Republic of Rwanda

NATIONAL INSTITUTE OF STATISTICS OF RWANDA

7Th INTEGRATED HOUSEHOLD LIVING CONDITIONS SURVEY REPORT

EICV7 | METHODOLOGICAL NOTE

2023-24

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NATIONAL INSTITUTE OF
STATISTICS OF RWANDA

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The Seventh Integrated Household Living Conditions Survey (EICV7) Report is produced by the National Institute of Statistics of Rwanda (NISR) based on data collected in 2023–2024.

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Acronyms

CERAI	: Centres d'Enseignement Rural et Artisanal Intégré
CERAR	: Centre d'Education Rurale et Artisanale au Rwanda
EDPRS	: Economic Development and Poverty Reduction Strategy
EICV	: Integrated Household Living Conditions Survey (Enquête Intégrale sur les Conditions de Vie des Ménages)
5RPHC	: Fifth Rwanda Population and Housing Census
RWF	: Rwandan Francs
ICLS	: International Conference of Labour Statisticians
ILO	: International Labour Organization
MINECOFIN	: Ministry of Finance and Economic Planning
NISR	: National Institute of Statistics of Rwanda
MIFOTRA	: Ministry of Public Service and Labour
NST	: National Strategy for Transformation
NST2	: The Second National Strategy for Transformation
SDGs	: Sustainable Development Goals
UK	: United Kingdom
UN	: United Nations
INES	: Institut d' Enseignement Superieur De Ruhengeri
PSU	: Primary Sampling Unity

Foreword

The Government of Rwanda requires timely and accurate information to monitor progress on poverty reduction. The country's strategies and targets for poverty reduction are outlined in key policy frameworks, including the second National Strategy for Transformation (NST2), the 2030 Sustainable Development Goals (SDGs), and Vision 2050.

The 2023/24 Integrated Household Living Conditions Survey (EICV7) is the seventh in a series of surveys that began in 2000/01. It also marks a break from previous rounds, as the methodology for data collection, processing, and poverty measurement was substantially revised to align with emerging best practices. Consequently, the poverty rates from this survey round mark the beginning of a new series.

This report focuses on poverty, presenting the main findings related and offering a detailed profile of the poor—an essential step in the ongoing efforts to identify vulnerable populations and address the challenge of eliminating poverty.

Companion reports provide in-depth analysis on thematic areas including education, utilities and amenities, economic activities, agriculture, gender, youth, and multidimensional (as opposed to solely monetary) poverty

The EICV7 survey revealed that 27.4% of the population was living in poverty in 2023/24. Modelling shows that if the same methodology had been applied in 2016/17, the poverty rate at that time would have been 39.8%. This represents a reduction in poverty of just over twelve percentage points over seven years. This is a significant drop in poverty, but it is also clear that much remains to be done in order to eliminate poverty.

I extend my sincere thanks to the National Institute of Statistics of Rwanda (NISR) for their excellent work on EICV7, and for the diligence, integrity, and professionalism that they demonstrated throughout the process of collecting, analyzing, and reporting the data for this report. I am also deeply grateful to the many collaborators ranging from the thousands of households who patiently answered the long survey questionnaire, to those who provided financial and technical assistance – whose inputs were essential to the successful production of this important report.

I encourage all stakeholders—government agencies, researchers, development partners, and the public—to utilize the findings of the EICV7 effectively to drive impactful actions that improve the lives of Rwandans.

MINISTRY OF FINANCE AND ECONOMIC PLANNING

Yusuf MURANGWA

Minister of Finance and Economic Planning

Acknowledgements

The Seventh Integrated Household Living Conditions Survey (EICV7) was conducted from October 2023 to October 2024, building upon the strong foundation of previous EICV surveys. Designed to provide timely and updated statistics, EICV7 supports the monitoring and evaluation of policies and programs related to poverty and wellbeing.

The protocols used to survey households and the methodology applied to measure consumption and poverty were significantly revised for EICV7 to align with evolving best practices. While the updated methodology is more robust, caution is advised when comparing the EICV7 results with those of previous EICV surveys, especially on poverty estimates. The NISR typically conducts an EICV survey every three years, a frequency made possible by the strong collaboration of our stakeholders and their support, as they share our commitment to evidence-based decision making and planning processes grounded in reliable, valid, and regular statistics.

We sincerely thank the thousands of households that participated in EICV7 for their willingness to provide data is the foundation of this report. The insights gained will play a key role in shaping policies and programs aimed at improving the living conditions of all Rwandans.

We extend our sincere gratitude to the Government of Rwanda for its strong commitment to the development of statistics in the country. Special thanks go to the Ministry of Finance and Economic Planning, as well as other government ministries and agencies, for their support and facilitation throughout the survey process. We are particularly thankful to our development partners for their vital financial and technical support. Our special appreciation goes to the World Bank team, especially Juan Carlos Parra, Christian Camilo Gomez Canon, and Nobuo Yoshida for their technical inputs during the EICV7 implementation.

We also appreciate the support of national and international experts, whose technical contributions enhanced the quality of data analysis and reporting. The EICV7 management team deserves special recognition for their dedication and effective coordination throughout the planning, data collection, and analysis phases of the survey.

Finally, we are truly grateful to the field teams and data processing staff for their professionalism and resilience during this survey round. The implementation of this survey required the efforts of approximately 240 people, including field workers, data quality monitors, IT personnel, cartographers, analysts and report designers. Their commitment was instrumental in ensuring the production of high-quality data and reports. Additionally, we acknowledge the invaluable support provided by the administrative and finance department of the National Institute of Statistics of Rwanda (NISR), which ensured the smooth execution of this exercise.

MURENZI Ivan

Director General, NISR

1 Introduction

The Integrated Household Living Conditions Survey (EICV) is designed and conducted by the National Institute of Statistics of Rwanda (NISR). This survey is an important source of socio-economic information on Rwandan household living conditions and is part of the ongoing monitoring of national and global development strategies such as the Second National Strategy for Transformation (NST2), the 2030 Sustainable Development Goals (SDGs), and Vision 2050, among others.

The 2023/24 Integrated Household Living Conditions Survey (EICV7) is the seventh iteration of the survey series, which began in 2000/01. Previous surveys include EICV1 (2000/01), EICV2 (2005/06), EICV3 (2010/11), EICV4 (2013/14), EICV5 (2016/17), and EICV6 (2019/20). Unfortunately, EICV6 (2019/20) could not be completed due to the COVID-19 pandemic, which disrupted the data collection process. EICV8 is planned to take place in 2026/27, returning to the original plan of a three-year cycle.

Methodology

The purpose of this document is to set out in detail how the survey was undertaken, and how the data were processed to obtain measures of poverty. It starts with a description of the logistical and practical arrangements; then discusses the sampling techniques, data analysis and report writing methods. Finally, it finishes with a description of the methodology used to measure headcount poverty.

Objectives

The main objectives of EICV7 are to:

- provide information on poverty and living conditions in Rwanda;
- measure changes in living conditions over time as part of the on-going monitoring of the Poverty Reduction Strategy, including poverty incidence at the district level and other Government policies;
- serve as a key input for updating the consumer price index (CPI).

The Data

The data come from two different samples: the EICV7 cross-section sample, and the VUP sample. In line with the outlined objectives, NISR conducted EICV7 from 16th October 2023 to 15th October 2024. In order to facilitate the data collection operations, and maintain the representativeness of the data, the 12-month data collection period was structured into 9 cycles, with each cycle further divided into 3 sub-cycles. Each cycle spans 36 days of data collection.

Institutional Framework

Many different stakeholders and institutions were involved in the implementation of EICV7. At the National level, the EICV7 project was closely overseen by a steering committee that was co-chaired by MINICOFIN and NISR. At the technical level, EICV7 activities were performed by NISR staff, supported as needed by experts on sample design, data processing, and poverty analysis. Other partners in the EICV7 project were:

- Republic of Rwanda
- European Union
- World Bank
- UNFPA
- UNICEF

2 EICV7 Preparation and Data Collection

Recruitment of EICV7 field staff

The recruitment of field staff for EICV7 adhered to the laws and regulations governing recruitment in Rwanda. This process was organized and implemented by the Human Resources and Administration Unit of NISR, in collaboration with the Statistical Methods, Research, and Publications (SMRP) department.

A total of 184 field staff were recruited to collect data for the EICV7 survey across the country. The team consisted of 93 enumerators working on the EICV7 cross-sectional survey, 31 team leaders for the cross-sectional survey, 30 enumerators involved in the Non-Standard Unit (NSU) survey, 24 enumerators working on the VUP sample, and 6 team leaders for the VUP sample. The distribution of field staff across districts and survey components is further detailed in Table 2.1 below.

Procurement of EICV7 materials and equipment

The materials and equipment, including tablets, hired vehicles, printed questionnaires, instruction manuals, and reporting forms, were procured through the standard administrative procedures used in Rwanda. All field materials and data collection tools were available and in good condition prior to the training of enumerators.

Consultation meetings with stakeholders to validate EICV7 questionnaire.

After the design of the EICV7 questionnaire, NISR organized meetings with key stakeholders and partners to review and discuss the questionnaire, agreeing on the necessary revisions. On June 23, 2023, NISR hosted a workshop at its training center with representatives from various government ministries and institutions (MINECOFIN, MINEDUC, MINALOC, NCDP, MINICOM, MIFOTRA, MoE, MINICT, MINEMA, RDB, RSSB, LODA, REMA, REG/EDCL) as well as EICV7 partners (UNICEF, World Bank Group). The purpose of the workshop was to validate the EICV7 questionnaire. During the workshop, participants agreed on the required modifications, which were then incorporated by the EICV7 staff, resulting in an updated and validated version of the questionnaire to be used for data collection.

Training of EICV7 Pilot field staff

A two-week training session, held from July 17 to July 31, 2023, was conducted for 15 enumerators to test the EICV7 data collection process and the EICV7 CAPI application. Following the training, a field practice was carried out in Musanze from August 1st to August 12th, 2023, under the supervision of NISR staff. The valuable feedback obtained from the field practice was instrumental in refining the data collection tools for the EICV7 main survey.

Main Training of all EICV7 field staff

The EICV7 main training to prepare enumerator candidates for high-quality data collection took place from August 21st to September 29th, 2023 at the NISR Training center. During this training, practical exercises were conducted in Kigali to simulate real data collection scenarios.

Out of the 208 trainees who began the training for EICV7 data collection tools, 204 successfully completed the training. Following the evaluation, 184 trainees were selected to participate in EICV7 data collection. The 184 EICV7 field staff included 124 staff members who collected data for the cross-sectional sample, 30 staff members who worked on the VUP sample, and 30 staff members gathered data on Non-Standard Units of Measurement (NSU) and collected information on restaurants for meals eaten outside the home.

Table 2.1. The Distribution of field staff across districts and survey components.

Teams	Cross sectional survey			VUP sample	
	Enumerators	Team Leader	NSU	Enumerators	Team Leader
Total	93	31	30	24	6
ZONE 1	21	7	6	8	2
Nyarugenge	3	1	1	-	-
Gasabo	3	1	1	-	-
Kicukiro	3	1	1	-	-
Kigali city	3	1	-	-	-
VUP Kigali1	-	-	-	4	1
VUP Kigali2	-	-	-	4	1
Bugesera	3	1	1	-	-
Gicumbi	3	1	1	-	-
Kamonyi	3	1	1	-	-
ZONE 2	18	6	6	4	1
Nyanza	3	1	1	-	-
Gisagara	3	1	1	-	-
Nyaruguru	3	1	1	-	-
Huye	3	1	1	-	-
Nyamagabe	3	1	1	-	-
Ruhango	3	1	1	-	-
VUP South	-	-	-	4	1
ZONE 3	18	6	6	4	1
Karongi	3	1	1	-	-
Rutsiro	3	1	1	-	-
Ngororero	3	1	1	-	-
Rusizi	3	1	1	-	-
Nyamasheke	3	1	1	-	-
VUP West	-	-	-	4	1
Muhanga	3	1	1	-	-
ZONE 4	18	6	6	4	1
Rulindo	3	1	1	-	-
Gakenke	3	1	1	-	-
Musanze	3	1	1	-	-
Burera	3	1	1	-	-
VUP North	-	-	-	4	1
Rubavu	3	1	1	-	-
Nyabihu	3	1	1	-	-
ZONE 5	18	6	6	4	1
Rwamagana	3	1	1	-	-
Nyagatare	3	1	1	-	-
Gatsibo	3	1	1	-	-
Kayonza	3	1	1	-	-
Kirehe	3	1	1	-	-
Ngoma	3	1	1	-	-
VUP East	-	-	-	4	1

Additionally, EICV7 had 20 reserve field staff who were on standby to replace any team member who resigned or fell ill during the fieldwork.

Concerning the collection of price data, which is of central importance in the EICV analysis, 17 new graduate students were recruited as price collectors. These recruits had training for two weeks in July 2023 (July 17th – 31st, 2023) followed by field practice in August and September 2023. The objective of the training and practice was to have sufficient skills to collect accurate price data at markets and outlets across all districts of the country.

EICV7 staff deployment and Extra-practice

Following the EICV7 main training, qualified enumerators who passed the training exam were deployed through a random draw method all over the country. To help enumerators become familiar with field operations in their respective districts, a two-week period was allocated for testing data collection tools and acclimating to the data collection process in preparation for the main data collection, which began on October 16th, 2023. The data gathered during these two weeks of practice were used to address remaining issues in the EICV7 CAPI application, but they were not included in the official analysis of the EICV7 data.

Data collection tools

To improve the quality of EICV7 data, the questionnaire was programmed in CSPRO, and data collection was carried out using the Computer Assisted Personal Interviewing (CAPI) approach. In this method, enumerators used tablets to gather data directly from households. This electronic data collection method, which has been in use since EICV5, replaced the traditional Paper Assisted Personal Interviewing (PAPI) approach, which involved recording responses on paper.

EICV7 Data collection activities

As outlined in Table 3.8 (EICV7 Enumeration Plan), data collection for the EICV7 survey commenced on October 16th, 2023, and covered the full year till October 15th, 2024. The data collection period was divided into 9 cycles.

Prior to collecting data in each sampled Enumeration Area (cluster), enumerators began by listing all households within the cluster. The team leader then selected 9 households for enumeration and assigned 3 households to each enumerator within the team. The entire process of listing, sampling, and assigning households, and sending the data collected to NISR servers, was carried out electronically using tablets and the EICV7 CAPI application.

EICV7 Field Organization

The field work activities were organized at national, regional, district, and team levels

National level

Three national coordinators were in charge of coordinating the EICV7 field activities. Their responsibilities were to oversee all EICV7 field work.

There was also one National Coordinator who was tasked with coordinating the activity of price collection in the areas that were not covered by CPI team.

Provinces / 5 Regions

Rwanda was divided into five regions (Central, Eastern, Western, Northern, and Southern) to streamline the supervision of EICV7 fieldwork at the regional level. Each region was assigned two supervisors responsible for addressing any challenges encountered in the field on a daily basis within their respective region. All supervisors reported directly to the National Coordinators.

Districts

Each district was assigned to one cross-sectional team. However, since the sample size in Kigali districts was larger compared to other districts, an additional cross-sectional team was allocated to the City of Kigali to enumerate clusters in Gasabo, Nyarugenge, and Kicukiro districts. This brought the total number of cross-sectional teams nationwide to 31.

In addition to the cross-sectional teams, there were 6 additional teams designated to collect data for the VUP sample. Team leaders were responsible for reporting any challenges or issues encountered during data collection to their direct supervisor within the region.

Monitors

To ensure the quality of the EICV7 data collected during the data collection period, the monitors were tasked with distributing errors and inconsistencies identified by EICV7 analysts to the team leaders and ensuring that the necessary corrections were made.

There was also one price collection monitor who was in charge of ensuring the best quality of price data being collected.

Team

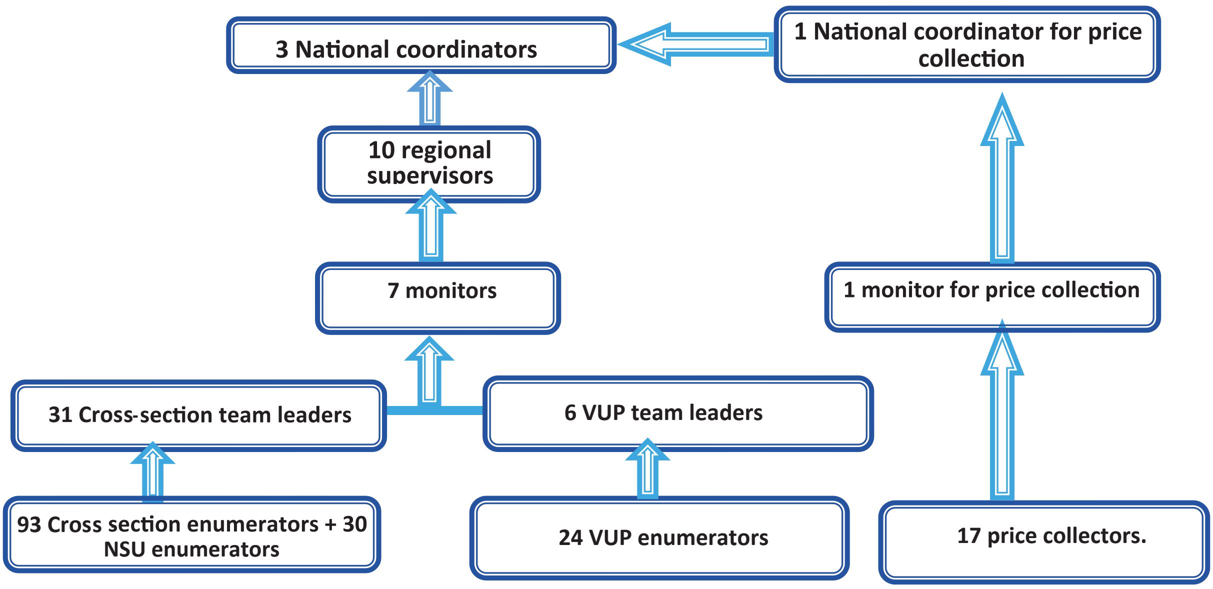
In total, EICV7 consisted of 37 teams, including 31 teams responsible for collecting data for the cross-sectional sample and 6 teams for the VUP sample. Each cross-sectional team was made up of 3 enumerators, resulting in 93 enumerators. Additionally, there was a separate team of 30 enumerators tasked with collecting data on Non-Standard Units used in markets, shops, and similar settings.

On the other hand, each VUP team consisted of 4 members, bringing the total number of enumerators for the VUP sample to 24. In total, combining both the cross-sectional and VUP samples, there were 147 enumerators and 37 team leaders, which brought the total number of EICV7 field workers to 184.

There was another team of 17 enumerators who collected prices from districts which were not already covered by the CPI division, and this allowed one to have EICV7 prices at district level

In brief The EICV7 field organization could be summarized as in Figure 2.1.

Figure 2.1. EICV7 Field Organization Chart



3 Sampling Methodology

Sample Design of EICV7 cross-sectional survey

The EICV7 Cross-Sectional Survey is designed to provide information on poverty and living conditions in Rwanda, and to allow for the measurement of changes over time as part of the on-going monitoring of the Poverty Reduction Strategy and other Government policies. As in the case of the EICV5, the Government of Rwanda requires EICV7 results to include poverty incidence at the district level. The EICV7 Cross-Sectional Survey is designed to represent the current household-based population of Rwanda over the 12-month period of the survey data collection.

A stratified two-stage sample design was used for the EICV7 Cross-Sectional Survey. The NISR developed a Master Sample of primary sampling units (PSUs) based on the data from the 2022 Rwanda Census of Population and Housing, designed to provide samples for various national household surveys during the intercensal period, including the EICV. The census enumeration areas (EAs) were operational segments delineated for the census data collection, with well-defined boundaries identified on maps, so that each EA could be covered by one census enumerator. A total of 24,347 EAs and 3,312,743 households were enumerated in the 2022 Rwanda Census. The distribution of the EAs and households in the 2022 Census by district, urban and rural stratum, is shown in Table 3.1 below

The PSUs for the Master Sample were defined as individual EAs. For the purpose of the Master Sample, the sampling frame from the 2022 Census was made more effective by combining some small EAs and subdividing large EAs with more than 300 households. The PSUs in the Master Sample are stratified by district, urban and rural stratum. A total of 4,000 sample EAs were selected for the Master Sample. The allocation of the Master Sample EAs by district, urban and rural stratum, is presented in Table 3.2.

Within each stratum the Master Sample PSUs were selected with probability proportional to size (PPS), using the number of households enumerated in the Census as the measure of size for each EA. The sample EAs for each national survey will be selected as a subsample of the Master Sample EAs in each stratum.

In order to determine the sample size for the EICV7, the NISR first examined the sampling errors and 95% confidence intervals for the estimates of the poverty rate at the district level from the EICV5 data. Although the level of precision of the EICV5 results at the district level was fairly reasonable, it was decided to increase the sample size slightly and adjust the sample design for the EICV7 to provide an improved level of precision for the district-level results. For the three districts of Kigali Province, where 60 sample clusters were selected per district for EICV5, this was increased to 72 sample clusters per district for EICV7. In the case of the districts in the remaining regions, the number of sample clusters was increased from 40 to 54. Within each district the sample EAs were allocated to the urban and rural strata proportionally to the total number of households in the Census frame. The breakdown is shown in the table 3.3

At the second sampling stage in EICV5, 9 households were selected per cluster for the three districts of Kigali Province, while 12 households were selected per sample cluster for the remaining districts. For EICV7 it was decided to select 9 households per sample cluster for all districts, which will slightly reduce the design effects for the districts outside of Kigali Province, and thus improve the level of precision of the estimates for those districts.

Table 3.1. Distribution of EAs and Households in the 2022 Rwanda Census by District, Urban and Rural Strata

District	Total		Urban		Rural		% urban households in district
	Number of EAs	Number of Households	Number of EAs	Number of Households	Number of EAs	Number of Households	
Nyarugenge	689	103,993	604	91,608	85	12,385	88.1
Gasabo	1,677	249,402	1,381	206,597	296	42,805	82.8
Kicukiro	901	135,467	892	134,218	9	1,249	99.1
Nyanza	681	93,010	61	9,087	620	83,923	9.8
Gisagara	729	99,562	25	3,398	704	96,164	3.4
Nyaruguru	558	73,806	13	1,902	545	71,904	2.6
Huye	708	96,036	117	17,208	591	78,828	17.9
Nyamagabe	678	90,555	50	7,390	628	83,165	8.2
Ruhango	714	94,507	71	10,576	643	83,931	11.2
Muhanga	679	93,244	134	21,092	545	72,152	22.6
Kamonyi	813	116,379	232	36,566	581	79,813	31.4
Karongi	674	88,881	64	8,786	610	80,095	9.9
Rutsiro	663	86,803	40	4,949	623	81,854	5.7
Rubavu	906	124,075	498	69,471	408	54,604	56.0
Nyabihu	600	76,400	134	18,483	466	57,917	24.2
Ngororero	694	92,622	33	4,560	661	88,062	4.9
Rusizi	786	104,937	255	35,057	531	69,880	33.4
Nyamasheke	742	95,229	56	7,349	686	87,880	7.7
Rulindo	712	91,908	70	9,893	642	82,015	10.8
Gakenke	723	93,607	27	4,006	696	89,601	4.3
Musanze	858	119,382	392	58,425	466	60,957	48.9
Burera	710	91,788	70	9,160	640	82,628	10.0
Gicumbi	823	109,375	50	6,905	773	102,470	6.3
Rwamagana	854	121,052	283	41,927	571	79,125	34.6
Nyagatare	1,180	160,435	265	40,104	915	120,331	25.0
Gatsibo	996	134,459	90	14,323	906	120,136	10.7
Kayonza	826	114,187	113	17,230	713	96,957	15.1
Kirehe	770	101,676	52	7,698	718	93,978	7.6
Ngoma	773	102,589	69	9,196	704	93,393	9.0
Bugesera	953	137,777	358	55,625	595	82,152	40.4
Total	24,070	3,293,143	6,499	962,789	17,571	2,330,354	29.2

Source: Rwanda 5th Population and Housing Census,2022(NISR)

In order to distribute the sample interviews evenly over the 12-month data collection period, for logistical purposes this period was divided into 9 cycles of about 41 days each. Each cycle was further divided into three sub-cycles of 12 days each, so that two sample clusters can be enumerated by a team each sub-cycle. There is one day between each sub-cycle for the team to rest and reach the sample clusters assigned to the next sub-cycle, and three days between cycles. In each district of Kigali, 8 sample clusters are enumerated each cycle. In addition to having one team of enumerators for each district of Kigali Province, a fourth team was used to cover part of the EAs in the same districts each cycle.

Table 3.2. Distribution of Master Sample EAs by District, Urban and Rural Strata

District	Total	Urban	Rural
Nyarugenge	122	101	21
Gasabo	211	164	47
Kicukiro	141	138	3
Nyanza	122	17	105
Gisagara	125	8	117
Nyaruguru	116	6	110
Huye	123	27	96
Nyamagabe	121	15	106
Ruhango	122	18	104
Muhanga	120	30	90
Kamonyi	135	44	91
Karongi	121	18	103
Rutsiro	123	12	111
Rubavu	149	81	68
Nyabihu	116	31	85
Ngororero	123	10	113
Rusizi	139	50	89
Nyamasheke	133	16	117
Rulindo	121	18	103
Gakenke	122	9	113
Musanze	138	65	73
Burera	125	19	106
Gicumbi	134	14	120
Rwamagana	137	50	87
Nyagatare	169	46	123
Gatsibo	150	21	129
Kayonza	136	26	110
Kirehe	129	14	115
Ngoma	127	18	109
Bugesera	150	60	90
Rwanda	4,000	1,146	2,854

The NISR collected the data for the listing and the EICV7 main data collection using computer-assisted personal interviewing (CAPI) with computer tablets, similar to the data collection for EICV5 and EICV6. For the listing operation, the tablet of the team leader includes an application for combining the listing files from the tablets of the individual listing enumerator groups, and assigning serial numbers to the eligible households. Then a CAPI application was used for selecting 9 households in each sample cluster using random systematic sampling, and selecting 3 additional households as a reserve for possible replacement.

Table 3.3. Distribution of Sample EAs and Households by District, Urban and Rural Stratum, for EICV7 Cross-sectional Survey.

District	Total EICV7 Sample		Urban		Rural	
	No. sample EAs	No. sample households	No. sample EAs	No. sample households	No. sample EAs	No. sample households
Nyarugenge	72	648	61	549	11	99
Gasabo	72	648	58	522	14	126
Kicukiro	72	648	70	630	2	18
Nyanza	54	486	5	45	49	441
Gisagara	54	486	2	18	52	468
Nyaruguru	54	486	2	18	52	468
Huye	54	486	11	99	43	387
Nyamagabe	54	486	6	54	48	432
Ruhango	54	486	6	54	48	432
Muhanga	54	486	13	117	41	369
Kamonyi	54	486	17	153	37	333
Karongi	54	486	5	45	49	441
Rutsiro	54	486	3	27	51	459
Rubavu	54	486	29	261	25	225
Nyabihu	54	486	13	117	41	369
Ngororero	54	486	3	27	51	459
Rusizi	54	486	18	162	36	324
Nyamasheke	54	486	4	36	50	450
Rulindo	54	486	6	54	48	432
Gakenke	54	486	2	18	52	468
Musanze	54	486	27	243	27	243
Burera	54	486	5	45	49	441
Gicumbi	54	486	3	27	51	459
Rwamagana	54	486	20	180	34	306
Nyagatare	54	486	13	117	41	369
Gatsibo	54	486	5	45	49	441
Kayonza	54	486	8	72	46	414
Kirehe	54	486	3	27	51	459
Ngoma	54	486	5	45	49	441
Bugesera	54	486	22	198	32	288
Rwanda	1,674	15,066	445	4,005	1,229	11,061

Assigning EICV7 Cross-Sectional Survey Sample EAs by Cycle

Following the selection of sample EAs based on the allocation by stratum specified in Table 3.3, it was necessary to assign each sample EA to one of the 9 cycles in such a way that the sample is geographically representative for each cycle within each district. Since the sampling frame of EAs in the sampling frame for each district, urban and rural stratum, was sorted geographically prior to the selection of sample EAs systematically with PPS for the Master Sample, the geographic ordering of the sample EAs in each stratum was used for assigning these EAs systematically to the 9 cycles so that each cycle is geographically representative. It was also necessary to ensure that the urban and rural EAs were evenly distributed between the first five cycles and the last four cycles, so that seasonality was represented geographically in both urban and rural areas across the cycles. Since the first 5 cycles have a nationally-representative subsample of the full EICV7 sample, the data from these first 5 cycles were used for a preliminary analysis of the EICV7 Cross-Sectional Survey results, and helped to identify any quality issues to followed up in the remaining 4 cycles.

Basic Weighting Procedures for EICV7 Cross-Sectional Survey

The design weights for the households selected for EICV7 are based on the inverse of the overall probabilities of selection, taking into account the probability at each sampling stage. Based on the stratified multistage sample design, the overall probability of selection can be expressed as follows:

$$p_{hi} = \frac{n_{Mh} \times M_{hi}}{M_h} \times \frac{n_{Eh}}{n_{Mh}} \times \frac{m_{hi}}{M'_{hi}} = \frac{n_{Eh} \times M_{hi}}{M_h} \times \frac{m_{hi}}{M'_{hi}}$$

where:

p_{hi} = overall probability of selection for the EICV7 sample households in the *i*-th sample EA of stratum *h*

n_{Mh} = number of EAs selected in stratum *h* for the Master Sample

M_{hi} = total number of households in the *i*-th sample EA of stratum *h*, from the 2022 Rwanda Census frame (measure of size)

M_h = total number of households in stratum *h*, from the 2022 Census frame

n_{Eh} = number of sample EAs selected for the EICV7 from the Master Sample for stratum *h*

m_{hi} = 9 = number of sample households selected for EICV7 in the *i*-th sample EA of stratum *h*

M'_{hi} = total number of households listed in the *i*-th sample EA of stratum *h*

Each component of this probability corresponds to the individual sampling stages. The first component is the probability of selection of the EA in the Master Sample for the stratum. The second component represents the subsampling rate for selecting the EA for EICV7 from the Master Sample for the stratum. The third component is the last stage sampling rate for selecting the EICV7 sample households from the listing for the EA. It can be seen that this probability simplifies to that of a stratified two-stage sample, where the EAs are selected directly from the 2022 Census frame with PPS.

The basic weight for the sample households is calculated as the inverse of this probability of selection, so it can be expressed as follows:

$$W_{hi} = \frac{M_h \times M'_{hi}}{n_{Eh} \times M_{hi} \times m_{hi}}$$

where:

W_{hi} = basic weight for the EICV7 sample households in the *i*-th sample EA of stratum *h*

Although most non-interviews were replaced, the final weighting procedures may also have an adjustment factor for nonresponse.

VUP sample

The main objective of the VUP sample conducted alongside the EICV7 Cross-sectional Survey is to study the socioeconomic characteristics of the VUP beneficiary households for each of the seven types of VUP programmes, which are:

- Direct Support (DS)
- Nutrition Sensitive Direct Support (NSDS)
- Classic Public Works (PWc)
- Expanded Public Works (ePW)
- Asset Transfers
- Financial Services (FS)
- Skills Development

The NISR had conducted similar VUP samples beginning with EICV4, and a VUP Panel Survey was included in EICV5, but previously the VUP programme only had three components: DS, Public Works (PW), and FS. The NISR and other stakeholders will use the VUP sample data to compare poverty and consumption indicators of the different types of VUP beneficiaries to the non-beneficiary households in the EICV7 data in order to measure the impact of these programmes and evaluate different aspects of each programme.

The basic sampling frame for the EICV7 VUP sample was based on a comprehensive list of 545,278 current VUP beneficiaries from the Ministry of Local Governments (MINALOC) in a database that includes the name of each beneficiary, the geographic location including the village code and name, and the type of VUP programme. The distribution of the VUP beneficiaries in the sampling frame by province and VUP component is shown below in the Table 3.4. It can be seen in this table that the number of VUP beneficiaries in the Skills Development programme is much smaller than that for the other programmes. The Asset Transfers component also has a relatively small number of beneficiaries. The total number of beneficiaries also varies by province, with a much smaller number of beneficiaries in Province 1 (Kigali City). Since the VUP data will not be analyzed by province, it is only necessary to have a proportional allocation of the sample for each stratum to the provinces to ensure representative estimates at the national level.

Table 3.4. Distribution of VUP beneficiaries by province and programme in final VUP sampling frame.

VUP Component	Province					Total
	Kigali City	Southern	Western	Northern	Eastern	
DS	3,955	33,717	30,276	26,317	23,219	117,484
NSDS	19	46,596	53,053	44,064	18,075	161,807
cPW	5,268	26,415	35,412	23,471	23,191	113,757
ePW	3,490	23,999	28,170	14,678	20,851	91,188
Asset Transfers	214	516	763	974	1,494	3,961
FS	2,444	18,797	15,401	11,512	8,294	56,448
Skills Development	325	53	45	210	0	633
Total	15,716	150,095	163,123	121,230	95,129	545,278

In order to satisfy the analytical requirements and make the data collection operationally practical and efficient, a stratified two-stage sample design was used for the EICV7 VUP sample, similar to the sampling approach used for the VUP samples conducted with previous rounds of the EICV. In this case the primary sampling unit (PSU) is defined as a cluster of VUP beneficiaries in one or more villages within a cell, with a minimum of 20 beneficiaries. The first step in compiling the sampling frame of clusters was to aggregate the beneficiaries to the village level, with a count of the number of beneficiaries by type of programme for each village. Any village with at least 20 beneficiaries (including all VUP components) is considered an individual cluster. In the case of villages with fewer than 20 beneficiaries, they are combined with neighboring villages in the same cell until the threshold of 20 beneficiaries is reached to form a cluster. However, if the entire cell has less than 20 beneficiaries, the cluster consists of all the villages in the cell, even though the cell has less than 20 beneficiaries. In this way a total of 11,751 clusters of VUP beneficiaries were formed in the sampling frame.

After combining the villages within each cell into clusters with a minimum of 20 beneficiary households each, it was found that there were 343 cell clusters with a total of less than 20 households each if all villages are combined. In reviewing the distribution of these small clusters, it was found that 271 clusters had between 12 and 19 beneficiary households. It was decided to keep these clusters in the sampling frame, since there is a good chance that an effective sample of 9 or 12 sample beneficiaries can be selected in each of these clusters following the updating of the frame. In the case of the 72 clusters with fewer than 12 beneficiary households each, it was decided to exclude them from selection, since they only represent a very small proportion of the total beneficiaries, and it would not be cost-effective to include them in the frame.

In order to improve the efficiency of the sampling frame and ensure a balanced distribution of the sample beneficiaries by VUP component, the sampling frame of clusters was stratified by the predominant VUP component of each cluster. In determining the VUP component with the highest number of beneficiaries in each cluster, it was found that in some cases two components were tied for the highest number of beneficiaries. In these cases priority was given to the component with fewer beneficiaries at the national level, based on the frequency shown in Table 3.4. The VUP component Skills Development was not predominant in any cluster, and the component Asset Transfers was only predominant in 17 clusters. Therefore a special stratification strategy was needed for these two components. In reviewing the distribution of the clusters with beneficiaries from each of these components, it was found that 200 clusters had 5 or more beneficiaries of Asset Transfers, and 140 clusters had 2 or more beneficiaries of Skills Development. Therefore, after the other strata were defined based on the predominant VUP component, any cluster with 5 or more beneficiaries of Asset Transfers were assigned to this stratum, and any cluster with 2 or more beneficiaries of Skills Development were assigned to this stratum.

In order to examine the average size of the clusters in the VUP sampling frame and the distribution of the beneficiaries by VUP component within the clusters for each stratum, Table 3.5 shows the average number of beneficiaries of each component per cluster, by stratum.

In the last column of Table 3.5 it can be seen that the overall average total number of beneficiaries per cluster is about 47, and it varies by stratum. It is interesting that the largest clusters are in the Asset Transfers stratum, although this does not have much effect on the overall distribution. In the diagonal of this table it can be seen that the distribution is consistent with the predominant component of most strata. In the case of the Skills Development stratum, the average number of Skills Development beneficiaries per cluster is 3.35, reflecting that this stratum was identified as all the clusters with at least 2 beneficiaries for this component. The predominant VUP component in the Skills Development stratum is actually DS. The Asset Transfers stratum includes all the clusters with at least 5 Asset Transfers beneficiaries, with an average of about 8 beneficiaries per cluster for this component. The predominant component in this stratum is actually cPW.

Table 3.5. Average number of beneficiaries of each VUP component per cluster, by stratum

Stratum	Average number of beneficiaries of each VUP component per cluster							
	DS	NSDS	cPW	ePW	Asset Transfers	FS	Skills Development	Total beneficiaries
DS	16.44	7.57	6.10	5.40	0.16	4.49	0.02	40.17
NSDS	8.83	21.73	6.87	6.77	0.16	4.26	0.01	48.64
cPW	9.38	8.55	22.01	7.25	0.23	4.17	0.01	51.59
ePW	8.58	5.77	6.54	16.30	0.33	3.79	0.03	41.32
Asset Transfers	9.14	11.98	14.48	10.30	7.96	3.40	0.02	57.31
FS	7.98	4.43	5.39	3.93	0.14	15.80	0.01	37.67
Skills Development	15.38	2.25	8.22	9.86	0.99	6.70	3.35	46.75
Total	10.04	13.85	9.73	7.80	0.34	4.83	0.05	46.64

Following this stratification process, the final distribution of the clusters in the sampling frame by stratum is shown later in the first column of Table 3.6.

Table 3.6. Total number of clusters in the VUP sampling frame by stratum, and allocation of sample clusters and households by stratum

Stratum	Total number of clusters in sampling frame	Number of sample clusters	Number of sample beneficiary households (9 per cluster)
DS	1,718	46	414
NSDS	5,338	46	414
cPW	2,285	46	414
ePW	1,460	46	414
Asset_Transfer	200	47	423
FS	610	46	414
Skills Development	140	47	423
Total	11,751	324	2,916

Based on the budget and logistical considerations, as well as the survey objectives, the total sample size for the VUP sample was initially determined to be 324 clusters, with 9 sample beneficiary households per cluster, for a total of 2,916 sample beneficiary households. This sample size is moderately higher than that for the previous rounds of the VUP sample, which only covered three VUP components. However, in the previous rounds one survey objective was to analyze the survey data by VUP component by province, so the sample for each VUP component stratum was allocated equally by province as well as component stratum. For the new VUP sample it was decided that it was not necessary to analyze the data by province, so the sampling frame is not stratified by province. Instead, the beneficiary households in the sampling frame for each VUP component stratum was sorted by province to provide an implicit stratification by province. This will provide an approximately proportional allocation of the sample clusters in each stratum by province, thus providing an effective geographic distribution of the sample for the VUP sample.

In order to allocate the sample beneficiary households as evenly as possible to the seven VUP components, a similar number of sample clusters was allocated to each stratum. However, given the much smaller proportion of the beneficiaries in the Asset Transfers and Skills Development strata, these two strata were allocated 47 sample clusters each, and the remaining five strata were allocated 46 sample clusters each. Even with this slightly larger sample of clusters for the two smaller strata, there will be fewer sample beneficiary households for Asset Transfers and Skills Development because of their smaller frequency. The sample allocation by stratum is shown in Table 3.6.

Table 3.6 shows the total number of sample clusters in the VUP sampling frame by stratum, and the allocation of the sample clusters and households by stratum for the VUP sample. The preliminary number of sample beneficiary households in each stratum shown in this table is based on a sample of 9 beneficiary households per cluster. Based on discussions with stakeholders on the proposed analysis for the VUP sample data, there was concern that the expected total number of sample beneficiaries by component would result in minimum detectable error (MDE) values that were relatively higher than desired for detecting statistically significant differences in poverty between the VUP beneficiary households (treatment group) and the non-beneficiary households (control group) in the EICV7 data. Therefore, the NISR agreed that starting with the second cycle the number of sample beneficiary households per cluster would be increased to 12 for the VUP sample. In this case the total number of sample beneficiary households will be increased from 2,916 to 3,780.

Within each VUP component stratum, at the first sampling stage the sample clusters were selected systematically with PPS. For each stratum, the measure of size of each cluster used for the PPS selection was the number of beneficiaries of the corresponding VUP component, in order to increase the number of sample beneficiaries for that component within the stratum. In the SPSS database with the sampling frame of clusters, a new measure of size (MS) variable was generated by copying the number of beneficiaries of the VUP component in each cluster according to the stratum. This made it possible to select the PPS sample for all strata in one iteration.

In the case of the Skills Development stratum, there were 4 clusters for which the total number of beneficiaries for this component was larger than the corresponding sampling interval, so they were selected with a probability of 1. These 4 larger clusters were identified with a code of 1 for a new variable SR (self-representing) in the sampling frame database. For this stratum a sample of 43 non-self-representing (NSR) sample clusters were selected after excluding the 4 SR clusters, to obtain the total sample of 47 clusters. It is important to identify the SR sample clusters, since the formula for the weight for these clusters will be different from that for the NSR sample clusters.

Following the updating of the list of beneficiaries for each sample cluster in the field, a sample of 9 (or 12 starting with the second cycle) beneficiary households was selected using random systematic sampling, for all strata except for the Asset Transfers and Skills Development strata. This sample selection was implemented in the field with a tablet application. It was recommended that the updated listing for each sample cluster be sorted by VUP component prior to the systematic selection of beneficiary households. In the case of the Asset Transfers and Skills Development strata, a different sampling procedure was used, given that the beneficiaries for these components are less frequent. For the Asset Transfers stratum, in sample clusters with 6 or less Asset Transfers beneficiaries, all of these beneficiaries were selected. The other sample beneficiary households were selected systematically from the remaining beneficiaries (belonging to the other VUP components) in order to obtain a total of 9 (or 12) sample beneficiary households for the cluster. In the case of clusters with more than 6 Asset Transfers beneficiaries, a random systematic sample of 6 of these beneficiaries was selected from the updated listing, and 3 (or 6) sample beneficiaries were selected from the remaining beneficiaries in the cluster. A similar second stage selection procedure was used for the sample clusters in the Skills Development stratum, with up to 6 sample Skills Development beneficiaries selected first, and the remaining sample beneficiaries selected from the other components to obtain a total of 9 (or 12) sample beneficiary households for the cluster.

In order to estimate the expected total number of sample beneficiary households per VUP component in the final VUP sample dataset, a simulation exercise was conducted. This simulation was conducted for three different scenarios:

Scenario 1:

This is the original sampling approach of selecting a random systematic sample of 9 beneficiaries for each sample cluster in all strata except for Asset Transfers and Skills Development. In the latter two strata we select all the beneficiaries of the corresponding component up to 6, and randomly select the remainder of the 9 sample beneficiaries in the cluster from the other strata.

Scenario 2:

Following the first cycle of data collection based on Scenario 1, this is the modified approach of selecting a random systematic sample of 12 beneficiaries for each sample cluster in all strata except for Asset Transfers and Skills Development, beginning in the second cycle. In the latter two strata we select all the beneficiaries of the corresponding component up to 6, and randomly select the remainder of the 12 sample beneficiaries in the cluster from the other strata.

Scenario 3:

This is similar to Scenario 2, but in the case of the Asset Transfers and Skills Development strata, starting in the second cycle we could select up to 8 beneficiaries of the corresponding component (instead of 6) in each cluster, and randomly select the remainder of the 12 sample beneficiaries in the cluster from the other strata.

The results of the simulation of the final sample distribution under these three scenarios are presented in Table 3.7. Since the database used for the simulation did not include the assignment of the 324 sample clusters to the cycles, for Scenarios 2 and 3 the average number of beneficiary households per cluster for all 9 cycles was assumed to be 11.67 (based on 9 beneficiaries per cluster for the first cycle and 12 beneficiaries per cluster for the remaining 8 cycles). In the case of Scenario 1, the total number of sample beneficiary households would actually be 2,916. For Scenarios 2 and 3 the total number of sample beneficiary households would be 324 for the first cycle and 3,456 for the remaining 8 cycles, for a total of 3,780 sample beneficiaries. It can be seen in Table 3.7 that the total number of beneficiaries under each scenario is slightly different from these totals because of rounding error in the simulation calculations. However, these estimates should be fairly close to the distribution of the sample that can be expected based on the sampling frame and sampling procedures under each scenario.

Table 3.7. Expected number of sample beneficiaries by VUP component under 3 Scenarios based on simulation of sampling procedures

VUP component	Number of sample beneficiaries		
	Scenario 1	Scenario 2	Scenario 3
DS	623	847	834
NSDS	461	618	610
cPW	516	696	675
ePW	452	620	609
Asset Transfers	285	295	344
FS	396	527	520
Skills Development	169	170	183
Total	2,902	3,773	3,775

In comparing the distribution of the sample of beneficiaries under Scenarios 2 and 3, it can be seen that Scenario 3 has more sample beneficiaries for the Asset Transfers and Skills Development components, but slightly less beneficiaries for the remaining VUP components. After discussing these alternative scenarios with the team that will be working on the analysis of the data, it was decided to implement the sampling for the VUP sample based on Scenario 2.

Basic Weighting Procedures for VUP sample

The design weights for the beneficiary households selected for the VUP sample are based on the sampling frame and sample design for this survey. As described above, the strata were defined based on the predominant VUP component for each cluster. The overall probabilities of selection for the different strata except for Asset Transfers and Skills Development can be defined as follows:

$$p_{Vhi} = \frac{n_{Vh} \times M_{Vhi}}{M_{Vh}} \times \frac{m_{Vhi}}{M'_{Vhi}}$$

where:

p_{Vhi} = overall probability of selection for the VUP sample sample households in the *i*-th sample cluster in stratum *h*

n_{Vh} = number of clusters selected in stratum *h* for the VUP sample

M_{Vhi} = total number of VUP beneficiaries in the sampling frame for the *i*-th sample cluster of stratum *h*

M_{Vh} = total number of beneficiaries in the sampling frame for stratum *h*

m_{Vhi} = number of VUP beneficiary households selected from the updated listing for the *i*-th sample cluster of stratum *h*, generally equal to 9 or 12

M'_{Vhi} = total number of VUP beneficiary households in the updated listing for the *i*-th sample cluster of stratum *h*

The basic weight is calculated as the inverse of this probability, as follows:

In the case of the Asset Transfers stratum, separate weights are calculated for the Asset Transfers beneficiary households and for the remaining sample beneficiary households in each cluster. If all the Asset Transfers beneficiary households in the cluster are included in the sample, the second stage probability will be equal to 1. The weighting procedures will be similar for the sample beneficiary households in the Skills Development stratum.

Production of cluster maps and household listing

The Geographic Information Systems (GIS) Section played a key role in supporting the implementation of the EICV7 survey. They were provided with the EICV7 cross-sectional sample, consisting of 1,674 clusters, for which they produced maps to be integrated into the EICV7 CAPI application used during data collection.

Production of cluster maps

The GIS section generated high-quality, georeferenced maps and spatial layers necessary for efficient fieldwork execution. These maps were produced in GeoJSON format, designed specifically to be integrated with the CSPro application used by enumerators on the field.

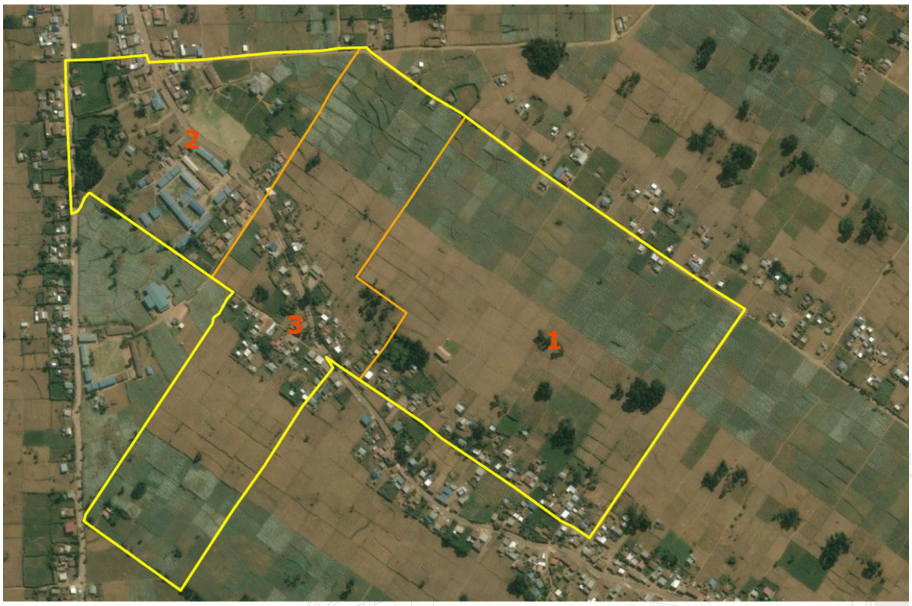
The GeoJSON format was preferred over traditional shapefiles due to its compatibility with modern mobile applications and its lightweight, human-readable structure. While shapefiles (.shp) are still widely used, they often require multiple associated files (.shx, .dbf, etc.) and are less suited for web and mobile environments. GeoJSONs, by contrast, provide a simplified and flexible way of encoding geographic data structures such as points, lines, and polygons, making them ideal for embedding within digital data collection tools like CSPro which NISR uses.

Using ArcGIS Pro and ArcGIS Online, the GIS team developed cluster-level boundaries and geographic identifiers, which were exported as GeoJSON files. These layers enabled the survey team to differentiate between listed and unlisted households, identify structures located outside the predefined cluster boundaries, and prevent duplication during data collection. The maps also helped enumerators verify their coverage areas and ensured that no eligible households were omitted or redundantly surveyed.

Household Listing

During the household listing phase of the EICV7 survey, a systematic approach was adopted to improve efficiency, accuracy, and equitable workload distribution among enumerators working within the same cluster. Each cluster was assigned to a team of three enumerators, and the GIS section played a key role in supporting their work by subdividing the clusters into three manageable segments. The subdivision of clusters was guided by both spatial data and operational needs. Using data from the 2022 National Census, which included the geolocations of residential structures, the GIS team was able to identify and quantify the number of housing units in each cluster. This census data served as the baseline for estimating workload and ensuring that each enumerator would be responsible for a roughly equal number of structures within the cluster.

To implement the subdivisions, the GIS team overlaid the census housing data onto high-resolution satellite imagery. This imagery allowed for the visual identification of physical features such as roads, rivers, and natural barriers, which were used as guides to create logical and accessible boundaries for each sub-cluster. Using ArcGIS Pro, the GIS team then digitized these boundaries to create three distinct zones per cluster, with consideration for both geographic contiguity and accessibility.



This spatial division had several benefits:

- Workload Balance: Each enumerator was assigned a segment with a comparable number of housing units, promoting efficiency and fairness in task distribution.

- Operational Clarity: Subdivided maps reduced confusion in the field, as each enumerator could clearly identify the geographic extent of their segment.
- Enhanced Monitoring: Supervisors could track progress more accurately, segment by segment, and respond to challenges more effectively.
- Improved Data Quality: With clearly defined responsibilities and boundaries, the risk of duplication or omission of households was minimized.

Questionnaire Design

The EICV7 questionnaire was designed for collecting data on individual and household characteristics. The questionnaire is composed of the following 10 sections:

- **Section Zero**: Household Identification,
- **Section One**: General Characteristics of the household members
- **Section Two**: Migration
- **Section Three**: Health
- **Section Four**: Education
- **Section Five**: Housing
- **Section Six**: Economic activity
- **Section Seven**: Agriculture
- **Section Eight:** Household expenditure/consumption and subsistence farming
- **Section Nine**: Transfers of incomes, expenditures, VUP components and other revenues.
- **Section Ten**: Credit, durables and savings.

The EICV7 questionnaire was programed in CSPRO by Data processing team at NISR with support of a data processing expert.

Enumeration plan

The EICV7 field activities were carried out over a span of 12 months, organized into 9 cycles, with each cycle further divided into 3 sub-cycles (sub-cycle A, sub-cycle B, sub-cycle C). Each team was assigned to enumerate 2 clusters per sub-cycle, totaling 6 clusters per cycle per team. The main household enumeration was preceded by a listing activity to update the number of households within the sampled cluster. Throughout the data collection period, each household was visited 5 times, with each visit corresponding to different sections of the survey. The enumeration plan for EICV7 is summarized in the table below (Table 3.8).

***Table* 3.8. *EICV7* Enumeration plan.**

			Section 1,2,3,5	Section 4, 8B, 8C	Section 7,8A1,8B,8C	Section 9,8A2,8B,8C	Section 6,8A3,8B,8C,10	
Cycle	**SubCycle**	**Listing**	**Visit 1**	**Visit 2**	**Visit 3**	**Visit 4**	**Visit 5**	**Break**
Cycle 1	SubCycle A	16-17/10/2023	18-19/10/2023	20-21/10/2023	22-23/10/2023	24-25/10/2023	26-27/10/2023	10/28/2023
	SubCycle B	29-30/10/2023	31/10-01/11/2023	02-03/11/2023	04-05/11/2023	06-07/11/2023	08-09/11/2023	11/10/2023
	SubCycle C	11-12/11/2023	13-14/11/2023	15-16/11/2023	17-18/11/2023	19-20/11/2023	21-22/11/2023	23-25/11/2023
Cycle 2	SubCycle A	26-27/11/2023	28-29/11/2023	30/10-01/12/2023	02-03/12/2023	04-05/12/2023	06-07/12/2023	12/8/2023
	SubCycle B	09-10/12/2023	11-12/12/2023	13-14/12/2023	15-16/12/2023	17-18/12/2023	19-20/12/2023	12/21/2023
	SubCycle C	22-23/12/2023	24-25/12/2023	26-27/12/2023	28-29/12/2023	30-31/12/2023	01-02/01/2024	03-05/01/2024
Cycle 3	SubCycle A	06-07/01/2024	08-09/01/2024	10-11/01/2024	12-13/01/2024	14-15/01/2024	16-17/01/2024	1/18/2024
	SubCycle B	19-20/01/2024	21-22/01/2024	23-24/01/2024	25-26/01/2024	27-28/01/2024	29-30/01/2024	1/31/2024
	SubCycle C	01-02/02/2024	03-04/02/2024	05-06/02/2024	07-08/02/2024	09-10/02/2023	11-12/02/2023	13-15/02/2024
Cycle 4	SubCycle A	16-17/02/2024	18-19/02/2024	20-21/02/2024	22-23/02/2024	24-25/02/2024	26-27/02/2024	2/28/2024
	SubCycle B	29/02-01/03/2024	02-03/03/2024	04-05/03/2024	06-07/03/2024	08-09/03/2024	10-11/03/2024	3/12/2024
	SubCycle C	13-14/03/2024	15-16/03/2024	17-18/03/2024	19-20/03/2024	21-22/03/2024	23-24/03/2024	25-27/03/2024
Cycle 5	SubCycle A	28-29/03/2024	30-31/03/2024	01-02/04/2024	03-04/04/2024	05-06/04/2024	07-08/04/2024	4/9/2024
	SubCycle B	10-11/04/2024	12-13/04/2024	14-15/04/2024	16-17/04/2024	18-19/04/2024	20-21/04/2024	4/22/2024
	SubCycle C	23-24/04/2024	25-26/04/2024	27-28/04/2024	29-30/04/2024	01-02/05/2024	03-04/05/2024	05-07/05/2024
Cycle 6	SubCycle A	08-09/05/2024	10-11/05/2024	12-13/05/2024	14-15/05/2024	16-17/05/2024	18-19/05/2024	5/20/2024
	SubCycle B	21-22/05/2024	23-24/05/2024	25-26/05/2024	27-28/05/2024	29-30/05/2024	31/05-01/06/2024	6/2/2024
	SubCycle C	03-04/06/2024	05-06/06/2024	07-08/06/2024	09-10/06/2024	11-12/06/2024	13-14/06/2024	15-17/06/2024
Cycle 7	SubCycle A	18-19/06/2024	20-21/06/2024	22-23/06/2024	24-25/06/2024	26-27/06/2024	28-29/06/2024	6/30/2024
	SubCycle B	01-02/07/2024	03-04/07/2024	05-06/07/2024	07-08/07/2024	09-10/07/2024	11-12/07/2024	7/13/2024
	SubCycle C	14-15/07/2024	16-17/07/2024	18-19/07/2024	20-21/07/2024	22-23/07/2024	24-25/07/2024	26-28/07/2024
Cycle 8	SubCycle A	29-30/07/2024	31/07-01/08/2024	02-03/08/2024	04-05/08/2024	06-07/08/2024	08-09/08/2024	8/10/2024
	SubCycle B	11-12/08/2024	13-14/08/2024	15-16/08/2024	17-18/08/2024	19-20/08/2024	21-22/08/2024	8/23/2024
	SubCycle C	24-25/08/2024	26-27/08/2024	28-29/08/2024	30-31/08/2024	01-02/09/2024	03-04/09/2024	05-07/09/2024
Cycle 9	SubCycle A	08-09/09/2024	10-11/09/2024	12-13/09/2024	14-15/09/2024	16-17/09/2024	18-19/09/2024	9/20/2024
	SubCycle B	21-22/09/2024	23-24/09/2024	25-26/09/2024	27-28/09/2024	29-30/09/2024	01-02/10/2024	10/3/2024
	SubCycle C	04-05/10/2024	06-07/10/2024	08-09/10/2024	10-11/10/2024	12-13/10/2024	14-15/10/2024	

4

Data Processing, Data Analysis, and Report Writing

EICV7 data security and management

Data security is essential for safeguarding confidential information, ensuring the privacy of research participants, and adhering to relevant protocols and regulations.

The use of technologies in EICV7 processes such as data collection, data transmission, data reception and hosting started with EICV5 previously in EICV1 up to EICV4, the data collection was conducted using Papers and many other processes were performed manually.

The new technology started in EICV5 using file transfer protocol FTP which also had its downsides like much time taken to get data from the field , time taken for editing process to get data file, later in EICV6 which was not full completed due to covid-19, The FTP technology was improved by including other security features and the implementation of csweb data reception system that incorporates other layer of security by applying Transport Layer Security during data transmission from enumerators devices and ensuring secured communication channels between tablets and Data reception systems. This approach brought many advantages such as the benefit of getting real time data from field, reducing time it took for findings preparation by eliminating editing processes that were time consuming during previous EICVs.

EICV7 adopted the use of data capturing and processing technologies where data collection conducted using tablets that connected to the central data hosting system via internet connection established using GSM technologies from two internet service providers (Airtel and MTN) while data analysis was performed from remote systems built with high computing servers accessed through virtual private network(VPN).

The use of these digitalization technologies involves the setup of data security and management infrastructure that incorporates the following 3 main environments:

- Data Collection and Transmission
- Data Reception and Hosting Environment
- Data Analytics Environment

Data Collection and Transmission

EICV7 was conducted using tablets as the end point devices for data collection, EICV7 questionnaires were transformed into digital questionnaires in the form of data entry programs developed using cspro data programming language for census and surveys data processing systems. The data transmission was made by internet connectivity established by two main internet services providers (Airtel and MTN) to avoid any issue of network connectivity that might interrupt data reception from field at a real time.

Data reception and Hosting Environment

The data reception and hosting environment were structured around a centralized CSWeb web server application, which facilitated real-time data ingestion from field.

Remote Analytics Environment

The remote analytics environment was built on a Windows platform, supporting simultaneous multi-user connections. To ensure secure remote connectivity and data access, a Virtual Private Network (VPN) was configured, providing a protected channel for authorized users to access the environment.

EICV7 data was accessed through a remote desktop, and analysts, coordinators, and consultants working with the data were provided with credentials to securely connect to the remote system. This approach enhances data security, as it eliminates the risk of storing data on personal computers, which could be lost, stolen, or damaged, potentially compromising confidentiality

EICV7 data quality assurance

EICV7 data collection began in October 2023. Like with any survey, the quality of the data collected was regularly monitored each day. Various checks and controls were implemented to ensure the data met the highest quality standards. This section outlines how the quality of EICV7 data was assessed.

The quality checks performed for EICV7 Data, were summarized as follows:

- **High-Frequency Checks**: Inconsistencies and errors in the EICV7 data were identified at the end of each visit. This process followed a step-by-step approach, where syntax developed by analysts was executed and compiled by section. These were then given to monitors, who forwarded any issues to the team leaders in the field for investigation and correction. Once the team leaders addressed the issues, they sent the files back with comments on each correction. Supervisors then reviewed these comments and, if necessary, reached out for further clarification.
- **Spot-Checks:** During the EICV7 data collection, EICV7 coordinators and supervisors conducted unannounced visits to various districts. They visited different teams to assess team organization and follow up on any issues, ensuring the quality of the data collected.
- **Key Indicators Monitoring:** EICV7 supervisors created syntax to monitor key indicators. This syntax was executed at the end of each sub-cycle through the data collection period.

EICV7 data analysis and report writing

EICV7 data was analyzed by NISR staff, with support from data analysis experts and World Bank experts. NISR management identified potential staff members to be part of the data analysis team. A total of 11 staff were selected to analyze various components of EICV7, which covered several areas in addition to the household consumption and expenditure, the primary objective of EICV. These staff members were assigned different thematic reports based on their areas of expertise. The 11 thematic reports included: the Poverty Profile Report, Main Indicators Report, Agriculture Thematic Report, Economic Activity Thematic Report, Education Thematic Report, Gender Thematic Report, Youth Thematic Report, Multidimensional Child Poverty Report, Multidimensional Poverty Index Report, Utilities and Amenities Report, and the VUP (Vision-Umurenge Program) Report.

From the start of EICV7 data collection, in addition to monitoring data quality, the EICV7 data analysts developed Stata syntax for tables to be included in their respective thematic reports. After completing five cycles of data collection, the sample size was sufficient to provide estimates with good precision. As a result, the EICV7 data analysts produced tables and drafted their respective reports, which were reviewed by NISR's senior management. This process was instrumental in preparing the final reports once data collection was completed.

After the data collection concluded on October 15, 2024, the EICV7 data analysts performed the necessary final data cleaning to prepare the final EICV7 data files for the concluding analysis and report writing. The analysis and report writing process took two months, with the first draft of the reports completed by the end of December 2024.

After completing the first draft, NISR organized a workshop in Huye District from January 19 to 25, 2025, with key stakeholders and partners. The purpose of the workshop was to review the reports and incorporate feedback, ensuring that the final EICV7 reports were thoroughly enhanced and comprehensive. The final EICV7 reports were then designed using infographics to enhance readability.

5

Measuring Poverty

Background

The key results of the Rwanda Poverty Profile Report (NISR 2025) are shown here in Table 5.1. Based on the EICV7 survey (undertaken from October 2023 through October 2024), and the methodology used, 27.4% of the population was poor in 2024. Given sampling variation, we have 95% confidence that the poverty rate was between 26.4% and 28.4%.

Based on a regression model (with multiple imputation), the poverty rate (using the "EICV7 methodology") would have been 39.8% in 2017, representing a reduction of 12.4 percentage points over a period of 7 years.

A succinct description of the methods used to collect and analyze the data are given in Section 3 of the *Rwanda Poverty Profile Report* (NISR 2025). **The purpose of the remaining sections of this documentation is to set out the methodology in more detail, and to explain the decisions that were made in establishing and applying these methods.** This is particularly important because many changes were made to the methods used in earlier EICV surveys, in an effort to incorporate current best practice in poverty measurement and imputation.

Table 5.1. Headcount Poverty Rate in 2024 (actual) and 2017 (modelled) by province

	EICV7 actual	EICV5 predicted adj.	Change		95% confidence interval	
	2024	2017	2017 to 2024		2024	
	% of individuals who are poor		% point change	% change	Lower bound	Upper bound
Province						
Kigali City	9.1	14.3	-5.3	-37	7.0	11.2
South	34.7	47.6	-12.9	-27	32.7	36.7
West	37.4	51.7	-14.3	-28	35.0	39.8
North	20.2	33.0	-12.8	-39	18.1	22.3
East	26.8	39.1	-12.4	-32	24.7	28.8
Rwanda	27.4	39.8	-12.4	-31	26.4	28.4

Predictions for 2017 are based on an OLS regression model of the log of consumption/ae p.a. in January 2024 prices, with multiple imputation. The confidence interval for 2017 is 37.7-41.4, conditional on the model used.

History

Although Rwanda undertook a National Household Budget and Consumption Survey in 1982-83, a consistent series of household surveys only dates back to 1999-2001 when the first *Enquête Integrée de Conditions de Vie* (EICV1) was undertaken.

There were subsequent surveys in 2005-06 (EICV2), 2010-11 (EICV3), 2013-14 (EICV4), and 2016-17 (EICV5). The 2019-20 (EICV6) survey was cancelled in early 2020, midway through data collection, due to the COVID-19 pandemic.

A central purpose of all of these surveys was to measure poverty. In this note, we explain how poverty is measured using EICV7. This should provide enough detail for others to replicate our results. This note also includes some comments of measures of inequality.

Methodological Changes for EICV7

For reasons explained below, important changes were made to the methods of data collection and analysis in EICV7. The result is that *direct* comparisons of poverty and consumption between EICV7 and earlier surveys are not legitimate, although many of the other socio-economic measures are comparable. It is also possible to model poverty rates, as explained below, which yields some estimates of the evolution of poverty over time.

The protocols for collecting data, and the nature and scope of the questions, were relatively similar from EICV1 (1999/2001) through EICV6. Meanwhile, best practice in poverty measurement has evolved – see, for instance, Mancini and Vecchi (2022) on the construction of a consumption aggregate, or the recommendations of the East African Community (EAC 2023) – so a number of important methodological changes were made for EICV7. While further details are provided in later sections of this Note, it is worth summarizing the most important changes, which included:

- **Fewer visits per household:** EICV7 collected data from five visits to each household at two-days intervals, instead of 8 (in rural areas) or 11 (in urban areas) as done for EICV5;
  - This reduced the heavy time demands on respondents, as well as being more economical.
- **Collected information on seven days of food consumption** (instead of 14 or 30 days as done in earlier EICV surveys);
  - Simulations based on EICV5 showed that careful collection of information over seven days is as accurate as collecting over 14 or 30 days. Visits 2-4 asked about the details of food consumption in the previous day (visit 2) or since the previous visit (visits 3-5), as Table 5.2 shows.

Table 5.2. Illustration of Food Collection

Visits	Day of the week	Food Consumption Data Collected For
Visit 1	Monday	No food consumption data collected
Visit 2	Wednesday	Tuesday
Visit 3	Friday	Wednesday and Thursday
Visit 4	Sunday	Friday and Saturday
Visit 5	Tuesday	Sunday and Monday
Notes: Days of the week are used for illustrative purposes; Visit 1 may occur on any day of the week.		

- **Separate questions on food acquisition and consumption** allow for a true measure of food consumption.
  - Previous EICV surveys asked about the amount of food bought or received ("acquisition"), whether or not it was consumed in the survey period. EICV7 measures the amount of food actually consumed during well-defined periods, which is a more accurate reflection of the welfare measure of consumption.
- **More-detailed questions on food consumed away from home**, including school meals, allowing these to be included in the consumption aggregate;
  - School meals are an important source of nutrition, and were not included in past EICV surveys.
  - An expanded set of questions on food consumed away from home provided more complete information than in earlier EICV surveys. This is an increasingly important source of food intake.
- **Additional questions to allow for the measurement of gifts and in-kind payments** for non-food items;
  - The EICV7 survey asks in more detail about whether each consumption item was purchased, came from home-production, or was received as an in-kind payment or gift.
- A more realistic method to compute the use value of durable goods;
  - Durable goods are consumed over a long time period, and the annual value provided by durables is estimated based, in part, on depreciation rates. EICV7 uses data on the age and life expectancy of durable goods to estimate depreciation rates.
- **Deflation to the prices of January 2024 using household-level Paasche deflators**, rather than the regional-level indexes used in EICV5;
  - Regional-level price deflators apply a single price index to all households in a region, regardless of their pattern of spending. Household-level deflation properly takes into account the differing spending decisions made by each household.

- **The adult equivalence scale has been redefined** to allow for economies of scale in non-food consumption;
  - Previous EICV analyses used an equivalence scale entirely based on caloric needs. The revised scale is based partly on caloric needs, and also on household size and demographic composition.
- **The poverty line starts with a calorie threshold of 2,400 kcals/adult equivalent/day** (instead of 2,500), and values it using the consumption pattern of households in the second quintile (rather than the bottom two quintiles).
- The 2,400 kcals threshold was determined from first principles, recognizing the caloric needs based on the weight and activity levels of Rwandans. It also brings Rwanda's threshold more in line with current East African practice.

The measurement of wellbeing: consumption

There are many dimensions of human wellbeing, but most fundamental of all is the ability to provide enough food, clothing, and shelter. The monetary approach to the measurement of poverty seeks to determine whether households have sufficient resources to provide for their basic needs.

A well-established measure of wellbeing is the value of consumption, which we define more carefully below. Richer countries often measure wellbeing by looking at income, which is easier to measure when most households earn wages or salaries, but Rwanda has not yet reached this stage.

Surveys like the EICV mainly collect information at the level of the household, but wellbeing is best measured at the individual level, so the measure that we use is real consumption per adult equivalent. For EICV7, this is defined as household consumption in the national prices of January 2024 divided by the number of adult equivalents in the household. In section 5.16 below, we have an extended discussion of how we determine appropriate adult equivalents, and of how we value consumption in January 2024 prices.

What is included in consumption: broadly

For each household, total consumption is obtained by adding several categories of items. These include:

- Food consumed at home. For a long list of 148 items, households are asked how much they consumed in the two days since the previous visit by the enumerator (for visits 3-5), or during the previous day (for visit 2), and how much of this consumption came from purchases, own-production, or gifts and in-kind acquisitions.
- Food consumed away from home. This includes school lunches, as well as restaurant meals and snacks and beverages.
- Non-food items, purchased (or home-produced or received in-kind) over the past year, month, or week, using a list of 165 items.
- The use value of durable assets such as phones and bicycles.
- Spending on education.
- Spending on routine health-related items.
- Spending on housing, including rent paid (for renters) or estimated rent (for owners).

Not every household expenditure is included in the consumption aggregate. It does not include non-consumption expenditures, such as payments of taxes, purchases of business or farm inputs, or purchases of durable goods. Also excluded are exceptional expenses such as weddings and funerals, hospital stays, and other emergency medical expenses. These items are excluded because the goal is to measure a household's normal level of consumption, which could be distorted by including large and unusual items of spending. Discussion of the issues involved in measuring consumption may be found in Deaton and Zaidi (2002), with an updated version in Mancini and Vecchi (2022).

How the data were collected

At the first interview, households were given a diary (Appendix 2) in which to record food purchases and consumption for the day prior to the second visit, and for the time between each of the subsequent visits. The diaries were used to assist enumerators, who went through each of the 148 food items with the interviewee at each visit. Thus, by the last visit, there was a record for each household with details of food consumption over the previous seven days, with a breakdown of the amounts originating from purchases, own-production, and gifts.

The previous complete survey, EICV5 (2016-17), used a different protocol for collecting information on food, which is why the results of the two surveys cannot be compared directly. In EICV5, information was collected on food purchases, but not on food consumption. Moreover, rural households were interviewed 8 times over 14 days and urban households 11 times over 30 days. Research based on the EICV5 data showed only slight evidence of respondent fatigue, but led to the conclusion that data carefully collected over seven (rather than 14 or 30) days would allow one to measure poverty at least as accurately and would be more accurate than asking households on just one occasion to recall their consumption over the previous seven days (Haughton et al. 2022).

What is included: in detail.

Households were asked about their consumption of 148 food items. They were also asked about purchases or use of 165 non-food items, whether over the past week (23 items), month (65 items) or year (77 items). There were separate questions about spending on utilities (water, electricity), education, and rent. Table 6.1 provides more details.

Table 6.1. Components of the household consumption aggregate

Component	Items covered	Questionnaire section
Food consumption at home	148 items. Includes quantity of consumption from items that were purchased, home-produced, or received as gifts/transfers, as well as the value and quantity of purchases; and the estimated price of home-produced food. Based on diary and recall since previous visit (or just previous day, for visit number 2).	8B
School meals	The value of the government subsidy was imputed, using separately-collected information, for those reporting receiving school meals. Parents also contribute to the cost of meals.	See 4Aq15a
Other food consumption outside the home	Amount paid for (or estimated value of) meals, snacks, beverages, and alcohol consumed outside the home. Based on recall since previous visit (or just previous day, for visit number 2).	8C
Non-food spending	Purchases, home production, and gifts received over the past year of 77 infrequent non-food items.	8A1
	Purchases, home production, and gifts received over the past four weeks of 65 other non-food items. Excludes in-kind value of ARV drugs.	8A2
Purchases, home production, and gifts received over the past week of 23 frequently-acquired non-food items; and the value of own production of wood and charcoal (for cooking) 8A3		
Education expenses	Fees, contributions, and other expenses (e.g. uniforms) related to household members attending school	4Aq14
Durable goods	Estimated consumption flows ("use value") of durable goods, derived from reported value of durable goods and estimated depreciation and interest rates.	10B
Housing expenses	For renters, actual rent. For owners, or those in subsidized housing, self-reported rent (but imputed rent in case of outliers).	5B
	Expenses on water and electricity	5C

Not every household expenditure is included in the consumption aggregate. Thus, we did not include non-consumption expenditures, such as payments of taxes, purchases of business or farm inputs, or purchases of durable goods. We also excluded exceptional expenses such as weddings and funerals, or hospital stays and other emergency medical expenses. This is because our interest is in measuring a household's normal level of consumption, which would be distorted were we to include large and unusual items of spending.

Durable goods

Durable goods, such as a sofa, bicycle, or cellphone, provide services over a several years. In principle, the appropriate way to measure their contribution to consumption is by including their rental value: if it would have cost 30,000 Rwf per year to rent a bicycle (that would have cost 100,000 Rwf to buy), then the "consumption" of the bicycle should be measured as 30,000 Frw.

In practice, it is common to approximate the rental value of a durable good with its user cost, which is given by

$$UC \approx p_t(r_t + \delta)$$

where is the current value ("price") of the durable good as estimated by the respondent, is the real annual interest rate (i.e. the opportunity cost of locking up capital in the asset) and is the depreciation rate (i.e. the loss of real value of the asset from one year to the next). For the EICV5 survey, depreciation rates of 10%, 20%, and 40% (for cars, bicycles, and motorbikes) were used, but the origins of these rather arbitrary rates is unclear. For EICV7, we use a depreciation rate of

$$\delta = \frac{1}{E(\text{years of remaining life})}.$$

So, if an asset is expected to last for four more years, the depreciation rate would be 0.25. For almost every asset, households report its age (A). We assume that the maximum age of an asset is the age of the asset at the ninety-fifth percentile (A95). The expected remaining life is then this value minus its actual ag; for the few items older than that, we apply the mean age of assets (A). This gives

$$E(\text{remaining life}) = \max\,(A^{95} - A, \bar{A}).$$

For the real interest rate (rt) we use 4%. This is the value of the average of the deposit and lending rates reported by the IMF (International Monetary Fund), adjusted for inflation, over the period 2018-2023, rounded down to the nearest integer. A list of durable goods and the associated depreciation rates is given in Table 6.2.

Research using EICV5 data to simulate the effects of different methods to measure the user cost of durable goods found that the choice has a limited effect on the measurement of the poverty rate, but does influence the measurement of inequality (Haughton et al. 2022).

Table 6.2. User cost rates by product using alternative methods to measure depreciation, applicable to Rwanda in 2016/17

Durable good	Mean age	Age 95th percentile	Mean depreciation rate	User cost rate
Living room suite (table + chairs)	6.5	20.5	7.7	11.7
Dining Table (table + chairs)	8.0	23.8	6.7	10.7
Beds	7.8	25.2	6.3	10.3
Mattresses	4.6	14.7	10.7	14.7
Table	8.9	26.8	6.0	10.0
Chairs	8.8	28.5	5.6	9.6
Bench	8.1	26.0	6.1	10.1
Car for home use	4.4	12.4	12.9	16.9
Motorcycle for personal use	4.6	12.3	13.4	17.4
Bicycle/tricycles for personal use	5.7	19.8	7.9	11.9
Solar lamps	3.7	11.4	13.8	17.8
Refrigerator/Freezer	5.0	14.2	11.5	15.5
Electric/Gas Cooker	3.2	8.3	20.3	24.3
Washing Machine/Dryer	3.6	12.2	12.1	16.1
Electrical Iron	5.0	15.2	10.6	14.6
Microwave	4.8	12.0	13.7	17.7
Blender/Mixer	2.8	7.5	22.0	26.0
Water dispenser	3.6	10.3	16.1	20.1
Mobile handsets (basic)	1.8	5.6	28.0	32.0
Mobile handsets (smartphone)	1.2	3.9	39.8	43.8
Computer (desktop/laptop)	3.1	9.0	17.9	21.9

Durable good	Mean age	Age 95th percentile	Mean depreciation rate	User cost rate
Tablet	3.2	8.4	19.7	23.7
Television sets	4.3	13.3	12.1	16.1
Radio sets	4.1	15.2	10.0	14.0
Home theater, CD and sound players	2.2	7.2	21.6	25.6
Cameras (still, digital, video)	6.0	13.3	12.9	16.9
Garden tractors (grass cutting machine)	4.1	8.6	19.2	23.2
Notes: "Mean age" gives the mean reported age (in years) of assets; "Age 95th percentile" is the age of the 95th percentile asset (i.e. almost the oldest). "Mean depreciation rate" is the mean of depreciation rates of assets owned by surveyed household. "User cost rate" is the depreciation rate plus 4%, and is applied to the reported value of durable goods to give the use value of durables.				

Food consumed outside the home

A detailed set of questions inquired about the consumption of meals, snacks, and other food outside the home, for each household member. This allowed us to measure the value of such food consumed outside the home.

Also of interest, especially when constructing the poverty line, is the number of calories that individuals obtain from this consumption. In order to measure the cost (in RWF) per calorie consumed outside the home, we took the following steps:

- We interviewed a sample of restaurants in order to obtain information on the cost of the ingredients (from a list of 150 items) that they bought for the day, and the number of meals sold (at different prices).
- By applying information on the calorie content of each ingredient, we were able to compute the median revenue per kilocalorie sold for the sample. The exercise was done separately for breakfast, lunch, and dinner, with the results shown in Table 6.3. Thus, for instance, a lunch meal that provided 1,500 kcals would cost, on average, about RWF750. This is only slightly higher than the average cost of calories from home consumption (0.454 RWF/kcal).

The data refer to the period July-October 2024: data collection began when it was clear that the information would be needed. There were no differences in revenue per kcal from one month to the next.

Table 6.3. Restaurant revenue per calorie by meal, July-October 2024

Meal	Revenue per kcal (RWF)	Sample size (restaurants)
Breakfast	0.688	144
Lunch	0.501	182
Dinner	0.817	55

School meals

School meals are subsidized, but parents are also expected to make a contribution. For a student in primary school, for instance, parents typically pay RWF 3,000 per year, and the government provides a subsidy of RWF 135 per day (which is equivalent to RWF 24,975 over the 185 school days of the year). The official contributions are summarized in Table 6.4.

Table 6.4. Parental and governmental contributions to school meals

	Parents pay per day (RWF)	Government pays per day (RWF)
Pre-primary and primary	15	135
Secondary	300	56
Boarding	934	56
Source: Ministry of Education. There are 185 school days per year.		

The EICV7 questionnaire asked about parental contributions to school meals, and we used these values (or the government-prescribed values, if these were higher). We included the government subsidy as part of household consumption.

To determine the number of calories per school meal, we surveyed a variety of schools, collecting information on their purchases of inputs (rice, potatoes, salt, etc.) and the number of each type of meal produced. The median numbers of calories per meal are shown in Table 6.5.

Table 6.5. Calories per school meal, July-October 2024

Meal	kcal per meal	Sample size (schools)
Breakfast	264	133
Lunch	535	449
Dinner	990	330

Housing

Housing provides shelter, and this is an important component of consumption. For households that rent their dwelling, we use the value of rental payments to measure the value of the services provided.

Households who own their dwelling, or live in free or subsidized housing, are asked to estimate what it would cost if they had to rent their housing. They are also asked to estimate the value of their dwelling. On average, estimated reported rents are about 4.8% of the estimated value of the dwelling. However, there are some extreme cases, where reported rental rates are implausibly low (below 1%) or high (above 25%).

We proceed as follows. First we use the data from households that rent, in order to estimate a "hedonic price equation", which is a regression of rental payments (the y or outcome variable) against a set of variables that reflect the location of the dwelling and its characteristics. More specifically, the right-hand variables include:

- Type of settlement (Umudugudu, modern, unplanned)
- Building type (single, multiple household, multistory, compound)
- Walls (mud, mud with cement, fired bricks, wood/trees)
- Roofs (corrugated iron, tiles)
- Floors (mud, tiles, cement)
- Water source (piped in, standpipe, wells/springs, other)
- Time required to fetch water
- Source of electricity (grid, solar, none)
- Cooking area (kitchen, bedroom, separate, outdoors, unknown)
- Toilet (flush, improved latrine, other)
- Toilet sharing (individual, shared)
- Districts
- Square meters of dwelling
- District interacted with square meters

The regression, which is based on 2,951 observations on renters (of which 1,039 are in rural areas), fits well, with an adjusted R-squared of 0.8. The estimates are set out in Table 6.6.

We then apply this regression to households that are not renters, using it to predict what they would be expected to have to pay in rent. We use these predicted ("imputed") rents if:

- Households estimated that their rent would be below 1% or above 25% of the reported value of their dwelling, or
- Households estimated rentals that were below 25% or above 400% of the rentals predicted by the hedonic price regression.

This gives more credence to self-reported estimated rents than was done in EICV5, where imputed rent was used for all owner-occupied dwellings, but it in effect replaces outlier values of self-reported rents.

Table 6.6. Estimates of Hedonic Regression for Home Rentals

		Coefficient	p-value		Coefficient	p-value
Outcome variable						
ln(actual rent paid, RWF/yr)						
Right-hand variables						
Settlement (umudugudu)						
Modern		0.275	0.00			
Unplanned		0.012	0.65			
Building type (house)						
Multiple household		0.010	0.69			
Multistory		0.255	0.07			
Compound		0.078	0.01			
Wall (mud)						
Mud bricks with cement		0.136	0.00			
Fired bricks with cement		0.373	0.00			
Tree trunks		0.112	0.00			
Roof (corrugated iron)						
Tiles		-0.189	0.00			
Floor (mud)						
Tiles		0.895	0.00			
Cement		0.524	0.00			
Water source (piped in)						
Standpipe		-0.349	0.00			
Well/spring		-0.416	0.00			
Other		-0.350	0.00			
Source of electricity (grid)						
Solar		-0.362	0.00			
None		-0.460	0.00			
Cooking area (kitchen)						
Bedroom		-0.111	0.01			
Separate		-0.008	0.76			
Outdoors		-0.138	0.00			
Unknown		-0.107	0.13			
Toilet (flush)						
Improved latrine		-0.548	0.00			
Other		-0.603	0.00			
Toilet (individual)						
Shared		-0.044	0.08			
District				District x sqm		
Kigali	11	0.620	0.00		0.004	0.11
	12	0.676	0.00		0.000	0.96
	13	0.618	0.00		0.002	0.50
South	21					
	22	0.435	0.04		-0.014	0.03
	23	-0.115	0.65		0.002	0.74
	24	-0.134	0.30		0.000	0.89
	25	0.180	0.29		-0.005	0.20
	26	-0.107	0.47		0.000	0.93
	27	0.293	0.03		-0.005	0.16
	28	0.185	0.15		0.000	0.98
West	31	0.054	0.76		0.001	0.86
	32	-0.477	0.06		0.004	0.53
	33	0.255	0.03		0.000	0.89
	34	0.098	0.53		-0.002	0.55
	35	-0.023	0.92		-0.006	0.34
	36	0.068	0.63		-0.001	0.79
	37	-0.468	0.02		0.005	0.28
North	41	0.260	0.26		-0.001	0.91
	42	-0.358	0.05		0.012	0.01
	43	0.266	0.06		-0.002	0.64
	44	-0.129	0.57		0.001	0.86

		Coefficient	p-value		Coefficient	p-value
	45	0.195	0.39		0.001	0.87
East	51	0.023	0.85		0.003	0.35
	52	0.353	0.01		-0.008	0.06
	53	-0.085	0.66		0.002	0.68
	54	0.189	0.16		-0.003	0.43
	55	-0.184	0.21		0.004	0.35
	56	0.009	0.95		0.000	0.89
	57	0.111	0.34		0.001	0.69
Square meters of dwelling		0.009	0.00			
Time to fetch water (mins)		-0.002	0.01			
Intercept		11.781	0.00			
Source: EICV7. Based on rental observations for 2,951 households. Adjusted R2: 0.822. Reference category for discrete variables is shown in parentheses.						

Exceptional items

As noted above, the consumption aggregate does not include expenditure on exceptional items such as wedding and funerals. It also excludes spending on the following the items listed in Table 6.7, which are considered to be unusual.

Non-Standard Units

Some food items are purchased in non-standard units, such as a bottle of oil or a single avocado. In EICV5, each enumerator was equipped with a weighing scale; however, it was only used to measure food consumed from home production. In EICV7, enumerators also used the scale to measure food consumption during the interview. In addition to that following the recommendations of the EAC (2023), We gathered information on non-standard units and added it to the CAPI application, along with pictures to help convert food items into standard units like kilograms or liters. An example is shown in Figure 6.1

Figure 6.1. Example of Visual Aid to Non-Standard Units

Line	Information	Picture
1	Sector: Nyamiyaga Product: Pepper NSU: Medium piece Equivalent: 0.079 Kilogramme (KG) Price: 100 Frw	
2	Sector: Nyamiyaga Product: Pepper NSU: Small piece Equivalent: 0.043 Kilogramme (KG) Price: 50 Frw	

Table 6.7. Unusual Spending Items, Excluded from the Consumption Aggregate

Item
Exceptional Non-food Items
Construction wood
Materials for the maintenance repair of the dwelling (e.g. cement, ironsheets,sand, nails); carpets; small plumbing items,)
Security equipment (e.g. smoke detectors, surveillance cameras, fire extinguisher, etc.)
Mattresses
Electric clothes iron
Non-electric clothes iron
Musical instruments
Exceptional Health Items
Hospitalization
Giving birth
Emergency transportation and emergency rescue services
Assistive health products for mobility and daily living (e.g., crutches, therapeutic footwear, wheelchairs, prosthesis)
Diagnostic and laboratory tests, such as blood tests and x-rays, for other reasons than preventive care.
ARV drugs (to the extent they are provided free of charge)

Handling outliers

Outliers are observations that appear to be too high or too low.

In the field, the CAPI software used by enumerators was designed to flag potential outliers, which often allowed the numbers to be checked, and if necessary corrected, on the spot. At the end of each day, the data collected in the field were further checked by the local supervisor.

In the course of compiling and analyzing the data, we came across evident outliers from time to time, and first checked whether these were simply errors. With a few exceptions, noted below, we made no further adjustments to data that were plausibly correct.

As noted in Section 2.8, we replaced some of the values of estimated rent (by homeowners) with imputed values (from an hedonic regression based on data from renters).

The only other instances where outliers were replaced with imputed values (using a regression-based imputation method) involved exceptionally high education expenditures: one case involved payment for study abroad, which was considered atypical, and three other cases reflected implausibly large payments for education at public schools.

Our "light-touch" treatment of outliers contrasts with the approach taken when processing the EICV5 data, where major food spending items that were at least 3.5 standard deviations away from their (log) values were replaced by the mean values of those items. As a general rule, the handling of outliers has little influence on the measured poverty rate, but can influence measures of inequality.

Deflating to prices of January 2024

Households were surveyed in different parts of Rwanda at different times of the year. They thus faced different prices, which vary over time and space. Before we can compare households, we need to value their consumption in a consistent set of prices.

Anticipating the need for good-quality price data nationwide, the NISR has, since October 2023, collected data on prices of hundreds of items in markets and shops in all thirty districts. These "CPI prices" were collected with careful attention to consistency in units and quality over time and space.

The household survey also collected information on the quantity and value of items purchased; by dividing value by quantity one gets "unit values", which are essentially imputed prices, but lack the rigorous quality control of the CPI prices.

Households were also asked to put a value on items that they consumed from their own production, but these "own-production prices" are only available for a subset of consumption items.

The theory of economic welfare says that "utility", which is equivalent to wellbeing, may be measured by "real consumption", which may be approximated by

$$u^h \approx \frac{x^h}{P^h}$$

where is the nominal value of household consumption (i.e. measured using the prices households actually paid, as far as possible) and is a Paasche price index for each household, which may be written as

$$P^h = \left(\sum w_i^h \frac{p_i^0}{p_i^h}\right)^{-1}.$$

Here the are the shares in nominal total consumption of spending on good , and the prices and refer to the prices of each good in the base period, and at the time and place where the household was interviewed, respectively.

A number of practical problems need to be addressed when measuring real consumption (rather than acquisition).

- In principle, we need to measure using the prices that households face. When goods are bought and consumed, this is straightforward. But there are several other cases that have to be treated differently:
  - Goods that were consumed by the household and that come from the household's own production and effort. These were valued at the price that the household reports it could get if it were to sell the items.
  - Goods that are consumed by the household, but were not purchased by the household during the period of the interviews. In this case we use the district-level median unit values (if there are at least five observations) in the relevant month; or failing that, the regional-level unit values; or the national-level unit values.
  - Where unit values and self-reported prices are not available – for instance, for some gifts, or items such as bottled beer bought prior to the interview period – we use CPI prices.
  - As noted above, we use special procedures to value durable goods, some (imputed) house rentals, and school meals.
- To construct the price index (), we first have to obtain base-period prices for each good (). The procedure is as follows: For as many items as possible, we find the median CPI prices at the district level as of January 2024 (or in a handful of cases, unit values, or administrative prices). We then obtain the population-weighted averages of these medians. For this purpose, the three districts in the City of Kigali – Nyarugenge, Gasabo, and Kicukiro – are treated as a single unit. In a few cases where CPI prices are not collected, representing about 5% of food costs, we use unit values, but only when we consider these unit values to be sufficiently robust.
  - Note that it is not possible to include every item in computing the price index. This mainly occurs when there is no CPI price and the item is not well-defined (such as the category of "other flour of cereals"), or when there is a CPI price but it is clear that the data collected in different districts used different or ill-defined units (such as "Women's haircut (stylist & treatment)".
  - Once the index was constructed, it was applied to all nominal spending. This has the effect of deflating those items that were not included in the construction of the index, using the average deflation based on the included items.
  - There is a separate price index for each household. This is to allow for differences in the consumption patterns ("baskets") from one household to the next.

Determining adult equivalence

Households differ in size and composition, so, as noted above, total household consumption has to be adjusted to take these factors into account. Some researchers have tried to create equivalence scales "objectively" – see Bellù and Liberati (2005a) for a discussion – but these are not entirely satisfactory (Deaton 1997). We therefore need to make some choices, which will necessarily be more "subjective" (Bellù and Liberati 2005b).

For prior EICV reports, Rwanda relied entirely on a calorie-related scale, which recognizes that household members of different ages and gender have different nutritional needs. The scale, which was first used for the 1982-83 Enquête Nationale sur le Budget et la Consommation des Ménages (ENBC), has some odd quirks, and it is not clear how it was derived. Perhaps more importantly, it does not allow for economies of scale, which is the idea that the cost of providing for a household does not rise in proportion to its size: for instance, it is cheaper to house two people under one roof than in two separate dwellings.

For EICV7 we use a hybrid scale, putting two thirds of the weight on caloric needs, and applying economies of scale to the remaining third of spending. This gives

AE = (2/3) (Calorie-based equivalence scale) + (1/3) (Non-food-based equivalence scale).

These proportions (2/3, 1/3) are used because poor people in Rwanda (and elsewhere) devote about two-thirds of their spending to food.

The relative caloric needs for the calorie-based scale are shown in Table 8.1. The index is set to 1.00 for men aged 20-29. The numbers come from the relative caloric needs published by the East African Community (EAC 2023), and are very close to the numbers that we arrived at independently (Haughton et al. 2022).

Table 8.1. Calorie Scale Used In Calculation of (Part Of) Adult Equivalence

Calories			Calories		
Age	Male	Female	Age	Male	Female
0	0.21	0.20	13	0.91	0.78
1	0.31	0.28	14	0.98	0.80
2	0.37	0.34	15	1.04	0.82
3	0.41	0.38	16	1.09	0.82
4	0.44	0.41	17	1.11	0.82
5	0.48	0.43	18	1.00	0.83
6	0.52	0.47	19	1.00	0.83
7	0.56	0.51	20-	1.00	0.83
8	0.60	0.56	30-	0.97	0.79
9	0.63	0.61	40-	0.97	0.79
10	0.70	0.65	50-	0.97	0.79
11	0.77	0.70	60-	0.80	0.71
12	0.83	0.74	70+	0.80	0.71

The non-food-based equivalence scale is given by

$$(A + 0.3C)^{0.8}$$

where A is the number of adults in the household and C is the number of children aged 16 or younger. The coefficient 0.3 in this equation reflects the observation that children appear to cost only about 30% as much to house and clothe as adults, based on our estimates using EICV5 data. The 0.8 exponent is a measure of economies of scale: if it were 1, there would be no economies of scale. Deaton and Zaidi (2002) suggest that a value of about 0.9 would be appropriate; our estimates based on EICV5 data put the number closer to 0.7, but we consider that a compromise of 0.8 is likely to be appropriate.

To illustrate how the adult equivalence scale works, consider three households:

- A 70-year old women living alone.

  AE = (2/3) × 0.71 + (1/3) × ($1^{0.8}$) = 0.81.

- A 35-year old man, 32-year old woman, a boy aged 8 and a girl aged 6.

  AE = (2/3) × (0.97 + 0.79 + 0.60 + 0.47) + (1/3) × (2 + 0.3×2)0.8 = 2.76.

- Four females (aged 73, 49, 24, 2) and four males (aged 52, 48, 28, 0)

  AE = (2/3) × (0.71 + 0.79 + 0.83 + 0.34 + 0.97 + 0.97 + 1.00 + 0.21) + (1/3) × (6 + 0.3×2)0.8 = 5.39.

It is worth noting that perhaps the most widely-used measure of welfare is consumption per capita, which is equivalent to assigning every household member an adult equivalence of 1 (Deaton and Zaidi 2002). International comparisons such as the World Bank's PovCalnet use per capita measures in arriving at poverty rates and indexes of inequality. However, the measure does not take into account the fact that household members have different minimum needs, especially nutrition, at different ages. Nor does it recognize that as households get larger, they benefit from economies of scale in consumption.

Establishing the poverty line

Principles

A new poverty line was created from first principles, using a cost-of-basic-needs approach, which establishes a level of consumption that provides for basic nutritional requirements, as well as essential non-food needs such as shelter and clothing. A useful background reference in Ravallion (1998).

The establishment of the poverty line follows a cost-of-basic-needs approach, which establishes a level of consumption that provides basic nutritional requirements, as well as essential non-food needs such as shelter and clothing. In 2014, a task-force established that the cost of providing 2,500 Kcals per adult equivalent per year would be RWF 105,064 (in January 2014 prices), with a diet largely based on roots and tubers. Given that households whose food consumption was within (plus or minus) 10% of the food requirement spent about 66% of their income on food, the cost of food was grossed up to RWF 159,375 to establish the standard poverty line. This poverty line was used again for EICV5 data (2016-17), after adjusting for changes in prices over the intervening period.

It is now appropriate to re-establish a cost-of-basic-needs poverty line from first principles. More specifically, we want to measure the cost of providing enough food and non-food essentials for an adult male. The caloric needs of others can then be determined by using the relative caloric scale given in Table xxx, which is based on a recent publication by the East African Community, but is also close to the results of our own independent research on the issue.

How many Calories per adult per day?

The most important basic need is food, but the question immediately arises of how much food is needed for a minimally acceptable standard of living. We focus here on the number of calories that are needed, while recognizing that a truly satisfactory diet should ideally also provide enough other nutrients including protein, minerals, and vitamins.

For prior EICV surveys, and the ENBC of 1982-3, it was assumed that an adult male needed 2,500 kilocalories of energy per day. When the poverty line was re-established in 2014, the expert panel suggested that this threshold might be too high, but chose not to make any changes, to ensure comparability with earlier Rwandan surveys. Most other countries in the East Africa region use a lower cutoff, including Kenya (2,250), Tanzania (2,200), Burundi (2,250), and Ethiopia (2,200). Given this background, we decided to examine the issue anew. This is also useful in the context of the Indian "calorie-consumption puzzle" (Ram 2017), where real incomes for most Indians rose from the 1990s onwards yet calorie consumption appears to have fallen.

Caloric needs vary by age, gender, and weight, and also by how active the individual is. The energy required for a body at rest is measured by the basal metabolic rate (BMR), which is the "amount of energy per unit of time that a person needs to keep the body functioning at rest," including for breathing, circulating blood, and controlling body temperature. The BMR declines slowly after age 20, by 1-2% per decade (Wikipedia 2024).

The effect of activity is usually represented as a multiple of the BMR: a multiple (Physical Activity Level (PAL) or Physical Activity Rate (PAR)) of 1.4-1.69 represents light activity, while a multiple of 1.7-1.99 reflects "moderate" activity (FAO 2024, chapter 5). The FAO (2025) publishes tables of caloric needs by age, gender, weight, and physical activity. For example, a man aged 18-29.9 who weighs 50 kg. and has a PAL of 1.6 would need 2,300 kcals daily.

Our interest is in determining how many calories are needed, at a minimum, for people to function acceptably well. This is the minimum dietary energy requirement (MDER), which varies by age and gender.

To compute the average MDER, we need to:

- Find the heights of people at each age, by gender.

  We obtained the heights of men aged 20-39 from the Demographic and Health Survey (DHS) of 2014-15 (Rwanda 2016), which is the most recent study for which such information is available. Based on 3,537 observations, the mean height was 1.667m. Over time, populations tend to get taller, but the effect is slow. In the DHS survey, younger adult men were not taller than older adult men, suggesting little if any secular increase in heights over time.

- Given that different weights are consistent with a given height (for age, gender), pick the "lowest acceptable weight-for-height." This is typically taken as the 5th percentile of the Body Mass Index (BMI) for a healthy population, and is equivalent to be a BMI of 18.5 (CDC 2024). The BMI is defined as weight (in kg) divided by height (in meters) squared, and someone with a BMI below 18.5 is considered to be undernourished.

  Based on this method, we found the minimally acceptable weight was on average 51.27 kg.

- Use these weights to measure the basal metabolic rate (BMR) – i.e., one's energy needs when resting but awake – using established equations that link this to weight, age, and gender. FAO does this using the Schofield equations (James & Schofield 1990), but other methods have also been used, of which the Mifflin-St. Jeor equations are considered the most accurate, and are the ones we use.

  Applying steps (i)-(iii) to all young men in the DHS survey of 2014-15, using the Mifflin-St. Jeor equations, we found an average basal metabolic rate of 1,465 kcals per day.

- Add a provision for activity, using a physical activity level (PAL) index. The lowest acceptable activity level ("light activity," or "sedentary lifestyle") is often given by a PAL of about 1.55, although some countries, such as the UK, use a PAL of 1.4.

The final results are sensitive to the choice of physical activity level. The computations are set out in Table 9.1. The activity levels of the working-age population are assigned to the categories of light, moderate, and high physical activity, based on the occupations reported in the Labor Force Surveys of 2024. The penultimate column shows the physical activity levels that we use for each group. These represent the minimally acceptable levels (rather than the ideal levels), which is the appropriate choice when constructing a poverty line.

The result is an estimated mean PAL of 1.64. When we multiply this by the estimated basal metabolic rate for men aged 18-29, we arrive at a minimum caloric need of 2,400 kilocalories per day (rounded to the nearest 10). This is the threshold that we use to calculate the poverty line.

Table 9.1. Calculation of PAL and Daily Caloric Needs for an Adult Male

Activity level	Occupations	% of working age population	Active hours per week	PAL	
Employed					
Light	Managers, professionals, technicians and associates professionals, clerical support workers, service and sales workers.	15.3	58	1.40	FAO scale runs from 1.4-1.69
Moderate	Craft and related trade workers, plant and machine operators manufacturing and assembly, Food preparation, street sales and other elementary occupations.	7.0	54	1.70	FAO scale runs from 1.7-1.99
High	Skilled agricultural, forestry and fishing, Laborers in agriculture, mining, construction, and domestic services.	31.2	57	2.00	FAO scale runs from 2.0-2.4
Out of labor force & Unemployed					
Moderate/light	Participated in subsistence agriculture.	22.3	45	1.55	
Light	Students and others out of the labor force.	24.2	11	1.40	
Working Age Population		100.0	43	1.64	Mean PAL

Activity level	Occupations	% of working age population	Active hours per week	PAL	
BMR	Basal Metabolic Rate, male 18-29			1,465	
	Mean caloric threshold	kcals/AE/day		2,400	
Notes: Breakdown of working age population, and active hours, from Labor Force Survey, 2024 rounds. Physical Activity Levels (PAL) from FAO. For BMR, see text. Caloric threshold rounded to nearest ten.					

Valuing calories

The next step in constructing a poverty line is to determine how much it costs to acquire the necessary calories (2,400 kcals per day). This will depend on the dietary choice: a well-off family that can afford a richer diet can easily spend twice as much per calorie consumed as a poor household.

Our approach is to use the dietary composition of households in the second quintile. First we sort everyone in the sample by real consumption per adult equivalent, and then we identify those who are in the second poorest quintile – i.e. those who are between the 20th and 40th percentiles. We choose this group because our prior expectation is that the poverty rate is likely to be somewhere within this range, and we want to mimic the diet of those who are near the poverty line – an assumption that turned out t be correct. It is also important to have a sufficiently large sample to give a robust breakdown of the diet.

The EICV7 survey listed 148 different food items. However, some of these are rarely, if ever, consumed by the poor. So we excluded items consumed by fewer than 0.1% of households in the second quintile, on the grounds that these are atypical.

For every food item, we then need to measure the average quantity consumed, and the associated number of calories, as well as the price. The caloric content of different foods comes from food composition tables, which provide the conversion factors. In the past, these have come from FAO sources that are listed "for international use" (https://www.fao.org/4/x9892e/X9892e05.htm)

We have used more up-to-date and geographically appropriate conversion factors. The main source is an extensive set of conversion factors compiled by the FAO based on information from West (and sometimes Central) Africa. Where necessary, we complemented this information with conversation factors for Kenya (FAO 2018), or Tanzania (2008), or the FAO international source. For a few food items, it was not possible to find conversion factors, and we have had to exclude these items. A small number of food items have zero calories (e.g. salt, tea, vinegar), but we have included these in the diet on the grounds that they are clearly components of the diet of poor people.

The full list of food items is shown in Table 9.2. Items that are consumed by fewer than 0.1% of households are marked with an asterisk, and are excluded as being non-typical. Only items for which we have information on price, and on calories, provide enough information to be included. We show the calorie conversion rates and the sources used, along with the quantities consumed per adult equivalent by households in the second quintile, and the daily cost of consuming the item.

For most food items we have the quantity consumed per adult equivalent in the second quintile, the base-period price, and the caloric content per kilo or litre. This gives us the cost of buying 1,933 kcals per day; the number would be higher if we had complete price and calorie-content information on all items of food consumed at home. We then add the calories from school meals, and consumed outside the home. This gives us the cost of 2,169 kcals. To find the cost of the threshold of 2,400 kcals, we gross up the cost of food consumed at home, to compensate for the missing information on home consumption.

The cost of this basic diet per year gives us a food poverty line of RWF 356,432 per adult equivalent per year in January 2024 prices. This is also the poverty line used to measure extreme poverty.

As noted above, two additional sources of calories need to be taken into account: school meals, and other food consumed outside the home. Adding this information (from tables discussed above), we get the results summarized in Table 9.3. The cost of 2,400 kcals per day comes to RWF 356,432, in the national prices of January 2024. This is also the food poverty line.

Table 9.2. Food-Calorie Conversion Rates and Consumption Levels and Costs

ITEMS	COICOP	Price	Cals	Quantity	Quantity (Adjusted)	Unit	kcals/100g	Source	Cost/day
COMMON ITEMS									
Dry bean	01.1.7.5.01	607	374.95	0.117	0.131	Kg	320	WA	79.879
Fresh bean	01.1.7.3.02	892	22.43	0.027	0.031	Kg	82	KE	27.368
String bean	01.1.7.3.01	740	0.56	0.002	0.002	Kg	37	WA	1.254
Groundnut flour	01.1.6.8.03	1836	42.36	0.007	0.008	Kg	574	WA	15.203
Irish potato	01.1.7.7.01	388	108.27	0.152	0.171	Kg	71	WA	66.401
Sweet potato	01.1.7.8.01	381	285.15	0.356	0.400	Kg	80	WA	152.365
Cassava (root)	01.1.7.8.02	440	93.02	0.078	0.088	Kg	119	WA	38.562
Tarot/amateke	01.1.7.8.05	589	65.14	0.060	0.067	Kg	109	WA	39.502
Banana-cooking (Inyamunyo)	01.1.6.2.02	436	109.78	0.134	0.150	Kg	82	WA	65.444
Corn (flour from Mill)	01.1.1.6 .07	957	127.06	0.036	0.040	Kg	353	WA	38.676
Cassava flour (yasekuwe)	01.1.7.8.04	914	29.72	0.009	0.010	Kg	341	WA	8.941
Cassava (fermented)	01.1.7.8.03	683	2.76	0.002	0.003	Kg	119	WA	1.782
Local rice	01.1.1.1.01	1256	118.51	0.034	0.038	Kg	351	WA	47.593
Imported rice	01.1.1.1.02	1449	28.77	0.008	0.009	Kg	351	WA	13.328
Maize (fresh)	01.1.1.6.01	303	73.58	0.052	0.058	Kg	142	WA	17.592
Dry maize (grain)	01.1.1.6.02	519	49.24	0.014	0.016	Kg	350	WA	8.192
Tomato	01.1.7.3.04	676	5.48	0.027	0.031	Kg	20	WA	20.757
Fresh milk	01.1.4.1.01	804	10	0.016	0.018	L	64	WA	14.100
Curdled Milk	01.1.4.5.02	782	5.66	0.009	0.010	L	62	WA	8.007
Cakes/Chapati/Mandazi	01.1.1.4.01	100	93.6	0.037	0.041	Piece	424	KE	4.146
Sugar (imported)	01.1.8.1.02	1957	12.6	0.003	0.004	Kg	400	WA	6.919
Sugar (local)	01.1.8.1.01	1968	9.7	0.002	0.003	Kg	400	WA	5.352
Salt	01.1.9.2.01	413	0	0.009	0.010	Kg	0	WA	4.143
Local banana beer	02.1.3.1.05	411	4.77	0.010	0.011	L	47	FAO	4.681
Sorghum juice(Ubushera)	02.1.3.1.04	304	9.15	0.023	0.026	L	40	WA	7.811
Local sorghum beer(ikigage)	02.1.3.1.03	412	2.41	0.006	0.007	L	40	FAO	2.787
EDIBLE OILS									
Peanut oil	01.1.5.4.01	3495	72.44	0.008	0.009	L	900	WA	31.569
Palm oil	01.1.5.4.02	2373	7.33	0.001	0.001	L	900	WA	2.169
Other plant oils	01.1.5.4.03	3142	8.42	0.001	0.001	L	899	WA	3.299
Lard of pork	01.1.5.9.1.1	2000	0.28	0.000	0.000	Kg	902	FAO	0.069
MEAT									
Beef meat	01.1.2.1.01	4150	1.36	0.001	0.001	Kg	131	WA	4.831
Sheep /Mutton / lamb meat	01.1.2.3.01	3500	0.1	0.000	0.000	Kg	139	WA	0.277
Goat meat	01.1.2.3.02	4637	0.13	0.000	0.000	Kg	115	WA	0.596
Pork meat	01.1.2.2.01	3072	0.78	0.001	0.001	Kg	152	WA	1.759
CEREALS									
Sorghum	01.1.1.6.03	729	1.57	0.000	0.001	Kg	345	WA	0.372
Wheat (grain)	01.1.1.6.05	1015	0.16	0.000	0.000	Kg	329	WA	0.057
CEREAL FLOURS									
Sorghum (flour)	01.1.1.6.08	979	10.3	0.003	0.003	Kg	351	WA	3.2245
Wheat (flour)	01.1.1.6.09	2464	0.97	0.000	0.000	Kg	352	WA	0.7601
Millet (flour)	01.1.1.6.10	1295	0.13	0.000	0.000	Kg	367	WA	0.0519
FOOD PRODUCTS									
Pasta	01.1.1.3.01	1042	1.14	0.000	0.000	Kg	354	KE	0.3749
POULTRY & PRODUCTS									
Eggs	01.1.4.7.01	203	4.27	0.007	0.007	Piece	131	WA	1.4860
FISH									
Fish (fresh / frozen)	01.1.3.1.01	2809	1.13	0.001	0.001	Kg	112	TZ	3.1833
Small Sized Fish (dry)	01.1.3.2.9.3	3026	7.72	0.002	0.003	Kg	335	TZ	7.8305
DAIRY & PRODUCTS									
Milk powder	01.1.4.3.01	11685	0.02	0.000	0.000	Kg	493	WA	0.0480
Butter (local)	01.1.5.1.01	1500	0.13	0.000	0.000	Kg	743	WA	0.0294
Butter (imported)	01.1.5.1.02	7000	0.02	0.000	0.000	Kg	743	WA	0.0206
FRUITS									
Banana fruit (Imineke)	01.1.6.2.01	772	9.72	0.013	0.015	Kg	75	WA	11.2295
Banana - beer (Ikakama/Inkashi)	01.1.6.1.2.2	200	5.56	0.012	0.013	Kg	47	FAO	2.6537
Mangos	01.1.6.5.02	763	2.1	0.004	0.005	Kg	50	WA	3.5897
Papayas	01.1.6.7.03	577	1.3	0.004	0.004	Kg	37	WA	2.2807

ITEMS	COICOP	Price	Cals	Quantity	Quantity (Adjusted)	Unit	kcals/100g	Source	Cost/day
Avocado	01.1.6.5.01	391	33.79	0.030	0.034	Kg	111	WA	13.3740
Pineapple	01.1.6.7.01	367	0.61	0.002	0.002	Kg	36	WA	0.6988
Guava	01.1.6.7.02	320	2.27	0.003	0.004	Kg	67	WA	1.2147
Orange (local)	01.1.6.1.01	863	0.23	0.001	0.001	Kg	32	WA	0.6891
Orange (imported)	01.1.6.1.02	801	0.03	0.000	0.000	Kg	32	WA	0.0797
Tangerine	01.1.6.1.04	997	0.03	0.000	0.000	Kg	53	TZ	0.0627
Citron - Lemon	01.1.6.1.03	1699	0.05	0.000	0.000	Kg	24	WA	0.3845
Passion Fruit	01.1.6.7.04	2252	0.25	0.001	0.001	Kg	43	TZ	1.4726
Plums	01.1.6.5.03	1478	0.09	0.001	0.001	Kg	15	WA	0.9433
Apples	01.1.6.1.05	3954	0	0.000	0.000	Kg	53	WA	0.0187
LEGUMES									
Soya Flour	01.1.9.4.03	1220	7.94	0.002	0.002	Kg	437	KE	2.4858
Sunflower flour	01.1.1.2.9.1	1667	3.41	0.001	0.001	Kg	584	USDA	1.0912
Ground nuts (peanuts)	01.1.6.8.01	1975	0.6	0.000	0.000	Kg	574	WA	0.2305
Grilled ground nuts	01.1.7.5.7.1	3502	0.76	0.000	0.000	Kg	574	WA	0.5214
Soya (fresh)	01.1.9.4.02	916	1.42	0.000	0.000	Kg	415	TZ	0.3529
Soya (dry)	01.1.9.4.04	1200	0.6	0.000	0.000	Kg	381	WA	0.2112
Green pea (fresh)	01.1.7.3.03	1587	1.1	0.001	0.001	Kg	84	TZ	2.3265
Green pea (dry)	01.1.7.5.02	2021	0.64	0.000	0.000	Kg	324	KE	0.4459
VEGETABLES									
Onion	01.1.7.4.01	1408	1.51	0.005	0.005	Kg	33	WA	7.2427
Pumpkin	01.1.7.3.08	293	4.01	0.017	0.020	Kg	23	WA	5.7311
Cucumber	01.1.7.3.06	898	0.08	0.001	0.001	Kg	12	WA	0.6332
Eggplant	01.1.7.3.07	398	3.55	0.014	0.016	Kg	25	WA	6.3508
Carrot	01.1.7.4.03	539	1	0.003	0.004	Kg	31	WA	1.9480
Leeks	01.1.7.4.04	1942	0.06	0.000	0.000	Kg	35	KE	0.3611
Lettuce	01.1.7.1.01	1395	0	0.000	0.000	Kg	12	WA	0.0126
Celery	01.1.7.1.07	1748	0.01	0.000	0.000	Kg	16	Web	0.0813
Parsley	01.1.7.1.02	2294	0	0.000	0.000	Kg	40	WA	0.0049
Mushrooms	01.1.7.4.05	3000	0.23	0.001	0.001	Kg	27	TZ	2.8983
Cassava leaves	01.1.7.1.06	507	11.52	0.018	0.020	Kg	65	WA	10.0969
Amarante (small leafed green)	01.1.7.1.04	239	10.22	0.034	0.038	Kg	30	WA	9.1285
Cabbages	01.1.7.2.01	142	5.56	0.023	0.026	Kg	24	WA	3.6910
Spinach	01.1.7.1.03	442	0.06	0.000	0.000	Kg	20	WA	0.1607
Amarante (large leafed green)	01.1.7.1.05	266	1.37	0.005	0.005	Kg	30	WA	1.3677
Chayote	01.1.7.3.09	93	5.13	0.027	0.030	Kg	19	EICV4	2.8251
Pepper	01.1.7.3.05	822	0.08	0.000	0.000	Kg	28	WA	0.2795
ROOTS TUBERS									
Yams/Ibikoro	01.1.7.8.06	497	0.52	0.000	0.001	Kg	110	WA	0.2613
SUGAR & PRODUCTS									
Sugarcane	01.1.8.1.03	299	7.8	0.030	0.034	Kg	26	TZ	10.0556
Honey	01.1.8.2.02	3293	0.25	0.000	0.000	Kg	326	WA	0.2832
SPICE & OTHER FOOD ITEMS									
Mayonnaise	01.1.9.1.02	4290	0.01	0.000	0.000	Kg	680	USDA	0.0041
Pepper-raw	01.1.9.2.02	2392	0.04	0.000	0.000	Piece	19	TZ	0.5420
NON-ALCHOHOLIC BEVERAGES									
Mineral water	01.2.2.1.01	492	0	0.000	0.000	L	0	WA	0.0381
Local banana juice	01.2.2.3.01	392	5	0.010	0.012	L	48	EICV4	4.5841
Passion fruit juice	01.2.2.3.02	8912	0.01	0.000	0.000	L	54	USDA	0.1515
Coffee (local)	01.2.1.1.01	8043	0	0.000	0.000	Piece	0	FAO	0.0065
ALCHOHOLIC BEVERAGES									
Other local beer	02.1.9.0.0.1	1200	0.05	0.000	0.000	L	27	WA	0.2656
Commercial beer (local)	02.1.3.1.01	987	0.07	0.000	0.000	L	41	WA	0.1906

Table 9.3. Computing the Food Poverty Line

	Kcals/ae	Cost (RWF)/ae	Notes
Total Food at Home (measured)/ae/day	1,933.7		
Food at home (adjusted so total gives 2,400 kcals)/ae/day	2,170.0	878.3	Sum, last column of Table 9.2
Food School Cost/ae/day	110.8	30.2	
Restaurant food Cost/ae/day	119.2	68.0	B'fast 5.7; Lunch 90.7; Dinner 22.8
Total Food/ae/day	2,400.0	976.5	
Annual Food Cost/ae/year = food poverty line		356,432	

Notes: Food at Home adjusted 2,170= 2,400 - (110.8 + 119.2)

Adding a Non-Food Component

Food is not the only basic need: people need clothing, fuel for cooking, shelter, and other essentials. To find the total poverty line, we identify those households – there are 2,083 of them – whose value of food consumption is within 10% of the food poverty line. The median proportion of food to total consumption for this group is 63.6%, and so we gross up the food poverty line using this proportion, to give a total poverty line of RWF 560,127 per adult equivalent per year in January 2024 prices.

It is worth noting that we use the median (rather than mean) food share. The latter would be theoretically appropriate if we had individually-tailored information on essential food needs; but given that we are using an average approximation to food needs (i.e. 2,400 kcals/ae/day), the more robust mean value is preferred.

What's different/new in EICV7

Numerous changes have been made in the course of the seventh round of the EICV surveys. Most of these have been discussed already, but Table 10.1 provides a complete list of the changes, with some further clarifying comments. As noted earlier, EICV1 was launched a quarter of a century ago, and there was a need to reconsider and, where appropriate, update the methods used to collect and process the data. Briefly, EICV7 uses a more complete set of prices, applied a more efficient protocol for collecting data from households, reconstructed the poverty line, uses a more compelling measure of adult equivalence, and includes a fuller set of items in its measure of consumption.

Table 10.1. Changes Related to Measuring Poverty and Inequality, from EICV5 to EICV7

EICV7	EICV5	Comments
Survey protocol		
5 visits per household	8 visits per rural household, 11 per urban household	Reduced number of visits makes fewer demands on households. Research shows that the results are just as accurate.
Recall periods for food of 1 day, then 2 days (three times).	Recall periods for food of 2 days (seven times) in rural areas, and 3 days (10 times) in urban areas.	Our research using EICV5 data shows that collecting food consumption data over four visits/7 days is accurate.
Diaries used to aid recall	Less use of diaries	Diaries used as an aid, not as the sole source of information on consumption and acquisitions.
Questionnaire		
Extended module on food consumed outside home: xxx questions	Limited number of questions (xxx)	More-detailed questions yield more complete information. About 20% of food consumed (by value) is outside home.
Asked separate questions about food consumption and acquisition (purchases, own-production, gifts)	Asked about acquisition but not consumption	The measure of wellbeing is consumption, but past surveys only measured acquisitions.
For each item (food and non-food), asked about purchases, own-production, and gifts/in-kind receipts.	Questions about gifts/in-kind receipts were less detailed	More-detailed questions provides more-complete responses.
Construction of measure of consumption		
Included value of school meals	Not included	An important source of calories for school-goers.

EICV7	EICV5	Comments
Included more non-food items, most notably own-production of firewood	Home-produced firewood not included	Firewood represents almost a third of non-food consumption, and is mainly home-produced/gathered.
Revised formula to compute use value of durable goods	Original formula had some excessive depreciation rates (e.g. for cars), and excluded an interest rate.	Simulations show that this change affects measures of inequality more than measures of poverty.
Prices		
CPI prices collected in each of the 30 districts in each month	CPI prices were collected in the 5 provinces	CPI prices provide a consistent set of prices.
Deflation to get real consumption in prices of January 2024 use consumption weights at the household level	Deflation used a poor-person price index constructed at the level of each of the 5 regions and with set of consumption weights based on the spending pattern of household in the bottom two quintiles.	Household-level deflation better reflects the experience of individual households. It is used by Kenya.
Adult Equivalence		
Uses a hybrid scale that combines calorie needs (for food) and allows for economies of scale and differential costs of children (for non-food)	Used a scale that (imperfectly) reflected calorie needs.	The hybrid scale more closely reflects the relative cost of providing for basic need for households with different demographic composition.
Poverty Line		
Starts with a calorie threshold of 2,400 kcals/day for a male aged 18-29.	Uses a calorie threshold of 2,500 kcals/day.	Our analysis suggests that the 2,400 kcal/day threshold more closely reflects minimum adequate caloric needs than the (sometimes criticized) older cutoff.
Uses food consumption patterns of households in second quintile.	Used food consumption patterns of households in bottom two quintiles, adjusted by committee to put a high weight on tubers.	Revised consumption pattern should more closely mirror actual food consumption patterns of those near the poverty line.
Applies up-to-date calorie conversions (i.e. calories per 100g of each food)	Used FAO "international" calorie conversions.	Most of the revised calorie conversions are based on West African rather than a generic "international" experience.

Definition of urban areas

The definition of urban areas used in EICV5 was based on the 2012 Census, and by this definition, 17.8% of the population was urban in 2017, and 18.0% in 2024. After the publication of the 2022 Census, the definition of urban areas was expanded to include urbanizing areas, and using this new standard, 28.4% of the population was urban in 2024.

Comparing EICV7 with earlier surveys: Imputation

Given the changes in methodology in EICV7 relative to EICV5, particularly in the recall periods used for frequently-consumed foodstuffs, it is not possible to directly compare expenditure per adult equivalent between the two surveys. We may think of this as a missing data problem.

There is a substantial literature on the subject, including the "Great Indian Poverty Debate." The large household surveys undertaken in India in 1993/94 and 1999/2000 used different recall periods, making it inappropriate to make direct comparisons of poverty rates between the two. Several researchers, including Deaton and Tarozzi (2005), modeled the change in consumption based on the responses to those parts of the questionnaire that did not change over time. The latter found a substantial reduction in poverty during this period (by about 7 percentage points over a six-year period), although this was less than the official reduction in poverty of about 10 percentage points.

Modeling the change in poverty

Although many changes were made in coverage, collection protocols, poverty line, and deflation techniques in EICV7, many of the variables were measured in exactly the same way. This included most of the demographic variables, the socio-economic indicators (such as asset ownership and the quality of the dwelling), and spending on non-food consumption items.

The existence of these common variables allow us to create a model that predicts consumption or poverty based on the EICV7 data, and to then apply it to the EICV5 common variables to obtain predictions for 2017.

Our preferred approach was to start by using the EICV7 data to estimate a linear Ordinary Least Squares (OLS) equation (with 20-fold multiple imputation) where the outcome (i.e. left-hand) variable is the log of consumption per adult equivalent in national prices of January 2024. The right-hand variables include measures related to:

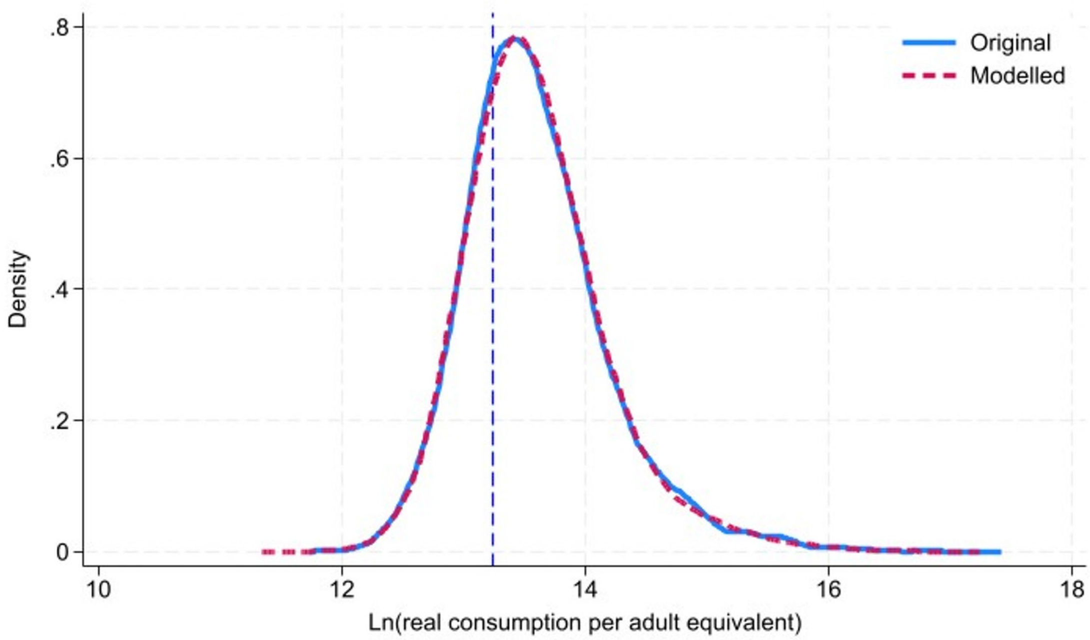
- The age, gender, education and marital status of the household head;
- The size of the household, and the proportions of members who are young, teenagers, adults, employed, and disabled;
- The district of the household, and whether it is in an urban or rural area;
- Several variables related to the quality of the house itself, including its size, and the materials of which it is constructed;
- The nature of the utilities such as water, sanitation, and electricity, to which the household has access;
- The value of the durable assets owned by the household, including the number of animal (cattle, sheep, etc.) that it owns;
- The log of expenditure on non-food items.

Care was taken to include only items that can be measured in the same way with EICV5 and EICV7 data, that were correlated with poverty, and that were likely to have a stable relationship with poverty over time. Monetary values were expressed in the prices of January 2024; the EICV5 prices were deflated to January 2024 using the non-food price component of the consumer price index.

Separate regressions were estimated for urban and for rural data (using the 2012 definitions of urban/rural). The basic regressions using EICV7 data fit well, with adjusted R2 values of 0.89 (urban) and 0.68 (rural); details are shown in Table 11.1, with the coefficients of the ordinary least squares models, associated p-values, and (unweighted) mean values of the variables.

The multiple imputation technique then allows us to get projected values of the log of real consumption per adult equivalent for EICV7, and for EICV5, with appropriately wide distributions. Figure 11.1 graphs the distribution of the log of consumption per adult equivalent (solid curve), along with the modelled predicted distribution (dashed curve), for 2024. The two curves are close, which suggests that the model tracks the actual data quite well.

Figure 11.1. Model Performance Test Using EICV7 data



The predicted values of consumption may then be compared to the EICV7 poverty line to get predicted poverty rates, and these may be disaggregated by dimensions such as regions, district, and so on. The changes in poverty rates are based on comparing the predicted consumption levels of EICV5 and EICV7, and these modeled trends serve as the basis for the analysis throughout the poverty report. An advantage of this method is that it allows one to compute confidence intervals, and so determine the precision of the predictions.

Table 11.1. Regression Estimates for Urban and Rural Models of ln(consumption/ae)

	Urban model				Rural model			
			EICV5	EICV7			EICV5	EICV7
	Coeff	p-val	Mean	Mean	Coeff	p-val	Mean	Mean
Kigali								
Nyarugenge			0.157	0.146			0.012	0.021
Gasabo	0.032	0.10	0.150	0.156	-0.041	0.10	0.013	0.019
Kicukiro	-0.021	0.25	0.185	0.187	-0.083	0.00	0.006	0.012
South								
Nyanza	-0.080	0.08	0.014	0.014	-0.126	0.00	0.037	0.036
Gisagara	0.016	0.86	0.010	0.003	-0.110	0.00	0.038	0.038
Nyaruguru	0.026	0.71	0.010	0.007	-0.075	0.00	0.038	0.038
Huye	0.086	0.01	0.029	0.034	0.057	0.02	0.034	0.032
Nyamagabe	-0.127	0.00	0.014	0.017	-0.171	0.00	0.037	0.036
Ruhango	0.087	0.05	0.014	0.017	0.075	0.00	0.037	0.036
Muhanga	-0.006	0.85	0.029	0.031	0.024	0.32	0.034	0.033
Kamonyi	-0.058	0.13	0.024	0.024	-0.165	0.00	0.035	0.034
West								
Karongi	0.088	0.07	0.014	0.014	-0.091	0.00	0.037	0.036
Rutsiro	0.002	0.98	0.010	0.003	-0.088	0.00	0.038	0.038
Rubavu	-0.118	0.00	0.071	0.071	-0.188	0.00	0.025	0.024
Nyabihu	0.061	0.08	0.024	0.034	0.039	0.11	0.035	0.032
Ngororero	0.182	0.00	0.010	0.010	0.008	0.73	0.038	0.037
Rusizi	-0.110	0.00	0.029	0.027	-0.155	0.00	0.034	0.033
Nyamasheke			0.010		-0.096	0.00	0.038	0.039
North								
Rulindo	0.008	0.94	0.010	0.003	-0.036	0.13	0.038	0.038
Gakenke	0.050	0.57	0.010	0.003	0.062	0.01	0.038	0.038
Musanze	-0.022	0.41	0.052	0.068	-0.033	0.18	0.029	0.025
Burera	0.201	0.03	0.010	0.003	0.020	0.40	0.038	0.038
Gicumbi	0.093	0.09	0.014	0.010	0.118	0.00	0.037	0.037
East								
Rwamagana	0.125	0.00	0.019	0.017	-0.006	0.80	0.036	0.036
Nyagatare	-0.043	0.28	0.024	0.027	-0.120	0.00	0.035	0.033
Gatsibo	0.110	0.02	0.010	0.014	0.066	0.01	0.038	0.036
Kayonza	-0.129	0.00	0.019	0.020	-0.147	0.00	0.036	0.035
Kirehe	-0.014	0.88	0.010	0.003	0.125	0.00	0.038	0.038
Ngoma	0.076	0.39	0.010	0.003	-0.003	0.89	0.038	0.038
Bugesera	-0.033	0.33	0.014	0.031	-0.053	0.03	0.037	0.033
Rural	0.004	0.93						
No. of household members	-0.018	0.00	4.217	3.894	-0.030	0.00	4.438	4.166
ln(spending on education/ae)	0.012	0.00	6.736	7.012	0.010	0.00	5.998	6.916
ln(house rent/ae)	0.150	0.00	11.782	11.934	0.072	0.00	9.994	10.196
Head is male	0.013	0.46	0.764	0.751	0.010	0.34	0.740	0.734
Marital status: together			0.620	0.618			0.699	0.692
: single	0.003	0.83	0.380	0.382	0.037	0.00	0.301	0.308
Age of household head	0.000	0.60	35.447	36.495	0.000	0.32	40.376	41.640
Education of head: none			0.112	0.065			0.293	0.189
some primary	-0.017	0.46	0.260	0.245	0.015	0.04	0.410	0.475
finished primary	-0.026	0.31	0.191	0.163	0.032	0.00	0.202	0.188
some secondary	-0.033	0.19	0.151	0.187	0.046	0.00	0.059	0.089
finished secondary	-0.043	0.12	0.125	0.142	0.111	0.00	0.022	0.034
some university	0.064	0.03	0.161	0.199	0.218	0.00	0.014	0.025
Proportion of hh: children	-0.084	0.18	0.197	0.182	-0.051	0.06	0.250	0.225
teenagers	-0.162	0.00	0.173	0.153	-0.153	0.00	0.208	0.202
adults	-0.144	0.00	0.599	0.629	-0.101	0.00	0.475	0.478
Proportion of adults employed	0.124	0.00	0.494	0.574	0.037	0.01	0.503	0.566
Proportion of members disabled	0.014	0.74	0.135	0.114	0.002	0.92	0.168	0.136
Habitat: umudugudu			0.287	0.460			0.668	0.730

	Urban model				Rural model			
			EICV5	EICV7			EICV5	EICV7
	Coeff	p-val	Mean	Mean	Coeff	p-val	Mean	Mean
isolated	-0.065	0.05	0.037	0.029	0.021	0.00	0.216	0.191
modern	0.035	0.01	0.104	0.295	0.017	0.39	0.001	0.019
other	0.002	0.89	0.572	0.216	-0.002	0.90	0.115	0.060
Dwelling: single house			0.625	0.595			0.962	0.921
shared house	0.023	0.12	0.177	0.237	-0.007	0.57	0.025	0.049
shared enclosure	-0.003	0.83	0.158	0.159	0.000	0.98	0.007	0.018
single enclosure	-0.042	0.43	0.041	0.009	-0.023	0.31	0.006	0.013
No. of bedrooms	0.005	0.77	0.827	0.894	0.038	0.00	0.784	0.967
Roof: corrugated iron			0.891	0.938			0.574	0.675
clay tiles	0.009	0.70	0.109	0.062	0.019	0.01	0.426	0.325
Wall: mud bricks			0.159	0.101			0.404	0.329
mud bricks with cement	-0.014	0.52	0.538	0.617	-0.008	0.26	0.224	0.359
fired bricks	0.038	0.16	0.135	0.176	0.049	0.00	0.017	0.028
wood, trunks with mud	0.021	0.55	0.064	0.033	0.014	0.09	0.287	0.200
trunks with mud and cement	-0.023	0.41	0.104	0.073	0.009	0.41	0.069	0.084
Floor: beaten earth			0.280	0.173			0.787	0.693
dung, bricks	-0.056	0.27	0.013	0.012	0.032	0.04	0.054	0.029
wood, tiles, cement	-0.021	0.33	0.707	0.815	0.037	0.00	0.159	0.277
Home: owned			0.454	0.398			0.854	0.813
rented, or employer provided	0.033	0.03	0.487	0.552	-0.033	0.00	0.083	0.125
free	0.014	0.57	0.059	0.050	-0.017	0.13	0.063	0.062
Lighting: electric grid			0.749	0.889			0.143	0.397
lamp, battery lantern	0.039	0.12	0.238	0.081	0.009	0.23	0.716	0.351
firewood	0.150	0.26	0.007	0.002	0.065	0.00	0.048	0.015
solar, rechargeable battery	0.008	0.82	0.006	0.028	0.019	0.01	0.093	0.236
Cooking fuel: wood			0.295	0.223			0.944	0.891
charcoal	-0.097	0.00	0.614	0.528	-0.012	0.25	0.050	0.094
gas, electricity	0.004	0.86	0.091	0.230	0.170	0.00	0.006	0.013
none	0.182	0.00		0.019	0.082	0.07	0.000	0.002
House area, sq m	0.004	0.00	18.152	18.998	0.003	0.00	13.729	11.196
Water: piped to home			0.425	0.534			0.022	0.071
standpipe	0.001	0.95	0.357	0.334	-0.046	0.00	0.225	0.308
well, spring, surface	0.039	0.08	0.218	0.132	-0.042	0.00	0.752	0.621
Toilet: flush			0.102	0.157			0.001	0.006
pit, solid slab	-0.123	0.00	0.841	0.828	-0.175	0.00	0.834	0.927
pit no slab, or none	-0.055	0.27	0.057	0.015	-0.163	0.00	0.164	0.067
Household faced a shock	0.023	0.31	0.027	0.055	-0.055	0.00	0.015	0.033
ln(remittances/ae)	0.003	0.01	5.694	6.254	0.005	0.00	5.007	5.439
ln(durable assets/ae)	0.027	0.00	9.768	11.240	0.013	0.00	6.622	9.514
Animals/ae: cattle	0.016	0.17	0.092	0.098	0.003	0.01	0.167	0.164
sheep	0.021	0.38	0.016	0.021	0.028	0.00	0.055	0.053
goats	-0.008	0.26	0.091	0.104	0.023	0.00	0.233	0.187
pigs	-0.007	0.72	0.038	0.039	0.013	0.05	0.075	0.111
poultry	0.003	0.20	0.238	0.258	0.003	0.01	0.274	0.281
other	0.073	0.17	0.065	0.015	0.062	0.00	0.142	0.040
ln(nonfood spending/ae)	0.372	0.00	12.301	12.571	0.265	0.00	10.965	11.290
Intercept	7.461	0.00			9.862	0.00		
Number of observations			2,526	2,636			12,054	12,418
Adjusted R2	0.888				0.678			
Mean, ln(consumption/ae)				14.172				13.540

It is also possible to model the change in poverty more directly. A **logit or probit model** uses the same right-hand variables as indicated above, but the outcome variable is set to 1 if the household is poor and to 0 otherwise. Both logit and probit models show poverty trends that are close to, if slightly smaller than, those found using the multiple-imputation regression method, as Table 11.2 shows.

We also modeled the poverty rate directly using **random forests**, a popular machine-learning technique that uses the data to build "trees" that classify and sub-classify the data to maximize the ability to predict the outcome. The national results are also in line with those of the other models.

The main drawback of these methods is that they do not generally allow for a clear determination of the precision of the predictions, which makes it hard to judge the quality of the predictions of the poverty rate in 2017.

Table 11.2. Estimates of Headcount Poverty in 2017 Using Alternative Models

	EICV7	EICV7	EICV5	Change	EICV5
	Actual	Model	Model	Model	Adjusted
	2024	2024	2017	2017-24	2017
Rwanda					
Model poverty rate directly					
Logit	27.4	27.2	37.4	-10.2	37.6
Probit	27.4	27.3	37.7	-10.4	37.8
Random forest	27.4	27.4	38.7	-11.3	38.7
Model consumption, then poverty rate					
Multiple imputation linear regression	27.4	27.1	39.5	-12.4	39.8
Confidence interval: lower bound	26.4	25.8	37.7		38.0
Confidence interval: upper bound	28.4	28.4	41.4		41.7
Urban areas (2012 definition)					
Model poverty rate directly					
Logit	12.7	12.6	18.8	-6.2	18.9
Probit	12.7	12.6	18.9	-6.3	19.0
Random forest	16.7	16.7	13.5	3.2	13.5
Model consumption, then poverty rate					
Multiple imputation linear regression	12.7	12.7	18.9	-6.2	18.9
Confidence interval: lower bound	11.4	11.1	16.5		
Confidence interval: upper bound	14.0	14.3	21.3		
Rural areas (2012 definition)					
Model poverty rate directly					
Logit	30.6	30.4	41.4	-11.0	41.6
Probit	30.6	30.5	41.7	-11.2	41.8
Random forest	31.6	31.7	44.2	-12.5	44.1
Model consumption, then poverty rate					
Multiple imputation linear regression	30.6	30.3	44.0	-13.7	44.3
Confidence interval: lower bound	29.8	28.8	42.3		
Confidence interval: upper bound	31.4	31.7	45.8		

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Appendix 1: EICV7 Sampling Errors

	Coefficient	Std. error	95% lower bound	95% upper bound	cv	deff
National	**27.4**	**0.5**	**26.4**	**28.4**	**1.8**	**1.9**
Province						
Kigali City	9.1	1.1	7.0	11.1	11.8	2.8
South	34.7	1.0	32.7	36.7	2.9	1.5
West	37.4	1.2	35.1	39.7	3.1	1.9
North	20.2	1.1	18.1	22.3	5.3	1.7
East	26.8	1.0	24.7	28.8	3.9	2.3
District						
Nyarugenge	6.8	1.2	4.4	9.2	17.7	1.0
Gasabo	11.1	1.8	7.4	14.7	16.7	3.7
Kicukiro	6.9	1.3	4.3	9.5	19.3	1.5
Nyanza	43.3	2.8	37.7	48.8	6.5	1.3
Gisagara	45.6	2.7	40.4	50.9	5.9	1.3
Nyaruguru	39.7	2.5	34.7	44.7	6.4	1.0
Huye	24.2	2.7	18.9	29.5	11.2	1.7
Nyamagabe	51.4	3.2	45.1	57.7	6.3	1.7
Ruhango	15.0	2.4	10.2	19.8	16.3	1.8
Muhanga	15.0	2.2	10.7	19.2	14.6	1.4
Kamonyi	39.7	3.3	33.1	46.3	8.4	2.5
Karongi	38.2	3.4	31.6	44.8	8.8	2.0
Rutsiro	40.8	3.0	34.9	46.6	7.3	1.5
Rubavu	38.8	3.1	32.7	44.9	8.0	2.5
Nyabihu	20.2	2.3	15.8	24.6	11.1	1.1
Ngororero	30.2	2.7	25.0	35.5	8.9	1.3
Rusizi	44.2	3.4	37.4	50.9	7.8	2.7
Nyamasheke	42.8	2.6	37.8	47.9	6.0	1.3
Rulindo	21.6	2.1	17.5	25.7	9.7	1.1
Gakenke	24.5	2.9	18.8	30.2	11.8	1.9
Musanze	21.0	2.7	15.7	26.3	12.9	2.5
Burera	22.0	1.8	18.4	25.6	8.3	0.8
Gicumbi	13.3	2.1	9.2	17.4	15.8	2.0
Rwamagana	23.8	2.7	18.6	29.0	11.1	2.2
Nyagatare	36.4	2.8	30.9	41.8	7.7	2.5
Gatsibo	18.4	2.6	13.2	23.6	14.3	2.8
Kayonza	36.6	3.2	30.2	42.9	8.8	2.6
Kirehe	14.2	2.1	10.1	18.4	15.0	1.8
Ngoma	30.9	2.6	25.8	36.0	8.4	1.4
Bugesera	23.7	2.6	18.5	28.8	11.1	2.4

Appendix 2: EICV7 Diaries

#		Purchase	FOOD EXPENDITURE					
			Purchased food		Own production		Gifts and in kind	
		Value	Value	Quantity	Value	Quantity	Value	Quantity
1	Dry bean		Bowl	2	Kg	1	Kg	1
2	Fresh bean							
3	Groundnut flour							
4	Irish potato							
5	Sweet potato							
6	Cassava (root)							
7	Tarot							
8	Banana cooking							
9	Maize flour							
10	Cassava flour							
11	Local rice		Cup	1				
12	Imported rice							
13	Maize (fresh)							
14	Dry maize (grain)							
15	Tomato							
16	Fresh milk							
17	Cakes/capati /mandazi							
18	Bread							
19	Sugar (imported)							
20	Sugar (local)							
21	Salt							
22	Peanut oil							
23	Beef meat							
24	Local banana beer							
25	Soghum juice		Bottle	3	Bottle	3	Bottle	3
26								
27								
28								
29								
30								
34								

Name	Meals	Money
	Breakfast	500
	Lunch	
	Dinner	
	Food between the main meals (example: sambusa, Capati, barbacued, etc ...)	
	Hot beverage (example: tea, coffee, etc...)	
	Non alcoholic bevareges (example: fanta, juice, water, etc...)	
	Alcoholic beverages (example: local beer, sorghum juice, etc...)	10,000
	Breakfast	
	Lunch	
	Dinner	
	Food between the main meals (example: sambusa, Capati, barbacued, etc ...)	
	Hot beverage (example: tea, coffee, etc...)	
	Non alcoholic bevareges (example: fanta, juice, water, etc...)	
	Alcoholic beverages (example: local beer, sorghum juice, etc...)	
	Breakfast	
	Lunch	5,000
	Dinner	
	Food between the main meals (example: sambusa, Capati, barbacued, etc ...)	
	Hot beverage (example: tea, coffee, etc...)	
	Non alcoholic bevareges (example: fanta, juice, water, etc...)	
	Alcoholic beverages (example: local beer, sorghum juice, etc...)	

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