# Measuring non-monetary poverty in the coffee heartlands of Laos and Rwanda: comparing MPI and EDI frameworks

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## Abstract

Poverty reduction is a key objective of development interventions. Evaluating the effectiveness of policies and programmes thus requires practical, reliable and context-relevant measures of poverty. This article is the first to compare the newly presented Extreme Deprivation Index (EDI) framework with the increasingly used global Multidimensional Poverty Index (MPI) framework. Locally adapted versions of both non-monetary poverty measures were calculated for each household using an original survey in Rwanda's main coffee-producing region (a high deprivation context) and another in Laos' main coffee-producing region (a relatively low deprivation context). We highlight the crucial role of rural labour markets for many of the poorest and discuss the implications of our findings for policy design and evaluation. We find that, despite limited overlap, in both contexts each index identifies households that are consistently worse off on multiple key markers of poverty and can therefore be considered valid measures. In addition, our analysis shows that known key markers of poverty can predict adjusted global MPI status better than EDI status in Laos, whereas the EDI framework performs best in Rwanda. We conclude that the EDI framework provides a quick and reliable way to identify households with very low standards of living in high deprivation contexts. It is particularly useful for programmes with limited resources operating in comparatively poor rural settings.

**Keywords:** multidimensional poverty; poverty measures; evaluation; rural labour markets; Laos; Rwanda

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# Measuring non-monetary poverty in the coffee heartlands of Laos and Rwanda: comparing MPI and EDI frameworks

Poverty reduction is a key objective of development interventions. Evaluating the effectiveness of policies and programmes thus requires practical, reliable and context-relevant measures of poverty. This article is the first to compare the newly presented Extreme Deprivation Index (EDI) framework with the increasingly used global Multidimensional Poverty Index (MPI) framework. Locally adapted versions of both non-monetary poverty measures were calculated for each household using an original survey in Rwanda's main coffee-producing region (a high deprivation context) and another in Laos' main coffee-producing region (a relatively low deprivation context). We highlight the crucial role of rural labour markets for many of the poorest and discuss the implications of our findings for policy design and evaluation. We find that, despite limited overlap, in both contexts each index identifies households that are consistently worse off on multiple key markers of poverty and can therefore be considered valid measures. In addition, our analysis shows that known key markers of poverty can predict adjusted global MPI status better than EDI status in Laos, whereas the EDI framework performs best in Rwanda. We conclude that the EDI framework provides a quick and reliable way to identify households with very low standards of living in high deprivation contexts. It is particularly useful for programmes with limited resources operating in comparatively poor rural settings.

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## Introduction

The way poverty is defined and measured matters for development effectiveness: conceptual understandings of poverty and the empirical evidence produced by applying corresponding measures shape explanations and inform policy choices (Laderchi, Saith, and Stewart 2003). It therefore has important real-life implications, not least in mediating access to benefits for certain groups of people. Traditionally, monetary measures such as income and expenditure have dominated, and much has been said about their merits and pitfalls (Alkire and Foster 2011a; Howe et al. 2012; Reddy and Pogge 2010). Given the widely shared assumption that poverty is a multidimensional phenomenon, however, ever more non-monetary measures have been added to the discussion, from asset indices (see Deon Filmer and Kinnon Scott 2012; Ngo and Christiaensen 2019) to subjective measures of well-being (see Dolan, Peasgood, and White 2008; Lačný 2020). Their explicit goal is often to measure livelihood outcomes directly; yet, while research tends to focus on the comparison between the monetary and non-monetary poverty measures (e.g. Bader et al. 2016; Suppa 2018; Klasen and Villalobos 2020), there is a lack of comparative research among non-monetary poverty measures. This paper addresses that gap while following the useful precedent set by these studies in applying both measures to the same sample of households, identifying overlap and mismatch and comparing each measure against key variables. It differs in its focus on rural poverty, insistence on the importance of production and labour market variables and systematic assessment of implications for programme design.

This study thus contributes at three levels: methodologically, by advancing the discussion on measuring non-monetary poverty; empirically, by highlighting key markers of poverty in Laos and Rwanda; and practically to discussions on development effectiveness by deriving implications for policy and programme design and evaluation.

At the methodological level, we fill a research gap by comparing locally adapted versions of two recent non-monetary poverty measures: the global Multidimensional Poverty Index (MPI, see Alkire and Santos 2014) and the Extreme Deprivation Index (EDI, see Sender, Cramer, and Oya 2018). Both result in binary variables at household level though with different purposes. The global MPI directly measures deprivation among multiple dimensions of poverty. To do this, it requires data on all indicators for each household and is thus especially resource intensive. The EDI uses only a single dimension (private consumption goods) and serves as a proxy for low standards of living, requiring much less data while overcoming many of the measurement problems associated with income poverty. In theory, it could thus serve as an alternative for programme design and evaluation in situations where a full MPI assessment is not possible.

This is the first time that both frameworks have been applied to the same sample, allowing a direct comparison of the resulting categorisations. To validate our findings, we do this for two separate surveys, one in a high deprivation context (in Rwanda) and one in a relatively low deprivation context (in Laos).[1] Empirically, this article sheds light on the people left behind, using the MPI and EDI frameworks as tools to examine the poverty profiles of two key agricultural export regions. We also describe key markers of deprivation and highlight the under-researched role of rural labour markets (Oya 2013). This is particularly relevant in terms of policy effectiveness as agricultural growth is said to reduce poverty in developing countries more than growth in any other sector (de Janvry and Sadoulet 2010; Ivanic and Martin 2018).

The article proceeds as follows. After introducing the research sites, sampling and data collection methods, we discuss the measurement of non-monetary poverty using the MPI and EDI methodologies. As a first step, the design and results of each locally adjusted index are presented separately, allowing us in a second step to compare the two frameworks and to highlight the merits and pitfalls of each. The following section describes poverty at our research sites by examining the relationship between the EDI and MPI frameworks and what are widely believed to be key markers of poverty, with a focus on production and employment. The last section on development effectiveness then elaborates the implications of our findings for policy and programme design and evaluation before we conclude by synthesising our findings and outlining avenues for future research.

## Research sites and data collection

### *The coffee heartlands of Laos and Rwanda*

Laos and Rwanda are both classified as Least Developed Countries (LDCs) by the United Nations Conference on Trade and Development (UNCTAD 2020). Yet, both have recorded rapid and sustained growth over the last two decades, averaging annual GDP per capita growth of 5.41% in Laos and 4.59% in Rwanda between 1999 and 2019 (World Bank 2021). Coffee has been an important part of this success. Both countries export well over 90% of their coffee (Epprecht, Weber, et al. 2018; MINAGRI, 2019). In Laos, coffee accounts for about 14% of agricultural export value (World Bank 2018a). The respective share is 15% in Rwanda, where coffee is the second most important agricultural export product after tea (MINAGRI, 2019).

Our analysis was conducted in the coffee heartlands of both countries. In Laos, 96% of coffee-producing households are in the South and over 80% of the total coffee production area is located on the rich volcanic soils of the Bolaven Plateau that spreads across Champasack, Salavan and Xekong provinces (Epprecht, Weber, et al. 2018). In Rwanda, Nyamasheke district has the highest share of coffee-producing households (NISR, 2012) as well as the highest number of coffee trees nationally (Migambi 2014). The Lake Kivu shore, part of which is located in Nyamasheke district, is particularly noted for its good environmental conditions for coffee production (Nzeyimana, Hartemink, and Geissen 2014).

### *Sampling*

We used a multi-stage sampling procedure based on a combination of purposive and probability sampling in both countries. We started by identifying the main coffee-producing areas discussed above. In Laos, we purposely sampled six villages to have some with and without road access, with and without large-scale concession areas, as well as to include different ethnic groups and administrative districts. In Rwanda, four sectors of Nyamasheke were purposely chosen to include main coffee-producing areas as well as some for which detailed secondary data were available.[2] We then selected two villages per sector based on systematic random sampling, resulting in eight villages. In both countries, we also used systematic random sampling to sample households for the survey based on household lists provided by local authorities. To ensure a comparative set-up in both countries, the total number of households in the sampled villages (1873 in Laos and 1038 in Rwanda) serves as the reference population for statistical inference and all estimations account for complex survey design. Despite all villages being in the coffee heartlands, the number of coffee growers varies considerably between villages.[3] Since we are interested in the general dynamics in the coffee export regions (involving linkages beyond individual growers, especially wage work), we included all households in the sampling roster, regardless of whether or not they grow coffee.

### *Data collection*

We conducted a multi-day enumerator training in each country. It was crucial not only to acquaint the team with the survey and the handling of the data collection tablets – but also to discuss the local relevance and meaning of key concepts and adapt the questionnaire accordingly. A further focus was on probing, particularly with regard to household members and economic activities. Given the importance of rural labour markets to understanding rural poverty and the underreporting of casual wage labour especially (Oya 2013), we made sure to collect data on all economic activities during the last 12 months, including those paid in kind (Oya 2015). We further included questions on land rentals and sharecropping, which are important in Rwanda. While the survey was adapted to each country's local context, the overall structure and key questions remained the same. Concretely, we asked the same MPI indicator questions in Laos and Rwanda.

The Lao survey was implemented between late March and early May 2018 and the Rwanda survey between October and November of the same year. Data was collected with hand-held tablets. Live monitoring and regular team briefings ensured that emerging issues could be addressed immediately. Data collection was followed by a thorough data cleaning process in both countries. In addition to the survey, we also conducted several months of in-depth qualitative fieldwork in each country. While our qualitative data is not the focus of the present article, it contextualises our findings and informs our interpretation.

## **Measuring non-monetary poverty with the MPI and EDI frameworks**

### *Multidimensional poverty*

#### *MPI design*

The 'Multidimensional Poverty Index' (MPI) proposed by Alkire and Santos (2014) marks an important advancement in the measurement of non-monetary poverty. By applying the Alkire-Foster methodology (Alkire and Foster 2011b), it provides a flexible framework for including different forms of deprivation, adjustable weights and cut-off points, while satisfying a range of important axioms. It can be adapted to local contexts, but its global version also allows for cross-country comparisons and is continuously updated. The MPI is thus an important complement to monetary poverty measures and adds crucial information for policymakers that was hitherto overlooked (see below).

The global MPI is an aggregate measure of poverty consisting of three dimensions (health, education and standard of living), each weighted ⅓, and comprising various indicators based on household achievements that are weighted equally within each dimension (see table A1). For each indicator, a deprivation cut-off point is defined: if the cut-off is not met, a person is marked as deprived in that indicator (in practice, deprivations refer to households as 'the MPI uses any available information on all members of each household in order to identify all household members as poor or not' (Alkire and Santos 2014, 253). The weighted proportion of deprivations for each person is called a deprivation score. The poverty cut-off (k-value) then is 'the proportion of weighted deprivations a person needs to experience in order to be considered multidimensionally poor' (Alkire and Santos 2014, 253). For the global MPI, k=33.33%: i.e. a person needs to be deprived in at least a third of the indicators to be considered multidimensionally poor. The share of people that are MPI-poor is called H, the headcount ratio or incidence of multidimensional poverty. The intensity of poverty, measured by A, is defined as the average deprivation score of the multidimensionally poor, i.e. the average share of indicators in which a multidimensionally poor person is simultaneously deprived. The multidimensional poverty index is the product of H and A, i.e. MPI=H x A. Arguably more interesting are the individual deprivation headcounts and the intensity of poverty (A). The uncensored or raw headcount ratio simply refers to the share, out of all people, of deprived people in that indicator. The censored headcount ratio, on the other hand, refers to the proportion of people, out of all people, who are MPI-poor and at the same time deprived in that indicator.

In addition to the global MPI, the MPI framework also proposes a destitution measure to identify the poorest of the poor (Alkire, Conconi, and Seth 2014). The structure is the same but the individual deprivation cut-off (z) for some of the indicators are adjusted. As a result, 'the destitute are all MPI poor but also experience a more extreme level of deprivation for some indicators' (Alkire, Kanagaratnam, and Suppa 2020, 9). Given the higher level of deprivation in Rwanda (the adjusted global MPI identifies 81% of households as poor in our sample), the destitution measure is more appropriate for this context. We therefore calculate an (adjusted) destitution measure for Rwanda and an (adjusted) global MPI for Laos. In both cases, we stuck as closely to the most recent version of the global MPI and the destitution measure respectively (Alkire, Kanagaratnam, and Suppa 2020) as was possible with the FATE surveys. There are, however, four main differences which are explained in appendix A.

*MPI results*

Having laid out the design and calculation of the different MPI measures, this section contextualises the results. We compare FATE data with rural or local averages in both countries. These were calculated by running adapted versions (to mirror the adjusted MPI design used here) of the do-files provided by OPHI on the DHS (Demographic and Health Surveys), respectively MICS (Multiple Indicator Cluster Surveys) data. The results are presented in tables 1 and 2. It emerges clearly that the sampled villages in Laos are consistently and considerably better off than the national rural average. This is due to the Bolaven Plateau's relative wealth: the percentage of the population living below the poverty line is 17.89 on the Plateau as compared to 28.41 at the national level (including urban areas that typically have low poverty rates), according to the Population and Housing Census of 2015 (the results are presented in Epprecht, Nicholas, et al. 2018; parts of the data can be found at http://www.decide.la/en/).

Unfortunately, calculating the adjusted global MPI using MICS data for the Bolaven Plateau was not possible, as the Plateau spans a number of provinces, covering only a small part of each, and has unique characteristics that render provincial averages meaningless. We instead verified the reliability of our findings at village level by referring to similar indicators collected by the Census (see footnote 4 in appendix A).

The Rwandan sample lies fully within Nyamasheke district – the district with the highest monetary poverty rate of Rwanda (NISR, 2018a) – so the FATE data can be substantiated by looking at the DHS data for Nyamasheke district, where all households were classified as rural. Most of our own findings correspond very well to the DHS data. The only statistically significant differences in the raw headcounts are on the food and sanitation indicators, but we have strong reasons to believe that the FATE data are valid. We show in appendix A that the food and nutrition situation in our sample is much more dire than indicated by DHS data. Given the absence of child mortality data, the food indicator in Rwanda counts as an entire dimension and strongly drives the adjusted destitution measure, explaining the stark differences to the DHS data in the MPI and H. Regarding sanitation, it is important to note that households are often required by local authorities to improve their sanitation facilities. EICV5 data for rural Nyamasheke show that 10.52% of households use unimproved sanitation or improved sanitation that is shared with other households (NISR, 2018b). This corroborates our findings.

**Table 1:** Comparison of multidimensional poverty measures in Laos (population estimates based on sub-samples with complete MPI information)

| | | | **Adjusted global MPI for rural areas: k=33%**<br><br>MICS data<br>n=15,126 | **Adjusted global MPI: k=33%**<br><br>FATE survey<br>n=527 | **Mean difference and standard error of difference (in %)** |
|---|---|---|---|---|---|
| MPI | | | 0.125 (0.006) | 0.068 (0.007) | 0.057 (0.009*) |
| Share of households that are MPI-poor (in %) | | | 22.84 (0.85) | 14.99 (1.45) | 7.85 (1.68*) |
| H (Incidence of poverty, in %) | | | 25.42 (1.00) | 14.23 (1.45) | 11.19 (1.76*) |
| A (Intensity of poverty, in %) | | | 49.15 (0.41) | 47.73 (1.01) | 1.42 (1.09) |
| **Dimensions & Indicators** | | | **Headcount (in %)** | **Headcount (in %)** | |
| Health | Food/Nutrition | rawH | 25.18 (0.66) | 25.15 (1.85) | 0.03 (1.96) |
| | | censH | 14.24 (0.60) | 11.10 (1.31) | 3.14 (1.44*) |
| | Child mortality | rawH | 3.36 (0.20) | 2.49 (0.64) | 0.87 (0.67) |
| | | censH | 2.37 (0.18) | 1.62 (0.55) | 0.75 (0.58) |
| Education | Years of schooling | rawH | 31.11 (0.89) | 19.51 (1.59) | 11.60 (1.82*) |
| | | censH | 19.78 (0.87) | 11.39 (1.33) | 8.39 (1.59*) |
| | School attendance | rawH | 15.42 (0.74) | 12.18 (1.42) | 3.24 (1.61*) |
| | | censH | 11.44 (0.72) | 6.13 (1.00) | 5.31 (1.23*) |
| Standard of living | Cooking fuel | rawH | 97.65 (0.18) | 88.48 (1.26) | 9.17 (1.28*) |
| | | censH | 25.21 (0.99) | 13.24 (1.40) | 11.96 (1.71*) |
| | Sanitation | rawH | 37.76 (1.12) | 37.23 (1.91) | 0.54 (2.22) |
| | | censH | 19.44 (0.99) | 10.31 (1.25) | 9.12 (1.59*) |
| | Electricity | rawH | 9.87 (0.86) | 0.97 (0.34) | 8.91 (0.92*) |
| | | censH | 8.35 (0.79) | 0.55 (0.25) | 7.80 (0.83*) |
| | Flooring | rawH | 9.04 (0.65) | 0.87 (0.35) | 8.17 (0.74*) |
| | | censH | 5.61 (0.49) | 0.32 (0.20) | 5.29 (0.53*) |
| | Assets | rawH | 12.20 (0.62) | 2.12 (0.56) | 10.08 (0.84*) |
| | | censH | 9.23 (0.58) | 1.90 (0.56) | 7.33 (0.81*) |

Notes: Standard errors are in parentheses
*p<.05 (corrected for survey design)

**Table 2:** Comparison of multidimensional poverty measures in Rwanda (population estimates based on sub-samples with complete MPI information)

| | | | Adjusted destitution measure for Nyamasheke (all rural): k=33%<br><br>DHS data<br>n=360 | Adjusted destitution measure: k=33%<br><br>FATE survey<br>n=198 | Mean difference and standard error of difference (in %) |
|---|---|---|---|---|---|
| MPI | | | 0.069 (0.012) | 0.251 (0.019) | -0.182 (0.023*) |
| Share of households that are MPI-poor (in %) | | | 19.18 (2.31) | 45.15 (3.08) | -25.97 (3.85*) |
| H (Incidence of poverty, in %) | | | 16.48 (2.68) | 45.38 (3.43) | -28.90 (4.36*) |
| A (Intensity of poverty, in %) | | | 41.96 (1.44) | 55.27 (0.97) | -13.31 (1.74*) |
| **Dimensions & Indicators** | | | **Headcount (in %)** | **Headcount (in %)** | |
| Health | Food/Nutrition | rawH | 4.79 (1.43) | 41.66 (3.44) | -36.87 (3.73*) |
| | | censH | 4.79 (1.43) | 41.66 (3.44) | -36.87 (3.73*) |
| Education | Years of schooling | rawH | 1.84 (0.59) | 3.78 (1.11) | -1.94 (1.26) |
| | | censH | 1.84 (0.59) | 3.78 (1.11) | -1.94 (1.26) |
| | School attendance | rawH | 1.98 (0.51) | 2.17 (0.99) | -0.19 (1.11) |
| | | censH | 1.98 (0.51) | 2.17 (0.99) | -0.19 (1.11) |
| Standard of living | Cooking fuel | rawH | 99.60 (0.19) | 98.01 (0.93) | 1.59 (0.95) |
| | | censH | 16.48 (2.68) | 44.54 (3.42) | -28.06 (4.34*) |
| | Sanitation | rawH | 28.67 (3.23) | 9.13 (1.92) | 19.55 (3.76*) |
| | | censH | 10.30 (2.02) | 7.04 (1.79) | 3.26 (2.70) |
| | Electricity | rawH | 78.94 (6.13) | 76.41 (2.56) | 2.53 (6.65) |
| | | censH | 15.98 (2.63) | 38.54 (3.27) | -22.56 (4.20*) |
| | Flooring | rawH | 87.20 (2.63) | 88.99 (2.02) | -1.79 (3.32) |
| | | censH | 16.36 (2.65) | 43.05 (3.41) | -26.69 (4.32*) |
| | Assets | rawH | 28.10 (2.10) | 32.15 (3.12) | -4.04 (3.76) |
| | | censH | 11.13 (1.92) | 19.95 (2.69) | -8.82 (3.31*) |

Notes: Standard errors are in parentheses
*p<.05 (corrected for survey design)

### *'Extreme' deprivation*

#### *EDI design*

In an effort to simplify the measurement of poverty and its interpretation for policy and programme evaluation, Sender et al. (2018) propose what they call the 'Extreme Deprivation Index' or EDI. The EDI works at the household level and is based on ownership of '*the most basic of non-food wage goods*, a very small bundle of consumer goods each of which can make a huge difference to rural life' (Sender, Cramer, and Oya 2018, 2, italics in original). A cut-off point for the resulting distribution is chosen arbitrarily to define, for example, the bottom quintile as deprived. Sender et al. (2018, 2) argue that the index captures extreme deprivation and 'allows a quick, reliable and cost-effective way of identifying people who have extremely low standards of living and of assessing the impact of policy interventions'.

Goods are selected based on local consumption patterns and the EDI is therefore always context-specific. The number of items included is not pre-determined and might depend on the data available. A careful selection is arguably more important than the number of items.[4] Two considerations stand out in particular. First, goods included should be private consumer/wage goods. The EDI's focus on consumer goods is welcome as it is conceptually clear and simple to interpret.[5] It is thus more specific than many asset indices that often lump together a variety of very different items than can lend themselves to misleading results unless clearly specified (see the discussion in Johnston and Abreu 2016). Consumer goods exclude not only non-tangible 'assets' such as education but also capital (so-called producer or investment) goods or inputs such as land and goods that might be directly linked to income-earning activities. Means of transport are often borderline cases: while 'tok-toks' in Laos are to be understood as producer goods as is often the case with bicycles in Rwanda, which are frequently used by transportation cooperatives, the classification is sometimes less clear for other vehicles (e.g. cars) or in other contexts. It is thus preferable to exclude means of transport altogether. Additionally, EDI goods should be based on private consumption and function independently of public service provision. This means that publicly provided goods (often related to sanitation or health) or goods that are mandatory by law or required by authorities (such as shoes in Rwanda) should be excluded. Similarly, goods that depend heavily on access to electricity such as TVs should be excluded unless, as is the case in our Laos site, access to electricity is so widespread (99% of households) that we can presume the goods can be used reliably.[6] Mobile phones, on the other hand, do not need to be permanently plugged in and can be used rather reliably in households without electricity (using for example plugs in shops or bars to occasionally recharge). Items selected for the index should also be more or less independent from one another; it follows that they should not be substitutes of one another which would make interpretation difficult (e.g. are households too poor to afford a basic mobile phone or do they not have one because they already have a smartphone?).[7] Given that housing conditions are often a strong marker of differentiation, slow to change, tangible and easy to enumerate, relatively independent of public provision and other consumer goods and usually closer in character to private consumption than investment goods, we also added an indicator of context-specific housing conditions in the EDI, treating them as wage-good equivalents.[8]

The second consideration is that the included consumer goods should be considered basic necessities and have a high income elasticity of demand – reflected in relatively widespread ownership. Preferably, these are durable consumer goods, reflecting longer term accumulation and use independent of seasonal variations. Additionally, they should be seen as meaningful and important in the context, i.e. as making a difference to the quality of life of people in our sample, which is evident in the case of a cooking pot, for example. 'Luxury' goods such as computers, often included in national surveys but with little relevance for the understanding of poverty in rural areas, are less important. We only included goods that were owned by at least 10% and not more than 90% of households in our sample.[9] It is helpful to have some variation in ownership, with some goods owned by most households and some that only a minority of households have access to. The overall distribution of goods owned (see figures B1 and B2 in appendix B) should similarly span from households that own none of the selected goods and to households that own all of them. This shows that the index picks up differentiation and is realistic in that it is also not uncommon to own all items.

*EDI results*

Tables 3 and 4 show the selected items and proportion of households owning them for each of our samples and compared to other data sets. For Laos, this systematically highlights the wealth of the Bolaven Plateau relative to other rural areas in general as measured by the MICS data (Lao Statistics Bureau 2018). In a context of lower deprivation, the character of goods selected based on local consumption patterns changes. Of course, a TV might not be understood as a 'basic' necessity and as such the EDI in Laos might not measure *'extreme'* deprivation. Its application as a way to identify deprived households in relative terms based on non-food wage groups remains valid nevertheless.

**Table 3:** Proportion of households in Laos owning consumer goods included in the Laos EDI (population estimates based on sub-sample with complete EDI information: n=707)

| **Consumer goods Laos** | **Proportion of households owning it (in %)**<br>Source: FATE survey (2018) | **Proportion of households owning it (in %)**<br>Source: Average for rural areas based on MICS data (2017) | **Mean difference and standard error of difference (in %)** |
|---|---|---|---|
| Washing machine | 18.09 (1.18) | 13.49 (0.58) | 4.60 (1.32*) |
| Speaker | 47.05 (1.57) | Not available | NA |
| Fridge | 68.14 (1.49) | 53.59 (1.05) | 14.55 (1.82*) |
| Improved walls[1] | 87.44 (1.01) | Answer code not comparable | NA |
| Television set | 88.08 (1.02) | 72.21 (0.92) | 15.86 (1.37*) |
| Any type of mobile phone | 88.37 (1.05) | 86.57 (0.54) | 1.80 (1.18) |

Notes: Standard errors are in parentheses
*p<.05 (corrected for survey design)
[1] Made of wood, concrete, sheet metal or adobe

**Table 4:** Proportion of households in Rwanda owning consumer goods included in the Rwanda EDI (population estimates based on sub-sample with complete EDI information: n=230)

| **Consumer goods Rwanda** | **Proportion of households owning it (in %)**<br><br>Source: FATE survey (2018) | **Proportion of households owning it (in %)**<br><br>Source: Average for rural Nyamasheke based on EICV5 data (2018) unless otherwise indicated | **Mean difference and standard error of difference (in %)** |
|---|---|---|---|
| Improved floors[1] | 12.58 (1.86) | 15.06 (2.26) | -2.48 (2.93) |
| Radio | 35.48 (2.77) | 40.24 (2.77) | -4.76 (3.91) |
| Any type of mobile phone | 50.77 (2.83) | 70.05 (2.67) | -19.28 (3.89*) |
| Torch | 58.64 (2.83) | 11 [Erlebach, 2006] | NA |
| Metal or wooden bed | 59.78 (2.73) | 83.58 (2.02) | -23.80 (3.40*) |
| Table | 64.04 (2.67) | 74.60 (2.19) | -10.56 (3.46*) |
| Blanket | 82.06 (2.22) | 76 [Erlebach, 2006] | NA |
| Metal cooking pot | 84.17 (2.06) | 79 [Erlebach, 2006] | NA |
| Plastic basin | 87.75 (1.91) | 68 [Erlebach, 2006] | NA |
| Panga (machete) | 89.36 (1.77) | 89.88 (1.62) | -0.52 (2.40) |

Notes: Standard errors are in parentheses
*p<.05 (corrected for survey design)
[1] Made of wood, vinyl, ceramic or cement

In Rwanda, the EDI can be interpreted as measuring extreme deprivation, given the basic character of the goods selected, and largely corresponds to its use by Sender et al. (2018). As some of these necessities are unfortunately not covered in standard surveys, we have to compare the FATE data with different sources in the literature. For some goods, we could not find any recent data from rural areas but we can draw a more or less direct comparison from the results provided by Erlebach (2006), which were collected in 2002 in an area close to our own research sites, showing that households in Nyamasheke were able to accumulate goods over time. Nevertheless, the comparison with recent EICV data reported in table 4 indicates that the sampled villages are consistently worse off than the Nyamasheke average. Although some indicators within the MPI framework might reflect improved government provision or pressures on households to invest in these areas, the lack of basic necessities hints at lower private consumption in these villages in line with the above-mentioned nutrition problem.

The distributions of consumer goods are given in figures B1 and B2 in appendix B. A disadvantage of the EDI is that these figures do not allow us to identify any desired proportion of respondents as deprived, but in order to compare the EDI to the MPI framework, it is meaningful to select cut-off points that identify similar proportions of households as poor with both indices so that we compare households with the same relative poverty for each index.

To identify the bottom end of the distribution, households owning none, one or two of the selected goods in Laos are classified as deprived, i.e. 13.86% of households for which we have both MPI and EDI information. In Rwanda, applying a cut-off point of six consumer goods identifies 49.70% of these households as deprived.

***Comparing EDI and MPI frameworks***

The EDI and MPI frameworks both measure some form of non-monetary deprivation. Table 5 summarises some of the key similarities and differences between the two. Unlike monetary measures, MPI and EDI measures result in binary variables at the household level and therefore cannot be directly used to provide household rankings. At the same time, they have the benefit of requiring less recall from respondents than many monetary measures and of most indicators being relatively little affected by seasonal fluctuations. There are, however, key differences between the MPI and EDI frameworks.

MPIs have stronger normative meaning, most notably by measuring livelihood outcomes directly, and is more comprehensive as it includes multiple forms of deprivation. This is at the same time its advantage and limitation. The choice of indicators is often driven by data availability but has been criticised for excluding 'fundamentally important determinants of the standard of living of rural children and adults' such as working conditions or exposure to teenage pregnancy (Cramer, Sender, and Oqubay 2020, 206). Moreover, the need for a single composite index has been questioned as the MPI is frequently disaggregated again for policy purposes, leading some to prefer a dashboard approach showing multiple single indices instead (Ravallion 2011). Additionally, MPI measurement is not only very resource intensive and has higher data requirements but it also includes more cut-off points and weighting problems, which all introduce their own arbitrariness and problems for policymaking (Ravallion 2012). On the upside, this is precisely what makes the index so flexible as it can be adjusted for different purposes and to different data constraints. Its complexity also allows for more nuanced analyses that can inform policy-making, for example, by aggregating it to the (sub-)population level (see below).

The EDI framework, on the other hand, does not attempt to portray the experience of poverty or reflect its multidimensional character. It simply claims to identify 'people who have extremely low standards of living' (Sender, Cramer, and Oya 2018, 2) and as thus it is argued that it works as a good proxy to identify other markers of poverty. The EDIs' primary use is the identification of relative deprivation, i.e. the lowest end of the distribution. It requires much less complex data (we could calculate it for over 98% of both samples) and sometimes ownership can even be confirmed visually by enumerators. Another advantage of the EDI framework is that it excludes goods that are either provided or required by government authorities, thus giving a clearer picture of differentiation among the poor. Its primary downside is that it remains a proxy and does not measure livelihood outcomes directly. While the components in the EDIs are tangible goods and the indicators in the global MPI are 'objective' measures, both indices can be adapted to reflect community priorities. In the MPI framework, 'subjective' well-being indicators can also be used as we do for the food and nutrition dimension.

EDIs have to be constructed based on local consumption patterns but since they only directly measures one dimension (private consumption) and we are interested in the bottom end of the distribution, they can be used for cross-country comparisons. Moreover, the global MPI, using the exact same indicators and weighting across countries, has been explicitly designed for international comparison. Our priority, however, has been to construct two locally appropriate EDI and MPI versions in one high and one low deprivation context and thus the focus is on the comparison between the two indices in one country (the following statistical analysis therefore refers to the locally adjusted versions laid out above).[10] Widespread deprivation in Nyamasheke required the use of an adjusted MPI destitution measure, rendering cross-country results incomparable.[11] In each country, we have instead identified similar proportions of households as deprived by both indices.

**Table 5:** Comparison of MPI and EDI frameworks

| MPI framework | EDI framework |
|---|---|
| Non-monetary poverty: multidimensional deprivation | Non-monetary poverty: private consumption goods only |
| Claims to measure acute poverty directly by a shortfall in basic needs/functionings | Claims to be a good proxy for extremely low standards of living, including deprivations in education, nutrition, and limited access to decent jobs |
| Binary indicator can be calculated at the household level, cannot reflect intra-household inequality | Binary indicator can be calculated at the household level, cannot reflect intra-household inequality |
| Cut-offs changeable (deprivation and poverty cut-offs respectively) | Cut-off changeable (one cut-off only) |
| Decomposable into indicators and aggregated at population level | Can neither be decomposed nor aggregated |
| Each dimension has equal weight, but indicator weights vary | Consumer goods have equal weights within a country |
| High data requirements that necessitate complex survey design and index construction | Low data requirements for which simple survey design and index construction are sufficient |
| Some data are hard to verify by enumerators | Data easily verifiable by enumerators |
| Can be context-specific but does not need to be | Must be context-specific |
| Mixes stock and flow variables | Stock variables only |

The Venn diagrams in figures B3 and B4 in appendix B illustrate that about 82% of households in Laos and 67% of households in Rwanda for which we have both EDI and MPI data are categorised the same with both indices. However, among households classified as deprived by either index, there is only limited overlap: in Laos only 36% of the MPI-poor are also EDI-poor while in Rwanda it is 68% (percentages are similar when taking EDI-poverty as reference point). We ran a number of tests to see if either EDI-poor only or MPI-poor only are significantly different from each other on any variables of interest, i.e. whether applying either one of the indices systematically excludes some groups of people.[12] In Rwanda, this was not the case and when comparing EDI-poor only and MPI-poor only respectively to the poorest of the poor (those households that were simultaneously EDI- and MPI-poor), we found only one significant difference (number of female-headed households) between the EDI-poor only and the poorest of the poor, while the MPI-poor only were also significantly better-off than the poorest of the poor on some education variables. This suggests that the EDI is slightly better at identifying households with the lowest standards of living on our variables of interest than the adjusted destitution measure in Rwanda. In Laos, the reverse is true: for example, the EDI-poor-only had significantly more adults with secondary education and more land than the poorest of the poor whereas there were no significant differences between the MPI-poor only and the poorest of the poor on any of our variables of interest. Unsurprisingly, EDI-poor only and MPI-poor only were also significantly different from each other on several variables of interest. This indicates that the Laos EDI, given the goods included, counts some better-off households as poor and that the MPI might be the preferred measure in this context. The EDI framework may be more appropriate in poorer rural settings such as in Rwanda because basic necessities can be readily used to differentiate households and might be more telling than, for example, services based on public provision included in the MPI framework, whereas in contexts such as Laos these necessities are owned by most households, requiring the inclusion of more ‘luxurious’ goods. However, more research with larger samples is needed to say anything definite about the different groups of poor households identified by only one of the two indices. What is crucial is how the poor identified by each of the indices (whether also classified as such by the other or not) compare on key markers of poverty and if overall they show different pictures of poverty.

## Describing poverty in Laos and Rwanda

This section examines how the poor, defined by the MPI and EDI frameworks and comprising similar proportions of households, differ in relation to the non-poor on a number of variables of interest. In doing so, we shine light on the profile of households left behind in the coffee heartlands of Laos and Rwanda and the role of rural labour markets in shaping material well-being. The selection of our variables of interest is guided by two principles. First, we include some variables that were found in the literature to be key markers of poverty and are behind so-called ‘stylised facts’ (see the discussion in Cramer et al. 2020). If our indices are to be useful, we would expect them to detect important differences for these variables. Many of these variables were also used by Sender et al. (2018) to justify use of the EDI framework and applying them allows these authors’ findings to be tested in different countries for the first time. Second, we argue that the way households are positioned in production and labour markets is key to the understanding and alleviation of poverty with implications for policy and programme design. That is, we also include key variables of production and employment that are often neglected in poverty analysis.

### *Education and nutrition*

Level of education, especially of women, is an uncontroversial marker of poverty: ‘A low level of female educational attainment is widely and correctly viewed as a particularly useful marker of poverty and of the adverse longer-term consequences of deprivation in Africa, because a woman’s lack of education is likely to be transmitted inter-generationally, negatively affecting the health, productivity, and lifetime earnings of her children’ (Cramer, Sender, and Oqubay 2020, 215). Similar observations, notably in relation to child nutrition, have been made in the Southeast Asian context (Bühler, Hartje, and Grote 2018).

**Table 6:** Education and nutrition indicators according to MPI and EDI measures (population estimates based on sub-sample with complete MPI and EDI information)

| Variables of interest | MPI measures | | | EDI measures | | |
|---|---|---|---|---|---|---|
| | NP | P | D | NP | P | D |
| Households contain member that completed secondary school (in %) | | | | | | |
| Laos | 61.95 | 5.17 | -56.79** (2.96) | 57.08 | 31.68 | -25.41** (5.47) |
| Rwanda | 22.88 | 15.23 | -7.66 (5.12) | 26.82 | 11.80 | -15.02** (5.04) |
| Households contain adult female that attended secondary school (in %) | | | | | | |
| Laos | 54.48 | 5.14 | -49.33** (2.82) | 50.03 | 28.33 | -21.70** (5.33) |
| Rwanda | 23.28 | 13.63 | -9.65 (4.96) | 25.00 | 12.59 | -12.41* (5.03) |
| Average share of illiterate adults in households | | | | | | |
| Laos | 0.22 | 0.49 | 0.28** (0.04) | 0.23 | 0.43 | 0.20** (0.04) |
| Rwanda | 0.34 | 0.49 | 0.16** (0.05) | 0.28 | 0.54 | 0.26** (0.05) |
| Average share of illiterate adults in households (<30 years old) | | | | | | |
| Laos | 0.07 | 0.45 | 0.38** (0.06) | 0.11 | 0.23 | 0.13* (0.05) |
| Rwanda | 0.09 | 0.25 | 0.16** (0.06) | 0.10 | 0.23 | 0.13* (0.06) |
| Households deprived in respective MPI nutrition indicator (in %) | | | | | | |
| Laos | 15.30 | 75.96 | 60.66** (5.05) | 20.93 | 45.43 | 24.50** (5.60) |
| Rwanda | 0 | 86.67 | 86.67** (3.22) | 24.28 | 54.16 | 29.88** (5.96) |
| Either household head consumed meat, poultry or fish the previous day or night (in %) | | | | | | |
| Laos | 93.36 | 89.29 | -4.07 (2.95) | 93.66 | 87.17 | -6.49 (3.34) |
| Rwanda | 24.75 | 9.48 | -15.27** (4.62) | 26.27 | 9.51 | -16.75** (4.81) |

Notes: NP: Among non MPI-/EDI-poor respectively
P: Among MPI-/EDI-poor respectively
D: Difference between P and NP
*p<.05, **p<.01 (corrected for survey design, standard errors in parentheses)

Table 6 shows education indicators proposed by Sender et al. (2018) and how they relate to the EDIs and MPIs of our samples. The EDI-poor are significantly worse off than the non-poor for all educational indicators in both countries. The MPIs provide the same picture but are not able to register significant differences regarding secondary education in Rwanda.

Another key characteristic of poverty is food insecurity and inadequate nutrition; large-scale studies found that both are concentrated among poor households in Rwanda (WFP 2018) and Laos (Lao Statistics Bureau 2016). This is reflected in our measures: there is, by design, a strong relationship between multidimensional poverty and the indicator for nutritional deprivation used in the adjusted global MPI and destitution measure respectively. Crucially though, this dynamic is also picked up by the EDIs in both countries. Further research on the EDI framework should collect anthropometric data. EDI- and MPI-poor in Rwanda are also much less likely to have consumed meat or fish on the previous day, underlining that nutrition is an important marker of differentiation in a high deprivation context.

### *Household composition and housing*

The relationship between household size and poverty is more controversial (White 2002) and does not seem to be an important marker of differentiation at our research sites. As for household composition, female-headed-only households are often found to be in particularly vulnerable positions (although this relationship is not straightforward either, see Chant 2004). This category is less pertinent in Laos where it only accounts for about 9% of households. In Rwanda, in contrast, around 32% of households in our sample are female-headed-only, partially as a consequence of the 1994 genocide.[13] Despite advances on gender equality, female-headed households in Rwanda are more likely to be poor (Carter 2018). Both indicators support this finding. The widespread use of categorising households according to headship has, however, been criticised. Sender et al. (2018) argue that it is more telling to look at the gender distribution of adults in a household. They find that households lacking access to adult male labour or counting more than 75% of women among all adults (said to be 'female-dominated') are more deprived. Indeed, there are more female-dominated households among the EDI- and MPI-poor households in our sample, and again, differences in Rwanda are statistically significant. The picture is the same for whether a household contains adult males.

In Laos, ethnicity has long been strongly associated with patterns of poverty, with the majority group of the Lao-Tai being considerably better off than other ethnic groups (Bader et al. 2016; World Bank 2017). A dummy variable for belonging to the Lao-Tai group shows significant differences in EDI and MPI deprivation, validating once more the two measures. In Rwanda, discussion of ethnic identifiers has been banned following the 1994 genocide (Huggins 2017), and we therefore did not gather any data on it – suffice to note that it seems to interlink with other socio-economic factors in complex ways (Dawson 2018).

Lastly, table 7 shows that even the EDIs reveal significant differences on the MPI sanitation indicator in both countries, highlighting again that housing characteristics are an important marker of differentiation.

**Table 7:** Household composition and housing indicators according to MPI and EDI measures (population estimates based on sub-sample with complete MPI and EDI information)

| **Variables of interest** | **MPI measures** | | | **EDI measures** | | |
|---|---|---|---|---|---|---|
| | NP | P | D | NP | P | D |
| Average household size (number of people) | | | | | | |
| Laos | 5.33 | 5.02 | -0.31 (0.20) | 5.33 | 5.03 | -0.30 (0.23) |
| Rwanda | 4.71 | 4.75 | 0.04 (0.28) | 4.93 | 4.53 | -0.40 (0.27) |
| Households are female-headed-only (in %) | | | | | | |
| Laos | 10.12 | 4.99 | -5.13* (2.58) | 8.59 | 14.07 | 5.49 (4.28) |
| Rwanda | 22.15 | 46.43 | 24.28** (6.16) | 19.93 | 46.36 | 26.44** (5.90) |
| Households are female-dominated (>75% of adults on HH roster are female, in %) | | | | | | |
| Laos | 4.60 | 5.71 | 1.11 (2.41) | 3.67 | 11.39 | 7.72* (3.64) |
| Rwanda | 12.90 | 26.11 | 13.22* (5.14) | 10.98 | 27.00 | 16.02** (5.00) |
| Households contain adult male (in %) | | | | | | |
| Laos | 96.63 | 94.29 | -2.35 (2.36) | 97.31 | 90.00 | -7.31* (3.45) |
| Rwanda | 87.22 | 74.19 | -13.04* (5.08) | 89.02 | 73.57 | -15.45** (4.94) |
| Households belong to ethnic minority (in %) | | | | | | |
| Laos | 53.29 | 75.04 | 21.74** (5.13) | 54.13 | 71.44 | 17.30** (5.22) |
| Households deprived in MPI sanitation indicator (in %) | | | | | | |
| Laos | 32.00 | 70.51 | 38.51** (5.30) | 32.34 | 71.19 | 38.85** (5.13) |
| Rwanda | 3.78 | 16.93 | 13.14** (3.98) | 3.03 | 16.48 | 13.45** (3.63) |

Notes: NP: Among non MPI-/EDI-poor respectively
P: Among MPI-/EDI-poor respectively
D: Difference between P and NP
*p<.05, **p<.01 (corrected for survey design, standard errors in parentheses)

***Production and the centrality of rural labour markets***

Thus far, the focus has been on ways of identifying the poor and describing key deprivations they experience. This sub-section argues that their embeddedness in production and labour relations also needs to be examined to deepen our understanding of poverty to formulate policy recommendations and improve programme design. After all, poverty is not necessarily the result of a lack of engagement with the growth process but can also be produced by adverse incorporation (Hickey and du Toit 2013; Rigg 2016). What matters are the terms of inclusion and, by extension, the role of production and especially of labour markets (Oya, McKinley, and Bargawi 2013).

Table 8 summarises the links between non-monetary poverty and production and labour market indicators. We start with land access as it is a chief concern in any agrarian setting. While it has been asserted that poverty is increasingly becoming delinked from land (Rigg 2006), this argument has less currency where employment opportunities are scarce or do not allow households to accumulate (notably in Nyamasheke), or where cash crop production remains one of the key accumulation strategies (notably on the Bolaven Plateau). Not coincidentally, therefore, we find that poor households have significantly smaller operational holdings and own less land. Nevertheless, landlessness is relatively rare in our research settings where households usually have access to some land – even though it may only be a small plot and far too little to provide a living. In Nyamasheke, the mean operational holding of the entire sample (excluding households with no farming land) is 0.29 ha, and many households remain marginal farmers dependent on at least occasional wage employment, as captured in Bernstein's (2010) notion of 'classes of labour'. As a result, programmes with the goal to increase the productivity of smallholder farmers, especially by raising coffee yields, might not reach many of the poorest directly (the poorest face important entry barriers to coffee farming in Rwanda and as a result many do not grow coffee themselves, see Illien, Niño, and Bieri 2021). Rather, the extent to which interventions can improve the quality and quantity of wage employment is likely to make a bigger difference in the life of the poorest. On the Bolaven Plateau, despite increasing pressures on land, respective landholdings are much larger with an average of 2.84 ha. Interventions to raise the profitability of household producers, notably coffee farmers, are more likely to be relevant here. Nevertheless, the under-researched role of rather worse-off domestic migrants that come to work on the Plateau is one of several factors that put the question of wage employment back at the centre.

**Table 8:** Production and work indicators according to MPI and EDI measures (population estimates based on sub-sample with complete MPI and EDI information)

| Variables of interest | MPI measures | | | EDI measures | | |
|---|---|---|---|---|---|---|
| | NP | P | D | NP | P | D |
| Average area of owned land (in ha) | | | | | | |
| Laos | 3.19 | 1.55 | -1.63** (0.15) | 3.08 | 2.07 | -1.01** (0.21) |
| Rwanda | 0.37 | 0.19 | -0.19 (0.11) | 0.45 | 0.13 | -0.31** (0.11) |
| Average area of agricultural operational holding (in ha) | | | | | | |
| Laos | 2.88 | 1.39 | -1.49** (0.15) | 2.79 | 1.85 | -0.94** (0.21) |
| Rwanda | 0.34 | 0.14 | -0.20* (0.09) | 0.41 | 0.09 | -0.32** (0.09) |
| Households hire in labour (in %) | | | | | | |
| Laos | 50.98 | 23.97 | -27.01** (5.72) | 52.67 | 12.32 | -40.35** (4.62) |
| Rwanda | 27.57 | 4.51 | -23.05** (4.27) | 27.06 | 7.13 | -19.93** (4.62) |
| For households hiring out labour: households with at least one job in casual agricultural wage employment (in %) | | | | | | |
| Laos | 38.60 | 97.12 | 58.52** (4.31) | 44.07 | 87.55 | 43.49** (6.97) |
| Rwanda | 59.50 | 86.38 | 26.88** (7.37) | 56.65 | 86.03 | 29.38** (7.57) |
| For households hiring out labour: households with at least one non-agricultural job with a written contract (in %) | | | | | | |
| Laos | 38.99 | 0 | -38.99** (3.49) | 36.18 | 6.28 | -29.90** (5.05) |
| Rwanda | 15.23 | 2.01 | -13.22** (4.76) | 17.08 | 1.84 | -15.24** (5.18) |
| For households hiring out labour: households with at least one job paid monthly (in %) | | | | | | |
| Laos | 50.51 | 13.57 | -36.95** (5.64) | 47.29 | 20.35 | -26.94** (7.28) |
| Rwanda | 38.63 | 13.19 | -25.44** (7.10) | 37.13 | 17.00 | -20.13** (7.49) |
| For households hiring out labour: households with at least one job involving migration (in %) | | | | | | |
| Laos | 28.52 | 9.21 | -19.31** (4.79) | 25.41 | 22.86 | -2.55 (7.61) |
| Rwanda | 19.62 | 18.79 | -0.84 (6.80) | 17.62 | 20.62 | 3.00 (6.77) |
| Households receive remittances (in %) | | | | | | |
| Laos | 10.46 | 1.18 | -9.27** (1.65) | 10.03 | 3.15 | -6.88** (2.31) |
| Rwanda | 4.52 | 6.83 | 2.31 (3.01) | 4.92 | 6.22 | 1.31 (2.90) |

Notes: NP: Among non MPI-/EDI-poor respectively
P: Among MPI-/EDI-poor respectively
D: Difference between P and NP
*p<.05, **p<.01 (corrected for survey design, standard errors in parentheses)

In both regions, rural labour markets are dynamic and intertwined with social differentiation. Only a few of the poorest households are in a position to hire workers. Table 8 also shows that the type of employment can make a large difference. Poor households engage predominantly in casual agricultural wage employment that typically has the worst conditions. Non-poor households, on the other hand, have significantly more access to better-paid and more secure formal work such as non-agricultural jobs with a written contract (e.g. government jobs such as teachers) or work paid on a monthly basis. Qualitative data reveals different rationales for participating in labour markets. For the poorest, wage work is primarily a survival strategy, as many cannot secure their livelihoods on their marginal holdings. This is especially the case in Nyamasheke, where land scarcity is high. However, employment opportunities are few and strongly seasonal, leaving poor households highly vulnerable and often critically underemployed. In addition, interview data indicate that poor households face barriers to access wage employment. These include, among others, a lack of social networks, poor health and the burden of care and domestic work for women. The combined lack of adequate land and of employment opportunities is thus a key marker of poverty. For better-off households with more land, on the other hand, wage work can open up opportunities for accumulation and reinvestment in production or higher education while own-account farming (not just subsistence farming but, crucially, also coffee production) provides a basic level of security.

In Laos, two additional elements stand out that structure labour markets in important ways. First, there has been a steep rise in land leases and concessions of state land since around 2000, covering a total of about 5% of the country's national territory, according to a conservative estimate and excluding mining exploration and hydropower projects (Schönweger et al. 2012). The impacts of these land deals have been assessed critically (Hett et al. 2020). The Bolaven Plateau itself has a high concentration of large-scale land investments (Schönweger et al. 2012) and the establishment of coffee plantations, mining projects and dams has increased pressure on land (Delang, Toro, and Charlet-Phommachanh 2013). Several of the villages in our sample have been directly affected by these developments. In focus groups and interviews, many respondents complained about negative socio-economic and environmental spillovers, ranging from dispossessions to unkept promises in village investments. In addition, it was sometimes mentioned that the companies do not provide enough local employment and are hiring workers from other areas instead (see below). Where companies do provide work, poor households are more likely to take these jobs as many seek to make a living out of a patchwork of labour days on different plantations. In Nyamasheke, on the other hand, mechanised large-scale plantations have been largely absent, not least due to the hilly terrain. Most coffee is grown by relatively small producers with low levels of mechanisation.

Second, the salience of migration and mobility has been increasing in rural Laos, prompting Cole and Rigg (2019, 173) to argue that 'while mobility has long, perhaps always, been a feature of rural life and living in Laos, today and increasingly we see mobility becoming defining of what it is to be rural'. Two dynamics are of particular importance. On the one hand, there is the labour migration of, predominantly young and often female, household members in Southern Laos to neighbouring Thailand, resulting in large inflows of remittances (Manivong, Cramb, and Newby 2014; Phouxay 2017). While these dynamics are certainly in play on the Bolaven Plateau, about 28% of households with wage employment have members migrating for work (not necessarily abroad) and a rather small number of households receiving remittances suggests that out-migration may be relatively less prominent on the Plateau where coffee production might act as a retaining factor. On the other hand, there is the internal seasonal migration which we hypothesise to be more prominent. The FATE survey shows that only about 46% of hiring households hired workers exclusively from within the same district. Discussions with concession companies, plantation workers and villages further revealed that large numbers of rice farmers from the lowlands in Southern and Central Laos are hired as seasonal labour by coffee-producing households and especially by large companies that provide some rudimentary housing. The extent of these movements, their drivers and dynamics on the Plateau have not yet been sufficiently documented and should be the subject of future research. Table 8 shows that MPI-poor households have significantly less jobs involving migration (domestic or international) which hints at the important role that remittances can play for some as is revealed by both the Laos MPI and EDI.

The Great Lakes region of Africa is also marked by massive migration movements, often linked to conflicts, and there were many respondents in our sample that returned from the Democratic Republic of the Congo after the genocide. Yet, from a snapshot perspective of the people staying in our sample villages, labour markets themselves are far more localised. While about 18% of households with wage employment have members migrating for work, over 91% of households that hired workers employed only people from Nyamasheke district and around 65% exclusively from within the same village.

This discussion has shown how many poor households engage in production relations and labour markets on different terms and for different reasons than non-poor households. Overall, EDI- and MPI-poor households struggle to survive and largely depend on combinations of often very marginal, own-account and precarious agricultural wage employment. Many are underemployed and therefore dispose of little negotiating power vis-à-vis employers. Non-poor households tend to manage by investing in production (notably through hiring labour and acquiring land) and/or education to access higher paid and more stable formal employment, usually in the non-agricultural sector.

***Regression and classification analysis***

Regression and classification analysis reflects these findings and underlines the differences between the EDI and MPI frameworks. Table 9 shows the results of logit regressions based on key markers of poverty as predictors. The salience of these markers for the respective research sites has been empirically demonstrated above and is supported by the relevant literature as we have seen. Figure 1 visualises the corresponding 95% confidence intervals. We immediately see that literacy is a key marker of poverty differentiation in both Laos and Rwanda. Holding size and employment type are also crucial, although holding size just misses the significance threshold in Rwanda whereas casual wage employment is highly significant. This substantiates our earlier work which argued that, given widespread land scarcity in rural Rwanda, labour relations are particularly important to understanding differences among generally land-poor households (X et al. 2021[blinded for reviewers]). Figure 1 also shows that lack of meat or fish consumption is a useful predictor in Rwanda and being part of an ethnic minority significantly increases the chances of being poor in Laos. In addition, table B1 reveals that the MPI model in Laos and the EDI model in Rwanda have good model fit: a McFadden Pseudo $R^2$ between 0.2 and 0.4 indicates excellent fit (McFadden 1979) and one of 0.17 indicates good fit (Schwarz et al. 2020).

**Table 9:** Average Marginal Effects (AME) for household characteristics on probability of household being MPI-/EDI-poor respectively (based on logistic regressions)

| | Average Marginal Effects | | | |
|---|---|---|---|---|
| | Laos | | Rwanda | |
| **Variable** | **MPI-poor** | **EDI-poor** | **MPI-poor** | **EDI-poor** |
| Operational holding | -0.048**<br>(0.010) | -0.023*<br>(0.010) | -0.080<br>(0.121) | -0.373<br>(0.200) |
| Casual agricultural wage employment | 0.111**<br>(0.027) | 0.021<br>(0.034) | 0.176**<br>(0.060) | 0.193**<br>(0.057) |
| Proportion of illiterate adults | 0.219**<br>(0.040) | 0.172**<br>(0.044) | 0.192*<br>(0.081) | 0.235**<br>(0.075) |
| Did not consume meat or fish the previous day | | | 0.213**<br>(0.078) | 0.196*<br>(0.075) |
| Ethnic minority | 0.106**<br>(0.031) | 0.069*<br>(0.031) | | |
| Number of observations | 485 | 485 | 181 | 181 |

Note: The table presents average marginal effects after logit regressions (see table A1 in the appendix). Population estimates in each country are based on the sub-sample with complete MPI and EDI information. The dependent variables are the two poverty categories for each country. Standard errors are in parentheses. *p<.05, **p<.01.

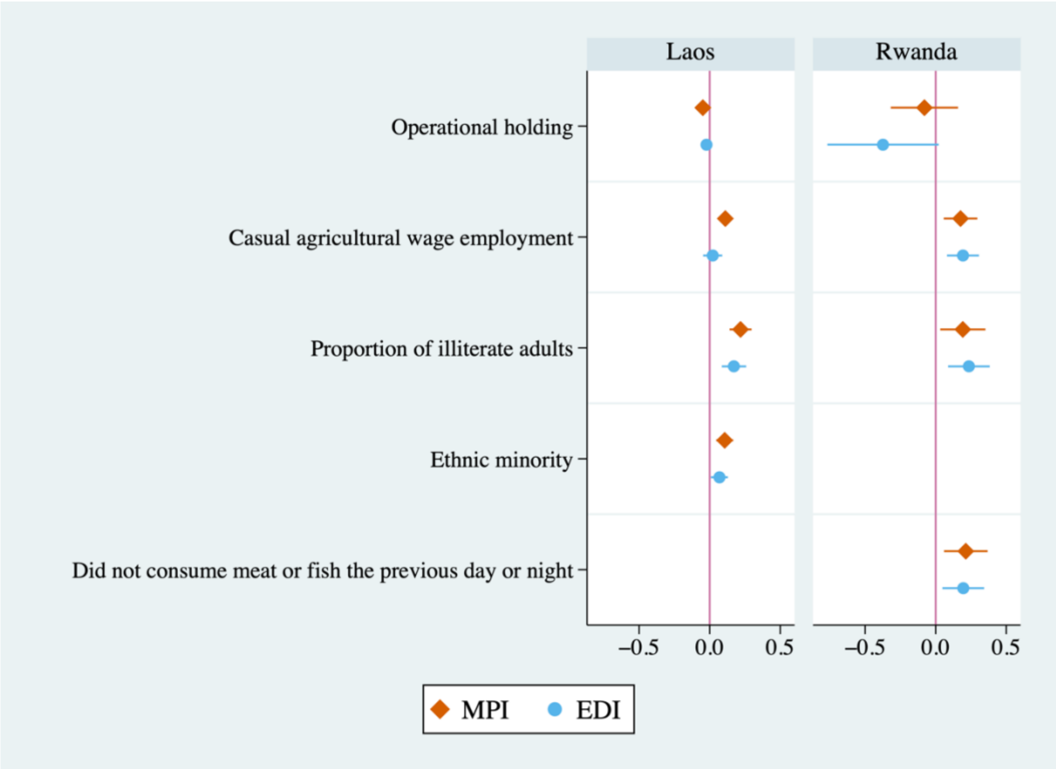


**Figure 1:** Average Marginal Effects (AME) with 95% confidence intervals

In order to compare predictive power across models, we conducted a binary classification analysis.[14] In a first step, we created confusion matrices to compare actual and predicted poverty status for the regression sub-sample with complete MPI and EDI information and based on the logit coefficients of the population estimates in table B1. The optimal cut-point for each model was set where the respective sensitivity (the true positive rate) equals, or is closest to, the respective specificity (the true negative rate), i.e. where the probability of incorrect classifications is the same, or almost the same, for poor and non-poor households (Larner 2015; Rui et al. 2019). Table 10 presents the confusion matrices, optimal cut-points and selected performance measures. The accuracy (the percentage of cases that have been correctly classified) is highest in the MPI model in Laos with 79% followed by the EDI model in Rwanda with 71%. This is relatively high given the inclusion of only four markers of poverty. The McNemar test, a non-parametric tests for paired samples and data with binary responses (Agresti 2019), reveals that the probability of a correct prediction of the MPI model is statistically significantly different to the probability of a correct prediction of the EDI model in Laos but not in Rwanda. The Matthews Correlation Coefficient (MCC) confirms the finding that known markers of poverty can predict MPI status better than EDI status in Laos and EDI status better than MPI status in Rwanda. The MCC is a robust and reliable binary classification metric that is unaffected by data set imbalance such as the imbalance in our Lao sample (Chicco and Jurman 2020). It is based on the Pearson Product Moment Correlation Coefficient and ranges from -1 to + 1 with 0 being the expected value of a coin flip (ibid.). Following the interpretation of the Pearson Coefficient in social sciences (see Weinberg and Abramowitz 2020), an MCC of 0.44 (MPI Laos) and 0.41 (EDI Rwanda) can be characterised as a moderate to strong positive relationship.

While the contingency matrices and their associated performance matrices depend on the chosen cut-point, receiver operating characteristic (ROC) curves plot the sensitivity against (1-specificity) for different cut-points, and the Area Under the ROC Curve (AUC) therefore represents "an effective way to summarize the overall diagnostic accuracy of the test" (Mandrekar 2010, 1315). The AUC can range from 0 to 1. Values of 0.5 indicate no discrimination, values between 0.7 and 0.8 are deemed acceptable and values between 0.8 and 0.9 are excellent (Mandrekar 2010). Again, we find in table 10 that the MPI model works best in Laos and the EDI model best in Rwanda. Across all cut-points, our MPI model in Laos will predict MPI status correctly about 85% of the time and the EDI model in Rwanda will predict EDI status correctly about 77% of the time.

Finally, figure 2 displays the relationship between accuracy and the probability cut-points for all four models. This is a more intuitive visualisation than ROC curves. For the balanced Rwanda data set (44% of households are MDI-poor and 49% are EDI-poor in the regression sub-sample), the meaningful cut-off range is around 0.5, whereas the pertinent range for the imbalanced Lao data set (14% of households are MDI-poor and 14% are EDI-poor in the regression sub-sample) is between 0.1 and 0.2. Figure 2 shows that the EDI model in Rwanda is consistently more accurate across all meaningful cut-points than the MPI model and vice versa for Laos.

Our regression and classification analysis shows that known key markers of poverty can predict adjusted global MPI status better than EDI status in Laos, whereas the EDI framework performs better than the MPI framework in Rwanda. These findings are in line with our bias analysis above and the bivariate analysis displayed in tables 6-8. We conclude that the EDI framework may therefore be most appropriate in high deprivation contexts whereas the MPI framework may be preferable in relatively low deprivation contexts.

**Table 10:** Confusion matrices and performance measures for EDI and MPI models in Laos and Rwanda

| Model | Confusion matrix | | | | | Accuracy | McNemar's chi-squared | MCC | AUC |
|---|---|---|---|---|---|---|---|---|---|
| **MPI Laos** | Cut-point: 0.16 | | *Predicted status* NP | *Predicted status* P | Total | 78.97% | 36.30** | 0.44 | 0.85 [0.81;0.90] |
| | *Actual Status* | NP | 329 | 88 | 417 | | | | |
| | | P | 14 | 54 | 68 | | | | |
| | Total | | 343 | 142 | 485 | | | | |
| **EDI Laos** | Cut-point: 0.14 | | *Predicted status* NP | *Predicted status* P | Total | 65.36% | | 0.22 | 0.72 [0.66;0.79] |
| | *Actual Status* | NP | 273 | 145 | 418 | | | | |
| | | P | 23 | 44 | 67 | | | | |
| | Total | | 296 | 189 | 485 | | | | |
| **MPI Rwanda** | Cut-point: 0.44 | | *Predicted status* NP | *Predicted status* P | Total | 67.40% | 0.58 | 0.35 | 0.72 [0.65;0.80] |
| | *Actual Status* | NP | 68 | 33 | 101 | | | | |
| | | P | 26 | 54 | 80 | | | | |
| | Total | | 94 | 87 | 181 | | | | |
| **EDI Rwanda** | Cut-point: 0.52 | | *Predicted status* NP | *Predicted status* P | Total | 70.72% | | 0.41 | 0.77 [0.70;0.84] |
| | *Actual Status* | NP | 65 | 27 | 92 | | | | |
| | | P | 26 | 63 | 89 | | | | |
| | Total | | 91 | 90 | 181 | | | | |

Notes:
NP: Non MPI-/EDI-poor respectively
P: MPI-/EDI-poor respectively
MCC: Matthews Correlation Coefficient
AUC: Area Under the ROC Curve
**p<.01

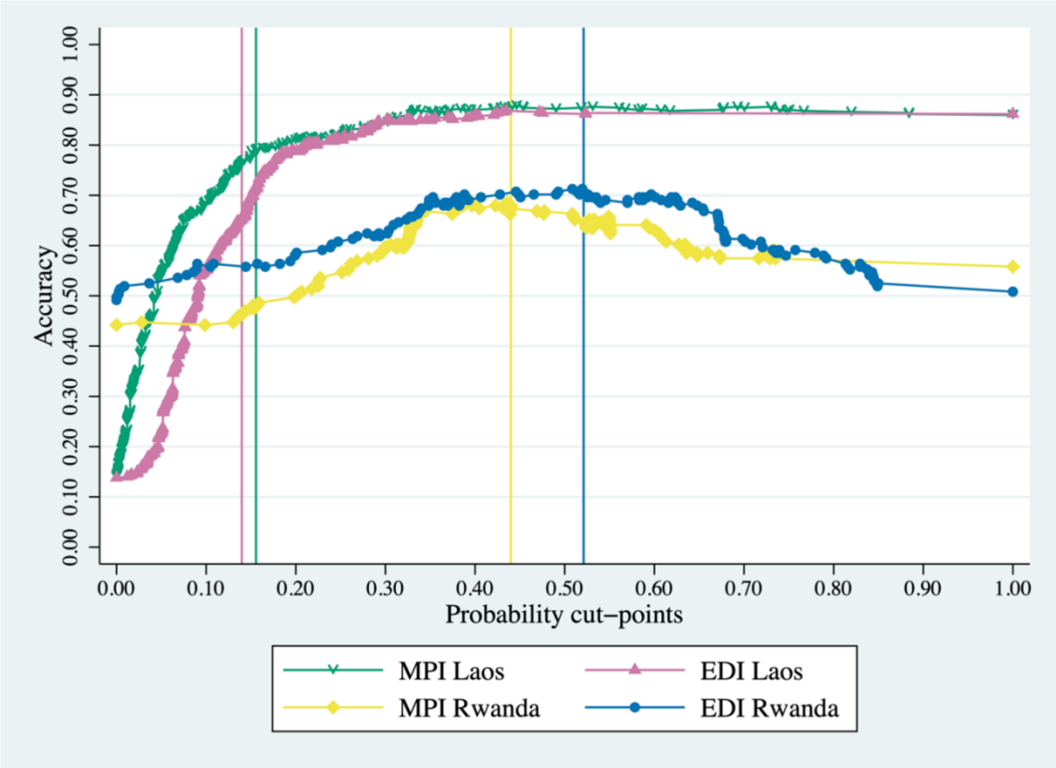


**Figure 2:** The relationship between accuracy and probability cut-points across all four models

**Implications for development effectiveness**

***Methodological implications for programme evaluation***

We have shown that the MPI and EDI frameworks, each with their distinct purposes and weaknesses, can both well identify households that are consistently worse off on multiple key markers of poverty. For policy or programme design, the MPI methodology offers substantially more options than the EDI methodology and has been widely used by governments to shape policy and inform beneficiary targeting (Alkire 2018), as well as by development agencies such as the World Bank and the United Nations Development Programme to track development progress (World Bank 2018b; UNDP 2020). Two factors make it particularly attractive: MPIs can be decomposed and aggregated at various levels, providing an 'information platform' that includes a headline number and sub-indices (ibid.), and it measures livelihood outcomes directly. MPI measures may be particularly useful to assess programmes aiming to improve the provision of public goods and services given that many of its indicators relate to these. The normative design of and implicit trade-offs in the MPI methodology, however, have to be made transparent and assessed critically, as the index could be constructed on any number of different indicators and therefore easily misused.

In contrast, the EDI framework has, to our knowledge, not yet been used for the design or evaluation of development programmes. This is understandable given its novelty and the lack of testing so far (something this paper hopes to partially remedy). Nevertheless, it is likely to be applied in the future, given that it was formulated with just such a purpose in mind: '[The EDI] may be particularly useful for evaluative purposes: to assess the extent to which polic[i]es and programmes are linked to positive outcomes for the most deprived' (Sender, Cramer, and Oya 2018, 2). The simplicity and unidimensionality of the EDIs avoid some of the normative trade-offs inherent in the MPIs but come at the cost of not permitting direct measurement of the satisfaction of basic needs beyond private consumption goods. In the remainder of this section, we consider the viability of the MPI and EDI frameworks as programme evaluation tools across three important dimensions: context relevance, reliability and practicality.

Context relevance relates partially to the validity of measurement. Face validity is high for both MPI and EDI methodologies, provided it is made clear what each index attempts to measure (shortfalls in basic needs and private consumption, respectively). In addition, our analysis has shown that the predictive validity of both measures is also satisfying as they identify significant differences on a number of key markers of poverty. Crucially, for both indices the directions of change and significances of most variables are the same.

Beyond validity concerns, context relevance also refers to the index's suitability to the context of the development intervention which is to be assessed. At the very least then, indices should allow flexibility in the indicator choices and cut-off points so that they can be adapted to local circumstances and carry meaning for the lives of research participants. While the global MPI imposes a set design for comparability, the Alkire-Foster methodology (Alkire and Foster 2011b) upon which it is based can be easily adapted to local contexts as we have done here, as can any EDI since it is based on local consumption patterns.

Second, poverty indices should be reliable. The global MPI has been shown to be robust to a number of different parameter specifications (Alkire and Santos 2014); however, research on its reliability is rather new and sometimes contested (Catalán and Gordon 2020; Santos and Villatoro 2020). While no study to date has directly tested EDI reliability, we would argue that EDIs are reliable indices given, on the one hand, the simplicity and easy verification of consumer goods included and, on the other hand, our findings which show that the EDIs adequately discriminate most-deprived and less-deprived on relevant variables, especially in a high deprivation context.[15] Our findings also show the EDIs to be robust to slight variations in design: for example, almost all statistical significances remain the same when we exclude either wall (Laos) or floor (Rwanda) materials from the respective EDIs and adjust the cut-off points accordingly to identify a similar proportion of households as EDI-poor. Moreover, we have also conducted our EDI analysis on the much larger samples where we have complete EDI data and all directions of change (except for the remittance dummy in Rwanda which is not statistically significant in either case) and almost all significances remain the same as the ones shown in tables 6-9 which were based on the sub-samples with complete EDI and MPI data. Finally, Sender et al. (2018) find that a weighted EDI based on principal component analysis identifies the same respondents to be EDI-deprived as their unweighted version.

Lastly, evaluation tools should ideally be practical enough to be used even for resource-constrained programmes. One of the motivations behind the creation of the MPI framework was in fact to provide a practical alternative to other measurement approaches (Alkire and Foster 2011a). To some extent, it has succeeded: the global MPI is based on a limited number of questions; can be adapted to practical considerations; and resources on its design and use are readily available. Yet, its application remains complex, especially because of its high data requirements and the combination of questions needed at both individual and household levels. Regarding the EDI framework, practicality is its main advantage: there are fewer questions; answers can often be directly verified by enumerators; and data cleaning and analysis are more straightforward. The result is a more affordable, and therefore accessible, tool.

To conclude, we offer two crucial considerations for the use of the MPI and the EDI methodologies in any development intervention. First, the design of either index has to be made transparent and based on local perceptions of desirable standards of living. Second, the design and choice of the index should depend on programme means and goals. What might be appropriate for one intervention may not be for another.

### *Policy implications*

In addition to the above considerations for programme evaluation, several policy implications emerge from our multi-country poverty profile analysis. A first observation is that the link between agricultural growth and poverty reduction is complex and mediated via a number of mechanisms (Irz et al. 2001). On the one hand, export-led agricultural growth is particularly promising because it provides much-coveted foreign exchange earnings and offers opportunities for value-chain upgrading at the macro level, while stimulating local labour markets and incentivising producers at the micro level (Cramer, Sender, and Oqubay 2020). On the other hand, agricultural transformations of this kind also carry significant risks, potentially exacerbating exclusions from land (Hall, Hirsch, and Li 2011) as well as inequality and poverty (McMichael 2013). This can be seen in our case studies where, despite the many benefits of coffee production, there is cause for concern. While the Bolaven region is among the richest in Laos, observers worry about rising poverty and inequality, not least due to contradictory impacts of large-scale land concessions (Baird 2011; Delang, Toro, and Charlet-Phommachanh 2013). The same concerns are raised in Rwanda in the context of green-revolution-style policies (Dawson, Martin, and Sikor 2016). Indeed, in Nyamasheke, export agriculture has not left this region any richer in regional comparison despite its vital importance for local livelihoods (NISR, 2018a). There is thus a need to safeguard the assets of the poor and to adopt additional policies if growth is supposed to be pro-poor.

We would argue based on our findings that increasing returns to labour (whether self- or wage-employed) is crucial for long-term poverty reduction. So-called supply-side policies are important in their own right. This is clearly the case of education. In addition, better education could improve access to higher skilled jobs; however, to the extent that there remain few such jobs, there are limits to what such policies can achieve (Amsden 2010). Another policy implication is that interventions should strengthen smallholder farmers' access to land as our findings show that land remains closely linked to poverty and is subject to growing pressures in both Laos and Rwanda.

The value of these supply-side measures notwithstanding, demand-side policies to improve working conditions and increase the number of paid working days would go a long way to improving the living conditions of the poor, many of whom lack access to high-skilled jobs or high-productivity self-employment. Moreover, assessing changes in working conditions and the number of paid work days could provide clear benchmarks and additional tools for evaluating programme interventions (see for example Oya 2015, for decent work indicators in rural areas). Our findings show that these interventions can never be purely technocratic but will always be embedded in unequal power relations, especially related to ethnicity, class and gender, that will shape programme success and should therefore inform programme design.

## Conclusion

Evaluating the effectiveness of development policies and programmes requires practical, reliable and context-relevant measures of poverty. Our paper, in the first such study, applied two promising frameworks of non-monetary poverty measurement, EDI and MPI, to the same samples in two different original surveys in order to study the characteristics of the most deprived in the main coffee-producing areas of Laos and Rwanda. Strikingly, the MPI and EDI frameworks yield similar and statistically significant results on key markers of poverty in both a relatively high (Nyamasheke) and low (Bolaven Plateau) deprivation context: they show that the poor are strongly characterised by lower levels of secondary, especially female, education and literacy; by rudimentary sanitation conditions; by a relative lack of access to land and a high dependence on casual agricultural wage employment; and by a high share of minority ethnic groups in the case of Laos and low meat consumption as well as a predominance of female household members and female-headed households in the case of Rwanda. Both locally adapted indices are thus capable of describing the main deprivations experienced by the poorest households.

Different conceptualisations of the two indices, however, result in limited overlap: in Laos only 36% of the MPI-poor are also EDI-poor while in Rwanda it is 68%. Our analysis shows that known key markers of poverty can predict adjusted global MPI status better than EDI status in Laos, whereas the EDI framework performs best in Rwanda. Each index has its strengths and can be used for different purposes. In particular, we argue that the EDI framework provides a quick and reliable way to identify households with very low standards of living in high deprivation contexts. It is particularly useful for programmes with limited resources operating in comparatively poor rural settings. Future research should explore how different distributions and weighting systems, selection criteria of consumer goods, and larger sample sizes affect the validity of the EDIs and to what extent the EDI methodology is useful for comparisons across time to enable programme benchmarking.

At the level of policy effectiveness, this article shed further light on the complex and uneven effects of export agriculture in producing regions. We have focused on how the poor are situated in production and labour relations to understand differences in poverty. This reveals that livelihoods remain very much linked to farming and therefore to land (through ownership or wage work), and that land remains a marker of wealth. Our analysis also underlines the centrality of wage work and dynamic labour markets in both Laos and Rwanda, albeit with very different characteristics. We encourage researchers to examine the regional and migratory dynamics introduced by large-scale concession companies in Laos and the impact on Rwandan labour markets of recent restructuring of the coffee value chain.

## Endnotes

[1] This research is part of the FATE (Feminization, Agricultural Transition and Rural Employment) project. We refer to our surveys as FATE surveys to distinguish them from other data sources.

[2] We selected two close to Erlebach's (2006) study site. This allows for some comparisons across time.

[3] One selected village in Laos is close to, but not part of, the Bolaven Plateau. Some inhabitants used to grow coffee in the past but production is now dominated by rubber plantations.

[4] While statistical techniques such as principal component analysis (PCA) can be helpful to identify a subset of a large number of eligible goods, it is more important to rigorously justify the selection process in the terms outlined here. The same goes for the assignment of weights to the index. Cramer et al. (2020, 205) note that 'unweighted indices of socio-economic status have often been found to perform just about as well in identifying low socio-economic status rural households as the indices constructed using PCA to estimate weights'.

[5] Since the focus is on private consumption, goods received as gifts or donations should ideally not be counted. This is a limitation of the FATE surveys which did not ascertain how goods were obtained.

[6] In the two instances where households reported having goods requiring reliable electricity but did not have access to electricity, we did not count these goods (i.e. these households count as non-owning). One of the households simply remained EDI-poor whereas the other changed from non EDI-poor to EDI-poor.

[7] For this reason, we combined the categories basic mobile phones and smartphones into whether the household has any type of mobile phone or not (landlines being irrelevant for private households in our sample). On the other hand, we included radios and torches separately from mobile phones as households in our sample frequently own them together with mobile phones.

[8] We thank an anonymous reviewer for this suggestion. After analysing wall, floor and roof materials in each sample, we included the indicator with the largest variation in each case: walls in Laos and floors in Rwanda.

[9] We thank Prof. John Sender for this suggestion.

[10] Despite the central importance of employment to poverty, we have not added any employment indicators into our MPIs and EDIs for four main reasons. First, the concept and design of the EDI framework is based upon private consumption only. Specifically, it derives from Engel-type expectations about the division of consumption between necessities and more luxurious goods and aims to identify people with extremely low living standards (see Sender, Cramer, and Oya 2018). Therefore, employment indicators have no part here conceptually. Second, the aim of the EDI framework is to provide a practical way of identifying the most deprived using easily verifiable answers. Most items in the EDIs are tangible and visible goods. Employment data is much more difficult to assess not least due to the informal and dynamic nature of most rural labour relations as well as occupational multiplicity and questions about household membership. This does not mean that employment data cannot or should not be collected. Quite the contrary, our article underlines its relevance. However, it is more difficult and resource-intensive to capture employment relations accurately (e.g. requiring more enumerator training and probing as well as a more complex survey design) and, therefore, it is not conducive to the aims of the EDI framework. Third, most global and national MPIs do not use employment data. In fact, the MPI framework neither requires nor precludes the inclusion of employment indicators. This not only highlights the flexibility of the MPI framework but also underlines a certain conceptual arbitrariness that is not present in the EDI framework. Fourth, as employment is neither inherently required in the MPI nor the EDI frameworks, it is revealing to leave it out in both indices and to assess the extent to which these measures help us understand the employment characteristics of poor households.

[11] We thank an anonymous reviewer for this observation.

[12] Variables that are part of the MPI framework have been omitted as there are significant differences by design: the reason that EDI-poor-only households are not also MPI-poor is mostly because many are not deprived in schooling and/or nutrition which are heavily weighted in the MPI framework.

[13] To create a dichotomous indicator, we exclude child-headed or male-headed-only households as they are negligible.

[14] Classification analysis is typically used in machine learning and its application to poverty research is relatively new (Gao et al. 2020). Whereas these machine learning classification models are built on algorithms that are trained and then tested on separate data sets with the same predicted variables, our goal here is not to train a machine learning algorithm but simply to evaluate the confusion matrices obtained from the regression models with known markers of poverty.

[15] Differences in the understanding of what constitutes ownership may however limit test-retest reliability.

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**Disclosure statement**

No potential conflict of interest was reported by the authors.

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**Appendix A: MPI adaptation**

In measuring the adjusted global MPI and destitution measure for our samples, we have stuck as closely to the most recent version of the global MPI (Alkire, Kanagaratnam, and Suppa 2020) as was possible with FATE surveys, bar four main differences. It is one of the merits of the MPI framework that such adaptations are possible while remaining consistent with the underlying Alkire-Foster methodology (Alkire and Foster 2011b). The structure of our adjusted global MPI and destitution measure is outlined in table A1.

First, we continued to use the flooring indicator as specified by Alkire & Robles (2017) in our calculations: a household is deprived if it has a dirt, dung, sand or unspecified type of floor.[1] Second, the FATE surveys did not differentiate between protected and unprotected wells and springs. However, DHS and MICS data reveal that both sources are rather important for rural areas. To avoid bias, we excluded the indicator on safe drinking water. Since it would have counted only 1/18 of the total, this exclusion barely affects H and the MPI.[2] The remaining main differences relate to the health dimension, which is notoriously the most difficult to measure.

Third, we did not collect data on child mortality in Rwanda, as we were advised it would be culturally inappropriate. Following the same procedure as for the global MPI (Alkire, Kanagaratnam, and Suppa 2020), we therefore increased the weight of the food and nutrition indicator to ⅓ in the Rwandan destitution measure and did the same for our benchmark destitution MPI based on DHS data to increase the comparability of the two data sets.

[1] Since 2018, the Oxford Poverty and Human Development Initiative (OPHI) has replaced the flooring with a housing indicator in the global MPI (Alkire, Kanagaratnam, and Suppa 2018). It counts a household as deprived if either the floor is made of natural materials or the roof or walls are made of natural or rudimentary materials including reused wood, wood planks or plywood. While it does make sense to consider walls and roofs as well, it does not seem adequate to include some of these materials in the deprived category and this level of detail is not differentiated in the FATE surveys.

[2] When calculated on the DHS and MICS data respectively for Nyamasheke (using the adjusted destitution measure) and for rural areas in Laos (using the adjusted global MPI), the multidimensional poverty headcount ratio and the MPI changed by less than 5 percentage points in either country when excluding the water indicator.

**Table A1:** Dimensions, indicators, weights and deprivation cut-offs applied to the adjusted global MPI and destitution measure based on Alkire, Kanagaratnam, and Suppa (2020)

| Dimension | Indicators | Weights[1] | MPI-poor, if | Destitution-poor, if |
|---|---|---|---|---|
| Health | | 1/3 | | |
| | Food/nutrition[2] | [1/6] | households regularly lack access to adequate food | households frequently lack access to adequate food |
| | Child mortality[3] | [1/6] | a child under 18 has died in the household in the five-year period preceding the survey | |
| Education | | 1/3 | | |
| | Years of schooling | [1/6] | no eligible household member has completed six years of schooling | no eligible household member has completed at least one year of schooling |
| | School attendance | [1/6] | any school-aged child is not attending school up to the age at which he/she would complete class 8 | any school-aged child is not attending school up to the age at which he/she would complete class 6 |
| Standard of living | | 1/3 | | |
| | Cooking fuel | [1/15] | a household cooks using dung, shrubs/straw/grass, wood, charcoal, or coal[4] | |
| | Sanitation | [1/15] | a household has unimproved or no sanitation facility, or it is improved but shared with other households[5] | |
| | Electricity | [1/15] | a household has no electricity | |
| | Flooring | [1/15] | a household has a dirt, sand, dung, or 'other' (unspecified) type of floor | |
| | Assets | [1/15] | a household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car, truck or tractor[6] | a household does not own any of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck[6] |

Note: [1] Nested weights are indicated in brackets.
[2] Different from the global MPI and destitution indicators and the ones used with the DHS/MICS data below.
[3] Only for Laos. In Rwanda, the nutrition weight as adjusted accordingly to 1/3.
[4] The FATE survey did not ask about agricultural crops as cooking fuel.
[5] We did not collect information on open defecation which would be needed to calculate the global MPI destitution indicator.
[6] We included the common two-wheel tractors in Laos, known as 'tok-tok'.

Fourth, we did not have the means to collect anthropometric data. We instead included two questions about food access and variability in the individual module of the questionnaire that was asked to both male and female household heads (usually the parents) if they were available.[3] This results in an uncensored headcount ratio in Laos that is very similar to the rural average based on anthropometric DHS data. The two indicators measure different, albeit related things. However, our results are also supported by the findings of the Lao Risk and Vulnerability Survey (MAF, 2013) which reports, based on data collected between December and February, that 18.6% of households in the Central and Southern Highlands were unable to access sufficient food for at least one day in the past month.

Rwanda presents a much bleaker picture with an uncensored headcount ratio of 42% in this dimension. This figure stands in stark contrast to the 5% based on the DHS destitution indicator. There are, however, solid reasons to believe that the food situation in Nyamasheke is much more problematic. First, although the World Food Programme (WFP 2018) classified 21% of households in Nyamasheke as food-insecure, a further 52% are only marginally food secure. Second, the same data show that 78% of women of reproductive age in Nyamasheke do not meet minimum dietary diversity (NISR, 2020). Third, our qualitative data strongly corroborate these findings.

We also calculated the Minimum Dietary Diversity Index for Women (MDD-W), defined as 'a dichotomous indicator of whether or not women 15–49 years of age have consumed at least five out of ten defined food groups the previous day or night. The proportion of women 15–49 years of age who reach this minimum in a population can be used as a proxy indicator for higher micronutrient adequacy, one important dimension of diet quality' (FAO and FHI 360 2016, 2). In Nyamasheke, the mean number of food groups consumed per female household head of reproductive age is 2.5 and the proportion who do not meet minimum dietary diversity is 97% according to FATE data. The WFP's numbers for Nyamasheke are 3.4 and 78% respectively (NISR, 2020). We suspect that the main reason for this difference is seasonality: the FATE survey was conducted in the 'lean season' (i.e. between planting and harvest), whereas WFP data were collected between March and April (outside the lean season) of the same year. In Laos, we found an average of 3.9 food groups consumed per female household head of reproductive age, 73% of whom do not meet the requirement after the coffee harvest season. The Lao Food and Nutritional Security Survey calculated the MDD-W for pregnant women or women with a live birth in the last two years and found corresponding numbers of 3.4 (rural without road), 3.9 (rural with road) and 81% (rural without road) and 67% (rural with road) respectively on data collected during the lean season (Lao Statistics Bureau 2016).[4]

MPIs can only be calculated for households with complete information on all indicators (Alkire, Kanagaratnam, and Suppa 2020). The response rate of each MPI indicator was above 90% in both Laos and Rwanda except for the nutrition indicator in Laos where we only have information on 76% of

[3] For the adjusted global MPI in Laos, households were counted as deprived if either household head indicated that they sometimes (during two to four months in the last 12 months) worried about not having enough food for the household and that they sometimes (during two to four months in the last 12 months) did not manage to buy the type of food they wanted to eat. Households were also considered as deprived if either household head said that either of these occurred often (during more than four months in the last 12 months, i.e. significantly more than during the entire lean season). For the adjusted destitution measure in Rwanda, households were counted as deprived only if either household head indicated that both of these occurred often (during more than four months in the last 12 months, i.e. significantly more than during the entire lean season). In cases where only one household head was available (e.g. widowed households), we based the indicator only on her or his responses for both the adjusted global MPI and the adjusted destitution measure.

[4] We also compared FATE data to the Lao Population and Housing Census of 2015 to verify the reliability of our data for other indicators: census data report that in the six villages sampled for this study, 94.05% of households have electricity, whereas the FATE survey finds 99.12%. The Census puts average household size at 4.98 persons, percentage of households with operational farmland at 94.42, and percentage of the literate population 15 years or older at 82.91. The numbers in the FATE survey are 5.24, 91.47 and 77.93 respectively, indicating that our data are reasonably reliable considering different survey designs, sampling procedures and a three-year time difference. Some of these indicators have been used in the poverty analysis above.

households. The food indicator was the only indicator constructed based on the individual survey module asked separately to each household head, adding data management difficulties, and explaining most of the sample drop in Laos. The EDIs, on the other hand, could be calculated for over 98% of households in our Laotian and Rwandan samples. Most of the sample drop was thus due to the MPIs, which have higher data requirements, and underlines the practicality of the EDI framework. Overall, our sample size was reduced from 714 households to 524 in Laos and from 233 to 198 in Rwanda. We therefore conducted a bias analysis, testing all our variables of interests on households for which an MPI and EDI could be calculated for significance and comparing these results to households for which there was not enough information to calculate an MPI or an EDI. The sample size reduction introduced almost no bias in Laos but some bias in Rwanda where a number of poorer households did not provide enough information for an MPI/EDI calculation.[5]

[5] In Laos, the excluded group is more deprived in asset ownership. All other MPI components or variables of interest are not significantly different between households with and without MPI/EDI data. In Rwanda, on the other hand, excluded households seem to be worse off on a number of indicators such as sanitation and size of operational holding.

**Appendix B: Figures and tables**

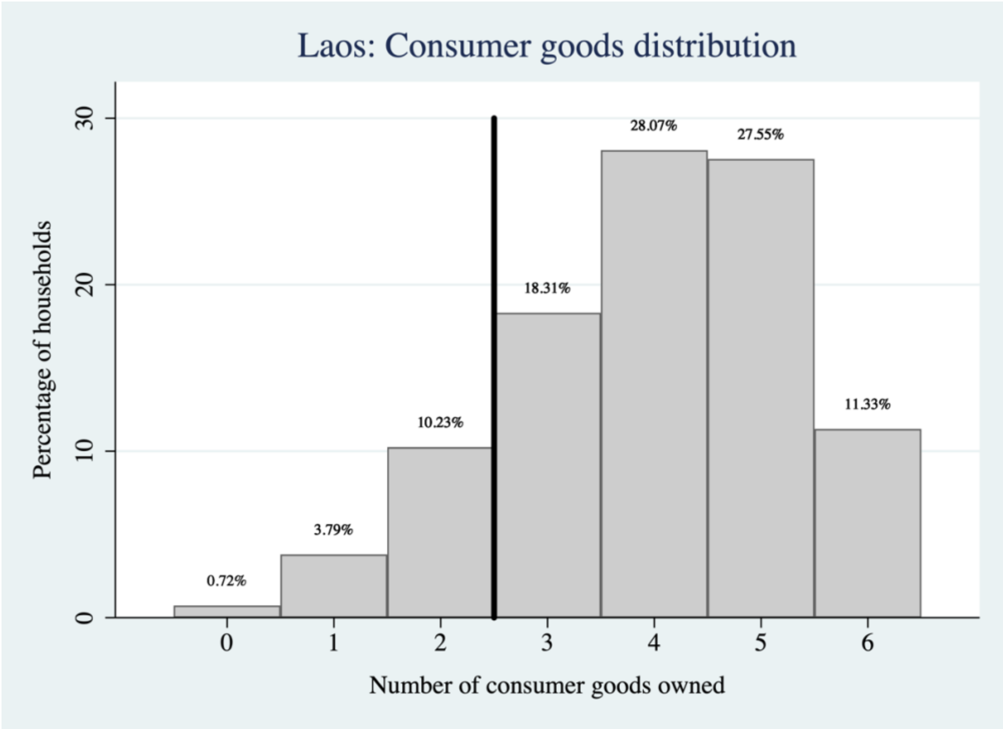


**Figure B1:** Distribution of consumer goods and cut-off used for the EDI in Laos (population estimates based on sub-sample with complete EDI information: n=707)

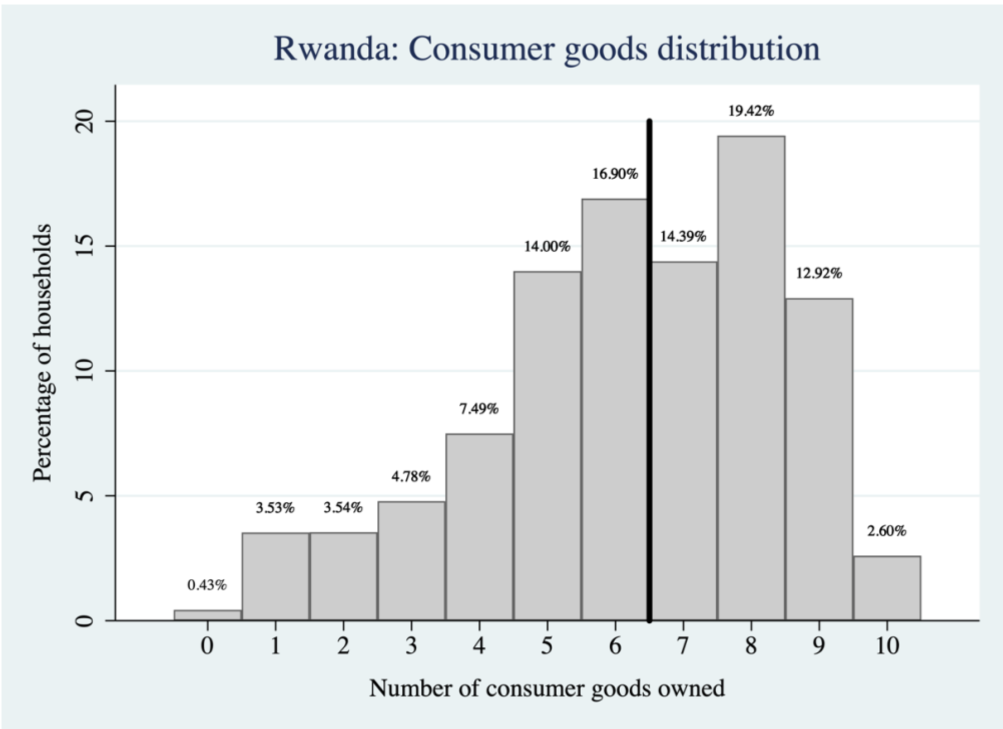


**Figure B2:** Distribution of consumer goods and cut-off used for the EDI in Rwanda (population estimates based on sub-sample with complete EDI information: n=230)

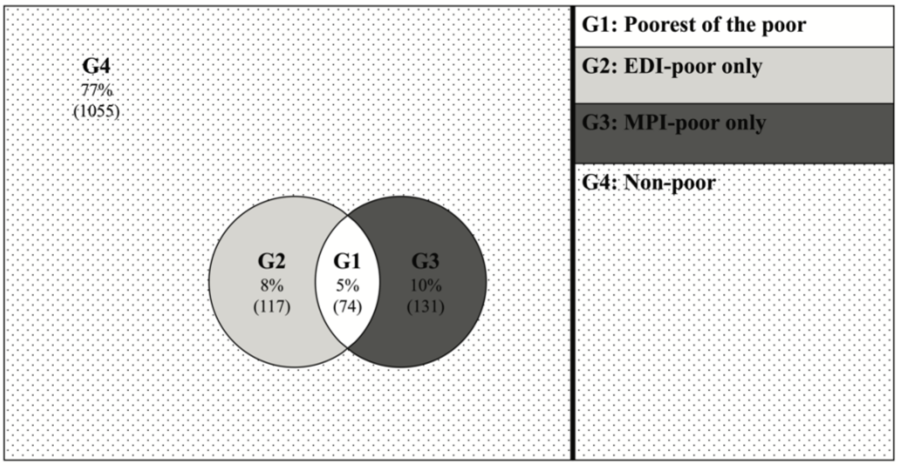


**Figure B3:** Poverty groups in Laos (population estimates based on sub-sample with complete MPI and EDI information: n=524)

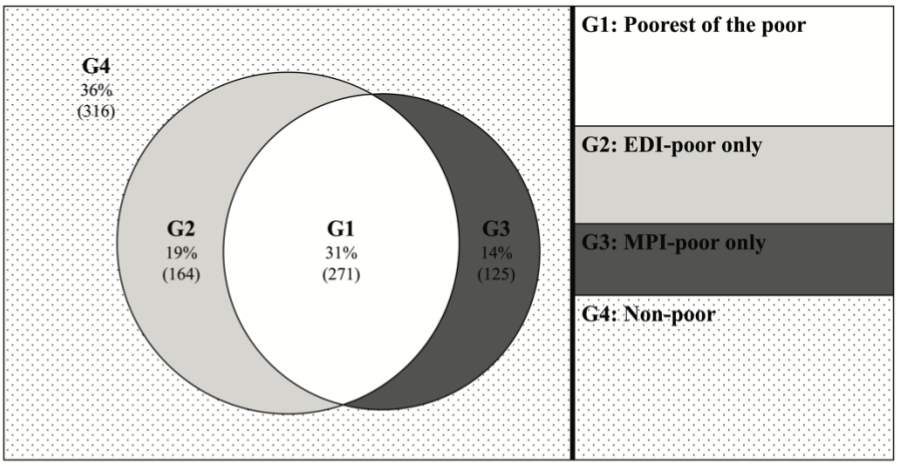


**Figure B4:** Poverty groups in Rwanda (population estimates based on sub-sample with complete MPI and EDI information: n=198)

**Table B1:** Logit model for household characteristics on probability of household being MPI-/EDI-poor respectively

| | Logit Coefficients | | | |
|---|---|---|---|---|
| | Laos | | Rwanda | |
| **Variable** | **MPI-poor** | **EDI-poor** | **MPI-poor** | **EDI-poor** |
| Operational holding | -0.517**<br>(0.102) | -0.206*<br>(0.088) | -0.369<br>(0.567) | -1.889<br>(1.050) |
| Casual agricultural wage employment | 1.183**<br>(0.302) | 0.191<br>(0.314) | 0.814**<br>(0.300) | 0.978**<br>(0.316) |
| Proportion of illiterate adults | 2.334**<br>(0.459) | 1.569**<br>(0.404) | 0.888*<br>(0.391) | 1.191**<br>(0.408) |
| Did not consume meat or fish the previous day | | | 0.986*<br>(0.384) | 0.990*<br>(0.401) |
| Ethnic minority | 1.135**<br>(0.339) | 0.626*<br>(0.278) | | |
| Constant | -2.620**<br>(0.376) | -2.293**<br>(0.283) | -1.668**<br>(0.385) | -1.426**<br>(0.406) |
| Number of observations | 485 | 485 | 181 | 181 |
| Adjusted Wald test (Prob > F) | 0.0000 | 0.0000 | 0.0007 | 0.0000 |
| Design degrees of freedom | *df*=479 | *df*=479 | *df*=173 | *df*=173 |
| McFadden's Pseudo $R^2$ | 0.255 | 0.086 | 0.095 | 0.171 |

Note: The table presents logit coefficients. Population estimates in each country are based on the sub-sample with complete MPI and EDI information. The dependent variables are the two poverty categories for each country. Standard errors are in parentheses. *p<.05, **p<.01.