditure will be lower in the final than in the initial period. Consequently, the poverty line for the final period will be higher (in real terms) than the poverty line for the initial period. Putting it differently, individuals with the same standard of living in terms of real income or consumption are treated differently (i.e. they will be compared with thresholds of different real value) depending on the year of the analysis. For this reason, the use of the FEI method to define poverty lines over time could result in inconsistent poverty comparisons even if the caloric requirement remains the same.

[5] A convincing explanation of the shift from food to non-food consumption is that non-food items became relatively cheaper over time.

ANNEX 4
SETTING A RELATIVE POVERTY LINE

The main difference between the relative and the absolute approaches to the definition of the poverty line lies in the fact that in the relative approach the poverty line does not represent the cost of a bundle of items that allows an individual or household to satisfy certain absolute basic needs; instead, it refers to the level of income or consumption required to maintain the average standard of living in a given society.

The main theoretical justification for using relative poverty lines is that the circumstances of the individual relative to other individuals in society influence her/his welfare, regardless of her/his absolute level of income or consumption.[6] Although there is some evidence supporting the idea that people perceive welfare and poverty as having both absolute and relative components (see for example Corazzini *et al.* [2011]), most studies indicate that the absolute components prevail over the relative ones, particularly in low- and middle-income countries.

As indicated, in the relative approach the poverty line represents the amount of income or consumption required to maintain the "average standard of living in a given society". In practice, this concept is operationalized by setting the poverty line as a fixed proportion of the mean/median income or consumption in the respective society. For example, Eurostat considers that a person is at risk of poverty if his/her equivalised disposable income[7] is lower than 60 percent of the national median equivalised disposable income. Such poverty lines are known as "strongly" relative poverty lines, and they are almost exclusively used in developed countries.

In spite of the theoretical and empirical underpinnings, the thinking that poverty is, to some extent, a relative situation has important implications one must not overlook. Setting a poverty line as a constant proportion of the mean/median income or consumption implies that the poverty rate will not change in a scenario in which the real income or consumption of all the population increases by the same proportion, given that the poverty line will increase by exactly that proportion. Moreover, in this approach poverty could increase even in scenarios where the real income or consumption of the poor grows, but at a lower rate than the growth in the mean real income of the population. The explanation of these seemingly paradoxical results is that behind the use of strongly relative poverty lines there is a "heroic" assumption: individual welfare depends entirely – not just in part – on relative income or consumption, and absolute income or consumption does not have any influence on its own.

Other methods do not set the relative poverty line as a constant proportion of the overall mean/median of variables such as income or consumption, precisely to avoid making the aforementioned heroic assumption and incurring in the problems that arise with this. When consumption is the welfare indicator used to measure poverty, an alternative approach is to anchor the line not to the mean/median of overall consumption, but to the mean/median of consumption of some basic goods, such as food, clothing, housing and so on. The resulting poverty line will increase at a less-than-proportional rate with the mean/median overall consumption of the

[6] The idea that the satisfaction individuals derive from their income or consumption depends on its relative magnitude in the society rather than on its absolute level was presented by Duesenberry (1949). It is known as the "relative income hypothesis". A second theoretical justification is the "social inclusion argument" (Ravallion, 2010). According to this argument, "poverty lines should allow for differences in the cost of social inclusion…the expenditure needed to cover certain commodities that…have a role in assuring that a person can participate with dignity in customary social and economic activities." The key assumption behind this argument is that the cost of social inclusion is directly proportional to the mean income of the society.

[7] Eurostat defines equivalised household income as "the total income of a household, after tax and other deductions, that is available for spending or saving, divided by the number of household members converted into equalised adults; household members are equalised or made equivalent by weighting each according to their age, using the so-called modified OECD equivalence scale."

population, given that the proportion of expenditure devoted to basic goods tends to decrease as consumption expenditure rises (as per Engel's Law).

Ravallion and Chen (2011) developed an alternative method to set a relative poverty line. This method, called "weakly relative poverty", is based on the "weak relativity axiom": if all incomes increase (or decrease) by the same proportion, then an aggregate poverty measure must fall (or rise). Their proposal mixes absolute and relative elements in the construction of a poverty line. The poverty line will be fixed up to a certain mean/median income or consumption level, and it will increase, less than proportionally, with mean/median income or consumption above that threshold level of income or consumption. The critical value after which the line increases with mean/median income or consumption reflects the fact that social inclusion has some fixed costs in all societies, but those costs increase with the development level of society after reaching a certain threshold of development.

ANNEX 5
SETTING A SUBJECTIVE POVERTY LINE

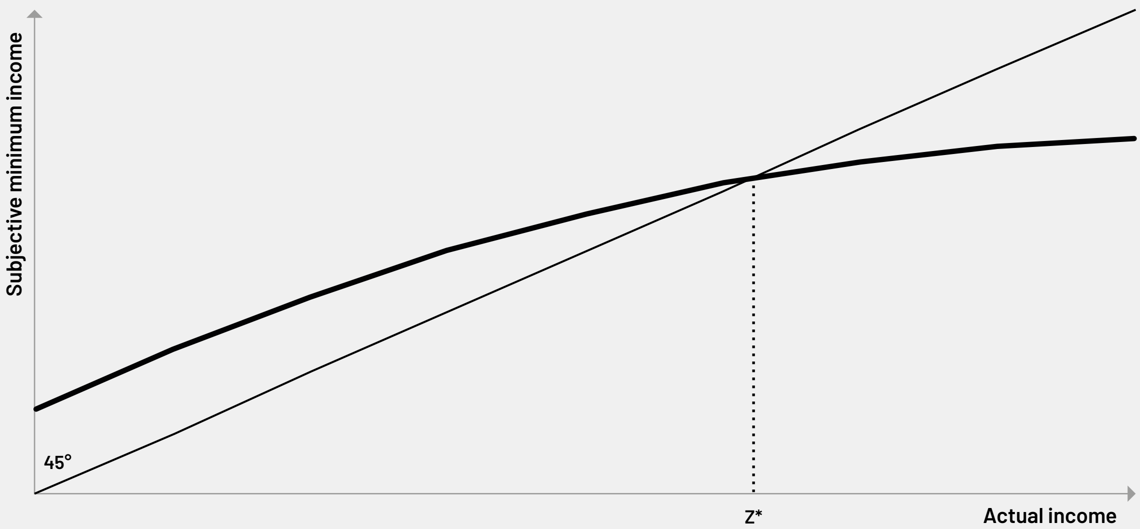
The subjective approach to poverty lines considers that the most adequate way of setting the poverty line for a given society is through the subjective judgements of its members. According to this view, the members of a given society are the ones in the best position to define the acceptable minimum welfare level in their society, as well as the minimum amount of money required to attain it.

While there are different methods to set a subjective poverty line, a common requirement to most of them is to carry out a representative household survey in the population of interest to gauge the opinion of its members about what constitutes an acceptable minimum welfare level. Most surveys collect that information by asking respondents a minimum income question (MIQ).[8] While the exact wording differs between surveys,[9] a typical MIQ asks about the absolutely smallest income level required "to live decently" or "to make ends meet". In addition, the surveys collect information on the actual income level of the respondent, as well as on other sociodemographic characteristics.

Figure A3 illustrates how a subjective poverty line can be obtained with the information provided by survey respondents. At point Z*, people tend to feel (on average) that their actual income is just enough "to live decently" or "to make ends meet", while people with income lower (or higher) than Z* tend to feel their actual income is not enough (or is more than enough) "to live decently" or "to make ends meet". Point Z* is an obvious candidate for a subjective poverty line. This point is known in the literature as the social subjective poverty line (SSPL).[10]

▶ FIGURE A3

The social subjective poverty line (SSPL)



Source: Ravallion, 2016.

[8] While the example of this section refers to income, the same procedure can be followed for consumption.
[9] Townsend *et al.* (1997) criticizes the use of different indirect questions to capture subjective poverty. They consider that the question should directly ask about the amount of money required to avoid poverty.
[10] A key assumption for this approach is that, at the individual level, the subjective minimum income is an increasing function of actual income. In general, the answers provided by survey respondents corroborate the assumption: the answers to the MIQ of richer individuals tend to be higher than the answers of poorer individuals to the same question.

However, actual income is not the only variable influencing the answers to the MIQ. There are other factors that are implicitly held constant in Figure A3. In that sense, the relationship between subjective minimum income and actual income changes (and the curved line shifts) when other factors change. If changes in other factors shift the curved line upward (or downward), then the value of Z* will increase (or decrease). Household size, household location and other demographic characteristics are among the most relevant factors potentially influencing the position of the curved line, and the value of the SSPL. The influence of these factors on the answers to the MIQ must be carefully assessed before deciding if it is worth setting specific subjective poverty lines for different population subgroups.

ANNEX 6
GLOSSARY

GENERAL

Census. A process involving the collection of data for all the units of a given population. A population census gathers sociodemographic information on all individuals and households of a country (or a particular region or area). While the general term *census* is often used to refer to a population census, there are other types of censuses depending on the unit of interest, including agricultural censuses, which collect information on all (or large samples of) agricultural holdings of a country (or region/area).

Cross-sectional data. Data collected from a set of units of observation (e.g. individuals, households or geographical areas) at one point in time.

Econometric models. Models developed using econometric methods that can be used to measure the relationship between various economic variables. In this way, they can be used to predict the behaviour and characteristics of entities such as individuals, households, farms or countries.

Econometrics. Econometrics expresses theories about economic phenomena in mathematical terms and verifies them by applying statistical methods to empirical quantitative data.

Household survey. A process aimed at collecting information on households. Household surveys use questionnaires that are administered to a sample of a population of interest. They are typically used to investigate the standards of living of a population. Household surveys are the most common source of data for measuring poverty, both at national and local levels.

Linear regression. The most common type of model used in econometric analysis, in which the value of a "dependent" variable is modelled as a linear function of one or more "independent" variables (also referred to as explanatory variables or covariates). For example, linear regression can be used to model the effect of various household characteristics (such as demographic composition and place of residence) on household income or consumption.

Logistic regression. Common type of model used in econometric analysis, in which the probability of a certain observation of assuming one or the other value of a binary independent variable is modelled as a logistic function of one or more independent variables (see linear regression). For example, logistic regression can be used to model the effect of various household characteristics on the household's probability to be poor.

Microdata. Unit-level data obtained from surveys, censuses or administrative data. It includes information on individuals or entities such as households, farms, firms or communities. In official statistics, microdata is used to produce aggregate information, such as the poverty rate in a country.

Panel (or longitudinal) data. Data collected from the same units of observation (e.g. individuals, households or geographical areas) multiple times, at different points in time.

Representativeness. Sample data is representative of a given population if it makes it possible to draw correct conclusions (e.g. the prevalence of poverty) about that population. To be representative, a sample should reflect accurately the characteristics of the population of interest. This is achieved through various sampling methods.

Robustness. Refers to whether the conclusions of an analysis depend on the methodological choices of the analyst. For example, in the context of poverty measurement, robustness could refer to the extent to which poverty estimates for a given population depend on the type of poverty measure that is used.

CHAPTER 2

Absolute poverty line. It represents the amount of money that individuals or households need in order to meet some absolute basic needs. Absolute poverty lines are set with reference to an absolute standard of what individuals or households should get access to in order to meet their basic needs. There are various methods to define absolute poverty lines but all anchor the value of the line to a non-monetary welfare indicator. In most cases, this indicator is the food-energy requirement for maintaining a certain body weight and sustaining a certain level of physical activity.

Alkire-Foster (AF) approach. This is the most common approach to multidimensional poverty measurement. It uses a counting approach to identify the poor, in which each household or individual is assigned a score equal to the weighted sum of the deprivations that it is found to experience at a particular time. A household or individual is considered poor if its score falls above a certain threshold named the poverty cut-off. The AF approach uses three main indicators to aggregate information on those who are considered multidimensionally poor. The headcount ratio informs about the incidence of multidimensional poverty in a population. The intensity of poverty reports the average number of deprivations suffered by those who are identified as poor. Finally, the adjusted headcount ratio, or multidimensional poverty index, combines the information of the poverty headcount and the intensity of poverty by multiplying one by the other.

Consumption smoothing. The phenomenon where households shift spending in time through saving, borrowing and other strategies in order to obtain a minimum level of consumption in periods characterized by lower incomes (e.g. during lean seasons).

Cost of basic needs (CBN) method. This is the most common method to define absolute poverty lines. It is composed of two steps. In the first step, a food bundle that allows individuals to meet the food-energy requirement defined by nutritionists is chosen and costed. Its cost represents the food poverty line, also known as the extreme poverty line. There are various ways to select the food bundle, but one of the most common is to base it on the consumption patterns of a reference group, typically comprised of households with relatively low levels of income or consumption. In the second step, an allowance for some basic non-food items is added to the food poverty line to obtain the total poverty line, sometimes referred to also as the "moderate poverty line" or simply "poverty line".

Deprivation cut-off (in multidimensional poverty). Threshold indicating the minimum level that an individual or household needs to reach in an indicator in order to be considered non-deprived in that particular indicator.

Dimensions (of multidimensional poverty). Conceptual categories of deprivation used to group the indicators of a multidimensional poverty index. They are a helpful way to interpret and communicate the results of multidimensional poverty estimates. The most common dimensions used in multidimensional poverty indices include health, education and standards of living.

Food-energy intake (FEI) method. Method used to define absolute poverty lines, which are defined as the level of total income or consumption expenditure at which an individual typically meets the food-energy requirement defined by nutritionists. This implies that the value of the poverty line defined by the FEI method already includes an allowance for non-food goods and services.

Foster-Greer-Thorbecke (FGT) poverty measures. This is the family of poverty measures that are most used for monetary poverty measurement. They include the headcount ratio, the poverty gap, and the severity of poverty index. The headcount ratio indicates the share of a population that lives in poverty. The poverty gap provides information on the depth of poverty in a given population. In other words, it communicates how poor the poor are. Finally, the severity of poverty index, or squared poverty gap, gauges the degree of income or consumption inequality among the poor.

Indicators (of multidimensional poverty). The variables that form the structure of a multidimensional poverty index. They are used to define the deprivation scores based on which individuals or households are identified as poor or not poor.

International poverty lines. International poverty lines are monetary poverty lines periodically updated by the World Bank and defined to guarantee comparability in poverty estimates between countries. Currently, the World Bank monitors global poverty using three international lines. The international extreme poverty line of USD 1.90 a day reflects the minimum level of welfare that is deemed necessary not to be considered poor in the poorest countries of the world. The international poverty lines of USD 3.20 and USD 5.50 a day reflect the typical standards of living of lower-middle-income and upper-middle-income countries, respectively. Comparability between countries is achieved by converting the USD values of the different lines to local currencies through purchasing power parity (PPP) indices. PPP indices represent the number of units of a country's currency required to buy the same amounts of goods and services in the domestic market as USD would buy in the United States of America.

Monetary poverty. Approach to poverty measurement in which the situation of poverty of an individual or household is determined by comparing its income or consumption with a monetary threshold (the poverty line). The monetary approach is the most common methodology used for measuring poverty.

Multidimensional poverty. An approach to poverty measurement whereby the situation of poverty of an individual or household is determined based on multiple indicators of deprivation.

Orshansky's multiplier. Coefficient used to estimate the allowance for non-food items in the context of the CBN method. It is defined as the ratio between total expenditures and food expenditures in a reference group, typically comprised of households with relatively low levels of income or consumption (see Cost of basic needs method).

Poverty cut-off (in multidimensional poverty). Threshold indicating the minimum level of deprivation an individual or household must suffer to be identified as multidimensionally poor.

Poverty line. In the context of monetary poverty, a poverty line is the minimum amount of income or consumption, expressed in monetary terms, that is considered necessary to purchase goods and services considered essential for well-being. Individuals or households whose income or consumption falls below the poverty line are considered poor.

Poverty measurement. An operation composed of two steps. In the first step, known as identification, the individuals or households of a given population are classified as either poor or non-poor by comparing an indicator capturing individual or household welfare to a threshold representing a certain minimum level of welfare. In the second step, known as aggregation, those who are identified as poor are aggregated into an overall measure of poverty.

Relative poverty lines. Poverty lines representing the level of income or consumption required to maintain an average standard of living in a given society. They are defined in relation to the distribution of income or consumption in a society. The concept is often operationalized by setting the poverty line as a fixed proportion of the mean/median income or consumption in a society.

Subjective poverty lines. Poverty lines defined in accordance with people's subjective perceptions of what constitutes poverty in a given society at a given time.

Unit of identification. In the context of poverty measurement, the entity that is identified as poor or non-poor, generally individuals or households (although it is also possible to use other entities, such as organizations and geographical areas, as the unit of analysis). Using the household, rather than the individual, as the unit of identification is more common because household surveys, the typical source of data for poverty measurement, often do not collect all the information needed to compute the indicators used in the measurement of poverty at the individual level.

CHAPTER 3

Conditional poverty profile. Analysis that uses econometric models to show the relationship, or conditional association, between various individual, household and area-level characteristics and poverty, in which the association between each characteristic and poverty is shown "holding all other characteristics constant".

Imputation techniques. Techniques used to replace missing or invalid data for observation units within a survey. In the context of poverty analysis, imputation refers to assigning individuals, households or areas a poverty status (or welfare variable to define poverty status) based on econometric models. Examples of imputation techniques used in poverty analysis are small area estimation (SAE) and proxy means testing (PMT).

Poverty map. An analysis used to identify and visualize how poverty varies across geographical areas. Poverty maps can have different resolutions. Low-resolution maps typically show how poverty varies across the main administrative divisions of a country, such as regions or provinces, while high-resolution maps show how poverty varies across more disaggregated areas, such as villages.

Poverty profile. Analysis that sets out the main facts about poverty conditions in a given context. It is usually composed of two parts. The first part shows how poverty varies across different subgroups of a population. In this part, the observations of a dataset are split into two or more groups according to some characteristic (e.g. by region or area of residence) and different measures of poverty are estimated for each group. The second part shows the characteristics of the those who are considered poor. In this part, the observations of a dataset are split into different groups according to their poverty status and described in terms of different variables (e.g. demographic, educational and labour characteristics).

Rural poverty profile. A poverty profile specifically designed for rural settings. It systematically addresses issues related to rural areas, exploring the particular features that characterize the rural poor. For example, some of these features include households' engagement in different economic activities of the agriculture sector, participation in off-farm and non-farm activities, access to natural resources, land tenure and access to agriculture-related services.

Small area estimation (SAE). A family of statistical techniques used to produce more precise estimates for small geographical areas that have limited or zero sample sizes in household surveys. In most applications, SAE consists of imputing, or predicting, a variable for the various observation units of a large database (a census usually) based on an econometric model estimated on a smaller database (a household survey usually).

CHAPTER 4

Broad targeting. A targeting process that seeks to concentrate the resources of an intervention in sectors that are more relevant to the target group.

Categorical targeting. Targeting method in which all the individuals, households or other entities that belong to an easy-to-verify category are considered eligible for an intervention.

Community-based targeting (CBT). Targeting mechanism through which beneficiaries are selected by community leaders or by a group of community members. It can be differentiated into delegated CBT, in which communities identify beneficiaries based on criteria pre-defined by the administrators of an intervention, and devolved community-based targeting, in which communities use their own criteria to identify beneficiaries. CBT is one of the methods of individual and household targeting.

Elite capture. Phenomenon where the benefits of an intervention that are intended for a certain target group are unduly seized by a restricted group of people thanks to their greater power and influence in society. It is often regarded as a potential issue of community-based targeting.

Errors by design. Targeting errors that occur when people who are part (or not part) of the target group are excluded from (or included in) an intervention due to its eligibility criteria.

Errors by implementation. Targeting errors that occur when people who are part (or not part) of the target group are excluded from (or included in) an intervention because its eligibility criteria are not implemented correctly.

Exclusion errors. Targeting errors that occur when people who are part of the target group do not participate in or do not receive the benefits of an intervention. This is also referred to as undercoverage.

Geographical targeting. Targeting mechanism that uses place of residence as the main criterion to allocate the benefits of an intervention. In its simplest form, it consists of allocating benefits to all potential beneficiaries that reside in one or more selected geographic areas. Geographical targeting is one of the methods of categorical targeting.

Inclusion errors. Targeting errors that occur when people who are not part of the target group participate in or receive part of the benefits of an intervention. This is also referred to as leakage.

Individual and household targeting. Targeting method used to verify, unit by unit, whether an individual or household complies with the eligibility criteria to participate in an intervention.

Means testing. Targeting mechanism through which the eligibility of each individual or household is assessed by collecting information on a welfare-related variable, such as income, and comparing the value of the welfare-related variable with an eligibility threshold. Means testing is one of the methods of individual and household targeting.

Narrow targeting. A targeting process that seeks to allocate the benefits of an intervention directly to the target group.

Progressivity. The progressivity of a programme relates to how the benefits are distributed across people in different welfare groups. In simple words, a programme is progressive if those with a lower level of welfare (e.g. the poor) receive a greater proportion of benefits than those who are better-off (e.g. the rich).

Proxy means testing (PMT). Targeting mechanism through which the eligibility of each individual or household is assessed using a welfare score calculated based on certain observable characteristics of the potential beneficiary and a formula. Typical variables used to calculate the score include quality of the dwelling, ownership of assets and sociodemographic characteristics. PMT is one of the methods of individual and household targeting.

Self-targeting. Targeting method in which everyone is considered eligible for an intervention, but the intervention is designed in such a way that take-up will be relatively greater among people in the target group.

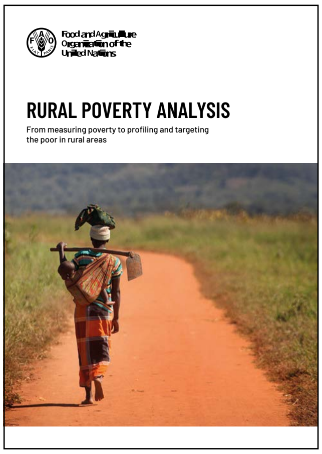
Sociodemographic targeting. Targeting mechanism that uses easy-to-observe sociodemographic characteristics (e.g. gender, age, ethnicity) to identify the beneficiaries of an intervention. Sociodemographic targeting is one of the methods of categorical targeting.

Target group. The group of people that an intervention aims to benefit. In the context of poverty reduction interventions, a target group is defined based on poverty analysis and based on the objectives and capacities of the organizations promoting and implementing the intervention.

Targeting mechanism. This refers to the set of criteria and rules used to define who is eligible to participate in or receive the benefits of an intervention.

Targeting performance. The ability of a targeting mechanism (or combination of mechanisms) to reach a given target group, minimizing exclusion and inclusion errors.

Universalism. This refers to providing, or at least offering, benefits, in equal amounts, to the entire population.



RURAL POVERTY ANALYSIS

From measuring poverty to profiling and targeting the poor in rural areas

Reducing rural poverty is a key objective of FAO. To achieve this goal, the Organization must reach the poor and the extremely poor in rural areas, analysing their needs and aspirations and providing effective guidance for the design of policies and investments that foster inclusive and sustainable development.

This guide was developed to strengthen the Organization's work on rural poverty reduction and inclusivity over the coming years. It provides key information to measure poverty, characterize rural populations, and identify their constraints to target them more accurately.

The guide includes five chapters. Chapter 1 explains the structure, content, and use of the guide, as well as its intended users and objectives. Chapter 2 discusses how poverty is measured, focusing on the different indicators that can be used, depending on the context, specific circumstances, data availability and policy objectives. Chapter 3 provides guidance on how to build a poverty profile and produce poverty maps to understand who the poor are and where they are located. Chapter 4 focuses on the targeting process, on various targeting techniques and on how to choose one over another to ensure that programmes and projects effectively combat poverty, particularly in rural areas. Finally, Chapter 5 sets the next steps for the development of further analytical guides.

The various chapters provide an overview of both widely used and emerging techniques in poverty analysis, focusing on quantitative methods, and giving constant attention to FAO's areas of work and the challenges posed by operating in rural areas.

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