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Measuring Poverty in Nepal:

Methodological Note for Poverty Estimation using Nepal Living Standards Survey 2022-23

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Introduction

The Nepal Living Standards Survey (NLSS), first conducted in 1995-96, marked a significant step in objectively measuring living standards and poverty levels in Nepal. The survey covered a wide range of topics related to household welfare, including demography, consumption, income, access to facilities, housing, education, health, employment, credit, and remittances, among others. Subsequent survey rounds, NLSS-II and NLSS-III, were conducted in 2003-04 and 2010-11, respectively. Since 1996, the NLSS survey has been used to update official measures of poverty and to monitor and track improvements in people's living conditions. Over this time, the methodology underlying how poverty is measured in Nepal has also been regularly updated, in line with the global best practice.

The fourth Nepal Living Standards Survey (NLSS-IV) was implemented by the National Statistics Office (formerly the Central Bureau of Statistics) from July 2022 to June 2023. NLSS-IV is the first living standards survey carried out in Nepal since the enactment of the new federal Constitution in 2015, which led to the restructuring of administrative and political boundaries. Like in the past, the NLSS-IV is a multi-topic survey that collects information on various aspects of household welfare, including household consumption expenditures, assets, income, health and education, and migration and remittances. NLSS-IV surveyed a nationally and provincially representative sample of 9,600 households. It was designed to generate statistically representative estimates at the national level and for 15 new analytical domains. These domains include an urban and rural domain each in each of the seven provinces (which adds up to 14 domains), with Kathmandu Valley Urban as a separate domain. The implementation of the survey included regular supervisory visits, with the aid of a real-time data quality monitoring dashboard.[1]

1 Details on the data collection and management systems are documented in the detailed statistical report (National Statistical Office, 2024).

The 12-year gap between the third and fourth NLSS survey rounds necessitated a comprehensive review of the poverty measurement methodology. The shift to a federal system also defined the need for precise sub-national poverty estimates for the newly formed provinces and domains. The National Statistics Office (NSO) and the World Bank, therefore, conducted a thorough technical review of the poverty estimation methodologies to revise the official approach, ensuring alignment with current international best practices and standards.

The technical review resulted in the adoption of a new poverty line using 2022-23 as the base year, replacing the decade-old national poverty line and raising the minimum living standards to align with Nepal's current realities and evolving aspirations. Most developing countries revise their poverty lines when there are extended gaps between surveys, and significant contextual changes. Nepal's regular revisions to the poverty line, first in 2011 and now in 2023, reflect the country's commitment to identifying the poor more effectively and inclusively for pro-poor programs in response to changing conditions. This new poverty line will also serve as a foundation for tracking poverty at both the national and provincial levels in Nepal going forward. This technical note documents the new poverty measurement methodology adopted in 2023 and details the underlying methodological choices.

The technical note is organized as follows. Section 2 discusses the poverty measurement methodology using the cost of basic needs approach that is used in Nepal (and in other developing countries globally). In addition, it provides an overview of the sample and survey design, data collection, and data quality and describes the rationale behind updating the poverty line in 2023. Section 3 describes the methodology used to construct the welfare aggregate and its different components. Section 4 details the spatial and temporal adjustments that need to be made to the welfare aggregate. Section 5 documents the steps in estimating the new official poverty line and highlights methodological departures from the previous method. Section 6 presents key data and statistics on the domain-level cost of basic needs, price deflators, new poverty lines, and poverty rates in Nepal in 2023. In addition, this section presents estimates of vulnerability to poverty and statistics on sampling variability. Section 7 shows the decline in poverty rates since 2011.

Poverty Measurement *in* Nepal

2.1 Questionnaire Design

The NLSS-IV survey instrument is similar in design to the one used in 2010-11, but there are key differences that affect poverty estimation. Firstly, reflecting changes in consumption patterns between 2011 and 2023, the National Statistics Office (NSO) added new food items, a more detailed list of non-food non-durable goods, and an updated list of durable items relevant to households' welfare today. As a result, NLSS-IV captures more information on household consumption and expenditures than was covered in NLSS-III.[2] These additional items were also included, in part, to generate improved price data for the Consumer Price Index (at the request of the Nepal Rastra Bank). Second, while NLSS-IV maintains the same recall period for food and non-food consumption introduced in NLSS-III, it introduced an innovation in collecting data on food consumed away from home. For the latter, data were collected on meals consumed outside the home for each household member in a separate module. This individual-level module allows for a more accurate estimate of food expenditure outside the home compared to a household-level aggregate that was collected in the past.

2.2 Sample Design

NLSS-IV uses an updated sampling frame from the National Population and Housing Census 2021. It is nationally representative and representative for 15 domains (Strata)– urban and rural areas in the seven provinces and Kathmandu Valley. Rural and urban classification were based on the administrative classification of municipalities – rural municipalities were included in rural, all others urban. The survey was also designed to yield a representative sample for the three climatic seasons in Nepal (dry, rainy, and winter seasons).

2 NSO conducted pretesting of survey modules before implementing the final survey. Based on observed consumption patterns during pre-implementation visits and pretesting of survey modules, additional items were included in the lists of durables, food items, and non-food items, among others, to supplement the lists included in NLSS-III in 2010-2011.

The sampling strategy followed a conventional two-stage stratified sampling. In the first stage, using the exhaustive list of census enumeration areas (EAs) from the 2021 Nepal Population and Housing Census as primary sampling units (PSUs), 800 EAs were selected from the 15 domains using probability proportional to size (PPS) for the NLSS-IV survey. In the second stage, a complete household listing of all households was conducted in the selected EAs. Following this, the process that was implemented to sample households involved: (i) sorting the household list based on household size (implicit stratification); and (ii) selecting 12 households randomly from each EA using all households from the post-listing sampling frame (sorted list of households) as the secondary sampling units (SSUs), with an equal probability of selection. [3]

Table 1 presents the number of selected EAs and the final sample of households across the 15 analytical domains. A total of 9,600 households were interviewed for the survey. The sample size in each domain is proportional to the share of the population in the 2021 Census.

TABLE 1. Sampled enumeration areas and households by analytical domain

Domain	Number of surveyed EAs	Number of surveyed households
Koshi Urban	64	768
Koshi Rural	54	648
Madhesh Urban	65	780
Madhesh Rural	51	612
Kathmandu Valley Urban	64	768
Bagmati Urban (excluding KTM Valley)	55	660
Bagmati Rural	50	600
Gandaki Urban	56	672
Gandaki Rural	44	528
Lumbini Urban	62	744
Lumbini Rural	56	672
Karnali Urban	43	516
Karnali Rural	41	492
Sudurpaschim Urban	52	624
Sudurpaschim Rural	43	516
Nepal		**9600**

3 This process was implemented in the field, using a custom application developed for this purpose.

2.3 Sampling Weights

In a survey sample, the probability of household selection into the sample is based on the sampling design. In general, each household in the sample is assigned a weight so that the estimates from the sample are representative of the population. Typically, the weight assigned is proportional to the inverse of the probability of a household's selection into the sample, as a lower likelihood of selection indicates that there are a large number of households that it represents and vice versa (Deaton, 2015).

Extending this rule to NLSS-IV, which adopted a multi-stage sampling design (discussed in Section 2.2), the process for calculating these weights is as follows:

1. **Estimate base weights:** Calculate design weight (w_i) for every EA selected in the sample a $w_i = \frac{1}{p_1}$, where p_1 is the probability of selection of the EA.

2. **Assign household weights within each EA:** Since 12 households were selected from the household listing within the EA, adjust the design weight by the probability of a household's selection into the sample to get the final household weight (w_h) as

$$w_h = \frac{w_i}{p_h}, \; where \;\; p_h = \frac{12}{\#listedhouseholds}$$

3. **Adjustment for final household weights:** These weights were further adjusted by a factor $\left(\frac{\#listedhouseholds}{\#censushouseholds}\right)$, such that the total of the final household weights adds to the officially recorded households in the 2021 Population Census.

For individual-level estimates, each household member is assigned the corresponding household weight to ensure that the sample estimates are representative of the entire population.

2.4 Poverty Measurement Methodology

There are two key methodological steps in the measurement of poverty. The first step involves the construction of a welfare aggregate, which allows for ranking of the population on the same scale. The second step relates to setting the poverty line, which defines the minimum welfare level below which individuals are considered poor.

2.4.1 Measuring Monetary Welfare

Monetary welfare is measured using either income or consumption, and the appropriate choice depends on the specific country context. Detailed and high-quality information on welfare measures is crucial, and this can be obtained through a survey questionnaire that is designed for this purpose. In developed countries, income is typically used as a metric of welfare due to the high degree of formalization, which ensures reliable information from all sources of earned income (Al-Salehi et al., 2018). In contrast, in poorer and more rural economies, measures of consump-

tion are often more accurate and reliable than income measures. This is primarily due to significant income volatility resulting from seasonal employment, a high degree of informal economic activity, and reliance on self-production. Therefore, consumption is a better measure of current standards of living, especially in rural and agrarian economies like Nepal (Ravallion, 1994; Deaton and Zaidi, 2002).

In Nepal, like in in previous survey rounds, the welfare aggregate is based, therefore on expenditures on the consumption of food[4] and non-food [5]items in the reference year (typically past one year).

2.4.2 Setting a Poverty Line: Cost of Basic Needs Approach

Nepal, like other developing countries, defines its poverty line using the Cost of Basic Needs (CBN) approach. The CBN approach defines the poverty line as the minimum expenditure required for an individual to meet their basic food and non-food needs. Anchored to a minimum nutritional requirement for food needs, the CBN method defines the poverty line as an absolute measure, establishing a benchmark standard of living that represents the minimum welfare level below which a person is deemed to be poor.[6]

The first step in setting a CBN-based poverty line is identifying the minimum nutritional requirement, typically measured in calories. This caloric threshold is developed based on global standards, which take into account demographic compositions and recommended national dietary allowances for different age groups and genders. The second step involves estimating the food poverty line, which is the cost of purchasing a reference food basket—reflecting local tastes and consumption patterns—that meets this caloric requirement of the reference population (representing the relatively poor). The third step augments the food poverty line with an allowance for basic non-food needs, resulting in the non-food poverty line. The absolute poverty line is then defined as the total cost of basic food and non-food needs, representing the minimum acceptable standard of living in the country. Individuals whose consumption expenditures are below this minimum monetary threshold are identified as poor. Section 5 details each step in the estimation of the poverty line in Nepal in 2022-23.

4 Households' food consumption is recorded for each item consumed by the household in the seven days prior to the interview.

5 Non-food expenditures are collected over the recall period of `past 30 days' and `past 12 months', depending on the item type. Section 3.2 provides further details on item specific recall periods.

6 Refer to Ravallion (1998) and Deaton and Zaidi (2002) For details on cost of basic needs approach and alternative ways of measuring welfare and poverty.

2.5 Updating the Poverty Line

The first CBN-based poverty line for Nepal was established in 1995-96 with the first living standard survey (NLSS-I). In 2010-11, following the NLSS-III survey, a decision was made to revise and establish a new poverty line to reflect both improvements in survey methodology, improvements in living standards, and rising economic aspirations over the 15 years since the initial poverty line was set.[7]

In 2023, 12 years after the NLSS-III survey, there was a need to revise the methodology underlying the 2010 poverty line for three reasons: (i) changes in the political and administrative structure of Nepal following the adoption of a new federal constitution in 2015 that defined new administrative units and analytical domains; (ii) current consumption patterns that include a more diverse set of food and non-food items compared to a decade ago; and (iii) improvement in living standards – both monetary and non-monetary across the population- that raise the bar for setting a minimum standard of living. A key additional objective of this reevaluation of the poverty measurement methodology in Nepal was to align with evolving global best practices for both national and international poverty lines.

Nationally representative data sources collected over the last decade suggest that Nepal has made significant progress on non-monetary welfare. Nepal's official Multidimensional Poverty Index (MPI), a measure of deprivation in non-monetary indicators reported a substantial decrease from 30.1 to 17.4 percent between 2014 and 2019 (UNICEF, 2021). This reduction has also been accompanied by progress in other non-monetary welfare indicators, such as life expectancy, education, and child and maternal health outcomes, as measured by other official surveys in Nepal. For example, life expectancy at birth increased from 67.3 to 70.5 years, and child and maternal health outcomes have improved. [8] [9]

7 For details on the methodology used in the previous rounds, refer to Lanjouw, Prennushi and Zaidi (1996), and Central Bureau of Statistics and World Bank (2014).

8 Data from World Development Indicators: https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=NP

9 Data from World Development Indicators: https://data.worldbank.org/indicator/SH.DYN.MORT.FE?locations=NP

Consistent with these improvements in non-monetary poverty and gross national income per capita[10] , data from the NLSS-IV survey shows significant improvements in a range of monetary living standards. First, average per person consumption spending increased by an average of 66 percent between 2010-11 and 2022-23, with substantial gains at the bottom of the expenditure distribution (Figure 1). This included (i) a 67 percent increase in real per capita consumption expenditure for the bottom decile from an average of 26,738 rupees to 44,583 rupees per person per year, and (ii) significant gains relative to 2010-11 for the poorest, with average real per capita expenditures of the bottom two deciles in 2022-23 exceeding that of the third and fifth decile in 2010-11, respectively. Second, there has been a noticeable shift in expenditure patterns, with a higher proportion of spending allocated to non-food items (Table 2). On average, the share of spending on non-food items increased from 38% in 2010-11 to 47% in 2022-23. This shift is particularly pronounced at the lower end of the expenditure distribution, with the average share of non-food spending among the bottom 10% in 2022-23 surpassing that of the seventh decile in 2011. Third, changes in asset ownership and food consumption patterns provide further evidence of improved living standards. Ownership of motorbikes, cars, and refrigerators more than doubled from 2010-11 to 2022-23, reaching 25.2, 1.9, and 26.9 percent, respectively (Figure 2). The percentage of households owning fans also increased from 34 to 61 percent, and those with a telephone or mobile phone increased from 62 to over 90 percent. In terms of food spending, there has been a shift toward more nutritious and expensive calories, with increased spending on vegetables (from 10 to 12 percent), fruits (from 3 to 7 percent), and meat (from 13 to 14 percent), and a decline in spending on cheaper calories like cereals (from 34 to 17 percent) (Figure 3). Fourth, there is evidence of a more diversified food basket, especially among the reference population (representing the relatively poor)[11] , with the share of food spending on the more restricted 40-item food basket used in 2010-11 dropping from 80% to 60% between 2010-11 and 2022-23.

10 The Gross National Income per capita increased from 2,777 (constant, 2017 PPP$) to 4,026 (constant, 2017 PPP$), an increase of 45 percent. https://hdr.undp.org/data-center/specific-country-data#/countries/NPL

11 For valid comparisons and consistency, estimates compared between 2011 and 2023 are based on the poverty methodology used in 2010-11. In this section, the reference population is identified as individuals in the 2nd to 5th decile of the spatially and temporally adjusted per capita consumption expenditure distribution, as defined in 2010-11. The reference group for the new poverty line, however, is revised (details in Section 5).

FIGURE 1. Average real per capita consumption expenditures (in 2022-23 prices), 2010-11 and 2022-23

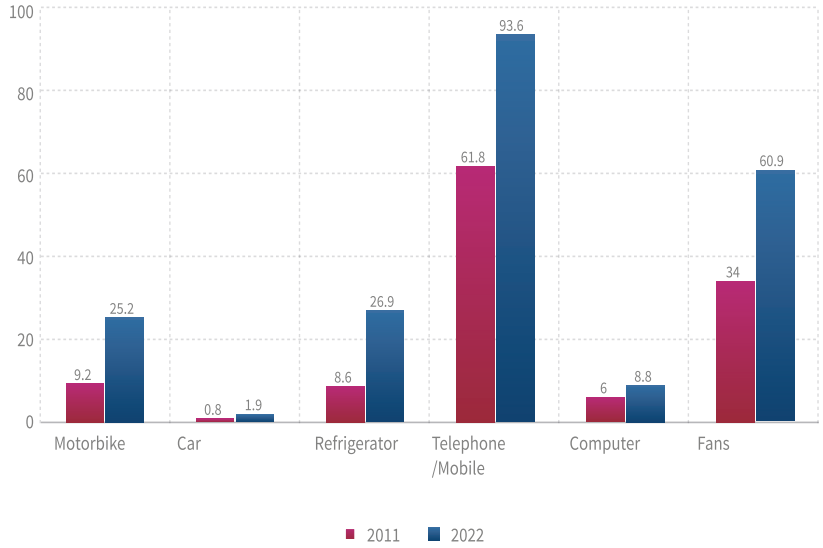
Note: The per capita consumption expenditures (in 2022-23 prices) are adjusted for price variations between seasons and domains. For comparability across rounds, the reported real per capita expenditures are based on the 2011 methodology for both years. D1 to D10 represents ten consumption expenditure deciles, i.e., ten equal parts of the population based on annual real per capita expenditures. Each decile represents 10 percent of the population.

TABLE 2. Share of non-food spending in the total per capita consumption expenditures

	Decile 1 (poorest)	D2	D3	D4	D5	D6	D7	D8	D9	Decile 10 (Richest)
2011	29%	31%	31%	33%	35%	37%	37%	42%	46%	57%
2022	39%	40%	42%	44%	46%	46%	49%	51%	56%	60%

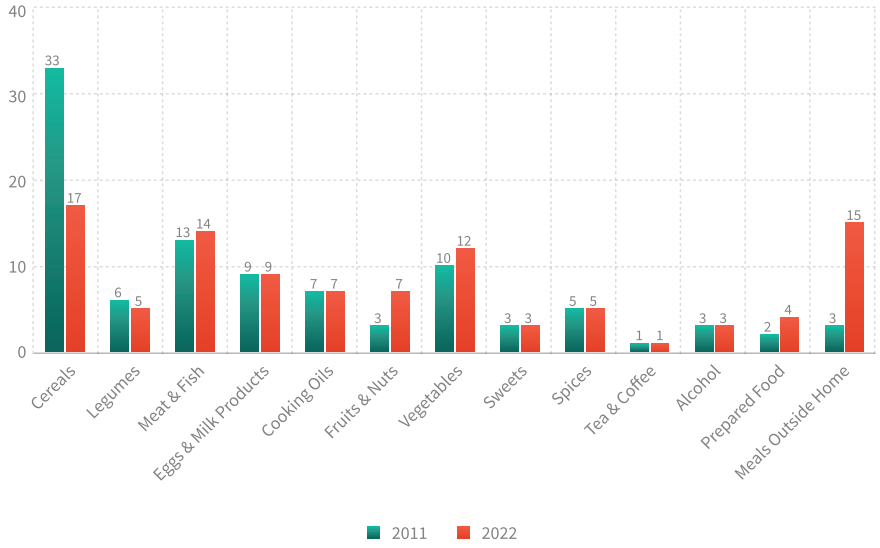
Note to Figure 1 applies.

FIGURE 2. Share of households owning assets, 2010-11 and 2022-23



Note: Select durable assets presented in this figure.

FIGURE 3. Components of food expenditures, 2010-11 and 2022-23



Note: For comparability, the food aggregate in both years is based on the 2011 methodology.

Constructing a revised poverty line for 2022-23 marks a significant milestone in Nepal: it establishes a higher standard of living that reflects the country's substantial progress over the past 12 years. and re-aligns the benchmark for measuring poverty going forward. This updated benchmark also acknowledges Nepal's evolving aspirations. Besides raising the benchmark, the revision also reflects current international best practices in poverty measurement and survey design improvements, which are detailed in the sections that follow.

Construction *of* Welfare Aggrement

The construction of the welfare aggregate in NLSS-IV follows the core guidelines used in NLSS-III[12], (Deaton and Zaidi (2002)) as while updating key elements that reflect either improvements in survey design or more recent methodology guidance (Mancini and Vecchi, 2022). The first step in constructing the welfare aggregate is to estimate the annual nominal household consumption expenditure by aggregating food and non-food consumption expenditures. Sub-sections 3.1 and 3.2 provide details on the construction of each of these components and describes the methodological improvements adopted in 2022-23. Section 3.3 discusses adjustments to the household consumption expenditures for household composition to get an estimate of individual well-being, the nominal welfare aggregate. The key differences in the construction of the welfare aggregate between 2010-11 and 2022-23 are summarized in Annex Table 27.

3.1 Food Aggregate

The NLSS-IV collected information on the consumption of 117 food items consumed by household members over the week before the interview[13]. These food items are categorized into 12 major groups: (i) grains and cereals; (ii) pulses and lentils; (iii) eggs and milk products; (iv) cooking oils; (v) vegetables; (vi) fruits and nuts; (vii) fish and meat; (viii) spices and condiments; (ix) sweets and confectionery; (x) alcoholic and non-alcoholic beverages; (xi) tobacco and tobacco products; and (xii) processed foods. For each item consumed by the household[14], the survey recorded weekly quantities and expenditures across three modes: (i) purchased from the market, (ii) produced at home, and (iii) received as gifts or in-kind. Additionally, a separate module

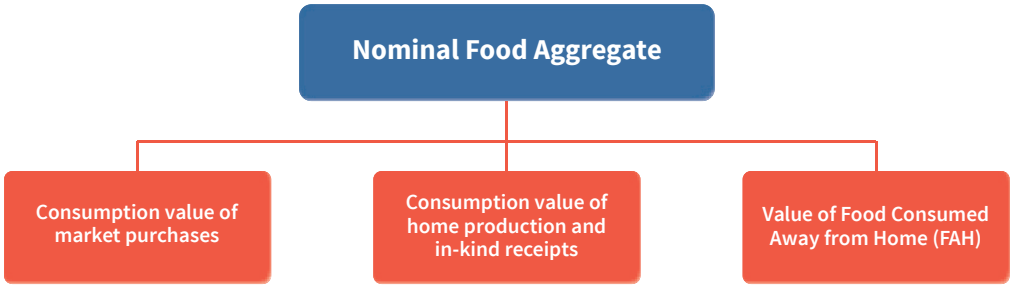
12 World Bank, (2014).

13 The NLSS-III introduced the "past 7 days" recall period for food consumption, a switch from "a typical month" recall used in the past rounds. The shorter reference period is less likely to be affected by recall bias.

14 This excludes except tobacco and tobacco products which are included in the non-food aggregate, for consistency with NLSS-III method.

collected individual-level details on meals purchased and consumed outside the home (food away from home (FAH)) in the past week[15]. The nominal food aggregate is the sum of annual expenditures on each item across all three modes of consumption, and food consumed away from home (Figure 4).

FIGURE 4: Nominal household food aggregate



3.1.1 Market purchases

The first component of the food aggregate generates the annualized consumption value of items consumed from market purchases. In 2010-11, this value was simply the sum of reported market expenditures on all items. However, in 2022-23, to reduce biases in self-reported expenditures, outlier corrections are applied using market-based median unit values. This correction mitigates the impact of extreme values, which could distort the overall expenditure estimates. Computing final annual expenditure on food consumption from market purchases reported by households over the past 7 days involves the following steps:

1. Multiply weekly expenditures and quantities by $\frac{365}{7}$, to generate annualized values of market expenditures on food16.
2. Calculate the implied unit value for each item by dividing the self-reported expenditure by the quantity consumed from market purchases.
3. Apply a rule[17] to identify outliers in the market-purchase-based unit values. All outlier values are set to missing.
4. Estimate a weighted median unit value for each item, at season-geography level (PSU, domain, urban/rural/Kathmandu, and national).
5. Use a hierarchical approach to correct for outlier unit values. For every household, a missing unit value is replaced with the item's weighted median unit value from the smallest geograph-

15 0.3% of households report zero market purchases but positive expenditures on meals consumed outside the home.

16 In 2011, the weekly values were multiplied by 52. The change in the conversion factor is adopted for precision reasons with negligible differences in the obtained annual values.

17 A value is an outlier if the standardized logarithmic unit value, $\frac{\ln(uv) - \overline{\ln(uv)}}{\mathrm{sd}(\ln(uv))}$, lies outside the interval (-2.5, 2.5).

ical level (estimated in step 4), moving to higher administrative units if necessary[18]. This approach ensures that the median unit values reflect local market prices for items of similar quality as that purchased by the household.

6. Estimate outlier-corrected item expenditures by pricing the purchased quantity at the outlier-corrected median unit values.

The imputed value of household consumption from market purchases is the sum of these outlier-corrected expenditures for all items. Figure 5a shows that the distribution of raw and imputed annual expenditures overlaps for market-purchased food, except at the extremes.

3.1.2 In-kind receipts and home production

The second component of the food aggregate captures the consumption value of items obtained through home production and in-kind receipts. In NLSS-IV, as in previous rounds, households provide estimates of the consumption value for the non-market purchases. However, these self-reported values often risk under- or over-estimating the true value, leading to potential biases in the data.

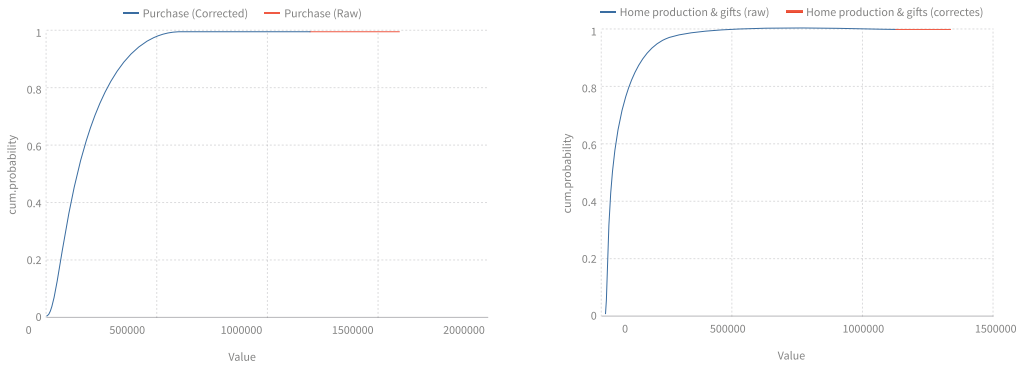
To minimize reporting biases, it is recommended that quantities consumed through in-kind receipts and home production are valued using the median unit values derived from market purchases (Mancini and Vecchi, 2022). Therefore, unlike in the 2010-11 survey where self-reported values were directly used, the 2022-23 methodology imputes expenditures for non-market consumption following the steps below:

1. For every item, multiply weekly quantities by $\frac{365}{7}$, to generate annualized values of food consumed.
2. Sum the quantities consumed through home production and in-kind receipts to derive the total annual household consumption from non-market purchased items.
3. Estimate imputed item expenditures for non-market consumption by multiplying the annual quantity consumed by the outlier-corrected market-based unit values derived in Section 3.1.1.
4. Aggregate all imputed expenditures across all items consumed by the household to arrive at the final household imputed consumption value on non-market purchases.

18 The outlier-corrected market purchase-based unit value remains identical to the implied unit value from self-reported expenditure and quantity for non-outliers. For outliers (values set to missing), we apply a hierarchical replacement method. If the unit value is available for at least nine households within the PSU, we use the PSU-season weighted median unit value. If not, we replace it with the weighted median at the season-domain level. Any remaining missing values are corrected sequentially using the weighted season-domain median, the season-cluster (urban/rural/Kathmandu Valley) median, and finally, the weighted season-national median.

Figure 5b shows that while imputed expenditures generally align with households' self-reported values they do not entirely overlap. This gap highlights the biases that arise when households estimate the value of consumption without precise knowledge of market prices for home produced items.

FIGURE 5. Distribution of expenditures on market purchases, home production, and in-kind consumption



Note: The figure plots the cumulative density functions for annual self-reported values and outlier-corrected expenditures.

3.1.3 Food away from home

The third component of the food aggregate is the value of food consumed away from home. In NLSS-III, these expenses were recorded as a single household-level item in the primary food module, capturing total spending on meals prepared outside the home in the past week across all household members. In 2022-23, NLSS-IV refined this approach by introducing a new individual-level module (Figure 6). This module recorded the frequency and value of various types of meals—such as breakfast, lunch, dinner, snacks, beverages, alcohol, and others—consumed outside the home by each household member during the past week. A shift to individual-level data provides a more accurate and detailed estimate of expenses for food consumed away from home, enhancing the precision over the previous household-level approach.

The household's consumption value of food away from home is calculated as the aggregate weekly expenditure on all meals for all household members multiplied by $\frac{365}{7}$.

FIGURE 6. Survey module capturing food consumed away from home

Section 5 Food Expenses and Home Producation Part B Food Away from Home the Country

ALL HOUSEHOLD MEMBERS

IDENTIFICATION CODE	(5.06) ID code of respondent WRITE RESPONDENT'S ID CODE FROM HOUSEHOLD ROSTER ID CODE	(5.07) Did you consume tea/coffee, snacks, meals, or any other food and/or drinks outside your household in the last 7 days, either by paying yourself or as a guest (for free)? YES 1 NO 2 ▼ NEXT PERSON	(5.08) How many times did you consume **tea/coffee, juice/lassi, or bottled** water in the last 7 days? What total value would this consumption be equivalent to?		(5.09) How many times did you have **breakfast (morning snack)** outside your household in the last 7 days? What total value would this consumption be equivalent to?		(5.10) How many times did you have **lunch (morning/afternoon meal)** outside your household in the last 7 days? What total value would this consumption be equivalent to?		(5.11) How many times did you have **afternoon snack** outside your household in the last 7 days? What total value would this consumption be equivalent to?		(5.12) How many times did you have **dinner (evening meal)** outside your household in the last 7 days? What total value would this consumption be equivalent to?		(5.13) How many times did you consume **carbonated/soft drinks (Coke, Pepsi, energy drinks, etc.)** outside your household in the last 7 days? What total value would this consumption be equivalent to?		(5.14) How many times did you consume **spirits, wine, beer, or other alcoholic drinks** outside your household in the last 7 days? What total value would this consumption be equivalent to?		(5.15) Excluding the aforementioned food items, meals and drinks, how much would be the total value of **other food and drinks** that you consumed outside your household in the last 7 days
			(a) No.	(b) Amount (Rs.)	(a) No.	(b) Amount (Rs.)	(a) No.	(b) Amount (Rs.)	(a) No.	(b) Amount (Rs.)	(a) No.	(b) Amount (Rs.)	(a) No.	(b) Amount (Rs.)	(a) No.	(b) Amount (Rs.)	Amount (Rs.)
01																	

3.1.4 Nominal food aggregate

The final annual household food expenditure is the sum of the imputed market expenditures (Section 3.1.1), home production and in-kind receipts (Section 3.1.2), and the value of meals taken outside the home (Section 3.1.3) (see Figure 4 above). Figure 7 shows the share of consumption across the three modes by consumption quintiles. The average share of consumption from home production and in-kind receipts is highest among households in the bottom quintile, at 32 percent. This share decreases as total spending increases, accounting for only 15 percent of the food expenditures in the top quintile. In contrast, the share of food spending on market purchases and food consumed away from home rises with increased overall spending.

Figure 8 shows the distribution of expenditure on different components of food expenditures. Households in the poorest quintile rely more on less nutritious and cheaper sources of calories, such as cereals, which constitute 27 percent of their total food spending. On the other hand, households in the top quintile spend less on cereals (11 percent) and more on relatively nutritious and expensive calorie sources such as fruits and nuts (9 percent), and meats and fish (14 percent). Additionally, food consumed away from home accounts for a significantly larger share of the food budget in the richest quintile (21 percent), more than double that of the poorest quintile (9 percent).

FIGURE 7. Average share of food spending through different consumption modes in 2023

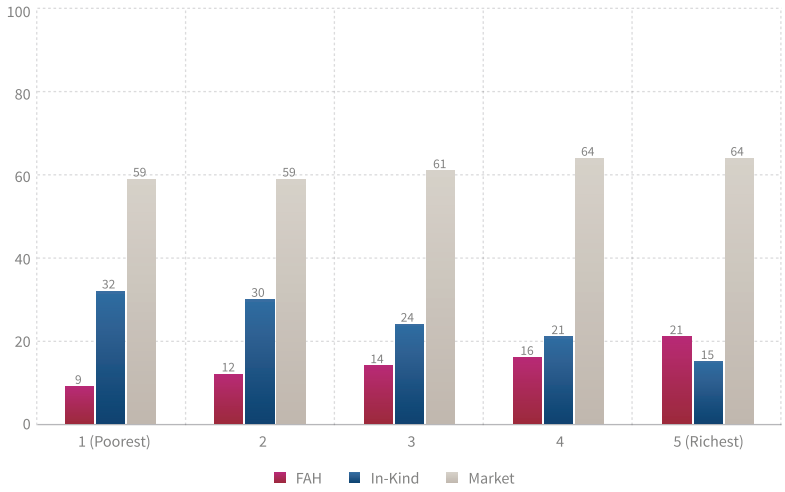
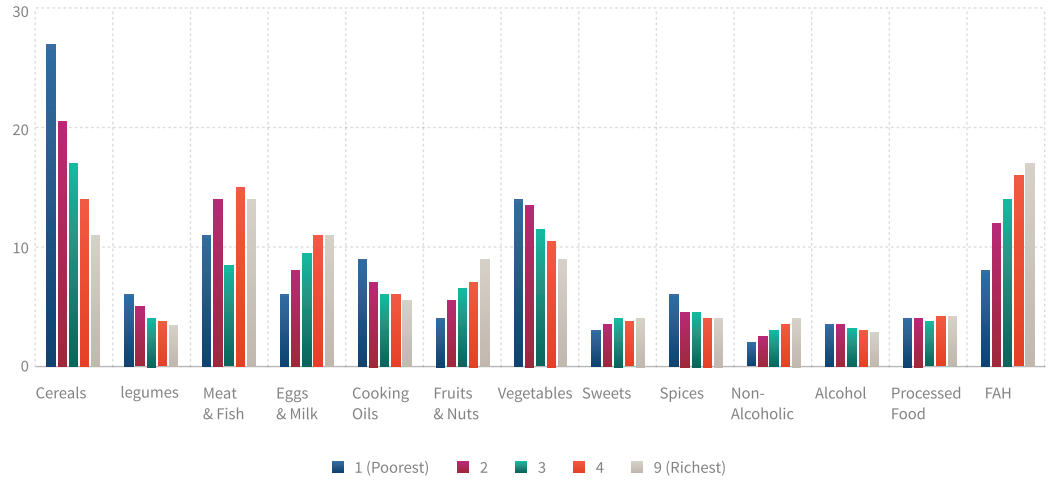


FIGURE 8. Components of food spending in 2022-23, by quintile

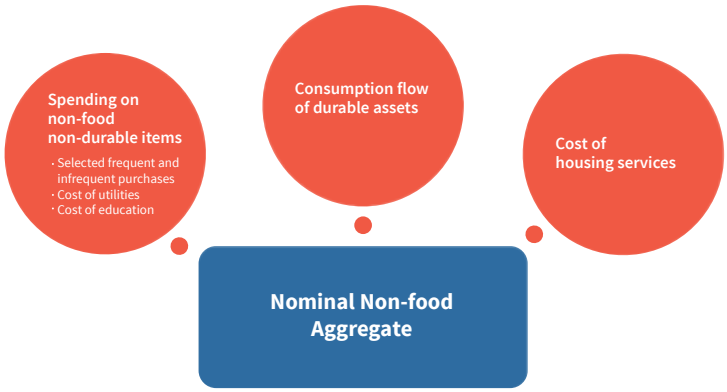


Note: The population is divided into five equal parts (consumption quintiles) based on total per capita consumption expenditure adjusted for prices differences across domains and seasons. These quintiles are ranked from poorest to the richest. The food category FAH represents the food consumed away from home (meals prepared outside the home). Non-alcoholic beverages combine carbonated drinks, juices, water, tea, coffee, and others.

3.2 Non-food Aggregate

The NLSS-IV also collected comprehensive data on non-food consumption spending. Specifically, this includes: (i) household expenditures on over 100 non-food, non-durable items in the past 30 days and past 12 months (Section 6A of the survey instrument); (ii) information on the ownership, purchase, and sale of durable assets over the past 12 months (Section 6C); (iii) annual expenditures on education for each household member who attended school in the past year (Section 7); (iv) monthly costs related to rents and household utilities such as electricity. The annual non-food consumption aggregate is calculated by aggregating (i) the reported expenditures on non-food non-durable items[19] , utilities, and education, (ii) the value of consumption services derived from durable goods, and (iii) the cost of housing services (Figure 9).

FIGURE 9: Nominal household non-food aggregate



3.2.1 Non-food non-durable expenditure

The non-food non-durable consumption expenditure is the sum of spending on (a) non-food items such as clothing and personal care items, among others, (b) education spending, and (c) the cost of utilities. The sub-sections detail the method for constructing each component.

a. Non-food non-durable items

Household expenditures on non-food non-durable items include spending on fuel, apparel, personal care items, other frequent expenditures (such as wages for regular services), infrequent expenses (such as wages for repair work), and other miscellaneous expenses (such as insurance

19 In line with 2010-11, this total includes annual spending on tobacco and tobacco products from Module 5 of the questionnaire.

and financial services)[20]. For every non-durable non-food item, the survey records household expenditure for two recall periods: the past 30 days and the past 12 months. Based on the two recall periods, two estimates of non-food non-durable spending are available for an item. To determine the final household estimate of non-food non-durable spending, the appropriate recall period for each item is selected using the following steps:

1. Classify items as regular or irregular based on spending patterns. An item is considered regular if the annualized median expenditure over the past 30 days is within 20 percent of the median spending over the past 12 months[21] ; otherwise, it is classified as irregular[22].
2. Calculate annual costs for regular-use items by multiplying the 30-day spending by 12. If 30-day data is missing, use the reported 12-month expenditure.
3. The annual costs for irregular-use items are the reported expenditure over past 12-months. If the 12-month is not reported, use annualized value of the 30-day spending.

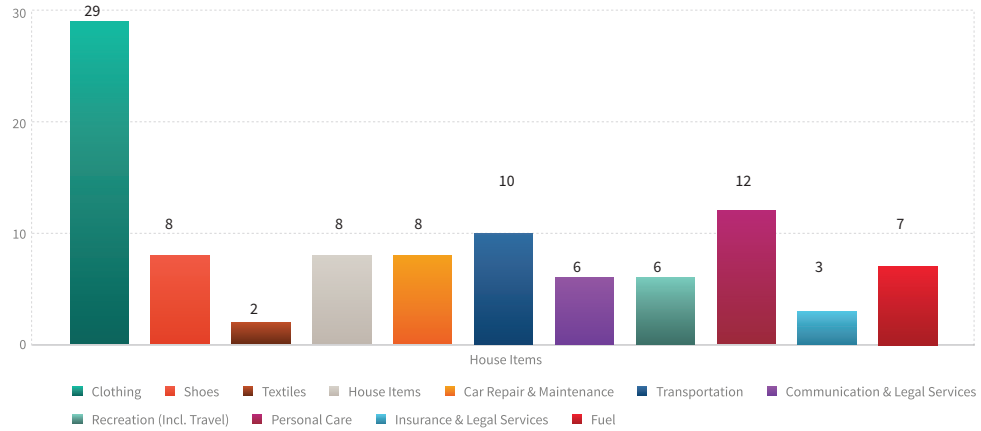
The sum of the estimated annual costs over all items, using respective recall periods, defines aggregate household spending on non-food non-durable items. On average, clothing (29 percent), personal care goods (12 percent), and transportation (10 percent) are the most significant spending categories among non-durable non-food items reported in 2022-23 (Figure 10).

20 While NLSS-IV carried a much longer and more elaborate list of items in Section 6 than NLSS-III, we are careful in including only the set of items that are comparable to those included in NLSS-III non-food aggregate. In addition, new items such as electric razors, that are in common use in the present time, are also included.

21 The 30-day recall is likely more accurate if purchases are at frequent intervals. On the other hand, if spending is irregular, a 12-month recall is likely to be more accurate.

22 This approach is similar to the method used in 2010-11, with one exception. The NLSS-III questionnaire split non-food, non-durable items into two sections: frequent-use and infrequent-use items. For infrequent-use items, only spending in the past 12 months was recorded, and therefore, the regular/irregular classification applied to frequent-use items only. This approach is different from the one used in earlier assessments. The NLSS-II, for instance, used monthly expenditures where available and replaced these with annual expenditures when items weren't consumed in the past 30 days, whereas NLSS-I used the recorded yearly spending.

FIGURE 10. Components of annual non-food non-durable expenditure



Note: House items include kitchen utilities such as crockery and cleaning items such as detergents. Car repair and maintenance include minor expenses on servicing, accessories, lubricants, and spare parts, among others. Transport includes airfares and other spending on domestic travel. Communication includes phone, internet, and fax bills, postal and courier expenses, phone repairs, and phone service costs. Recreation includes expenditure on music, toys, books, and travel. Personal care items comprise items of daily-use personal make-up and hygiene such as razors, toothpaste, soap, lotions, and perfumes. Fuel sums expenses on L.P.G. cylinder, kerosene, charcoal, coal, matches, and candles.

BOX 1. Items excluded from the non-food non-durable aggregate

The non-food, non-durable consumption aggregate excludes lumpy and infrequent expenditures and spending that do not contribute to the household's well-being. The list of items excluded comprises:

1. Health: The most controversial decision is whether to include or exclude health expenses in the overall welfare measurement. Health expenses, often a response to health shocks, are excluded despite their potential to improve welfare. Including health costs without accounting for the loss of welfare due to illness would be misleading. According to Deaton and Zaidi (2002): "The fundamental problem here is our inability to measure the loss of welfare associated with being sick, and which is (presumably) ameliorated to some extent by health expenditures. Including the latter without allowing for the former is clearly incorrect, though excluding health expenditures altogether means that we miss the difference between two people, both of whom are sick, but only one of which pays for treatment."
2. Remittances, transfers, gifts to other households: Such transfers decrease households' resources to spend on their own well-being. Moreover, since these transfers are consumed by the recipient households, the value of such gifts will be counted twice in consumption if they are included in the consumption of both the receiver and the giver (Deaton and Zaidi, 2002).
3. Donations to religious or charitable organizations: These expenditures do not contrib-

ute to household well-being but are deductions from household income.

4. Life event expenses: Expenditures on marriages, dowries, funerals, and other social ceremonies, which are once-in-a-lifetime expenses for households, that are very large compared to the total household budget. Households often save many years for such expenses and therefore, it is difficult to quantify annual costs.
5. Investments, savings, and loan repayments: These transactions are lumpy and a monetary outflow from the household's budget and do not represent current consumption.
6. Taxes and levies: These are mandatory payments that do not contribute to household welfare but are a deduction from household income.
7. Value of public services: The availability of public goods in the neighborhood improves household's well-being. However, attaching a value to these services is an empirical challenge.
8. Leisure time: The time spent on leisure activities increases welfare, but it is difficult to quantity its value.
9. Inputs for household businesses: These inputs are investments rather than additions to current household welfare.
10. Major household repairs or upgrades to a dwelling: Large, infrequent expenditures that provide utility over many years are excluded, though minor repairs with costs relevant to the current year are included.
11. For further discussion, please refer to Deaton & Zaidi (2002) and Mancini & Vecchi (2022).

b. Education

NLSS-IV collects data on education-related expenses in two sections: (a) Section 6A records aggregate household-level spending on admission, tuition, and exam fees for vocational training and basic, secondary, and higher education, and (b) Section 7 includes detailed expenses for each individual attending school, including fees, uniforms, textbooks, transportation, private tuition, and other related costs over the past 12 months. While Section 7 offers a comprehensive estimate of the household's total education expenditure for currently enrolled individuals, it does not account for the educational expenses of members not currently in school, such as drop-outs or absentee members, which are likely captured in Section 6. To ensure accurate calculation and avoid double counting, the final education expense is determined by taking the higher of the two estimates from Section 6 or Section 7, following the approach used in NLSS-III.

c. Utilities

The housing module (Section 2) of the NLSS-IV records monthly household expenditures on utilities. The annual cost of utilities includes the aggregate yearly spending on electricity, garbage collection, telephone, and water. Water-related expenses were collected for the first time in 2022-23 with the NLSS IV survey.

BOX 2. Expenditure on firewood is excluded from utilities

The NLSS-IV questionnaire collected detailed information on firewood usage from various sources, including market purchases, home production, and procurement from community-managed or government forests, over the past 12 months. Although more than two-thirds of households use firewood, and it significantly contributes to their welfare, only 24.8 percent of these households purchase it from the market. Due to the challenges in valuing firewood collected from forests, it is excluded from the welfare

3.2.2. Consumption flow of durables

Unlike non-durable goods, durable assets, such as cars or motorbikes, provide services over an extended period, often beyond the survey's reference period (past one year). These goods are also significant investments that depreciate over time, but surveys typically capture only the purchase price of the asset and not the cost of using it over the reference year.

BOX 3. Excluded durable assets

Kitchen utensils and furniture: While these items contribute to household welfare, they are excluded from the analysis of durable goods. Their heterogeneous nature and the variability in purchase and sale values make it difficult to accurately assess their worth.

Jewelry and Wristwatches: Jewelry and wristwatches are typically excluded from consumption flow estimates because they do not depreciate and may even appreciate over time. Including these items would distort estimates based on the asset's depreciated value (Deaton and Zaidi, 2002; Mancini and Vecchi, 2022).

To accurately reflect household consumption over the reference year, the consumption aggregate must include the "value of services" the household receives from using the durable goods during the year preceding the interview rather than the purchase price of items acquired within that period. Like in 2010-11, this consumption flow (` user cost') from durables is estimated using the method proposed by Deaton and Zaidi (2002). However, in contrast to the 2011 approach that used uniform depreciation rates to estimate user cost, the revised method in 2022-23 applies higher depreciation rates to more recently purchased items.

The survey contains detailed information on durable assets[23] owned by the household, including the number of each type of durable owned, the year of the last purchase, the purchase price,

23 Radio / Tape / CD/VCD/DVD player, Camera (Still / Movie), Bicycle, Motorcycle / Scooter, Motor car/Jeep, Refrigerator or Freezer, Microwave oven, Geyser (Gas / Electricity), Washing machine, Fans, Heater (gas/kerosene/electric), Television, Air conditioner/Cooler, Vacuum cleaner, Inverter, Solar panel (for electricity), Solar heater, Iron, Telephone sets/ Mobile phone/Tablet, Sewing machine, Computer / Printer

and the current estimated sale value (Section 6C). The user cost of an asset is estimated as the price a household is willing to pay to use the durable good over the year preceding the survey, that is, the monetary benefit forgone from not selling the durable item[24]. The methodology to estimate the user cost of durables is as follows:

1. For each durable asset (i) owned by the household, the per-unit purchase value (V_i0) of the asset is expressed in 2022-23 prices using the Consumer Price Index (CPI) data available from the Nepal Rashtra Bank from 1972-73 to 2022-23[25].
2. The **item-specific depreciation rate** δ_i is based on the age of the asset in the survey year (a), the purchase value (V_{i0}), and the estimated current value (V_{it}) as $\delta_i = 1 - \left(\frac{V_{it}}{V_{i0}}\right)^{\frac{1}{a}}$
3. An item-age specific weighted median depreciation rate is estimated at the national level, improving on the 2010-11 method:

   a. Compute weighted medians instead of unweighted medians calculated in 2010-11[26]. This modification has little effect on the estimates of consumption flow from durables.
   b. Estimate medians at the item-age group level, instead of a uniform item-specific depreciation rate applied in 2010-11. This step has a significant effect on estimation of user cost due to a change in the estimated median.

For example, in 2011, the estimated depreciation on a car and a refrigerator was 0.14 and 0.19, respectively, regardless of their age (Figure 11). Expectedly, under this approach, a newer vehicle or refrigerator also loses more value (depreciation rate of 0.3 and 0.29, respectively) than those owned for over ten years (depreciation rates of 0.1, and 0.13, respectively)[27].

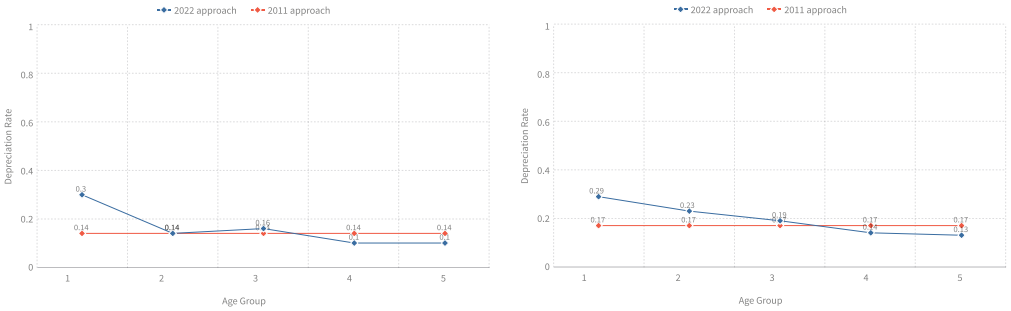
24 A household owning an asset faces two choices. It can either hold the asset until the end of the year, which will have a specific value after adjusting for the year's inflation and depreciation. Alternatively, the household can sell the durable asset at the beginning of the year and earn an inflation-adjusted interest rate on this value over the year—the difference between the two values accounts for the forgone value of the asset is an estimate of the user cost of keeping and using the asset.

25 The reported per-item purchase price is multiplied by a conversion factor $\left(\frac{CPI_{2022}}{CPI_{purchaseyear}}\right)$ to obtain the purchase value in 2022-23 prices. Moreover, since the survey module only asked for the purchase details of the latest purchased item for every asset, it is assumed that all items were bought at the same value and in the same year as the last purchased item.

26 Only positive values of depreciation rates are used to estimate medians.

27 Annex Table 27 presents median depreciation rates by item age for all assets in the module, illustrating the inverse relationship between age and depreciation rates for all assets.

FIGURE 11. Depreciation rates on cars and refrigerators, 2010-11 and 2022-23



Note: Assets are combined into 5 age groups based on year in which the last asset type was purchased relative to the survey year: 1 (0 to 1 year), 2 (2 to 3 years), 3 (4 to 5 years), 4 (6-10 years), and 5 (10+ years).

4. The **use cost of a durable good in the year preceding the survey** added to the welfare aggregate is based on the per-item sale value (V_{it}), number of each asset owned (n_i), real interest rate in the current year $(i_t - \pi_t$, nominal interest rate minus the rate of inflation) and the item-specific median depreciation rate (δ_{im}):[28]

$$V_{it} \cdot n_i \cdot \frac{(i_t - \pi_t + \delta_{im})}{(1 - \delta_{im})}$$

5. The **aggregate value** of this flow of services over all durable goods owned by each household is the **final consumption flow from durable goods.**

By construction, the consumption flow from durables in 2023 is expected to be higher than under the 2011 approach with uniform depreciation rates.

3.2.3. Cost of housing services

Like other durable assets, a home provides a long-term utility that often extends beyond the survey's reference period. Given the size of its associated investment, housing is also amongst the most valuable durable goods and, therefore, an essential component of the consumption aggregate (Mancini and Vecchi, 2022). Thus, the goal is to ascertain the flow of housing services in the year preceding the survey. Unlike other durable goods, rental markets for housing exist, and the rent paid most accurately reflects the market value of occupying the house and is, therefore, a measure of the `user cost' from housing services.

Section 2 of the survey captures both actual rents from renters and owners' self-reported es-

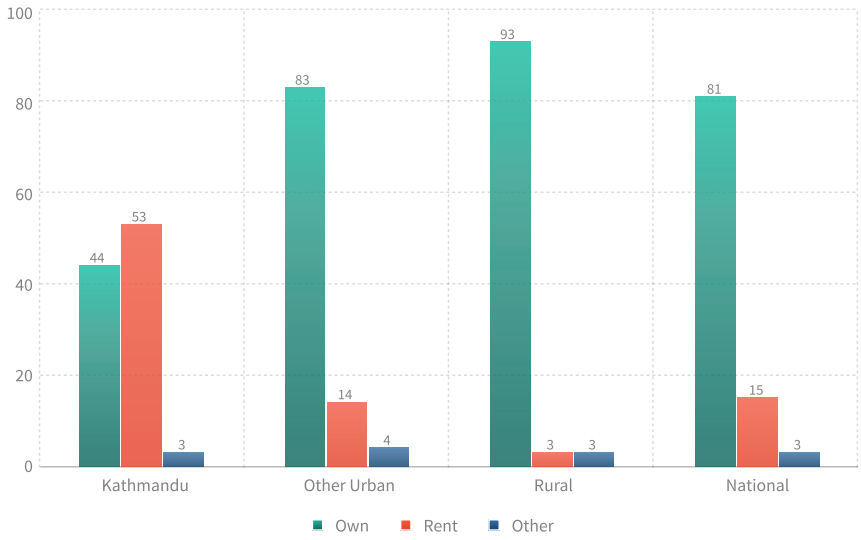
28 The real inflation rate is estimated based on the CPI data and the nominal interest rates available from the Nepal Rashtra Bank.

timates of their dwelling's rental value if it were rented. Figure 12 highlights the differences in local rental markets. While Kathmandu has a significant share of both renters and owners, rental markets are small in other urban and rural areas (the share of renters at 15 and 3 percent, respectively).

Hedonic model to estimate rental values for non-renters

Owners often incorrectly estimate rental values for the dwelling that they occupy, especially in areas with thin rental markets. Therefore, a standard approach is to estimate a hedonic model for rents to impute rents for non-renters. Such a model leverages observed rents from renters and self-assessed rental values from owners to price various characteristics of the dwellings (size, amenities, construction material, etc.).

FIGURE 12. **Housing status – national, KTM, other urban, rural, 2022-23**



For the 2022-23 rental regression model, various hedonic model specifications were tested, including both national and regional regressions over the sample of both renters and owners.[29] The model used in 2022-23 was selected based on (i) the predicted rental values being close to the actual rents reported by renters (using graphical inspections using residual plots), and (ii) achieving a high model R-squared and low Root-mean squared error (RMSE).

The selected hedonic model is a national regression model that includes PSU-level fixed effects

29 Other tested specifications related to (i) whether to include the value of durables or not, and (ii) a variety of geographic fixed effects (domain, macro region, district combined with number of households in the ward to capture density), among numerous other specifications that were tested both on the pooled sample of renters and owners and on the sample of renters only.

and uses the sample of both renters and owners. This model provides the best fit for the rental data, especially in rural areas where the number of renters is lower. While a model with regional regressions [30], as was done in 2010-11, performs similarly on the R-squared and RMSE, the larger sample size with a national model is an improvement especially for rural areas, where the sample of renters is low.[31] The following specification is used for the hedonic regression model:

$$\ln(rent_{ij}) = f(dwellingcharacteristics_{ij},\ valueofassets_{ij}, geographicFE_j, regionalrenterstatus_{ij}, \varepsilon_{ij})$$, (eq. 1)

where $\ln(rent)_{ij}$ is the log rental value for household i and PSU i. To account for biases in recall, the rental values are corrected for outliers.[32] The model controls for a range of household characteristics $dwellingcharacteristics_{ij}$, including (i) log value of house area, (ii) number of rooms, (iii) indicator variables for whether the dwelling has a kitchen, cement wall, cement foundation, and roof, (iv) dummy variables for access to utilities, like piped water, garbage disposal, municipal sewage, electricity, landline phone, internet, and road next to the house, (v) log value of durable assets owned by the household $(valueofassets_{ij})$, and (vi) an indicator variable each for whether a household is a renter in Kathmandu Valley, a renter in other urban areas, and a renter in rural areas. The specification also includes PSU fixed effects $(geographic\ FE_j)$.

Table 3 presents results from the hedonic regression model. The final flow of housing services is the annualized value of Duan-corrected predicted rental values[33] from the hedonic model for non-renters and those with missing rental values. For renters, the flow of housing services is the annualized value of the actual rent paid.

30 In 2010-11, three separate regressions were estimated, one each for Kathmandu Valley, other urban areas, and rural areas.

31 Housing markets vary significantly across different regions. For instance, the renters and owners in Kathmandu differ from those in rural areas. One method to account for these regional differences is to use separate hedonic models for each region, as was done in 2010-11. In NLSS-III, separate models were estimated for Kathmandu, other urban areas, and rural areas using data from both renters and owners. Alternatively, a national hedonic model with PSU (Primary Sampling Unit) fixed effects can be used to account for geographical differences in housing markets and other PSU-level characteristics.

32 Outlier values in rents are identified by ownership type (owner/renter/other) within a geographical area (Kathmandu Valley, rural, urban). A value is an outlier if the log-rental value is outside at least 2 standard deviations away from the mean. The outliers are replaced with missing. The percentage of outliers in rental values was largest in other urban (5.6 percent), followed by rural (3.8 percent) and Kathmandu (3.4 percent). This method of outlier detection is different from NLSS-III where fixed numerical cut-offs were applied to detect outliers (3.64 and 99.43 percentile) on the rental (actual and hypothetical) distribution.

33 Predicted log rental values were transformed to absolute numbers following Duan (1985) smearing transformation. This is different from the previous method which transformed predicted log values with an exponential transformation.

TABLE 3. Final hedonic regression and determinants of imputed rents in Nepal. 2022-23

Dependent variable: Log Monthly Rental Value			
Log(total area of dwelling)	0.274	Distance from secondary school (km)	-0.00302
	(0.0200)		(0.00410)
Number of rooms (max = 16)	0.107	Distance from government hospital (km)	0.000234
	(0.00589)		(0.00171)
Dwelling has a kitchen	0.168	Distance from bank (km)	-0.00579
	(0.0185)		(0.00258)
Dwelling has cemented wall	0.236	Distance from market (km)	-0.00255
	(0.0326)		(0.00225)
Dwelling has cemented foundation	0.182	Distance from police station (km)	0.00671
	(0.0328)		(0.00410)
Cemented or Tin roof	0.0728	Distance from ward (km)	-0.0160
	(0.0219)		(0.00546)
Piped water supply	-0.0178	Renter in KTM	-0.412
	(0.0250)		(0.0573)
Piped water inside dwelling	0.0655	Renter in other urban	-0.0893
	(0.0242)		(0.0329)
Communal garbage collection	0.166	Renter in rural	0.0656
	(0.0305)		(0.0631)
Paved road next to dwelling	0.0776	Has municipal sewage	0.122
	(0.0266)		(0.0338)
log(Value of durable goods)	0.0915	Electricity for lighting	0.0338
	(0.00690)		(0.0417)
Distance from child center (km)	0.0291	Dwelling has landline telephone	0.0713
	(0.00982)		(0.0634)
Distance from basic school (km)	-0.0331	Dwelling has internet	0.0661
	(0.00842)		(0.0176)
Observations	7810		
R2	0.751		

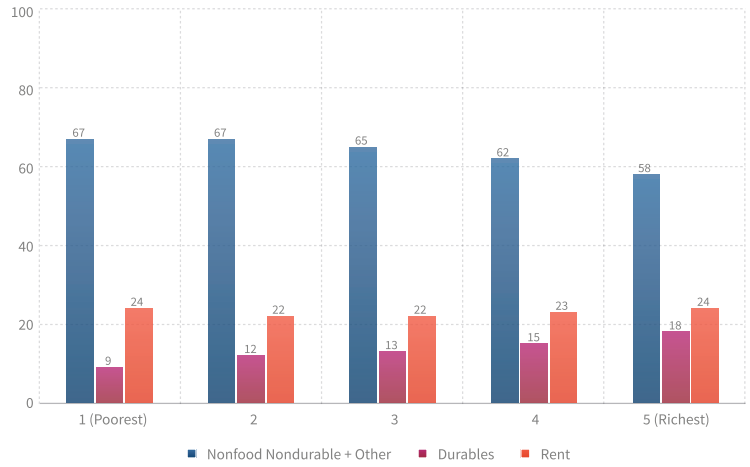
Note: The model is a regression with log of monthly rental value as the dependent variable. The control variables include various household characteristics (listed in the table above) in addition to PSU fixed effects in equation 1. The sample includes both the renters and owners. Standard errors are reported below the coefficients in parentheses.

3.2.4. Nominal non-food aggregate

The nominal non-food aggregate is the total annual cost of non-food non-durable items, cost of utilities and education (Section 3.2.1), consumption flow from durables (Section 3.2.2), cost of housing services (Section 3.2.3), and tobacco and tobacco products (see Figure 9 above).

The cost of housing services, followed by consumption flow from durable goods, account for the largest categories of non-food spending across the consumption quintiles (Figure 13). Not surprisingly, the average share of expenditures on durables increases as the level of aggregate spending increases (18 percent among the top quintile versus 9 percent among the bottom quintile).

FIGURE 13. Components of non-food aggregate, by consumption quintiles



Note: Refer notes to Figures 7 and 8 on the method to identify consumption quintiles. Non-food non-durables + other is a composite category that includes items in Section 6, education, and utilities, and tobacco.

3.3 Nominal Welfare Aggregate

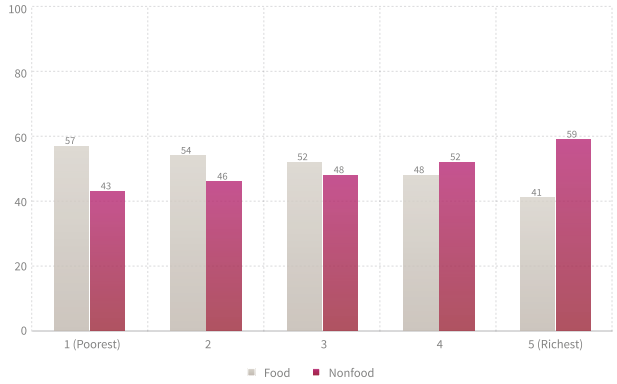
The NLSS-IV, similar to living standard surveys in other countries, gathers data on household expenditures. However, welfare and poverty are individual attributes (Ravallion, 2016). In line with previous poverty estimations in Nepal, we divide the household consumption expenditures by household size to obtain the consumption expenditure per person per year, which is the nominal welfare aggregate of interest.

The share of non-food spending in the total annual consumption expenditure increased over the past 12 years from about 38 percent in 2010-11 to 47 percent in 2022-23.[34] On average, ex-

34 The reported increase is based on comparable consumption aggregates in 2010-11 and 2022-23, constructed using the 2010-11 methodology.

penditure on food accounts for over half of the total spending of the population in the bottom 60 percent of the expenditure distribution in Nepal (Figure 14). Moreover, while individuals in the bottom quintile (lowest 20 percent of the total per capita consumption expenditures) spend 57 percent on food, those in the top quintile spend less on food (41 percent) and more on non-food items (59 percent).

FIGURE 14. Average share of food in per capita consumption expenditure, 2023



Note: Refer notes to Figures 7 and 8 on method to identify consumption quintiles.

Table 4 presents the average annual per capita nominal consumption expenditure for each analytical domain by consumption expenditure quintiles. The population is split into five equal parts (five quintiles) based on average annual nominal expenditures, ranked from the bottom 20 percent (first quintile) to the top 20 percent (fifth quintile). The last column presents the ratio of the mean annual per capita expenditures of the top 20 percent and the bottom 20 percent. While the average annual per capita expenditure among the top quintile is over five times that in the poorest quintile in Lumbini Urban and Kathmandu Valley, this ratio is only 3.18 for Sudurpaschim Rural, highlighting different levels of inequalities in nominal consumption expenditures across domains.

TABLE 4. 2022-23 mean annual per capita nominal consumption expenditures

Domain	Q1 (Poorest)	Q2	Q3	Q4	Q5 (Richest)	Ratio (Q5/Q1)
Koshi Urban	60963	91944	118077	151224	264011	4
Koshi Rural	44001	66739	86322	112544	203921	4.63
Madhesh Urban	42936	59611	78324	98950	181595	4.23
Madhesh Rural	36921	53259	65238	82677	121505	3.29
Kathmandu Valley	117115	172229	223449	291311	515230	4.40
Bagmati Urban (excl. KTM Valley)	67402	104713	140458	190591	343484	5.10
Bagmati Rural	45606	69459	91796	124853	227076	4.98
Gandaki Urban	75978	114723	151056	196574	344867	4.54
Gandaki Rural	60562	88424	113102	141209	218357	3.61
Lumbini Urban	50688	80186	110026	152949	270827	5.34
Lumbini Rural	45688	65522	84390	107781	174071	3.81
Karnali Urban	50570	70543	87817	116092	227197	4.49
Karnali Rural	41012	59347	75232	96010	144898	3.53
Sudurpaschim Urban	47506	68367	85967	110993	196992	4.15
Sudurpaschim Rural	38649	54964	67471	81003	123012	3.18

Note: Q1 to Q5 represent five consumption expenditure quintiles, i.e., five equal parts of the population based on annual per capita nominal consumption expenditures. Each quintile is 20 percent of the population. The per capita nominal consumption expenditures are not adjusted for price variations between seasons and domains.

Spatial *and* Temporal Price Adjustments

The Cost of Basic Needs (CBN) approach anchors poverty estimates to a fixed level of welfare across the country, allowing for welfare comparisons across the population. However, individuals often pay varying prices for identical goods and services either because they are purchasing it in different regions, or at different points in time over the survey year. To ensure a comparable measure of welfare across space and time, the welfare aggregate must be adjusted for both seasonal (temporal) and regional (spatial) price differences.

Temporal and spatial price indices (deflators) capture these price variations across locations and periods and consolidate them into a single metric. These deflators represent the price differential between different points in time and across locations.

4.1 Intertemporal adjustment

The survey period, spanning from July 2022 to June 2023, introduces the possibility that some households may report higher expenditures due to higher price inflation specific to the month of their interview. To prevent these seasonal price differences from distorting the ranking of households, within-survey price adjustments are crucial.

In 2011, season-specific temporal deflators were calculated as the ratio of nominal per capita food expenditures in a season to the weighted average of these expenditures across seasons based on the food basket of the reference population. In contrast, the 2023 temporal deflators are based on the consumption patterns of the entire sample, rather than just the reference population. Using detailed information on all food items for which expenditures and unit values (price per unit quantity) are available in the survey,[35] the process to create a temporal deflator in 2023 involves these steps:

35 Due to the unavailability of non-food prices, the temporal deflator is based on the household's food consumption. We use this deflator to deflate the aggregate consumption expenditures. The underlying assumption is that non-food prices vary across seasons to the extent of the differences in food prices.

1. For each food item, calculate **weighted median unit values** separately for each season.[36]
2. Construct a **national food basket**, ensuring the mean budget shares for each food item sum to one. This basket provides a consistent benchmark for comparing costs across different seasons.
3. Determine the **cost of the national food basket** using median unit values from each season to clearly depict how the cost of living fluctuates across seasons.
4. The t**emporal deflator** $temp\_def_s$ is the ratio of the price of the national food basket in the given season to the average cost of the basket over the three seasons, that is,

$$temp\_def_s = \frac{Cost\ of\ national\ basket\ in\ season\ s}{Average\ \cos t\ of\ national\ basket\ across\ seasons}$$

Table 5 shows that there is a narrow difference in the value of temporal price deflators across seasons, which is highest in season 2 and lowest in season 3. Since the temporal deflators are very close, the intertemporal adjustments only have a minor effect on the welfare aggregate.

TABLE 5. Temporal deflators, by season

	Season 1	Season 2	Season 3
Value	1	1.02	0.99

4.2 Spatial adjustment

Spatial price adjustment is essential for accurately comparing welfare across households in different regions. In 2022-23, the deflator is constructed in a single step, adopting a standard approach commonly used in other developing countries, instead of the iterative method used in 2011.[37] Food and non-food price deflators are estimated separately.

Food price deflator

A household-level Paasche price index is estimated to deflate food aggregates, using market-based unit values specific to each household, rather than a domain-level price deflators as

36 Alternatively, temporal deflators can be constructed within each stratum. However, this is not possible as the survey sample is not representative at the season-domain level.

37 Annex A1 provides details on the 2011 method. The iterative approach is accurate but non-standard in poverty measurement. In 2022-23, we adopt the more standard approach that is a one-step estimation.

done in 2011.[38] [39] This approach effectively captures price variability within a domain, particularly relevant in Nepal's geography where market access can vary significantly depending on location.

The steps to estimate the household-level Paasche index are as follows: The Paasche price index for food follows the methodology detailed in Deaton and Zaidi (2002) and uses information collected on household market purchases. [40]

1. Derive item unit values using market purchases for every item (p_{hi}) as the ratio of outlier-corrected[41] and inter-temporally adjusted expenditures to the quantity purchased.
2. Exclude all items with missing unit values.
3. Calculate the national weighted median unit values as the reference price level for each item (p_{0i}).
4. The household budget share on each item in the total food expenditure is estimated at w_{hi}.
5. The Paasche Index is, then, estimated for every household as:[42] $Paasche_h = \left(\sum_{i=1}^{K} w_{hi}\left(\frac{p_{0i}}{p_{hi}}\right)\right)^{-1}$,
6. If missing, the Paasche index is replaced by the weighted domain-level median value.

The per capita food expenditures are adjusted for local price variations using the Paasche deflator to generate the spatially adjusted per capita food spending.

Non-food price deflator

The Paasche index cannot be applied to the non-food component due to the lack of non-food unit price data. Instead, the spatial non-food deflator is derived using the domain-level cost of basic non-food needs, consistent with the approach used in NLSS-III.[43] The domain-level non-

38 Using market price data is ideal for such an index, usually collected from a market survey. However, unit values collected in the survey are often used to build this index for poverty measurements (refer to Deaton and Tarozzi (2005) on why unit values).

39 For alternative methods and the advantages of using a Paasche index, please refer to Deaton and Zaidi (2002).

40 Food items produced at home or received as gifts or food consumed outside home are excluded in generating this index. While reported expenditures on food received in-kind or produced at home are typically based on household self-assessment and needn't reflect market values, the survey does not allow imputing unit prices for meals eaten outside home as quantities are not collected.

41 See Section 3.1.1 for details on method to correct expenditures using market-purchase based unit values.

42 Equation 4.5, page 41 of Deaton and Zaidi (2002).

43 Alternatively, spatial deflators for non-food component can be based on (a) food deflators, (b) CPI or (c) deflators based on housing values. For a further discussion on these alternatives, refer to Deaton and Zaidi (2002), Central Administration of Statistics and World Bank (2015), Al-Salehi et al. (2018), and Amendola et al. (2023).

food deflator, applied to adjust all non-food monetary values, is calculated as the ratio of the basic non-food needs in the domain to their weighted average across domains.[44] Section 5.2 describes the construction of the cost of basic non-food needs, domain-level spatial non-food deflators, and the non-food poverty line.

44 This method uses implicit price information in the domain-level nominal non-food cost of to construct the spatial non-food deflators.

Constructing *the* Poverty Line

While the consumption aggregate measures an individual's well-being, the poverty line represents the threshold below which an individual is considered poor. A poverty line consists of two components: (i) the food poverty line, which represents the minimum cost of meeting minimum nutritional requirements, and (ii) the non-food poverty line, which is the minimum allowance required to cover basic non-food needs. In 2010-11, the poverty lines were established using an iterative approach, as detailed in Annex A1 (World Bank, 2014). Although this method is accurate, it is not currently widely used in other countries. For 2022-23, the poverty lines were determined using a one-step estimation method, which aligns with standard practices commonly followed internationally (Deaton and Zaidi, 2002; Mancini & Vecchi, 2022).

This section outlines the steps taken to construct the new official poverty lines for 2022-23 using NLSS-IV data. Annex Table 30 summarizes the key differences in poverty estimation in 2022-23 from the 2010-11 methodology.

5.1 Food Poverty Line

The construction of food poverty lines is a two-step process. First, the basic food needs are defined in terms of meeting a minimum calorie requirement per person per day. Second, the food poverty line is estimated by identifying and pricing the food basket of the relatively poor (reference population) that would fulfill minimum caloric needs.

More formally, the (annual) food poverty line is given by,

$$FPL = 365 \times reqdkcal \times \frac{\sum_{i,r} p_{ir} q_{ir}}{\sum_{i,r} kcal_{ir}}, \quad \text{(eq.2)}$$

where reqdkcal is the per person minimum required calories per capita per day, $\sum_{i,r} p_{ir}\, q_{ir}$ and $\sum_{i,r} kcal_{ir}$ are the total expenditure and total calories consumed from items *(i)* in the food basket consumed by the reference population *(r)*. Thus, the ratio $\frac{\sum_{i,r} p_{ir} q_{ir}}{\sum_{i,r} kcal_{ir}}$ is the average cost per calorie

per person per day, estimated using the food basket consumed by the relatively poor.

Figure 15 summarizes the steps in the estimation of the food poverty line that are further detailed in the following sub-sections.

FIGURE 15: Steps in the estimation of Food Poverty Line

5.1.1 Setting the minimum caloric requirement

The food poverty line anchors the minimum welfare level to a specific nutritional requirement, ensuring that basic food needs are met for various demographic groups within the population. Table 6 shows the recommended daily dietary allowance for different age-sex cohorts using the Food Consumption table for Nepal (Ministry of Agricultural Development, 2017)[45] and the composition of an average Nepali households in 2022-23 (NLSS-IV). Based on this data, the minimum caloric requirement for 2022-23 is set at 2,236 kilocalories (kcal) per person per day, slightly higher than the 2,220 kcal per day used in 2010-11. This increase reflects changes in household demographic composition over the past 12 years, as well as updated energy intake recommendations based on age and sex.

45 This table is identical to the 2012 caloric table for Nepal available from Food and Agricultural Organization (FAO) and published by Ministry of Agricultural Development (2012). Link to the FAO table: https://www.fao.org/fileadmin/templates/food_composition/documents/regional/Nepal_Food_Composition_table_2012.pdf

TABLE 6. Recommended daily dietary allowances and household composition

Demographic profile	Recommended daily allowance (kcal)	Average proportion per household (NLSS-IV)	Required kcal/day
Less than 1 year	553*	0.064	35
1-3 years	1,060	0.207	219
4-6 years	1,350	0.234	316
7-9 years	1,690	0.231	390
Boys 10-12 years	2,190	0.120	263
Girls 10-12 years	2,010	0.118	237
Boys 13-15 years	2,750	0.120	330
Girls 13-15 years	2,330	0.119	277
Boys 16-17 years	3,020	0.072	217
Girls 16-17 years	2,440	0.086	210
Men 18 and above	2,730	1.169	3191
Women 18 and above	2,230	1.459	3254
Average Household size		3.999	
Average Caloric requirement per household (kcal/day)			8941
Total per capita caloric requirement (kcal/day)			2236

*Note: *553 kcal is the simple average of 506 (0-6 months) and 600 (6-12 months); for a child less than 6 months 5.5 kg on average, for a child 6-12 months, 7.5 kg on average. Values of caloric intake of adult men and women are based on those who do moderate physical activities.*

5.1.2 Identifying the Food Basket

Individuals can achieve the minimum required calorie intake 2,236 Kcal per person per day through a variety of foods, and often at significantly different costs. A standard approach in poverty measurement is to identify a set of items typically consumed by the `relatively poor' population and then price this food basket to establish the food poverty line, which represents the cost at which the minimum nutritional requirements are met.

The NLSS-IV collected information on household consumption of a diverse list of 110 food items. Using the Food Consumption table for Nepal (Ministry of Agricultural Development, 2017)[46] , caloric values (# Kcal per unit quantity consumed) are assigned to 77 of these items which could contribute to meeting an individual's nutritional requirements.[47] This represents a significant increase from the 2010-11 food basket of 40 items (mapped to 44 items in NLSS-IV) that were used to estimate the 2010 poverty line.[48] Figure 16 shows the share of households consuming each of these 77 items that have an associated caloric value in 2022-23. While the majority of items in the old food basket remain relevant (Figure 16a), a significant share of the households also report consuming the newly added items in NLSS-IV (Figure 16b).

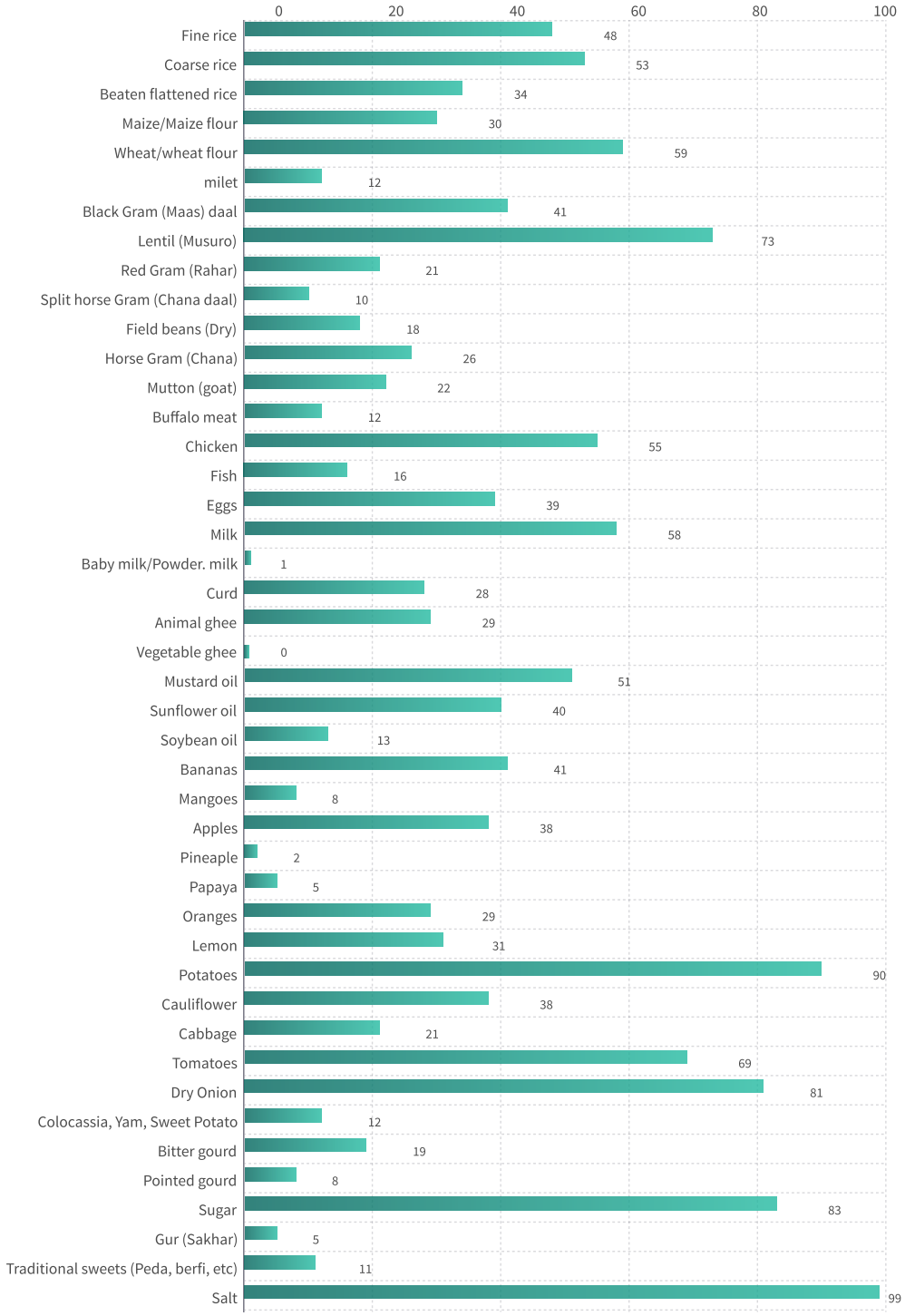
46 For a couple of items in the food basket in 2010-11, a caloric value could not be assigned using this recent nutrition table. These items are attached to the caloric value used in 2011.

47 Items dropped from caloric computations are the (i) unaccountable items such as "other grains" (ii) items to which no caloric value could be assigned based on the available caloric table condensed milk, jam/jelly, readymade masala, carbonated drinks among others; (iii) alcohol, and (iv) water.

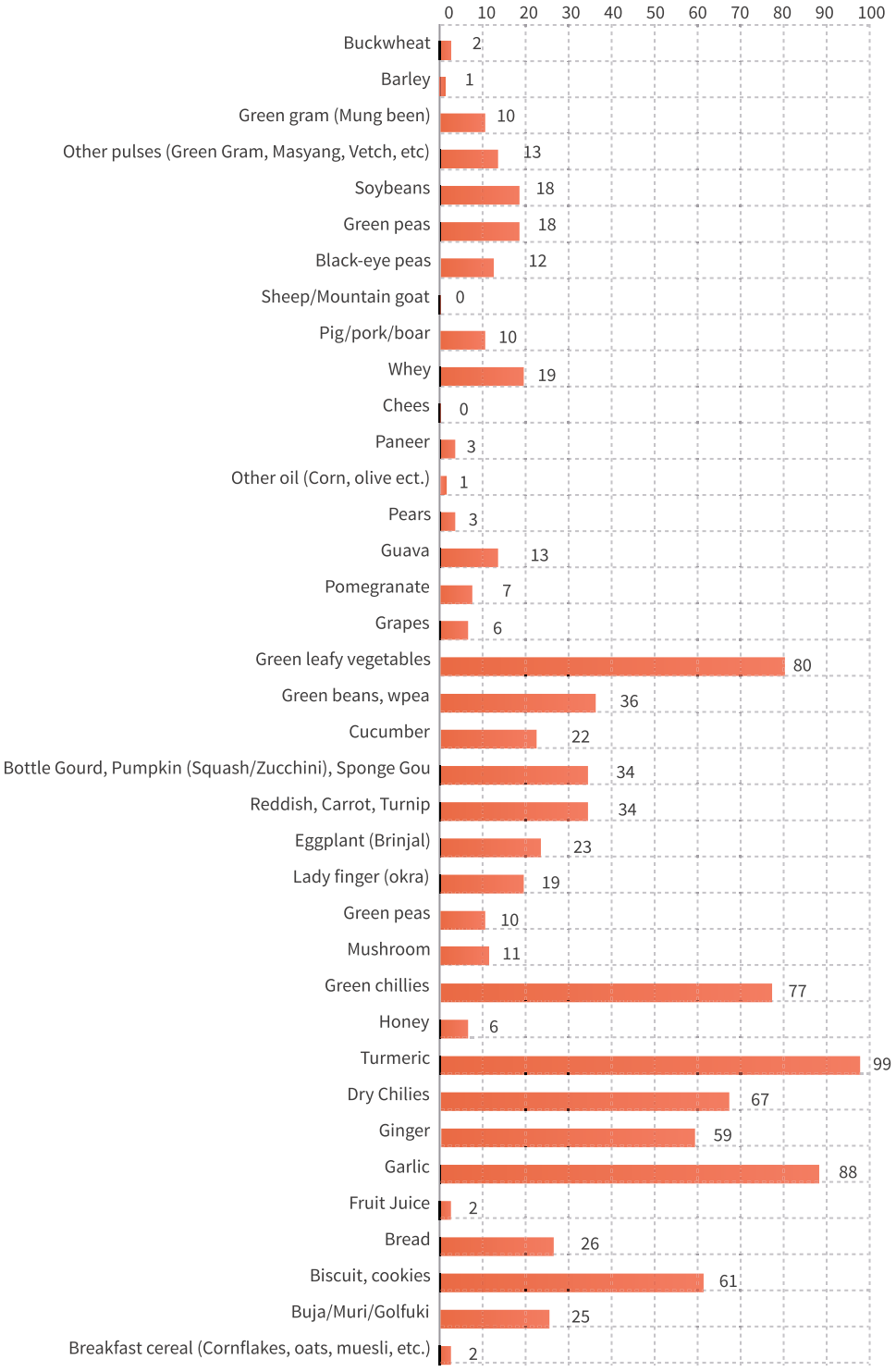
48 The 2010-11 food poverty line was based on a bundle of 40 items (of the 68 in the survey) to which a caloric value was assigned. The 40-item bundle in 2011 is mapped to 44 items in 2022-23. This bundle accounted for 78 percent of the food spending of the population (and 79 percent for the reference population).

FIGURE 16. Share of households consuming each food item in 2022-23

a. 44 items, representing the 2010-11 food basket



b. 33 additional items in the 2022-23 food basket



Note: Figure 16 plots the share of household consuming the 77 items to which a calorie value can be assigned. Figure 10a includes the 44 items in NLSS-IV that are directly mapped to the 40 items in the food basket used in 2010-11 poverty line estimation. Figure 10b includes the additional 33 items on the list.

The increased diversity in food consumption in 2022-23 is evident not only in the number of items consumed but also in their contribution to total calorie intake and their share in household food budgets. While the 44 items (2011 food basket) accounted for an average of 78 percent of total food spending in 2011, they account for only 61 percent in 2022-23 (Table 7). The additional 33 items included in the 2022-23 basket account for an average of 13 percent of total food expenditure and 8 percent of total calories. Moreover, the cost per calorie—calculated as the ratio of expenditures to calories consumed—is higher for the 33 new items (13.2) compared to the 44 items in the 2010-11 bundle (4.8).

TABLE 7. Food Basket, 2022-23

	Items overlapping 2010-11 Food Basket	Additional items in 2022-23 food basket
Number of items	44 items	33 items
Share in household food spending	61	13
Share in total calorie intake	92	8
Cost per calorie (in 2022-23 rupees)	4.8	13.2

Given the higher cost per calorie and significant share of households' food spending, the decision was made to expand the food basket to include all 77 items.[49]

5.1.3 Identify the Reference Population

Accurately determining the food poverty line requires selecting a reference population of relatively poor individuals. The food basket of this reference population will serve as the basis for calculating the average cost per calorie for the food poverty line. The reference group typically excludes wealthy individuals, whose consumption behaviors and preference for more expensive foods do not reflect the broader population's nutritional needs. Similarly, the poorest individuals are excluded, as their consumption patterns may be more indicative of economic hardship than actual needs and preferences. The selection of the population deciles that form the reference group involves determining who would classify as relatively poor in terms of being able to afford minimum nutritional require-

49 Several tests were conducted to select a restricted food basket from the 77 identified items, applying various exclusion criteria, such as the proportion of the population or reference group consuming each item, and additional restrictions based on domains. However, due to significant variations in consumption patterns across different domains and income deciles, all 77 items were ultimately included in the food basket. This comprehensive list ensures

ments.[50] For 2022-23, the reference group comprises of individuals in the 2nd and 3rd deciles of the distribution of temporally and spatially adjusted per capita food expenditures. Annex Table 27 presents results from the test of differences in non-monetary dimensions of welfare—such as housing, labor, and asset ownership—across various population deciles based on food expenditure distribution. Individuals in the 5th decile are significantly better off compared to those in the 3rd and 4th deciles. Additionally, the 4th decile displays noticeable differences from the 3rd decile, particularly in asset ownership. However, no significant difference exists between the 2nd and 3rd deciles. As a result, the 2nd and 3rd deciles were selected as the reference population, as they most accurately reflect the preferences and needs of those considered relatively poor.

The 2022-23 reference group differs from 2010-11, when the reference group included individuals in the 2nd to 5th deciles based on the distribution of spatially adjusted per capita total expenditures. Using this narrower band to identify the relatively poor also reflects the improvements in welfare observed over the past 12 years since the NLSS-III survey.

5.1.4 Estimating the cost per calorie

Based on the consumption of the 77-item food basket, per person the cost per calorie is estimated as the ratio of per capita total (spatially and temporally deflated) food spending and the total calories. Expectedly, the average price per calorie increases with each successive food consumption decile (Table 8). The average cost per calorie for the reference population, in the second and the third deciles is almost half of the cost per calorie among individuals in the top decile of aggregate spending.

that the 2022-23 food poverty line remains relevant and robust, preserving the integrity of the basket used to estimate minimum nutritional requirements for the foreseeable future.

50 The method employed to select the reference population in 2022-23 aligns with the standard approach used in most other countries, which is a one-step estimation method for poverty lines (see Al-Salehi et al., 2018). In contrast, the 2010-11 methodology employed an iterative approach to determine the poverty line and spatial deflators. In the initial iteration, the reference population was selected based on nominal total consumption expenditure within each domain. In subsequent iterations, the reference population was derived from the national distribution of spatially and temporally adjusted per capita spending obtained from the previous iteration. This multi-step process enabled a more refined identification of the relatively poor within the overall distribution of total expenditure. See Annex A1 for a summary of the 2011 methodology.

TABLE 8. Average cost per calorie, by food consumption decile

Decile	1 (poorest)	2	3	4	5	6	7	8	9	10 (richest)
Average cost per calorie	0.034	0.040	0.044	0.048	0.050	0.054	0.057	0.062	0.066	0.080

Note: The per capita consumption expenditures (in 2022 prices) are adjusted for price variations between seasons and domains. Deciles 1 to 10 represent ten food expenditure deciles, i.e., ten equal parts of the population based on annual real per capita food expenditures. Each decile represents 10 percent of the population.

Column (1) of Table 9 shows the difference in average cost per calorie across analytical domains for the entire population. Not surprisingly, Kathmandu Valley and Gandaki Urban have the highest cost per calorie consumed, whereas rural areas of Karnali and Sudurpaschim have the lowest cost per calorie. Column (2) of Table 9 presents the domain-level average cost per calorie for the reference population that underlies the food poverty line. The average cost per calorie for the reference population residing in Kathmandu Valley is 1.24 times the cost per calorie for relatively poor in rural Karnali and Sudurpaschim.

TABLE 9. Average cost per calorie, by domain

Domain	(1) Average cost per calorie	(2) Average cost per calorie (reference population)	Domain	(1) Average cost per calorie	(2) Average cost per calorie Reference population
Koshi Urban	0.056	0.043	Gandaki Rural	0.060	0.046
Koshi Rural	0.049	0.040	Lumbini Urban	0.055	0.044
Madhesh Urban	0.048	0.042	Lumbini Rural	0.052	0.044
Madhesh Rural	0.045	0.040	Karnali Urban	0.047	0.039
Kathmandu Valley Urban	0.065	0.046	Karnali Rural	0.041	0.037
Bagmati Urban (excl KTM Valley)	0.060	0.046	Sudurpaschim Urban	0.047	0.040
Bagmati Rural	0.055	0.043	Sudurpaschim Rural	0.040	0.037
Gandaki Urban	0.065	0.047			

5.1.5 Food Poverty Line

The national food poverty line is the weighted average of domain-specific lines. The domain-level cost of basic foods needs is generated from the annualized value of the domain-specific average cost per calorie based on the food basket of the reference population multiplied by the nutritional requirement of 2,236 Kcal per person per day (equation 1).[51] The national food poverty line in 2022-23 is 35,029 rupees per person.

5.2 Non-food Poverty line

Estimating the cost of essential non-food needs is not straightforward, as it is not anchored to a standard benchmark like the minimum caloric requirement used for the food poverty line. Even if a fixed bundle of non-food items were defined, pricing it accurately would be difficult due to quality variations.

Therefore, the non-food allowance is calculated as the average share of non-food spending for a subset of individuals whose food expenditures are close to the food poverty line. This method aligns with international best practices[52] and mirrors the approach used in 2010-11 poverty measurement in Nepal (World Bank, 2014). The underlying assumption is that households close to the food poverty line allocate just enough to cover essential non-food needs, with any additional non-food spending likely compromising their ability to meet minimum caloric requirements. [53]

The estimation of non-food poverty line and non-food spatial deflators follows the steps below:

1. **Convert the food poverty line to nominal terms in every domain (cost of basic food needs):** The domain-specific spatially adjusted food poverty line is converted to nominal terms by multiplying it by the inverse of the domain-level average Paasche food price deflator. This step is necessary because per capita non-food consumption expenditures are measured in nominal terms, and not adjusted for price differences across regions.
2. **Estimate non-food shares around the cost of basic food needs line:** Within each analytical domain, derive an average share of non-food spending for individuals whose food consumption is within one percent of the nominal cost of basic food needs. Repeat this calculation nine more times, each time increasing the interval by one percent.
3. **Calculate domain-level average non-food share** as the weighted average of the non-food shares over the ten iterations, placing more weight on households whose food consumption is closer to the nominal cost of minimum food needs.[54] The average non-food shares are

51 The national food poverty line can equivalently be estimated directly using the national average cost per calorie.

52 Refer to Ravallion, 1994 and Deaton and Zaidi, 2002.

53 This approach is equivalent to estimating the `upper poverty line' described in Ravallion, 1994.

lowest in rural Gandaki, Karnali, and Koshi (38.4, 41, 41.6 percent, respectively) and highest in Kathmandu Valley (67.6 percent) (Table 10).

TABLE 10. Average share of non-food expenditures around the poverty line, by domain

Domain	Average non-food shares	Domain	Average non-food shares
Koshi Urban	53.0	Gandaki Rural	38.4
Koshi Rural	41.6	Lumbini Urban	54.4
Madhesh Urban	42.9	Lumbini Rural	45.5
Madhesh Rural	41.8	Karnali Urban	47.6
Kathmandu Valley Urban	67.6	Karnali Rural	41.0
Bagmati Urban(Excluding KTM Valley)	52.5	Sudurpaschim Urban	54.2
Bagmati Rural	42.3	Sudurpaschim Rural	45.8
Gandaki Urban	54.4		

4. **Derive domain-specific per capita non-food allowance: The cost of basic non-food needs is calculated** by adjusting the cost of basic food needs as Cost of basic non-food needs = $\frac{nf}{1-nf}$ * Cost of basic food needs, where nf is the average share of non-food spending. Note that this cost is a nominal per person estimate within each domain.
5. **Estimate domain-specific non-food deflator** as the ratio of the domain-specific non-food allowance to the weighted average of non-food allowances across all domains.
6. **Calculate the national non-food poverty line**: Deflate the non-food allowances using the domain-specific non-food deflator obtained in the previous step. The weighted average of these spatially adjusted non-food allowances across domains represents the national non-food poverty line.
7. **Obtain spatially adjusted per capita non-food expenditures** by adjusting the per capita non-food expenditure for domain-level price differences using the non-food deflator.
8. **Derive the real welfare aggregate** as the sum of spatially and temporally deflated food and non-food expenditures. It ranks the entire population from the poorest to the richest based

54 The average over ten intervals implicitly places more weight on individuals whose food consumption is closer to the nominal food line, as they are included a greater number of times.

on their level of consumption spending. The level of poverty in the country is determined by comparing this real welfare aggregate against the poverty line.

The national non-food poverty line in 2022-23 is set at 37,879 rupees per person.

5.3 Official 2023 Poverty Line

The official national poverty line is the sum of the national food poverty line and non-food poverty line calculated in Section 5.1 and 5.2.[55] The new official poverty line in 2022-23 is estimated at 72,908 rupees per person per year (Table 11). The 2010-11 poverty line was set at 19,261 rupees per person per year, which when adjusted for inflation over the 2010-11 to 2022-23 period, amounts to 42,845 rupees per person per year.

TABLE 11. Poverty lines (rupees per person per year, in 2022 prices)

	2010-11 Poverty lines in 2022 prices	2022-23 Official Poverty Lines
National Poverty Line	42845	72908
Food Poverty Line	26936	35029
Non-Food Poverty Line	15909	37879

Note: Refer to Annex A2 for method used to inflate the 2010-11 poverty lines to bring them to 2022 prices.

Table 12 summarizes the cost of basic needs at the domain-level, separately for food and non-food components, and the spatial price indices used to adjust nominal consumption expenditures for spatial price variation. Individuals residing in Kathmandu Valley face the highest annual cost of basic food and non-food needs at 129,934 rupees per person. In contrast, rural Madhesh face the lowest cost, at 47,344 rupees. The spatial price index ranges from 1.78 in Kathmandu Valley to 0.65 in rural Madhesh.

55 Equivalently, national poverty line is the weighted average of domain-level spatially adjusted cost of basic food and non-food needs.

TABLE 12. Cost of Basic Needs and Spatial Price Index, by analytical domain

Domain	Cost of basic needs		Spatial Price Index	
	Food	**Non-food**	**Food**	**Non-food**
Koshi Urban	34613	39015	0.99	1.03
Koshi Rural	32310	23048	0.98	0.61
Madhesh Urban	30440	22894	0.89	0.60
Madhesh Rural	27535	19809	0.85	0.52
Kathmandu Valley Urban	42160	87774	1.12	2.32
Bagmati Urban (excl. KTM Valley)	39248	43413	1.04	1.15
Bagmati Rural	37052	27120	1.05	0.72
Gandaki Urban	41954	50140	1.09	1.32
Gandaki Rural	40028	24948	1.07	0.66
Lumbini Urban	34419	41049	0.96	1.08
Lumbini Rural	33415	27886	0.93	0.74
Karnali Urban	32562	29636	1.02	0.78
Karnali Rural	32739	22766	1.10	0.60
Sudurpaschim Urban	31088	36836	0.95	0.97
Sudurpaschim Rural	30403	25714	1.01	0.68

Note: For every domain, the nominal value (no spatial adjustments) of the cost of basic needs is reported.

Poverty Incidence *and* Inequality using *the* new 2022-23 Poverty Line

Against the revised benchmark standard, an individual in Nepal is classified as poor if their annual per capita total consumption expenditure, adjusted for price differences, falls below 72,908 rupees, the new official poverty line.

20.27 percent of the population in Nepal lives below the new official poverty line (Table 13). The incidence of poverty is notably higher in rural areas (24.66 percent) than in urban areas (18.34 percent).

Two complementary measures to understand the incidence of poverty include the poverty gap and the squared poverty gap. The Poverty Gap measures the extent to which the mean income of individuals on average fall below the poverty line as a proportion of the poverty line. It ranges between 0 and 100. A Poverty Gap index of 0 indicates no one is below the poverty line, and a value of 100 indicates zero income for all individuals. Nepal has a Poverty Gap index of 4.52 percent, implying that a total of 94.71 billion rupees is needed to bring the poor up to the minimum welfare threshold defined by the new poverty line in 2022-23, assuming perfect targeting and zero leakage. The average shortfall of mean incomes is more pronounced in rural areas (5.64 percent) compared to urban areas (4.03 percent).

While the headcount index and poverty gap measure the incidence and depth of poverty, they do not account for inequality among the poor. The Squared Poverty Gap addresses this by measuring the severity of poverty, a weighted sum of the poverty gaps, giving more weight to individuals whose consumption is farther away from the poverty line. Table 15 shows that relative deprivation for the poor individuals is more severe in rural areas (1.91 percent) than in urban areas (1.29 percent).

Lastly, the Gini Index, a measure of statistical dispersion, captures the extent of consumption inequality. This index, which ranges from 0 to 1, reflects the degree of inequality in per capita consumption expenditures, adjusted for spatial and seasonal price differences. A Gini index of 0

represents perfect equality, while a value of 1 indicates perfect inequality. In 2023, Nepal's Gini index stands at 0.30, with urban areas displaying slightly higher inequality (0.303) compared to rural areas (0.287). This suggests greater disparities in per capita consumption spending in urban areas.

TABLE 13. Poverty profile of Nepal in 2022-23

Region	Headcount rate	Poverty Incidence Poverty gap (percent)	Poverty gap squared (percent)	Gini Index
National Poverty	20.27	4.52	1.48	0.3

6.1 Seasonal poverty

Poverty is considerably lower in the third (dry) season, between October and January, at 17.56 percent (Table 14). The first (winter) and the second (rainy) seasons have a higher incidence of poverty at 20.87 and 22.50 percent, respectively [56]. The low poverty during the third season also coincides with the months of the largest festivals – Dashain and Tihar.

TABLE 14. Seasonal variation in poverty, 2022-23

	Poverty Incidence		
Season	Headcount rate	Poverty gap (percent)	Poverty gap squared (percent)
Season 1 (Feb - May)	20.87	4.34	1.35
Season 2 (Jun - Sep)	22.50	5.33	1.80
Season 3 (Oct - Jan)	17.56	3.94	1.29

6.2 Poverty in Provinces and Domains under the New Federal Structure

There is significant variation in poverty incidence across Nepal's seven provinces and 15 analytical domains. Four of the seven provinces have poverty rates exceeding the national average (Ta-

56 The sample was divided across the three seasons such that it is representative of the three seasons. A household is only interviewed in one of the seasons (one to three visits to complete the interview in the 5-6 days when the team is in the location) all in the same season.

ble 15). Sudurpaschim has the highest poverty rate at 34.16 percent, followed by Karnali at 26.69 percent, Lumbini at 24.35 percent, and Madhesh at 22.53 percent. In contrast, Gandaki, Bagmati, and Koshi provinces have lower poverty rates, at 11.88, 12.59, and 17.19 percent, respectively. Provinces with higher poverty headcounts also experience greater poverty depth and severity.

TABLE 15. Provincial poverty, 2022-23

	Poverty Incidence			Distribution	
Province	Headcount rate	Poverty gap (x100)	Poverty gap squared (x100)	of the poor	of the population
Koshi	17.19	3.84	1.25	13.80	16.26
Madhesh	22.53	4.62	1.36	25.08	22.56
Bagmati	12.59	2.64	0.89	12.68	20.42
Gandaki	11.88	2.33	0.71	4.88	8.34
Lumbini	24.35	5.80	1.99	22.76	18.96
Karnali	26.69	6.25	2.16	6.74	5.12
Sudurpaschim	34.16	8.41	2.87	14.02	8.32

Rural areas exhibit higher poverty rates than urban areas within each province, except in Lumbini and Gandaki (Table 16). In Gandaki, the poverty rate is slightly higher in urban areas compared to rural areas, while in Lumbini, poverty rates are nearly the same across both rural and urban regions. Poverty rates in Bagmati Rural are higher than the national average, with a quarter of its population below the poverty line.

TABLE 16. **Poverty across analytical domains, 2022-23**

Domain	Poverty Incidence			Distribution	
	Headcount rate	Poverty gap (x100)	Poverty gap squared (x100)	of the poor	of the population
Koshi Urban	15.90	3.39	1.03	8.38	10.68
Koshi Rural	19.67	4.72	1.66	5.42	5.60
Madhesh Urban	21.71	4.30	1.21	18.02	16.84
Madhesh Rural	24.96	5.54	1.80	7.06	5.74
Kathmandu Valley Urban	7.38	1.17	0.30	3.92	10.76
Bagmati Urban (excl. KTM Valley)	14.15	2.90	0.99	4.26	6.10
Bagmati Rural	25.61	6.64	2.49	4.52	3.58
Gandaki Urban	12.63	2.61	0.85	3.56	5.70
Gandaki Rural	10.27	1.72	0.41	1.34	2.64
Lumbini Urban	24.08	6.31	2.27	13.36	11.24
Lumbini Rural	24.73	5.06	1.57	9.40	7.70
Karnali Urban	23.16	4.99	1.65	3.16	2.78
Karnali Rural	30.86	7.73	2.76	3.58	2.36
Sudurpaschim Urban	30.86	7.67	2.57	8.20	5.38
Sudurpaschim Rural	40.21	9.77	3.42	5.82	2.94

6.3 Confidence intervals, relative standard errors, and the design effects

Table 17 presents measures of sampling variability in poverty headcount estimates for Nepal in 2022-23. The 95-percent confidence interval around the national poverty headcount is relatively narrow, indicating that the poverty rate lies between 18.6 and 21.9 percent. The low relative standard error [57] (4 percent) for the national poverty rate further underscores the high reliability

57 Relative standard error of an estimate is the standard error as a percentage of the estimate itself.

of these estimates. [58]

The table also shows that relative standard errors remain below 10 percent for the three seasons and range between 10 and 20 percent across different domains, explaining the slightly wider confidence intervals observed in domain-level poverty estimates.

Additionally, Table 17 includes design effect estimates, which capture the impact of the sampling design—specifically, the two-stage stratified random sampling—on the variability of the estimates compared to what would be observed under simple random sampling. A design effect of 1 would suggest no loss of precision due to the multi-stage sampling design. While a design effect of 4 is relatively high, it is not uncommon in large-scale multi-topic household surveys, such as the Living Standards Surveys (Kinnon Scott, 2005).

TABLE 17. Confidence intervals and design effects for poverty incidence in Nepal, 2022-23

		Estimate (%)	Standard error	Relative Standard Error	[95% confidence interval]	Design effect
National Poverty Headcount	20.27	0.83	4%	18.64	21.90	4.08
Season						
Season 1	20.87	1.40	7%	18.13	23.62	3.83
Season 2	22.50	1.48	7%	19.59	25.41	3.89
Season 3	17.56	1.48	8%	14.67	20.46	4.92
Domain						
Koshi Urban	15.90	2.21	14%	11.55	20.25	3.75
Koshi Rural	19.67	2.72	14%	14.32	25.01	2.52
Madhesh Urban	21.71	2.60	12%	16.60	26.82	6.45
Madhesh Rural	24.96	2.67	11%	19.72	30.20	2.09
Kathmandu Valley Urban	7.38	1.29	17%	4.85	9.92	2.52

58 Typically, a relative standard error below 10% is considered excellent and below 25% are considered acceptable, based on the complexity of the sample design. https://www.abs.gov.au/Ausstats/abs@.nsf/7d12b0f6763c78caca257061001cc588/70fe777a715ad9c3ca2577440021d5b2!OpenDocument

Bagmati Urban (excl. KTM Valley)	14.15	2.57	18%	9.10	19.19	3.18
Bagmati Rural	25.61	3.74	15%	18.26	32.96	2.52
Gandaki Urban	12.63	2.25	18%	8.22	17.03	2.50
Gandaki Rural	10.27	1.87	18%	6.59	13.94	0.96
Lumbini Urban	24.08	3.63	15%	16.96	31.20	7.77
Lumbini Rural	24.73	2.73	11%	19.37	30.09	2.96
Karnali Urban	23.16	3.64	16%	16.02	30.30	1.98
Karnali Rural	30.86	3.45	11%	24.08	37.64	1.26
Sudurpaschim Urban	30.86	3.54	11%	23.91	37.81	3.04
Sudurpaschim Rural	40.21	3.63	9%	33.07	47.34	1.55

6.4 Food Poverty

The food poverty rate assesses deprivation relative to the food poverty line, indicating the percentage of individuals whose food spending falls below the required level to meet basic nutritional needs. In 2022-23, 18.69 percent of the population reported lower food expenditures than the minimum amount necessary to fulfill basic caloric requirements (refer to Table 18). The 95-percent confidence interval for food poverty is between 17.2 and 20.2 percent. The table also presents the incidence of food poverty across all analytical domains, ranging from 3 percent in Kathmandu Valley Urban to 41 percent in Sudurpaschim.

TABLE 18. **Incidence of food poverty in Nepal, 2022-23**

	Estimate (%)	Standard error	Relative Standard Error	[95% confidence interval]		Design effect
National Food Poverty Headcount	18.69	0.77	4%	17.18	20.19	3.72
Analytical Domains						
Koshi Urban	11.71	1.62	14%	8.53	14.90	2.61
Koshi Rural	19.80	2.29	12%	15.31	24.29	1.77
Madhesh Urban	21.89	2.69	12%	16.61	27.17	6.84
Madhesh Rural	23.51	2.55	11%	18.50	28.52	1.99
Kathmandu Valley Urban	3.01	0.75	25%	1.54	4.48	1.98
Bagmati Urban (excl. KTM Valley)	10.09	1.76	17%	6.64	13.54	1.99
Bagmati Rural	22.39	3.11	14%	16.28	28.49	1.91
Gandaki Urban	7.02	1.73	25%	3.63	10.41	2.50
Gandaki Rural	8.46	1.70	20%	5.13	11.80	0.94
Lumbini Urban	20.18	2.46	12%	15.35	25.00	4.05
Lumbini Rural	24.98	2.81	11%	19.46	30.49	3.12
Karnali Urban	25.48	3.19	13%	19.22	31.75	1.43
Karnali Rural	37.72	3.67	10%	30.52	44.91	1.29
Sudurpaschim Urban	36.03	4.61	13%	26.98	45.08	4.77
Sudurpaschim Rural	41.01	3.55	9%	34.05	47.97	1.46

6.5 Vulnerability to Shocks

Although 20.27 percent of the population is below the poverty line in 2022-23, a significant share of individuals who are just above this threshold remain vulnerable to slipping into poverty if faced with a moderate to severe negative income shock.

To assess the extent of this vulnerability, a negative shock to per capita consumption spending is simulated across the data. The shock is assumed to reduce per capita spending uniformly across

the population. A minor shock, decreasing per capita spending by one percent across the board, would increase the poverty rate by over 0.5 percentage points, pushing an additional 136,370 individuals into poverty (Table 19). On the other hand, a shock that induces a 5 percent reduction in consumption expenditures, is expected to raise the poverty rate by 3.2 percentage points. A more severe shock, with a 10 percent decrease in per capita spending, would make nearly 2 million people vulnerable to falling back into poverty. Annex Tables 24, 25, and 26 show results on the increase in incidence of poverty to these shocks at the domain-level.

TABLE 19. Vulnerability to Poverty: Negative shock to per capita consumption expenditures

	Poverty Rate (%)	[95% conf. interval]		Additional Number of Poor
1% shock	20.74	19.11	22.38	136370
5% shock	23.44	21.75	25.12	909594
10% shock	26.92	25.11	28.74	1912458

Significant Decline *in* Poverty since 2011: Poverty Trend using *the* Old Poverty Line

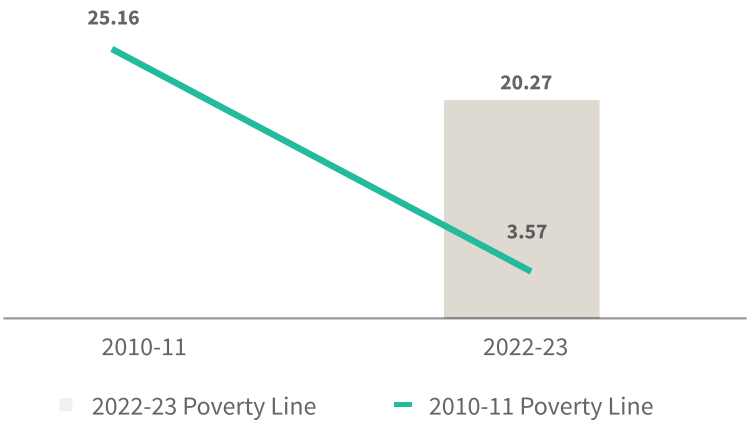
Measuring changes in poverty over time requires a consistent and comparable trend. Specifically, the old and the revised poverty lines represent two different levels of deprivation, with the revised poverty line raising the bar to set a higher minimum acceptable standard of living that is consistent with current consumption and expenditure patterns. A simple comparison, therefore, of two poverty rates based on two different poverty lines at two different points in time will be inaccurate.

For an accurate estimate of poverty reduction in the last 12 years, welfare comparisons in the two survey rounds should be made against the same minimum welfare threshold, as defined by the old poverty line in 2010-11, while replicating the construction of the 2010-11 welfare aggregate using the NLSS-IV survey.[59] Against the benchmark of 42,845 (old poverty line, in 2023 prices)[60] , poverty headcount in Nepal fell by 86 percent, from 25.16 in 2010-11 to 3.57 percent in 2022-23 (blue trend line, Figure 17). The new poverty rate, using the new national poverty line of 72,908 rupees per person per year is 20.27 percent (green bar, Figure 17). Future progress in poverty reduction will be measured using this new benchmark represented by the 2022-2023 national poverty line.

59 The Poverty Diagnostics Annex A presents technical details on the poverty estimation methodology followed in 2011 (Central Bureau of Statistics and the World Bank, 2014).

60 The method for inflating poverty lines to 2023 prices is detailed in Annex A1.

FIGURE 17. Trend in Nepal's Poverty Headcount using the 2010-11 Poverty Line



Note: For an exact comparison, the methodology to estimate per capita consumption expenditure in this graph is kept same across the two survey rounds. All statistics use sampling weights.

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Annexes

A1. 2010-11 poverty lines: The Iteration Approach

In 2022-23, we implement a one-step estimation method to construct the new official poverty lines. This approach is common and standard in poverty estimations across many countries and aligns with current best practices. In 2010-11, an iterative method was used to estimate the poverty lines as well as spatial deflators. The steps are summarized below:

Step 1: Set the minimum caloric requirement. The minimum caloric requirement was set at 2,220 kilocalories (kcal) per person per day, similar to the method described in Section 5.1.1 using an older Food composition table from 1993.

Step 2: Estimate the food poverty line at the domain-level. This entails pricing the food basket of the reference population to estimate the cost of attaining the minimum caloric requirement.

a. Select the reference population—the relatively poor—whose food consumption forms the basis for the food poverty line. In 2010-11, the 2nd to 5th decile of total consumption expenditures represented the reference population.
b. Assign a caloric value to each food item captured in the food consumption aggregate and determine the cost per kcal for each food item. 61
c. Estimate the food basket consumed (mean per capita consumption) by the reference population and rescale it such that it provides the required 2,220 kcal per person per day.
d. Determine the cost of this food basket in each of the 12 analytical domains at the time, by pricing the basket at the median prices per item in every season and domain. This cost is the domain-level food poverty line.
e. Calculate the national food poverty line as the weighted average of the domain-level food poverty lines.

Step 3: Calculate the temporal price index as the ratio of the cost of the reference group's food basket in a season to the weighted average across seasons.

61 As discussed in Section 5, a caloric value was assigned to the 40-item basket in 2010-11, to which calories could be assigned. To revert calorie intake to all items, the per capita quantities and calories for items in the bundle were rescaled by the inverse of the share of food spending on these 40 items. This assumes composition of food items in the bundle and not in the bundle is the same in terms of quantities and calories.

Step 4: Estimate the non-food and national poverty lines.

a. Estimate the non-food allowance around the food poverty line for each domain. This approach is similar to the approach explained in Section 5.2.
b. Obtain the domain-level total poverty line by dividing the domain-level food poverty line by the average share of non-food allowance around the food poverty line.
c. Determine the national poverty line as the weighted average of the domain-level poverty lines.
d. Calculate the non-food poverty line as the difference between the food and total poverty lines in each domain (and nationally).

Step 5: Derive the domain-level (spatial) price deflator (food, non-food, total) as the ratio of the domain-level poverty line to the national poverty line.

Step 6: Compute the spatially and temporally deflated per capita consumption expenditure. In the first iteration, the reference population is based on nominal per capita consumption expenditure within each domain (Step 2a). From the second iteration onward, the reference population is selected based on the deflated national per capita expenditures obtained in Step 6 of the previous iteration. The iterative process continues, with each cycle including a new estimation of the reference group, the food basket, its cost, and the price index—until the poverty lines converge. For further details on the estimation, refer to Annex A of the poverty measurement in 2010-11 (Central Bureau of Statistics and World Bank, 2014).

A2. Inflating the Old Poverty Line: Measuring Inflation across Survey Rounds

The old poverty line can be expressed in 2023 prices by accounting for inflation between the two survey years, using either (a) the Consumer Price Index (CPI) or (b) implied inflation rate using survey prices from the two NLSS rounds.

The CPI measures changes in market prices through a market price survey. In Nepal, CPI data is not linked to welfare monitoring surveys, and the latest CPI series, rebased in 2014, relies on the Household Budget Survey collected by the Nepal Rashtra Bank (not the NSO). According to CPI data, the inflation rate for food and non-food items between 2010-11 and 2022-23 is 121 percent and 117 percent, respectively (Table 20).

TABLE 20. CPI-based inflation rate between 2010-11 and 2022-23

Food inflation	121%
Non-food inflation	117%

However, the CPI tends to be biased towards urban preferences due to the location of markets, which determines the CPI weight for each item. In Nepal, the item basket and associated weights used to build the index were fixed in 2014. As consumption patterns have likely changed over the past 12 years (discussed in Section 2.6), the item weights in NLSS-IV may differ significantly from those used in CPI or even NLSS-III.

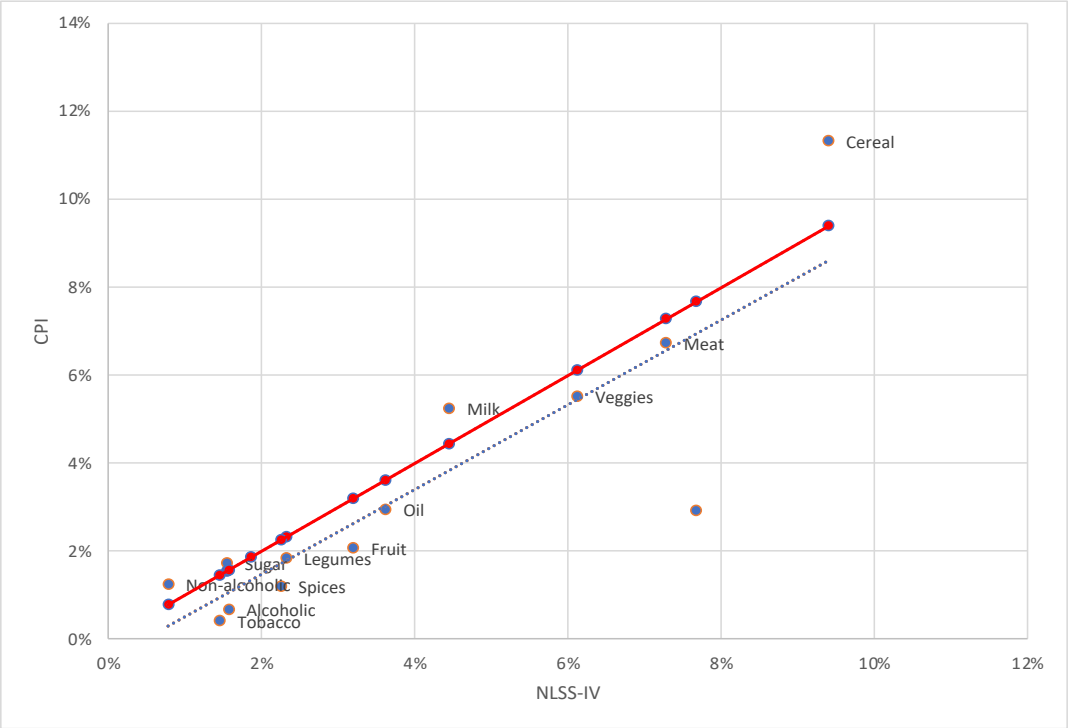
Table 21 shows the divergence in the weights used in CPI for different food groups and the weights implied by budget shares captured in NLSS-III and NLSS-IV. First, the CPI puts lesser weight on food than the two NLSS surveys. The importance of cereals in NLSS-III budgets is almost double compared to CPI, and the weight on cereals is lowest using NLSS-IV.

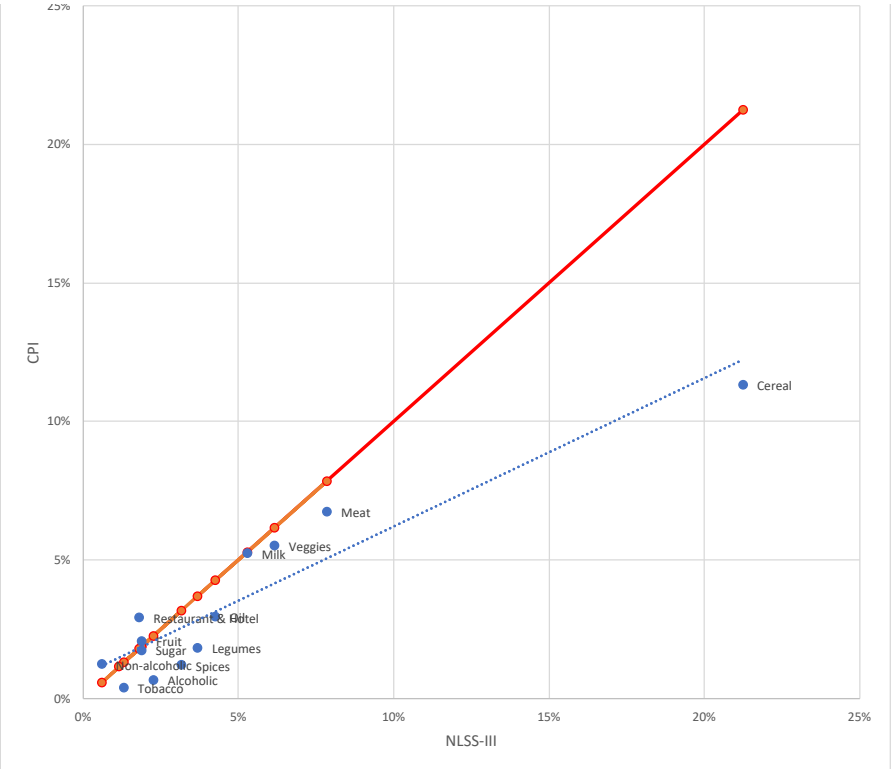
TABLE 21. Item group weights from different data sources

	CPI Weights	NLSS-III (weighted shares)	NLSS-IV (weighted)
Cereal grains and their products	11.33	21.2	9.4
Pulses and Legumes	1.84	3.7	2.3
Vegetable	5.52	6.2	6.1
Meat and Fish	6.75	7.8	7.3
Milk products and Eggs	5.24	5.3	4.4
Ghee and Oil	2.95	4.3	3.6
Fruit	2.08	1.9	3.2
Sugar and Sugar products	1.74	1.9	1.5
Spices	1.21	3.2	2.3
Non-alcoholic drinks	1.24	0.6	0.8
Alcoholic drinks	0.68	2.3	1.6
Tobacco products	0.41	1.3	1.5
Restaurant and Hotel	2.92	1.8	7.7
Prepared food	-	1.1	1.9
FOOD+TOBACCO	43.9	62.6	53.5

The divergence in item weights between CPI and NLSS surveys can be observed, with NLSS-III budget shares being farther from the other two data sets (Figure 18). While there are differences, the gap between CPI and NLSS-IV budget shares is smaller. Given the differences between CPI weights and those from the NLSS rounds, and the fact that almost a decade has passed since the CPI weights were last revised, it is more appropriate to estimate survey-based food price inflation to adjust the food poverty line using the unit values of items from household consumption recorded in NLSS-III and NLSS-IV.

FIGURE 18. Budget shares on food groups from NLSS-III, NLSS-IV, and official CPI

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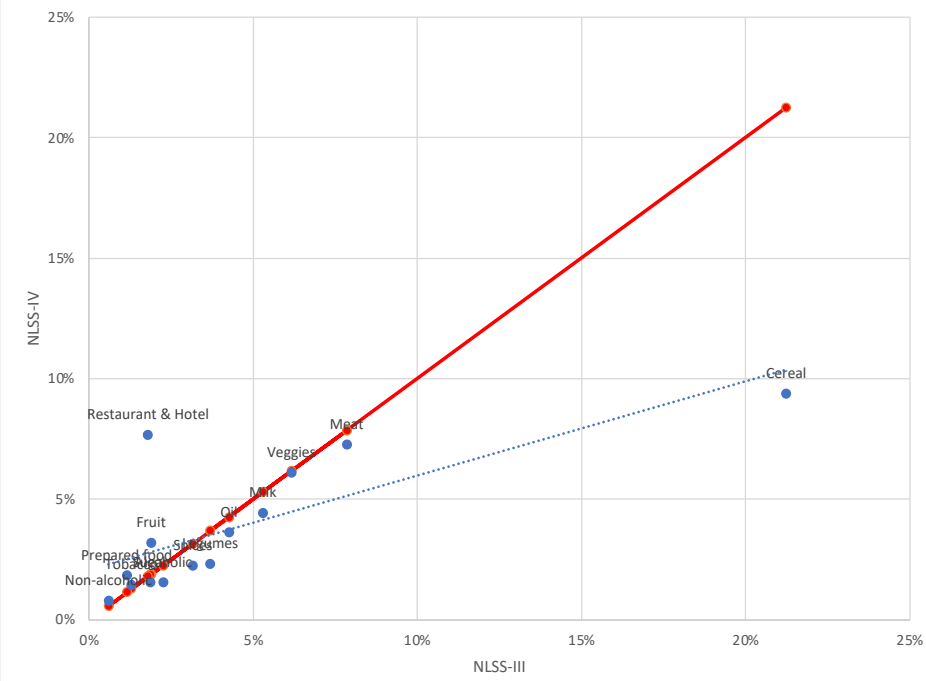
Restaurant & Hotel
Oil
Fruit
Sugar
Legumes
Non-alcoholic
Spices
Alcoholic
Tobacco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25%
NLSS-III
Cereal
Restaurant & Hotel
Meat
Veggies
Milk
Oil
Fruit
Sugar
Legumes
Prepared food
Tobacco
Alcoholic
Non-alcoholic

To estimate the survey-based food inflation, we construct a unit basket using the 40-item food basket underlying the old poverty line.[62] The weight of each item is fixed as the mean budget share (sum normalized to 1) in NLSS-III.[63] This unit basket of 40 items is priced at the median unit values for each item in both rounds of the survey. The cost of this unit basket with fixed budget shares in 2010-11 increased by 125.8 percent and is a measure of food inflation between 2010-11 and 2022-23 that can be used to inflate the old food poverty line.

Table 22 shows the survey-based food price inflation is slightly higher than the CPI-based inflation between the two rounds. Consequently, the 2010-11 food poverty line inflated from 2010-11 prices to 2022-23 prices using survey-based prices is higher.

TABLE 22. Different methods to inflate 2010-11 Food Poverty Line

2010-11 Food Poverty Line (in 2010-11 prices)		11929
Implied cost per calorie per capita per day in 2010-11		0.01485
	CPI-based inflation	Survey-based price inflation
Inflation rate	121%	125.8%
2010-11 Food Poverty Line (in 2022-23 prices)	26,368	26,937
Implied cost per calorie (in 2022-23 prices)	0.03284	0.03354

Survey-based price inflation, however, cannot be applied to the non-food dimension because unit values are not available. The 2010-11 non-food poverty line is, therefore, inflated using the CPI-based non-food inflation. The aggregate of the inflated food and non-food lines is the old poverty line expressed in 2022-23 prices. Table 23 shows that, by applying survey-based inflation for food and CPI-based inflation for non-food, the 2010-11 poverty line is 42,845 rupees in 2022-23 prices, which is only slightly higher than the line using CPI to inflate both food and nonfood components (42,277 rupees per person per year).

62 The unit basket is constructed such that the sum of mean budget shares on all items is 1.

63 The weights can also be fixed in 2022.

TABLE 23. 2010-11 poverty lines (rupees, per person per year) inflated to 2022-23 prices

	CPI-based food inflation	Survey-based food price inflation
Food poverty line	26368	26937
Non-food poverty line	15909	15909
Poverty Line	42277	42845

A3. Additional Tables

TABLE 24. Domain-level poverty incidence with a 1% shock to per capita spending

	Poverty Rate (%)	[95% conf. interval]		Additional Number of Poor
Koshi Urban	16.79	12.43	21.14	27169
Koshi Rural	20.38	14.88	25.88	11467
Madhesh Urban	21.97	16.86	27.08	12515
Madhesh Rural	25.50	20.16	30.85	8972
Kathmandu Valley Urban	7.50	4.96	10.03	3477
Bagmati Urban (excl KTM Valley)	14.36	9.34	19.39	3771
Bagmati Rural	26.01	18.57	33.45	4079
Gandaki Urban	13.28	8.68	17.87	10664
Gandaki Rural	11.39	7.75	15.03	8470
Lumbini Urban	24.54	17.35	31.73	14839
Lumbini Rural	24.93	19.51	30.35	4507
Karnali Urban	23.85	16.60	31.10	5525
Karnali Rural	31.65	24.87	38.42	5321
Sudurpaschim Urban	31.17	24.34	38.00	4806
Sudurpaschim Rural	41.49	34.31	48.67	10789

Note: Analysis assumed that the negative shock decreases per capita spending of all individuals by the same proportion.

TABLE 25. Domain-level poverty incidence with a 5% shock to per capita spending

	Poverty Rate (%)	[95% conf. interval]		Additional Number of Poor
Koshi Urban	18.05	13.43	22.67	66009
Koshi Rural	23.63	18.16	29.10	63763
Madhesh Urban	25.72	21.02	30.43	194201
Madhesh Rural	29.03	23.17	34.90	67120
Kathmandu Valley Urban	8.07	5.46	10.68	21213
Bagmati Urban (excl KTM Valley)	16.75	11.51	21.98	45497
Bagmati Rural	29.65	21.66	37.64	41508
Gandaki Urban	14.73	9.94	19.53	34561
Gandaki Rural	14.07	9.65	18.48	28754
Lumbini Urban	27.09	19.58	34.59	97051
Lumbini Rural	27.94	22.25	33.63	71140
Karnali Urban	27.57	20.23	34.92	35220
Karnali Rural	34.32	27.83	40.82	23389
Sudurpaschim Urban	36.03	27.82	44.24	80074
Sudurpaschim Rural	44.96	38.14	51.78	40092

Note: Analysis assumed that the negative shock decreases per capita spending of all individuals by the same proportion.

TABLE 26. Domain-level poverty incidence with a 10% shock to per capita spending

	Poverty Rate (%)	[95% conf. interval]		Additional Number of Poor
Koshi Urban	20.12	15.06	25.18	129426
Koshi Rural	26.85	21.15	32.55	115594
Madhesh Urban	29.81	24.76	34.86	391884
Madhesh Rural	33.95	28.09	39.80	148103
Kathmandu Valley Urban	9.75	6.85	12.64	73106
Bagmati Urban (excl KTM Valley)	19.59	14.05	25.14	95380
Bagmati Rural	33.09	24.63	41.55	76846
Gandaki Urban	16.68	11.56	21.81	66553
Gandaki Rural	17.09	12.33	21.86	51643
Lumbini Urban	31.49	23.18	39.81	239498
Lumbini Rural	32.00	26.22	37.77	160992
Karnali Urban	32.12	24.09	40.14	71454
Karnali Rural	40.52	33.54	47.50	65263
Sudurpaschim Urban	40.09	31.76	48.43	142989
Sudurpaschim Rural	50.13	43.18	57.09	83726

Note: Analysis assumed that the negative shock decreases per capita spending of all individuals by the same proportion.

TABLE 27. Depreciation rates for all durable assets, by age group

	Age group (in years)				
	0 – 1	**2 -3**	**4 - 5**	**6-10**	**10+**
Radio	0.5	0.36	0.27	0.21	0.15
Camera	0.3	0.24	0.19	0.17	0.15
Bicycle	0.52	0.32	0.24	0.18	0.15
Motorcycle / Scooter	0.27	0.21	0.18	0.15	0.13
Motor car, jeep, van, etc.	0.3	0.14	0.16	0.1	0.1
Refrigerator or Freezer	0.29	0.23	0.19	0.14	0.13
Microwave oven	0.38	0.25	0.21	0.14	0.15
Geyser (Gas / Electricity)	0.33	0.24	0.19	0.16	0.16
Washing machine	0.26	0.21	0.19	0.16	0.12
Fans	0.51	0.32	0.24	0.18	0.14
Heater (gas/kerosene/electric)	0.46	0.32	0.24	0.19	0.15
Television	0.38	0.24	0.19	0.15	0.14
Air conditioner/Cooler	0.25	0.19	0.17	0.14	0.1
Vacuum cleaner	0.47	0.29	0.21	0.17	0.14
Inverter	0.29	0.21	0.21	0.15	0.13
Solar panel (for electricity)	0.4	0.26	0.2	0.15	0.13
Solar heater	0.33	0.21	0.19	0.14	0.14
Iron	0.5	0.3	0.23	0.18	0.14
Telephone sets / Mobile phone / Tablet	0.56	0.37	0.24	0.2	0.17
Sewing machine	0.38	0.21	0.16	0.12	0.11
Computer / Printer	0.38	0.24	0.19	0.15	0.14

Note to Figure 8 applies.

TABLE 28. Coefficients from regressions of test of differences in non-monetary welfare between population deciles

		Value (5th decile) – Value (4th decile)	Value (4th decile) – Value (3rd decile)	Value (3rd decile) – Value (2nd decile)
Coefficient is the difference in value of the row variable				
HH Labor variables	Share in LF	0.00983	0.0362*	0.0415**
	Share employed among those in LF	0.0528**	-0.0159	-0.00544
Any HH income from mentioned source	wage_income	0.0128	-0.0414	-0.0112
	enterprise_own	0.0273	-0.0209	0.0819***
	ag_inc	0.0503*	-0.0189	-0.0286
Migrants (dummy variables)	remit_received	0.0455*	-0.00902	-0.0154
	abs_within_coun_tot (#)	-0.0213	0.077	0.0183
	abs_abroad_tot (avg #)	-0.304	-0.188	-0.379*
Number of items	#type_assets	0.367**	0.301**	0.382***
	#food items	1.446***	1.439***	2.085***
	#nonfood items	0.511*	0.183	0.508*
Housing Dummy	piped_inside	-0.00871	0.0767***	0.0329
	garbage	0.0417*	0.0439*	0.0463**
	electricity	0.0133	0.0213	0.00787
	internet	0.0535*	0.0502*	0.0453*
	own_house	0.0124	-0.0297*	-0.0132
	road_next_to_house	0.102***	0.0423	0.0554*

Asset Ownership Dummy	3 Bicycle	0.116***	-0.0625**	0.0026
	4 Scooter	0.0461*	0.0114	0.0792***
	5 Car/Jeep	-0.00723	-0.00295	0.00832
	6 Refrigerator	0.0450*	0.0504**	0.0459**
	9 Washing Machine	-0.00396	0.0154*	0.00868
	10 Fans (electric)	0.0708**	0.00242	0.00421
	12 Television	0.026	0.0707**	0.0656**
	13 Air Conditioner	0.00566	-0.0106*	0.00647
	21 Computer	-0.00645	0.00883*	0.00193

*Note: Every cell is a separate regression of row variable on a dummy variable with value 1 for higher decile and value 0 for lower decile (among the deciles mentioned in the respective column). The coefficient measures the difference between two deciles in the value of the row variable. The regressions include weights. Significance levels are reported at * 10% ** 5% *** 1%*

TABLE 29. Summary updates to the construction of welfare aggregate in 2022-23

	2010-11	2022-23
Food items	Use self-reported value of market purchases and home production and gifts. Meals eaten outside home a separate item on the list.	Adopt current international best practices: Outlier-correction in reported values, Value consumption from home-production and gifts at market-based unit values.
		Meals eaten outside home measured at individual-level in a separate module.

Non-food non-durable items	Include both frequent and infrequent expenditures. Infrequent items – use 12-month recall value. Frequent items – use 12-month or 30-day recall value based on whether items are regular or irregular, classified according to a rule. Utilities: Electricity, Gas, Telephone	No distinction between frequent and infrequent use items in the questionnaire Kept comparable categories to 2011 aggregate. Use 30-day or 12-month recall based on regular/irregular classification for all items. International best practice: Include a list of new expenditure items in the survey from the disaggregated lists, such as electric razors Additional utilities: Water
Consumption Flow from durables	User-cost approach to estimating consumption flow from durables. Uniform (unweighted) medians depreciation rate estimated by item at the national level.	User-cost approach to estimating consumption flow from durables. Adopt current best practices: Update formula to account for real interest rate in computing durable goods flow. Estimation of median depreciation rates on assets: •Weighted median •Median by item-age group at the national level •Drop negative depreciation rates when estimating medians.

	Use separate rental models for different regions (Kathmandu, Rural, Urban). Include domain fixed effects.	Use a national model with PSU FE's instead of separate regional models.
		Outliers identified based on a rule in the data.
	Outliers identified based on value threshold.	Weights added to the model.
Cost of housing services	Use the estimated coefficient for ownership status to adjust (by a fixed percentage) the owners' hypothetical rental values.	Use an imputed rent instead of an "adjusted rent" (self-reported rent * renter's premium) and use these values for non-renters and to replace missing values of rents.
	Use (corrected) predicted values to replace missing values.	Apply Duan's correction to transform predicted rental values into numbers.

TABLE 30. Summary updates to the poverty line methodology in 2022-23

	2010-11	2022-23
Approach	Iterative approach – iterate until the poverty line and spatial price index stabilizes	International best practice – Single-step estimation
Calorie Intake	Based on a 1990s Ministry of Agriculture caloric table.	Update to 2017 FAO food composition table in Nepal; consistent with 2017 Ministry of Agriculture itemized table.
Minimum Calorie Requirement	Computed based on the average demographic composition in NLSS-III.	Re-estimate minimum intake based on the average demographic composition (age-gender) in NLSS-IV.
Food Basket	40 food items in the food basket, for which calories were available in the 1990 calorie table ~ 78% of an average household's food spending.	Expand the list to 77 food items to which calories can be assigned. Old basket mapping to 44 items accounts for 61% of average household's food spending, and 37 new items account for 13%.
Temporal Deflator	Use within-survey food prices across seasons	Use within-survey food prices across seasons
Spatial Deflator- food	Domain-level aggregate price deflator to deflate food expenditures.	International best practice: Spatial adjustment uses household-level Paasche index to deflate food expenditures.
Spatial Deflator (aggregate / non-food)	Domain-level aggregate price deflator to deflate food expenditures.	Domain-level non-food price deflator to deflate non-food expenditures.
Reference group	Individuals in the 2nd – 5th deciles of the spatially and temporally adjusted deflated total per capita consumption expenditure.	Individuals in the 2nd – 3rd deciles of the spatially and temporally adjusted deflated food per capita consumption expenditure.