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How Well Does an Asset-Based Wealth Index Rank Households? Construction and Validation against Consumption in Bangladesh's Household Income and Expenditure Survey 2022

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Abstract

Asset-based wealth indices are the standard measure of household economic status in surveys without expenditure data, yet they are seldom built and tested inside surveys that also measure consumption well. This paper constructs a wealth index from Bangladesh's Household Income and Expenditure Survey 2022 (14,262 households) using the composite urban–rural principal component method of the Demographic and Health Surveys, and validates it against a consumption aggregate that reproduces the official national mean to within 1%. The index has a clear first component and yields steep, almost monotonic ownership gradients. Mean consumption per person rises from 4,260 taka a month in the poorest population quintile to 12,969 taka in the richest, while the food share of consumption falls from 60 to 40%. The Spearman correlation between the index and per-capita consumption is 0.61 (0.49 rural, 0.66 urban), and 76% of the population is placed in the same or an adjacent quintile by both measures. Household rankings barely change when survey weights, item imputation, multiple correspondence analysis or an alternative coding of categories are used (rank correlations 0.98 to 1.00), whereas an equal-weight count of durable goods performs worse. The paper also shows that the low Kaiser–Meyer–Olkin values often seen for such indices come from the full-dummy coding of housing variables rather than from weak common structure, and it documents a mistranslated questionnaire item that would otherwise distort the index. The index is a sound relative measure of long-run economic status in Bangladesh, but it ranks rural households less precisely.

Keywords Wealth index · Asset index · Principal component analysis · Consumption · Socioeconomic status · Bangladesh

1 Introduction

Since Filmer and Pritchett (2001) showed that the first principal component of a list of household assets could stand in for consumption, asset-based wealth indices have become the default measure of economic status in population and health research. The Demographic and Health Surveys (DHS) programme publishes one for every survey it runs (Rutstein & Johnson, 2004), and thousands of studies report outcomes by "wealth quintile" without any information on income or spending. In Bangladesh, as in most low- and middle-income

countries, most of what is known about socioeconomic gradients in child health, fertility and service use comes from such quintiles (NIPORT & ICF, 2024).

The method rests on an assumption that is rarely tested where it is applied: that the common factor behind ownership of many different goods is household wealth, and that a ranking on this factor agrees reasonably well with a ranking on consumption. Tests require a survey that collects both assets and a full consumption module. Howe et al. (2009) found 36 such datasets in a systematic review; agreement was weak in 22 of them. Filmer and Scott (2012) showed that conclusions about inequality in education and health care are fairly robust to the choice of measure, even though individual households are often ranked differently. The question is therefore not settled in general and has to be answered survey by survey.

Expenditure surveys offer the best setting for that test, but they are seldom used for it. Bangladesh's Household Income and Expenditure Survey (HIES) 2022 is the official source for poverty statistics. It records a 14-day food diary, monthly and annual non-food spending, detailed housing characteristics and ownership of 43 durable goods for more than 14,000 households (Bangladesh Bureau of Statistics [BBS], 2023). This makes it possible to build an asset index with exactly the method used by the DHS and to judge it against a consumption aggregate measured in the same households.

This paper does four things. First, it constructs a DHS composite wealth index from HIES 2022 and documents every construction choice, including two that are specific to this survey: a durable-goods item whose English label does not match the Bangla questionnaire, and the absence of piped water in rural records. Second, it validates the index internally, through ownership gradients, and externally, against consumption, food shares and education. Third, it rebuilds the index in seven other ways to see which choices matter for household rankings. Fourth, it explains why the Kaiser–Meyer–Olkin (KMO) measure, often reported as a test of whether the data suit principal component analysis (PCA), is misleadingly low under the standard DHS coding.

The results support the use of the index as a relative measure of long-run economic status, with one qualification: it is less precise for rural households, among whom ownership of the listed goods varies less. Section 2 reviews the literature. Section 3 describes the data and methods, Section 4 presents results, and Section 5 discusses what they imply for users of wealth quintiles.

2 Background

2.1 Asset indices and the DHS method

Using possessions as a proxy for living standards predates the PCA approach. Montgomery et al. (2000) tested simple asset and housing indicators against consumption in Living Standards

Measurement Study surveys and concluded that they were useful for ranking groups but weak predictors of any single household's consumption. Filmer and Pritchett (2001) gave the method its standard form. They took the first principal component of 21 asset and housing indicators from the Indian National Family Health Survey, showed that ownership of each item rose across the index, and checked it against consumption in surveys that had both. Their finding that the index ranked households about as well as consumption for explaining school enrolment explains much of its later spread. Sahn and Stifel (2000, 2003) used factor analysis on similar data and found that asset indices predicted child nutrition at least as well as expenditure.

Rutstein and Johnson (2004) set out the DHS Wealth Index. Each categorical question is broken into a full set of dummy variables, crowding enters as a continuous variable, the first principal component is the score, and quintiles are cut so that each holds one fifth of the household population. The index was soon criticised for an urban bias. Piped water, flush toilets and gas are close to universal in towns and rare in villages, so a single national PCA largely separates urban from rural households and says little about relative position within rural areas. Rutstein (2008) proposed the composite method now used in all DHS reports. Separate urban and rural indices are estimated with the items relevant to each area, including land and livestock in rural areas, and both are mapped onto a national index built from items common to the two areas. Rutstein and Staveteig (2014) later proposed adjustments for comparison across countries.

2.2 Construction choices

Vyas and Kumaranayake (2006) warn against clumping, where many households share a score because the list of items is short, and truncation, where the index cannot distinguish households at one end of the distribution. McKenzie (2005) showed that the choice of items matters most when the index is used to measure inequality. Howe et al. (2008) reviewed the decisions involved (which items to include, how to code them, whether to separate urban and rural areas, how to handle missing data) and concluded that they should be reported and tested because none is correct in every setting. Poirier et al. (2020) reached a similar conclusion in a review of approaches and alternatives to the wealth index published in this journal.

Another line of work questions the use of PCA on binary data. Kolenikov and Angeles (2009) showed by simulation that ordinary PCA on dummies loses information and proposed polychoric PCA, although in their own applications the ordinary and polychoric indices were highly correlated. Multiple correspondence analysis (MCA), designed for categorical data, has also been used (Booysen et al., 2008). Smits and Steendijk (2015) proposed the International Wealth Index, which applies fixed weights estimated from a large pool of

surveys so that scores can be compared across countries; it requires a fixed list of items that includes floor material.

2.3 Agreement with consumption

Agreement between asset indices and consumption is usually modest, partly because the two measure different things: a stock accumulated over years and a flow observed over days or weeks. In the review by Howe et al. (2009), agreement was weak in 22 of 36 datasets, moderate in 10 and strong in 4, and there was some evidence that it was better in urban areas, in middle-income settings and where the index used more and more varied indicators. Filmer and Scott (2012) showed that agreement is higher where per-capita expenditure is well predicted by household characteristics and carries little transitory noise, and lower where spending is dominated by private goods such as food. Houweling et al. (2003) and Lindelow (2006) showed that the measured size of health inequalities can depend on which welfare measure is used. Taken together, these studies suggest that an asset index should be evaluated against the questions it is used to answer, and that its agreement with consumption should be expected to vary with the setting.

3 Data and Methods

3.1 Data

HIES 2022 was conducted by the Bangladesh Bureau of Statistics throughout 2022 using a stratified two-stage design with 720 primary sampling units and 14,395 households, 7,199 rural and 7,196 urban (BBS, 2023). Urban areas are oversampled relative to their population share, so every estimate here is weighted. The household weight is used in the PCA and for household-level statistics. The population weight, equal to the household weight multiplied by household size, is used to form quintiles and for statements about people.

Indicators come from the housing module, the durable goods module, the land, livestock and farm equipment modules, and the member roster. A household is scored if it has both the housing and the durable goods modules; 14,262 households (99.1%) meet this condition. Of the remaining 133, 56 have neither module, 8 lack housing data and 69 lack durable goods data. These households are left unscored rather than given values that would be largely imputed.

3.2 Indicators

The aim was to include every item in the questionnaire that reflects the household's material standard of living and to exclude outcomes, behaviours and self-reported money values. Table 1 lists the 83 indicators. Following Rutstein and Johnson (2004), categorical questions are coded as one dummy per category, so the data decide the relative position of, for example, a flush toilet draining into a pit and a pit latrine with a slab. Crowding is measured

as household members per room, top-coded at the 99th percentile (five persons). Agricultural land is grouped at 0.5 acres, a common threshold for functional landlessness, and at 2.5 acres, which separates small from medium farms in Bangladesh's agricultural census.

Table 1 Indicators used in the wealth index

Domain	Indicators (number of variables)	Coding
Dwelling	Wall material (5); roof material (4)	Dummy per category
Sanitation	Toilet type (7 groups); toilet shared with other households (1)	Dummy per group
Drinking water	Main source (7 groups)	Dummy per group
Energy	Electricity as main light source (1); cooking fuel (6)	Dummies
Space	Members per room (1); separate kitchen (1); separate dining room (1)	Continuous; dummies
Communication	Landline telephone (1); computer, laptop or tablet (1)	Dummies
Durable goods	36 items, from bedstead and fan to air conditioner and washing machine	Owns (1/0)
Finance	Any household member has a bank account (1)	Dummy
Land	Agricultural land owned in three size classes (3); homestead land (1)	Dummies
Livestock	Cattle or buffalo; goats or sheep; chickens or ducks (3)	Owns any (1/0)
Machinery	Motorised or capital farm equipment (1)	Owns any (1/0)

Land, livestock and machinery enter the area-specific indices only (Section 3.3). The full list with weighted means and loadings is in Supplementary File 1

Five exclusions are worth stating because each changes the index. Item 1034 in the durable goods module is printed as "motor car" in the English questionnaire, but the Bangla questionnaire, which enumerators used, reads "motor etc."[1] About 5% of households report owning one, far above any plausible rate of car ownership in Bangladesh, and the reported resale value settles the question: the median is 4,000 taka and the 75th percentile 9,000 taka, against a median of 80,000 taka for motorcycles. The item records electric motors and similar equipment, and treating it as a car would give a large positive weight to a cheap pump motor. Kitchenware and crockery are owned by more than 95% of households and are too general to be informative. Desktop and laptop computers are combined with the housing module's question on computer ownership into a single indicator so that one possession is not counted three times. House tenure is excluded because owning the dwelling is typical of poor rural households and renting is common among well-off urban ones. Self-reported money values of the dwelling, land and financial assets are excluded because they measure wealth directly and with large reporting error, which is a different exercise from a proxy index. Floor material, a standard DHS item, is not collected in HIES 2022.

3.3 Estimation

For a set of K indicators, PCA is applied to the correlation matrix weighted by the household weight. The score of household i is the first principal component,

[1]The Bangla wording is “মোটর ইত্যাদি” (motor, etc.). Resale values are from the same module (question 3, value if sold today).

$$W_i = \sum_{k=1}^{K} a_k \frac{x_{ik} - \bar{x}_k}{s_k} \tag{1}$$

where $\bar{x}_k$ and s_k are the weighted mean and standard deviation of indicator *k*, and a_k is the *k*-th element of the first eigenvector. Because the sign of an eigenvector is arbitrary, each component is oriented so that owning a refrigerator raises the score, and each score is standardised to a weighted mean of zero and a standard deviation of one.

The composite index follows Rutstein (2008). A rural PCA uses all indicators that vary among rural households (81; no rural household reports piped water into the dwelling or yard). An urban PCA uses all 83. A common PCA on all households uses the housing, durable goods and financial indicators whose loadings have the same sign in the rural and urban PCAs; nine indicators fail this test and are left out of the common index.[2] Land, livestock and machinery are excluded from the common index by design because they are not a store of wealth for most urban households, leaving 66 common indicators. Within each area, the common score is then regressed on the area-specific score,

$$W_i^{\text{common}} = \alpha_{\text{area}} + \beta_{\text{area}} W_i^{\text{area}} + e_i \tag{2}$$

and the fitted value is the household's composite wealth score. The composite ranks households within each area by the area-specific index, which uses all information relevant to that area, while placing urban and rural households on one national scale.

Item non-response is small. No housing indicator is missing among scored households, durable goods are missing for between 1 and 36 households per item, and land for 60. Missing values are replaced by the weighted mean of the household's area. After standardisation such a value equals zero, so it neither raises nor lowers the score. Only 98 households have any imputed value. Quintiles and deciles are cut on the composite score with the population weight, so that each quintile contains 20% of the population, as in the DHS.

3.4 Validation and robustness

Validation follows Filmer and Pritchett (2001). Internal coherence is assessed by ownership of each item across quintiles. External validity is assessed against three measures that are not in the index: consumption per person, the food share of consumption and education. Consumption is aggregated from the survey's expenditure modules: food from the daily and weekly diaries, annualised by the number of days and weeks each household actually recorded, plus monthly and annual non-food spending including actual and imputed rent, with

[2] Wooden walls, flush toilet to pit, flush toilet to open drain, water from a neighbour's pipe or public tap, tubewell water, dress stand, feature phone, solar panel and own tubewell. In eight of the nine, at least one of the two loadings is below 0.04 in absolute value. The exception is owning a tubewell, which marks a better-off household in villages and the lack of a piped supply in towns.

purchases of durable goods excluded. The resulting mean is 30,823 taka per household per month (rural 26,302, urban 40,444), compared with 30,603 (26,207 and 39,971) in the official report (BBS, 2023), a difference of 0.7% at the national level. Seven households have no food diary; the four of them that have a wealth score are excluded from the comparison. Agreement is summarised by Spearman rank correlations, the share of the population placed in the same and in adjacent quintiles, and Cohen's kappa, unweighted and with linear weights. Education is measured by whether the household head has passed the Secondary School Certificate (SSC) and whether children aged 6 to 15 are attending school.

To test sensitivity, the index is rebuilt in seven ways: (R1) the composite without survey weights; (R2) the common-indicator PCA alone; (R3) a single national PCA on all 83 indicators; (R4) MCA on the same items, with crowding grouped into four classes; (R5) an unweighted count of durable goods; (R6) the composite estimated only on the 14,164 households with no imputed item; and (R7) the composite with one reference category dropped from each set of housing dummies. Each version is compared with the main index and with consumption.

3.5 Software and use of generative AI

All estimates were produced in Stata 16.1 using only built-in commands. The do-files that reproduce every table and figure from the raw survey files are provided as Supplementary File 2. An AI assistant (Claude, Anthropic) was used to help draft the Stata code and the text. The author checked the code against the questionnaire, ran all analyses, verified every reported number against the Stata logs, and takes full responsibility for the content.

4 Results

4.1 Principal components and sampling adequacy

Table 2 summarises the three PCAs. The first component explains 8.5% of the variance in the rural PCA, 13.4% in the urban and 14.6% in the common PCA. These shares are typical of indices built from many binary indicators, each of which carries a large amount of variance unrelated to any common factor. What matters for an index is that the first component stands clearly apart from the next: its eigenvalue is 2.3 times the second in the rural PCA, 2.2 times in the urban and 3.0 times in the common PCA.

Table 2 Eigenvalues and sampling adequacy of the principal component analyses

PCA	Indicators	λ1	Variance explained (%)	λ2	λ1/λ2	KMO, full dummies	KMO, reference category dropped
Rural	81	6.87	8.5	2.98	2.3	0.34	0.84
Urban	83	11.12	13.4	5.04	2.2	0.54	0.89
Common	66	9.61	14.6	3.22	3.0	0.64	0.91

λ1, λ2 first and second eigenvalues; KMO Kaiser–Meyer–Olkin measure of sampling adequacy. The last column refers to robustness version R7, which drops one reference category from each set of housing dummies

Under the standard DHS coding the overall KMO values are low: 0.34 in the rural PCA, 0.54 in the urban and 0.64 in the common PCA. By the usual rule of thumb a value below 0.5 would be taken to mean that the data are unsuitable for PCA. That reading would be wrong here. KMO compares simple with partial correlations, and when the categories of a question are coded as a full set of dummies they sum to almost exactly one, which drives their partial correlations towards −1. Housing dummies have item-level KMO values between 0.01 and 0.42 in the rural PCA, while most durable goods, which carry no such constraint, lie between 0.70 and 0.95. Dropping one reference category from each housing set raises the overall KMO to 0.84, 0.89 and 0.91, yet leaves household rankings almost unchanged (Section 4.6). The low values describe the coding, not the strength of the common factor.

4.2 Weights and the composite score

Table 3 lists the indicators with the largest positive and negative loadings in the common index. The positive end describes an affluent household: a sofa, a concrete roof, a computer, a WiFi router, brick walls and a refrigerator. The negative end describes a poor rural one: a tin roof and tin walls, a pit latrine, wood or crop residue as cooking fuel, and crowding. The last two columns express the loadings as score changes. Rare goods move the score most for those who own them (an air conditioner adds 1.13 standard deviations), while near-universal items mainly penalise those without them (no electricity subtracts 0.31).

Table 3 Largest and smallest loadings in the common index

Indicator	Households (%)	Loading	Score if yes	Score if no
Sofa set or divan	18.0	0.221	0.47	-0.10
Roof: brick or cement	22.3	0.218	0.41	-0.12
Computer, laptop or tablet	9.5	0.199	0.61	-0.06
WiFi router	8.9	0.196	0.63	-0.06
Walls: brick or cement	47.9	0.190	0.20	-0.18
Tea trolley or table	18.1	0.189	0.40	-0.09
Refrigerator or freezer	53.5	0.188	0.18	-0.20
Wardrobe	37.9	0.188	0.24	-0.15
Roof: tin (CI sheet)	76.0	-0.206	-0.12	0.37
Walls: tin (CI sheet)	41.3	-0.150	-0.18	0.13
Toilet: pit with slab, VIP, composting	53.3	-0.132	-0.12	0.14
Cooking fuel: wood or charcoal	53.0	-0.106	-0.10	0.11
Members per room (continuous)	1.87	-0.090	–	–
Toilet shared with other households	24.5	-0.071	-0.13	0.04

Score if yes/no = loading × (1 − mean)/SD and loading × (0 − mean)/SD, in standard deviations of the common score. Members per room is continuous; its mean is shown in persons

Land and livestock behave as expected in the area-specific indices. In the rural PCA, owning 0.5 to 2.5 acres of farmland loads at 0.095 and 2.5 acres or more at 0.081. Livestock loads close to zero in rural areas and negatively in urban areas (−0.04 to −0.07), where keeping

animals marks the urban fringe rather than wealth. A single national PCA would have to assign one sign to these items, which is the case for the composite method.

The area scores explain 98.0% of the variance of the common score among rural households and 99.2% among urban households (Equation 2; rural $\alpha = -0.304$, $\beta = 0.669$; urban $\alpha = 0.648$, $\beta = 1.236$). The higher intercept and steeper slope for urban households shift their distribution to the right and spread it out. The composite correlates 0.995 with the common score, and the regression of one on the other has a slope of 0.99 and a constant of zero, so the composite keeps the level and dispersion of the national index and only re-orders households within each area, as Rutstein (2008) reports for the DHS.

4.3 Distribution

Figure 1 shows the distribution of the composite score. Rural households are concentrated below zero with a long, thin right tail. Urban households are spread over the whole range, with a second concentration near the top. The quintile cut-offs (−0.75, −0.39, 0.03 and 0.72) are well separated, and there is no sign of clumping.



Fig. 1 Distribution of the wealth index score among rural and urban households, HIES 2022. Kernel densities weighted by household weights

Table 4 Population by wealth quintile, area of residence and division (row %)

	Poorest	Second	Middle	Fourth	Richest
Rural	25.1	23.8	22.5	18.7	9.8
Urban	8.8	11.6	14.5	22.8	42.3
Mymensingh	33.5	22.3	22.4	14.7	7.1

	Poorest	Second	Middle	Fourth	Richest
Barishal	31.6	25.6	20.0	12.3	10.5
Rangpur	30.1	26.6	18.9	14.6	9.7
Sylhet	23.1	21.7	19.6	17.8	17.8
Rajshahi	23.0	21.7	21.3	20.7	13.2
Chattogram	18.6	18.0	18.9	21.2	23.3
Khulna	17.9	20.0	21.3	22.2	18.6
Dhaka	10.1	16.1	19.6	23.4	30.7

Weighted by the population weight. Divisions are ordered by the share of the population in the poorest quintile

Table 4 shows the population in each quintile by area and division. A quarter of the rural population is in the poorest quintile, against fewer than one in ten urban residents, and 42.3% of urban residents are in the richest quintile. A third of the population of Mymensingh, Barishal and Rangpur divisions is in the poorest quintile, against one in ten in Dhaka division. This ordering broadly matches the regional pattern in official poverty statistics (BBS, 2023) and in the BDHS (NIPORT & ICF, 2024).

4.4 Internal coherence

If the index measures wealth, ownership of wealth-related items should rise across quintiles and the prevalence of poverty markers should fall. Figure 2 shows that this holds for the main items. Refrigerator ownership rises from 6% in the poorest quintile to 98% in the richest, brick or cement walls from 8% to 96%, and television from 14% to 88%. Computer ownership stays close to zero in the bottom three quintiles and reaches 42% in the richest, which shows that the index separates households at the top. Cooking with wood and using a pit latrine change little across the three poorest quintiles and then fall sharply. The full table for all indicators is in Supplementary File 1. Two items depart from a monotonic pattern for clear reasons: feature phones are owned by more than 80% of households in every quintile because richer households keep them alongside smartphones, and bicycle ownership peaks in the middle quintile and falls at the top, where motorcycles replace it.

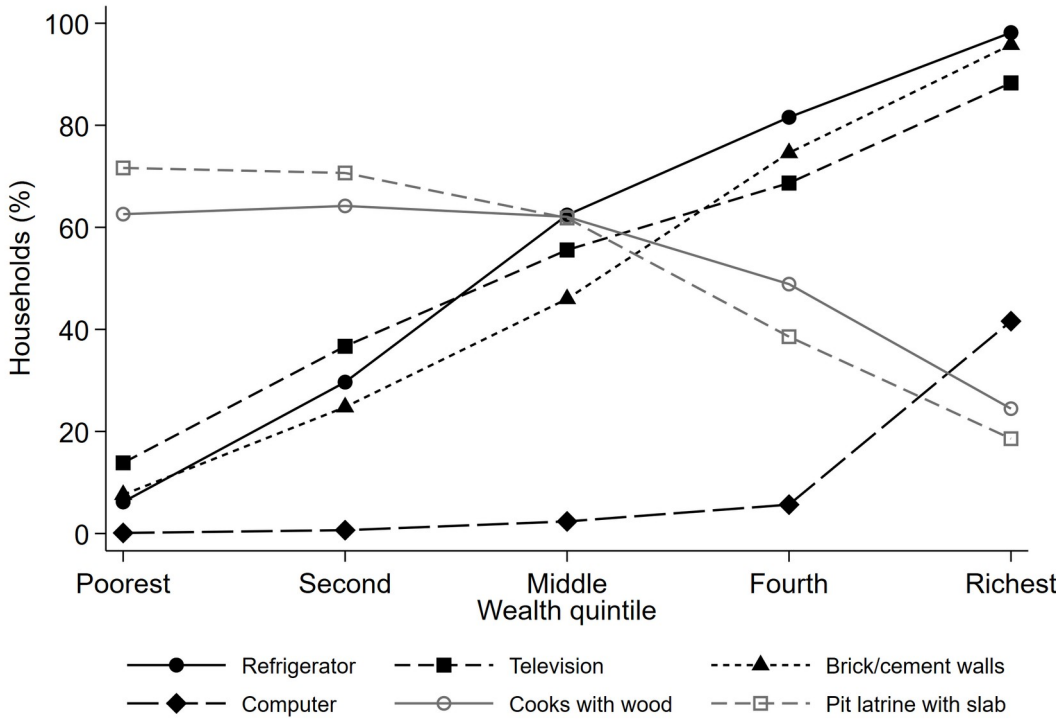


Fig. 2 Ownership of selected items by wealth quintile, HIES 2022. Percentages of households, weighted by household weights

4.5 Consumption and education

Table 5 reports the external validation. Mean consumption per person rises at every step, from 4,260 taka per month in the poorest quintile to 12,969 in the richest, a ratio of 3.0. The food share falls from 59.6% to 40.4%: Engel's law appears in a ranking constructed without any information on food spending. Figure 3 shows the same pattern by decile. Consumption per person rises in every decile, from 4,068 to 16,675 taka, and the food share declines from 61.8% to 35.9%. The share of household heads with SSC or higher rises from 4.6% to 60.8%, and school attendance among children aged 6 to 15 from 83.7% to 96.0%.

Table 5 Consumption and education by wealth quintile

	Poorest	Second	Middle	Fourth	Richest
Consumption per person, mean (taka/month)	4,260	5,285	6,178	7,608	12,969
Consumption per person, median (taka/month)	3,815	4,753	5,396	6,786	9,933
Food share of consumption (%)	59.6	54.9	51.7	48.3	40.4
Household head passed SSC or higher (%)	4.6	9.2	17.1	27.6	60.8
Children 6–15 attending school (%)	83.7	87.2	91.3	92.5	96.0
Urban share of population (%)	13.9	18.2	22.7	35.7	66.4

Consumption rows and urban share weighted by population weights; education rows by household weights. SSC Secondary School Certificate

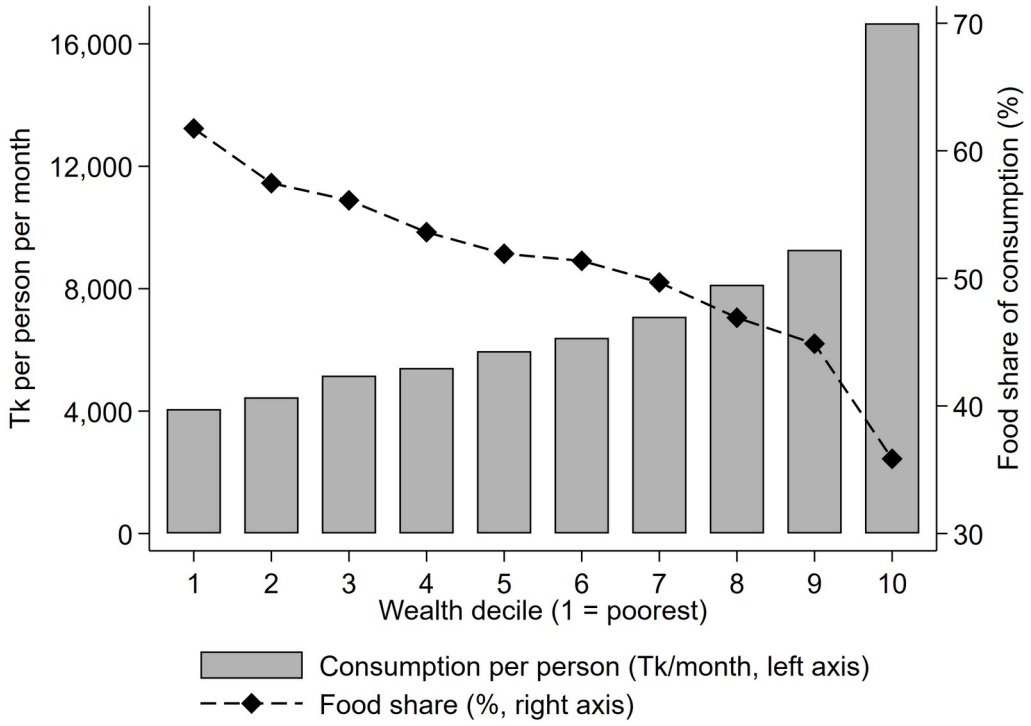


Fig. 3 Consumption per person and food share of consumption by wealth decile, HIES 2022. Means weighted by population weights

Table 6 summarises agreement at the household level. The Spearman correlation between the index and consumption per person is 0.61, and the Pearson correlation with log consumption is 0.67. Agreement is clearly weaker among rural households (0.49) than among urban households (0.66). 37.2% of the population is in the same quintile under both measures and 76.4% in the same or an adjacent one. Gross misclassification is rare. Only 0.9% of the people in the richest wealth quintile are in the poorest consumption quintile, and 3.1% of the people in the poorest wealth quintile are in the richest consumption quintile (Supplementary File 1).

Table 6 Agreement between the wealth index and consumption per person

Measure	Value
Spearman correlation, all households	0.606
Spearman correlation, rural households	0.491
Spearman correlation, urban households	0.664
Rank correlation, population-weighted	0.610
Pearson correlation with log consumption per person	0.666
Same quintile (% of population)	37.2
Same or adjacent quintile (% of population)	76.4
Cohen's kappa	0.218
Cohen's kappa, linear weights	0.417
Poorest consumption quintile also in poorest wealth quintile (%)	47.8
Richest consumption quintile also in richest wealth quintile (%)	56.1

N = 14,258 scored households with a consumption measure (7,138 rural, 7,120 urban). Quintile shares weighted by population weights; kappa statistics computed on unweighted observations

4.6 Robustness

Table 7 compares the seven alternative indices with the main index. The program that builds them first reconstructs the main index and reproduces it to six decimal places, so differences reflect only the choice being tested. Three groups emerge. Survey weights and the treatment of missing items make no practical difference: R1 and R6 place 97.7% and 99.8% of the population in the same quintile as the main index. The method of aggregation matters little: the common index alone (R2), MCA (R4) and the version with reference categories dropped (R7) correlate at 0.985 or more with the main index and keep more than 99.9% of the population within one quintile. All PCA- and MCA-based versions correlate with consumption between 0.60 and 0.61. Equal weighting performs worse: the count of durable goods (R5) correlates 0.87 with the main index and only 0.53 with consumption, because it treats a fan and an air conditioner as equal.

Table 7 Alternative constructions compared with the main index

Version	Spearman with main index	Same quintile (%)	Within one quintile (%)	Weighted kappa	Spearman with consumption
Main: DHS composite	1.000	100.0	100.0	1.000	0.606
R1 Composite: unweighted PCA	0.999	97.7	100.0	0.982	0.608
R2 Common-indicator PCA only	0.993	88.0	100.0	0.927	0.606
R3 Single national PCA, all indicators	0.980	78.3	99.9	0.881	0.603
R4 MCA, first dimension	0.987	82.4	100.0	0.904	0.607
R5 Count of durable goods	0.874	56.7	93.5	0.694	0.528
R6 Composite: complete cases only	1.000	99.8	100.0	0.999	0.606
R7 Composite: one reference category per housing set	0.985	84.2	100.0	0.902	0.603

R6 uses the 14,164 households with no imputed item; all other versions use 14,262. Quintile shares weighted by population weights; kappa with linear agreement weights

The single national PCA (R3) is also close to the main index overall (0.98), but it shifts households in the direction Rutstein (2008) warned about. Urban residents make up 9.0% of the poorest quintile under R3 against 13.9% under the composite, and 69.5% of the richest quintile against 66.4%. Without the area-specific step, poor urban households look less poor and well-off rural households look less well off.

5 Discussion

The HIES 2022 wealth index passes the tests that matter for its use as a measure of relative economic status. The first component is distinct, ownership gradients are steep, and the index orders households by consumption, food share and education in the expected direction at every step. Its correlation with consumption (0.61) indicates moderate agreement. That is

better than most datasets in the review by Howe et al. (2009), probably helped by the long list of durable goods in HIES. As in that review, agreement is better in urban areas.

The weaker rural agreement deserves attention because rural households are where most poverty in Bangladesh is found. Two explanations fit the evidence. First, many rural households share the same tin house, pit latrine, tubewell and wood stove and own few of the listed goods. The rural PCA therefore has less variation to work with, as its lower explained variance shows. Second, rural consumption depends more on harvest timing and own production, so a two-week diary captures more transitory variation, which Filmer and Scott (2012) identify as a main source of disagreement. The first problem lies with the index and the second with consumption. Both point to the same practical advice: analyses that focus on gradients within rural areas should report results under both measures.

Two findings have implications beyond Bangladesh. The first concerns the KMO statistic. Studies often report KMO values to justify PCA, and reviewers sometimes treat values below 0.5 as disqualifying. Under the DHS full-dummy coding, a low KMO is largely mechanical. In this survey, dropping one category per housing question raised the overall value from 0.34 to 0.84 in the rural PCA while the ranking barely moved. Researchers who report KMO for a wealth index should state how categorical variables were coded, and reviewers should not read a low value under full-dummy coding as evidence against the index. The second concerns questionnaire checking. A single mistranslated item, with 5% prevalence, would have given an apparent car to thousands of households that own an electric motor. Comparing reported resale values across items is a cheap check that should be routine when an asset list is used for the first time.

The robustness results agree with earlier work. Rankings are much less sensitive to the aggregation method (PCA, MCA, weighted or unweighted) than to the set of items and the way urban and rural households are combined (Howe et al., 2008; Kolenikov & Angeles, 2009). Unweighted asset counts, still used in applied work for their simplicity, lose a substantial part of the information in the data.

The study has limitations. The index is relative to this survey, so its scores cannot be compared directly with those from other years or countries; the International Wealth Index (Smits & Steendijk, 2015) cannot be built because floor material is not recorded. Piped water into the dwelling or yard is never recorded for rural households, which limits the rural index. Polychoric PCA was not estimated because it requires user-written software, although MCA, which addresses the same concern, gave nearly identical rankings. Finally, when an outcome of interest is itself an index item, such as sanitation or cooking fuel, that item should be removed and the index rebuilt; the code in Supplementary File 2 allows this.

6 Conclusion

An asset-based wealth index built from Bangladesh's HIES 2022 with the DHS composite method ranks households in close accordance with ownership patterns and in moderate agreement with consumption, more strongly in urban than in rural areas. The ranking is robust to weighting, missing data and the choice between PCA and MCA, but not to replacing estimated weights with a simple count. The index offers a stable measure of long-run economic status that can be compared directly with the wealth quintiles reported in the BDHS, and it complements the consumption aggregate rather than replacing it. The two practical lessons, that low KMO values under full-dummy coding are not evidence against an index and that asset items should be checked against their reported values, apply to any survey in which such an index is built.

Declarations

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Competing interests The author has no relevant financial or non-financial interests to disclose.

Author contributions Atikur Rahman is the sole author and was responsible for conceptualization, methodology, data curation, formal analysis, software, validation, visualization, and writing (original draft, review and editing).

Data availability The study uses the household-level microdata of the Household Income and Expenditure Survey 2022, produced and owned by the Bangladesh Bureau of Statistics (BBS). These data are not publicly redistributable; researchers can request them from BBS. The complete Stata code that reproduces every table and figure from the BBS files is provided as Supplementary File 2. The household-level wealth index scores can be shared by the author on reasonable request with researchers who hold access to the HIES 2022 microdata.

Ethics approval This is a secondary analysis of anonymised survey microdata collected by the Bangladesh Bureau of Statistics. The author had no contact with survey participants and no access to identifying information, so no ethics approval was required for this analysis.

Consent to participate Not applicable to this secondary analysis. Data collection, including respondents' participation, was carried out by the Bangladesh Bureau of Statistics.

Use of generative AI An AI assistant (Claude, Anthropic) was used to help draft the Stata code and the text. The author checked the code against the survey questionnaire, ran all analyses, verified every reported number against the Stata output, and takes full responsibility for the content (see Section 3.5).

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Supplementary Files

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