Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Multidimensional poverty among rural adults in China: regional disparities and measurement sensitivity in the 2020 and 2022 CFPS waves

Liyang Wan
Qingdao University of Technology
Cui Wang
Qingdao Hengxing University of Science and Technology
Xueli Jiang
jiangxueli@stu.qut.edu.cn

Qingdao University of Technology
Feifei Zhang
Qingdao University of Technology

Article

Keywords: multidimensional poverty, rural China, China Family Panel Studies, education, household energy, social protection, regional inequality, measurement sensitivity

Posted Date: November 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11173816/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

China's transition beyond extreme-poverty eradication raises a measurement-governance question: which disadvantages still overlap among rural adults, and who becomes visible when poverty is defined beyond income alone? This study analyses 7,717 adults in the 2022 China Family Panel Studies (CFPS) and reconstruct the same five-dimension Alkire-Foster index among 8,754 adults in 2020. At k = 1/3, survey-weighted poverty incidence was 35.39% in 2022 and 37.00% in 2020. The relative-income and multidimensional rules identified substantially different populations: 17.95% of rural adults in 2022 were multidimensionally poor without being income poor, compared with 17.44% poor under both rules; within the multidimensional-only group, reported household solid-fuel deprivation was pivotal to crossing the two-deprivation threshold for 47.82%. The corresponding 2020 estimates were 20.78%, 16.22% and 49.36%. Education remained the largest and most rank-stable contributor, Western incidence exceeded Eastern incidence by about 15 percentage points in both waves, and unrestricted entropy weighting reduced incidence by 12.76–16.29 points. Rural poverty monitoring should therefore report identification overlap, deprivation composition, uncertainty and specification sensitivity alongside any headline rate.

1 INTRODUCTION

Eliminating a national extreme-poverty threshold does not eliminate material or capability deprivation. Low income can coexist with limited education, poor health, reliance on polluting household energy and incomplete social protection. The Alkire-Foster (AF) counting framework makes the joint distribution of such disadvantages visible and decomposable while retaining an explicit rule for identifying who is multidimensionally poor (Alkire and Foster 2011a, 2011b; Alkire et al. 2015). This perspective is especially relevant after a successful campaign against extreme income poverty, when the remaining disadvantage is likely to be heterogeneous and poorly represented by a single monetary threshold.

Recent Chinese research documents persistent multidimensional and relative deprivation despite major reductions in absolute poverty. County- and household-level studies identify geographic inequality and education as recurring components of deprivation (Xu et al. 2021; Zou et al. 2023a, 2023b; He et al. 2024; Zhou et al. 2025a). Research on rural women and middle-aged and older adults further shows that deprivation profiles differ by age, gender and region, and that education often remains prominent (Wang et al. 2023; Li and He 2024; Zeng et al. 2022). These findings make rural adults a substantively important population rather than simply the rural subset of a national index.

Composite poverty measures also embed consequential choices. Dimension selection, deprivation cutoffs, weights and the cross-dimensional poverty threshold can change both who is identified and which policy priorities appear most important. Equal weights are transparent normative choices; data-driven weights answer a different question by giving greater influence to indicators with particular statistical distributions (Decancq and Lugo 2013; Greco et al. 2019). Critiques of composite poverty indices likewise caution that aggregation can conceal trade-offs and weak conceptual foundations

(Ravallion 2011). Measurement sensitivity is therefore substantive evidence, not a cosmetic robustness exercise.

Income-multidimensional poverty mismatch and sensitivity to measurement choices are established questions in China. Alkire and Fang (2019), using multiple CHNS waves, documented discordance between income and multidimensional poverty and examined stability under changes in weights and indicators. More recently, Zhong et al. (2026) proposed an Energy Engel Coefficient based on cooking-related energy consumption, illustrating how monetary and energy-based measures can identify different household groups. The present study extends this literature through an adult-level analysis of CFPS 2020 and 2022: it links observed classification overlap to the combinations that cross the poverty threshold, reports uncertainty for direct regional and group contrasts, and distinguishes sampling uncertainty from sensitivity to indicator weights. The household main-fuel item is treated as a living-condition indicator within an AF index, not as a new energy-consumption measure or an externally validated poverty classifier.

The analysis uses CFPS 2022 as the main wave and reconstructs CFPS 2020 as a cross-wave corroboration. The unit of analysis is the rural adult respondent, aligning education, health and insurance measures with the person to whom they refer. Five co-equal dimensions are represented by directly interpretable indicators: relative household income, reported household cooking fuel, completed education, self-rated health and public/basic medical coverage. The study asks: (1) how much do relative-income and multidimensional poverty identification overlap, and what characterises adults identified only by the multidimensional rule; (2) what are the prevalence, composition and rank stability of multidimensional poverty among rural adults; (3) how do incidence and deprivation profiles vary across macroregions and age groups; and (4) which conclusions are robust to defensible changes in cutoffs, survey weighting and index architecture? The contribution is a rule-explicit account of rural disadvantage: it shows not only how many adults are identified, but which non-income combinations cross the poverty threshold and how identification changes when weights change.

2 METHODS

2.1 Study design and data source

This study conducts repeated cross-sectional secondary analyses of the 2020 and 2022 China Family Panel Studies (CFPS). CFPS is a nationally representative, biennial longitudinal survey administered by the Institute of Social Science Survey at Peking University and collects information on individuals, families and communities across economic, educational, health and social domains (Xie and Hu 2014; Institute of Social Science Survey, Peking University 2015). Its multistage sampling design and survey weights are described by Xie and Lu (2015). Public-use Stata files for both waves were obtained through the official CFPS data platform under the data-use agreement. The more recent 2022 wave is the main analysis; 2020 is analysed separately under the same coding rules as a cross-wave corroboration.

The analysis combines the wave-specific adult person file, family roster file and family-economy file using the individual identifier (pid) and current household identifier (fid20 or fid22). The person file supplies age, sex, self-report status, self-rated health, medical-insurance participation, province, primary sampling unit (PSU) and the individual cross-sectional survey weight. The family roster file supplies current household residence, economic-household membership and completed education. The family-economy file supplies household per-capita income and cooking fuel (Supplementary Table S8).

2.2 Analytic population and sample construction

The target population is rural adults aged 18 years or older who completed a self-report adult interview, were current residents of the sampled household and were classified as economic members of that household. Rural residence was defined using the CFPS/National Bureau of Statistics urban-rural classification (urban20 = 0 or urban22 = 0), rather than household registration (hukou), because the analysis concerns current rural living conditions rather than administrative origin.

Sample construction was identical across waves. In 2022, the adult person file contained 27,001 records; 24,336 were aged 18 years or older, 21,105 completed self-report interviews, 9,706 were classified as rural, and 9,344 were current resident economic household members in sampled provinces. Of these, 8,458 had a valid positive individual cross-sectional weight and 7,717 had complete information for all five primary deprivation indicators. The 2020 file contained 28,530 person records, of which 25,779 were adults, 22,440 completed self-report interviews, 10,342 were rural, 10,195 were current resident economic household members, 9,263 had a valid positive weight and 8,754 formed the complete primary analytic sample (Supplementary Table S1).

The final 2022 sample represented 4,250 households and 137 PSUs; the 2020 sample represented 4,695 households and 142 PSUs. The analysis does not attempt to force the two waves to contain identical individuals or households. Accordingly, cross-wave comparisons are interpreted descriptively and not as causal estimates of change.

2.3 Multidimensional poverty framework

Multidimensional poverty was measured using the Alkire-Foster counting framework (Alkire and Foster 2011a; Alkire et al. 2015). Let g_ij denote whether adult i is deprived in indicator j, with g_ij = 1 for deprivation and 0 otherwise. Each of the five primary indicators receives weight w_j = 0.20. The weighted deprivation score for adult i is

$$c_i = \Sigma\square\, w\square g_i\square \qquad (1)$$

An adult is identified as multidimensionally poor when c_i > = k. The focal multidimensional cutoff is k = 1/3. Because the primary specification contains five equally weighted indicators, individual scores occur in increments of 0.20; therefore k = 1/3 identifies adults deprived in at least two of the five dimensions and is numerically equivalent to any cutoff greater than 0.20 and no greater than 0.40 in this

specification. This discrete structure is explicitly shown in the cutoff-sensitivity analysis rather than treated as a continuous scoring process.

Poverty incidence is H = q/n, where q is the weighted number of identified adults and n is the weighted population. Average deprivation intensity among the identified poor is A, the weighted mean of c_i among adults with c_i > = k. The adjusted headcount ratio is

$$M_0 = H \times A \qquad (2)$$

Indicator-specific censored headcounts were calculated after multidimensional identification, and each indicator's contribution to M0 was obtained by multiplying its censored headcount by its weight and dividing by M0. The same calculation was repeated within every bootstrap sample to obtain contribution intervals and rank probabilities. These decompositions distinguish prevalence in the full sample from contribution to joint poverty. A contribution share is an arithmetic component of the chosen index, not a causal effect or a sufficient ranking of policy value.

2.4 Indicator definitions

Table 1 summarises the five primary dimensions, source variables and deprivation rules.

Table 1
Measurement framework for multidimensional poverty among rural adults

Dimension	Indicator	CFPS variable(s)	Deprivation criterion	Weight	Rationale
Income	Relative income poverty	fincome1_per	Household per-capita income < 50% of the survey-weighted within-wave rural-adult median	0.20	Relative monetary deprivation; 40% and 60% median thresholds are sensitivity analyses.
Household energy	Reported household solid-fuel use	fa4	Household reports firewood or coal as its main cooking fuel	0.20	Household living-condition marker; not a direct measure of individual exposure.
Education	Below junior-secondary education	tb4_a20_p / tb4_a22_p	Completed education below junior secondary	0.20	Institutional benchmark based on nine-year compulsory education.
Health	Poor self-rated health	qp201	Self-rated health = unhealthy	0.20	Direct individual health measure; fair-or-poor coding is tested in sensitivity analysis.
Medical protection	No public/basic medical coverage	qp605_a_1, _2, _3, _5, _6	No participation in any listed public/basic medical-insurance scheme	0.20	Functional coverage replaces separate coding of substitutable historical insurance schemes.

Income. Relative monetary deprivation was defined using household per-capita income (fincome1_per). Within each wave, the poverty line was set at 50% of the survey-weighted median household per-capita income among otherwise eligible rural adults with valid income and survey weights. This produced lines of CNY 6,666.67 in 2020 and CNY 8,333.33 in 2022. Because this is the only explicitly distribution-relative component, the overall construct is described as multidimensional poverty rather than multidimensional relative poverty.

Living conditions. The indicator records whether the household reported firewood or coal as its main cooking fuel. It is treated as a household living-condition marker of reliance on polluting solid fuel, which is associated at the population level with household air pollution and wider time, health and environmental burdens (World Health Organization 2025). CFPS does not measure stove type,

ventilation, fuel stacking or each adult's time-activity pattern; the indicator is therefore not interpreted as a direct measure of individual exposure or disease risk.

Education. Adults whose highest completed education was below junior-secondary level were classified as deprived. The threshold is anchored to China's nine-year compulsory-education benchmark rather than to the sample distribution (Ministry of Education of the People's Republic of China 2009). This gives the education indicator an institutionally interpretable floor and avoids defining education deprivation relative to the median educational attainment of each wave.

Health. The primary health indicator uses the adult self-rated health question (QP201). Respondents selecting the lowest category, 'unhealthy', were classified as deprived. A broader definition that also includes the 'fair' category was examined in sensitivity analysis.

Social protection. Medical-protection deprivation was defined as having none of the public or basic medical-coverage options listed in QP605: government-funded medical care, urban employee medical insurance, urban resident medical insurance, the New Rural Cooperative Medical Scheme, or basic medical insurance for urban and rural residents. Supplemental medical insurance alone was not treated as basic public coverage. This functional definition is used instead of coding non-participation in each historical scheme as a separate deprivation. The latter can conflate eligibility, scheme substitution and institutional transition with welfare loss.

Two variables considered during construct development were excluded from the primary index. First, QN6016 and QN6017 ask respondents how serious medical-care and housing problems are in China; they are national-problem perceptions, not direct measures of the respondent's health or household housing conditions. Second, cooking-water source was not used in the primary specification because the CFPS categories do not consistently distinguish protected from unprotected wells or springs, making a binary safe-water interpretation uncertain. Pension participation was also kept outside the core index because eligibility and interpretation vary substantially by age, employment history and institutional route. These choices prioritise construct validity over indicator count.

2.5 Weighting and survey estimation

The primary specification gives each of the five dimensions equal weight (0.20). Equal weights are an explicit normative structure, not an empirical claim that the deprivations have identical welfare consequences. This transparent choice prevents a statistically rare or dispersed indicator from dominating identification solely because of its sample distribution and keeps the welfare concepts distinct (Decancq and Lugo 2013; Greco et al. 2019). Unrestricted entropy weights are therefore reported as a diagnostic sensitivity analysis rather than treated as an automatically superior specification.

Figure 1 summarises the primary measurement architecture. Identical eligibility criteria, deprivation coding, equal weights and the focal cutoff were applied separately to CFPS 2022 and 2020. The diagram distinguishes household-context indicators from individual-adult indicators and uses schematic profiles to show how the two-deprivation cutoff determines identification.

All main estimates use the CFPS individual national cross-sectional weight (rswt_natcs20n or rswt_natcs22n). Weighted medians were used for the relative-income threshold, and H, A, M0, deprivation incidences and censored contributions were estimated with the same person weights. Uncertainty was quantified using a design-informed stratified PSU-cluster bootstrap with 1,000 resamples. The six CFPS sampling frames, identified by the released subpopulation variable, were treated as strata; within each stratum, the observed PSUs were sampled with replacement, and respondents inherited multiplicity-adjusted cross-sectional weights according to the number of times their PSU was selected. The 2.5th and 97.5th percentiles of each bootstrap distribution form the reported 95% intervals. Intervals condition on the full-sample income thresholds and, where applicable, entropy weights. This procedure incorporates the released sampling-frame and PSU structure while retaining the survey weights, but it cannot reconstruct additional implicit within-frame stratification based on administrative and socioeconomic ordering.

2.6 Identification mismatch between income and multidimensional poverty

To assess what the multidimensional rule makes visible beyond the primary relative-income screen, adults were cross-classified into four mutually exclusive groups: poor under both rules, multidimensionally poor only (MPI only), income poor only, and poor under neither rule. Income poverty refers to the within-wave 50%-of-weighted-median household per-capita income indicator, whereas multidimensional poverty refers to the primary five-indicator equal-weight specification at k = 1/3. Within the MPI-only group, the reported household solid-fuel condition was classified as fuel-pivotal when removing that indicator would reduce the adult's deprivation score below k; as fuel-accompanying when solid-fuel deprivation was present but at least two other non-income deprivations were sufficient to retain multidimensional-poverty status; or as non-fuel MPI only when solid-fuel deprivation was absent. Selected characteristics not used to define these groups - age 60 years or older, sex, current employment, Western residence and Northeastern residence - were compared descriptively with adults classified as poor under both rules. Shares and direct profile differences were estimated using the same person weights and design-informed stratified PSU-cluster bootstrap with 1,000 resamples; current employment was evaluated only among adults with a valid released employment-status classification. Because income deprivation is itself one of the five index indicators and the focal rule requires at least two deprivations, an income-poor adult with no other core deprivation necessarily enters the income-only group. The asymmetric overlap is therefore partly a consequence of index construction, not an independent validation of either screen. These categories describe identification under two rules and are not interpreted as error rates, causal effects or evidence that either rule is uniquely correct. Complete classification, fuel-composition and profile-contrast estimates are reported in Supplementary Tables S16-S18.

2.7 Regional, age-group and robustness analyses

Macroregional estimates were produced for Eastern, Central, Western and Northeastern China using a fixed province-to-region mapping. For each region, the same equal-weight AF specification and design-

informed stratified PSU-bootstrap procedure were used. Regional differences in H were calculated within paired bootstrap resamples, yielding intervals for direct contrasts. To avoid reducing geography to a rank order, weighted prevalence of all five deprivations was also estimated by region; the 2022 profile is shown in Fig. 4 and full two-wave intervals appear in Supplementary Table S14. For the Western-Eastern comparison highlighted in Fig. 4c, the same paired resamples were additionally used to calculate direct differences in each component-deprivation prevalence, with positive values indicating higher prevalence in the Western region. The Western-Eastern comparison was highlighted because the overall H contrast was substantively interpretable and corroborated across waves; all six pairwise H contrasts are reported descriptively without multiplicity adjustment.

Age-group estimates were calculated for adults aged 18–44, 45–59 and 60 years or older. These subgroup analyses are descriptive and are reported mainly in Supplementary Table S6.

Five sensitivity analyses examined alternative income thresholds, health coding, survey weighting, indicator weights and the living-conditions specification. First, relative-income deprivation was recalculated using 40% and 60% of the weighted median. Second, the health indicator was broadened to classify both 'fair' and 'unhealthy' self-rated health as deprivation. Third, estimates were recalculated without survey weights. Fourth, an unrestricted entropy-weighting rule was applied to the same five indicators as a diagnostic of weighting sensitivity. Finally, an expanded specification added a conservative water-source indicator. The five dimensions remained co-equal: the living-conditions weight of 0.20 was split between cooking fuel and water (0.10 each), while income, education, health and social protection retained weights of 0.20. River/lake water, rainwater, cistern water and pond/spring water were treated as deprived; wells were not because CFPS does not distinguish protected from unprotected wells. This construct test is diagnostic, not the preferred index.

For the entropy sensitivity analysis, weights were estimated separately by wave from the survey-weighted binary deprivation matrix of the complete analytic sample. For indicator j, $p_{ij} = s_i g_{ij} / \Sigma_i(s_i g_{ij})$, where s_i is the person weight; $e_j = -\Sigma_{i:p_{ij} > 0}(p_{ij} \ln p_{ij}) / \ln(n)$, with n denoting the analytic sample size. Diversification was $d_j = \max(0, 1 - e_j)$, and the indicator weight was $d_j / \Sigma_l d_l$. Indicators with no weighted deprivation were assigned zero diversification; if all diversification scores were zero, equal weights were used. These distribution-derived weights were used only to assess sensitivity, not to establish welfare priorities.

Cutoff sensitivity was evaluated from k = 0.10 to k = 0.70. Given equal 0.20 weights, the resulting H, A and M0 curves contain expected plateaus because the set of identified adults changes only when the threshold crosses one of the discrete score levels.

2.8 Missingness and selection assessment

The main analysis uses complete cases for the five primary indicators and the survey weight. To assess observable selection, included adults were compared with otherwise eligible rural adults excluded because of missing core indicators. In 2022, the included sample had a weighted mean age of 50.62

years and a weighted female share of 48.02%; excluded adults had a mean age of 49.24 years and female share of 48.46%. The weighted median household per-capita income was CNY 16,666.67 among included adults and CNY 14,147.50 among excluded adults. In 2020, corresponding medians were CNY 13,350 and CNY 11,150 (Supplementary Table S7). Indicator-level missingness was also quantified among otherwise eligible adults with valid positive weights. Any core-indicator missingness affected 8.76% of eligible adults in 2022 (survey-weighted 9.58%) and 5.50% in 2020 (weighted 6.32%). In 2022, the largest weighted indicator-specific missingness rates were 5.77% for cooking fuel, 5.29% for income and 4.64% for medical coverage; education had no missing values in either wave (Supplementary Table S9). The income differences indicate potential selection bias, although its direction and magnitude for multidimensional poverty cannot be determined from this comparison alone. No claim is made that missingness is random.

2.9 Use of AI-assisted tools

OpenAI's ChatGPT was used to assist with drafting and debugging analysis code and with structural and language revision. All submission-ready CFPS microdata processing and statistical analyses reported in this article were executed locally by the authors. Subsequent AI-assisted checking and revision used public documentation and aggregate, non-identifying outputs rather than respondent-level data. The authors independently reviewed the source-variable mappings, analytic code, aggregate outputs, statistical calculations and manuscript text against the CFPS questionnaires and public-use files. The AI tool is not an author; the authors retain full responsibility for the analysis and final manuscript.

3 RESULTS

3.1 Overall multidimensional poverty

Table 2 reports the main survey-weighted estimates. In 2022, 35.39% of rural adults met the focal multidimensional poverty criterion (95% design-informed stratified PSU-bootstrap CI 31.78–39.13%). Among identified adults, average deprivation intensity was 0.498 (0.489–0.507), producing M0 = 0.176 (0.156–0.196). The weighted median household per-capita income was CNY 16,666.67, so the 50% relative-income line was CNY 8,333.33.

Table 2
Survey-weighted multidimensional poverty estimates in CFPS 2022 and 2020. 95% CIs are from 1,000 design-informed stratified PSU-cluster bootstrap replicates.

Wave	Adults	Households	PSUs	Median income (CNY)	50% line (CNY)	H, % (95% CI)	A (95% CI)	M0 (95% CI)
2022	7717	4250	137	16,666.67	8,333.33	35.39 (31.78–39.13)	0.498 (0.489–0.507)	0.176 (0.156–0.196)
2020	8754	4695	142	13,333.33	6,666.67	37.00 (32.93–40.92)	0.494 (0.487–0.501)	0.183 (0.162–0.203)

The separately reconstructed 2020 wave produced a similar overall level: H = 37.00% (32.93–40.92%), A = 0.494 (0.487–0.501) and M0 = 0.183 (0.162–0.203). The 2020 weighted median household per-capita income was CNY 13,333.33 and the 50% threshold was CNY 6,666.67. The study does not formally test between-wave change; the two waves are used to assess whether the main descriptive patterns recur. These estimates are not interpreted as evidence of a statistically identified decline.

3.2 Identification mismatch between relative-income and multidimensional poverty

The relative-income and multidimensional rules selected substantially different populations (Fig. 2a; Supplementary Table S16). In 2022, 17.44% of rural adults were classified as poor under both rules, 17.95% were multidimensionally poor but not income poor (95% CI 15.48–20.39%; unweighted n = 1,475), 3.10% were income poor only and 61.51% were poor under neither rule. In 2020, the corresponding shares were 16.22%, 20.78% (17.91–23.53%; n = 2,059), 2.67% and 60.33%. The MPI-only group was therefore approximately as large as the concordant-poor group in 2022 and larger in 2020. This is an identification difference under two measurement rules, not evidence that one rule supplies a uniquely correct classification.

Within the MPI-only group, the household solid-fuel indicator was pivotal to crossing the two-deprivation threshold for 47.82% in 2022 (95% CI 42.09–52.52%; unweighted n = 738) and 49.36% in 2020 (43.92–54.13%; n = 1,101), equivalent to 8.58% and 10.26% of the full analytic populations, respectively (Fig. 2b; Supplementary Table S17). Relative to adults classified as poor under both rules, the MPI-only group contained fewer adults aged 60 years or older (-13.05 percentage points in 2022 and − 16.64 points in 2020) and more currently employed adults (+ 5.89 and + 7.75 points); the bootstrap intervals for these differences excluded zero in both waves. The MPI-only group also had a larger Northeastern share (+ 5.97 points in 2022 and + 4.19 points in 2020), whereas Western-region contrasts were imprecise and included zero. The fuel-pivotal subgroup showed still larger age and employment differences. These contrasts describe group composition and do not establish causes of mismatch (Supplementary Table S18).

3.3 Deprivation structure and contribution to M0

Separate from who was identified, the indicator structure remained highly stable across waves (Supplementary Figure S1; Supplementary Tables S2 and S13). Education below junior-secondary level was the most common deprivation in both waves: 49.16% in 2022 (95% CI 46.79–51.78%) and 48.80% in 2020 (46.00-51.84%). It contributed 34.90% of M0 in 2022 (33.85–36.10%) and 35.14% in 2020 (34.16–36.18%), ranking first in all 1,000 bootstrap replicates in both waves.

Reported household solid-fuel use was the second-largest component. Its weighted prevalence was 27.15% in 2022 (21.85–32.25%) and 31.25% in 2020 (25.78–36.99%); its contribution was 23.78% (21.13–25.89%) and 25.57% (23.10-27.69%), respectively. It ranked second in 97.5% of 2022 and all 2020 bootstrap replicates. Relative income poverty contributed 19.80% and 17.74%, poor self-rated health 15.85% and 15.12%, and absence of public/basic medical coverage 5.67% and 6.43% (Supplementary Tables S2 and S13).

Two conclusions follow. First, educational disadvantage was the most stable component of the specified index, with reported household solid-fuel use usually second; this ordering remained stable across the bootstrap resamples under the primary specification. Second, decomposition does not by itself establish causal leverage or policy return. The lower 2022 prevalence of solid-fuel use and absence of basic medical coverage is descriptively consistent with improvement in those observed conditions, but the repeated cross-sectional design does not identify its causes.

3.4 Sensitivity to the multidimensional cutoff

Figure 3 shows H, A and M0 across alternative values of k. Under equal 0.20 weights, the curves are stepwise rather than smooth. At cutoffs from 0.10 to 0.20, adults deprived in at least one indicator were identified: H was 68.57% in 2022 and 70.38% in 2020. Once k exceeded 0.20, identification required at least two deprivations. Consequently, H remained at the focal values of 35.39% in 2022 and 37.00% in 2020 throughout the interval above 0.20 through 0.40, including k = 1/3. When the threshold exceeded 0.40 and required at least three deprivations, H fell to approximately 14% in both waves. At thresholds above 0.60, requiring at least four deprivations, only about 3.2% of rural adults remained identified.

As expected under AF identification, average deprivation intensity A increased as k became more restrictive because the remaining poor had more overlapping deprivations. M0 declined with higher cutoffs because the fall in incidence outweighed the rise in intensity. The near-parallel 2020 and 2022 profiles indicate that the overall deprivation-count distribution was similar across the two waves even when the poverty threshold changed (Supplementary Table S3).

3.5 Regional and age heterogeneity

Macroregional estimates reveal substantial heterogeneity (Fig. 4; Supplementary Table S12). In 2022, Western China had the highest H, 44.48% (95% CI 36.81–50.92%), followed by Northeastern China at 38.34% (32.05–43.60%), Central China at 32.72% (26.78–39.35%) and Eastern China at 29.13% (23.16–

34.18%). The paired Western-Eastern difference was 15.35 percentage points (6.57–23.87), directly supporting a broad east-west separation.

The 2022 profiles show why incidence should not be read as a regional label. Education deprivation was widespread in every region but reached 56.4% in the West; reported solid-fuel use was 39.1% in the West and 42.5% in the Northeast, compared with 17.7% in the East. Poor self-rated health was highest in the Northeast (22.1%), whereas relative-income deprivation was highest in the West (25.4%). Direct Western-Eastern contrasts further show that the overall H difference did not reflect uniformly higher Western deprivation across all dimensions. In 2022, the Western-Eastern difference was 21.36 percentage points for solid-fuel deprivation (95% CI 9.19–32.79) and 10.98 points for education deprivation (5.74–16.39); the relative-income difference was 6.84 points (-0.87 to 15.44), while the poor-health and no-medical-coverage contrasts were small and their intervals included zero. In 2020, the corresponding solid-fuel and education differences were 21.85 points (6.86–34.55) and 12.09 points (5.57–18.45), and the relative-income difference was 7.82 points (1.26–13.78). The 2020 overall Western-Eastern H contrast was 14.57 points (5.72–23.58), whereas the Northeast estimate remained high but imprecise. Taken together, the two waves support a broad east-west separation in overall incidence alongside compositionally distinct regional profiles, rather than a deterministic rank ordering.

Age-group results show a strong descriptive gradient (Supplementary Table S6). In 2022, H was 16.94% among adults aged 18–44, 36.57% among those aged 45–59 and 54.42% among those aged 60 years or older. The same ordering appeared in 2020: 17.66%, 40.30% and 57.72%, respectively. Because education and self-rated health are included in the index and both vary with cohort and age, these subgroup results should be interpreted as profiles of accumulated disadvantage rather than age effects.

3.6 Robustness to alternative specifications

Figure 5 connects incidence sensitivity with weight reallocation and the resulting identification boundaries. In 2022, using 40% of the weighted median lowered H by 1.80 percentage points (95% CI -2.30 to -1.34), while 60% raised it by 1.69 points (1.28-2.15); the corresponding 2020 changes were -1.78 (-2.17 to -1.39) and +2.69 (2.00-3.44). Conventional income-threshold variation therefore moved the headline incidence by fewer than three percentage points.

Broader health coding produced a somewhat larger increase: +3.90 percentage points in 2022 (95% CI 3.14 to 4.74) and + 4.71 points in 2020 (3.78 to 5.79). Removing survey weights changed H by + 1.45 points in 2022 (-0.39 to 3.33), an interval spanning zero, and by + 2.97 points in 2020 (0.82 to 5.07). Survey weighting therefore affects the estimate, but less than several construct-level choices.

The largest main-text sensitivity arose from unrestricted entropy weighting, which lowered H by 16.29 points in 2022 (95% CI -17.86 to -14.85) and 12.76 points in 2020 (-14.77 to -10.90). Entropy assigned only 0.111–0.114 to education and 0.152–0.164 to solid fuel, but 0.292–0.306 to the much rarer absence of medical coverage. Under these weights, 19.10% of rural adults in 2022 and 24.24% in 2020 were poor under both rules; 16.29% and 12.76% were identified only by equal weights, and none only by

entropy weights. The nesting follows from the full-sample estimated weights at k = 1/3: no single weight reaches the cutoff, so entropy-poor adults must also meet the equal-weight two-deprivation rule. The three smallest weights sum to 0.474 in 2022 and 0.484 in 2020; consequently, all profiles with three or more deprivations remain identified under both rules. Classification differences are confined to two-deprivation profiles. In 2022, education combined with fuel, income or health yields entropy scores below the cutoff (Fig. 5c); the education-health score is above the cutoff in 2020. The water-source architecture test remains in Supplementary Table S11 because CFPS cannot distinguish protected from unprotected wells. These diagnostics explain sensitivity to the chosen rule without establishing a superior specification.

4 DISCUSSION

4.1 Principal findings

This study reconstructs multidimensional poverty among rural adults using harmonised CFPS 2022 and 2020 data. Five findings are central. First, about 35% of rural adults in 2022 and 37% in 2020 were deprived in at least two of five co-equal dimensions. Second, relative-income and multidimensional poverty rules identified markedly different populations: 17.95% of rural adults in 2022 and 20.78% in 2020 were MPI only, and the reported household solid-fuel condition was pivotal to crossing the primary threshold for approximately half of that group. Third, education was the largest and most rank-stable contributor, with reported household solid-fuel use usually second. Fourth, a roughly 15-point Western-Eastern incidence gap was corroborated across waves, but regional profiles show that the mix of education, fuel, income and health deprivation also matters. Fifth, the headline incidence was more sensitive to weighting architecture than to conventional income-threshold changes.

These findings matter substantively because they shift attention from a single residual-income problem towards a bundle of persistent capability and living-condition disadvantages. They also matter for interpretation: the numerical poverty rate depends on the stated indicators, weights and cutoff. A credible policy reading therefore requires both the observed deprivation structure and evidence about the stability of that structure under plausible measurement alternatives.

4.2 Education and household energy as persistent rural disadvantages

Education is the most prominent dimension in the rebuilt index. Nearly half of rural adults in both waves had not completed junior-secondary education, and education accounted for roughly one-third of M0. This agrees with Chinese multidimensional-poverty studies in which education is a major component of rural, female or older-adult deprivation (Zou et al. 2023b; He et al. 2024; Li and He 2024; Wang et al. 2023). The result does not show that current schooling policy has failed: the adult sample spans many birth cohorts, so completed education partly records historical access. The age gradient reinforces that cohort interpretation. For present policy, school-age interventions remain necessary but insufficient;

adult learning, employability, digital inclusion and accessible services must account for a large stock of older rural residents with low formal education.

Reported household cooking fuel is the second-largest contributor in the primary index. More than one quarter of the weighted rural-adult population in 2022 lived in a household reporting firewood or coal as its main cooking fuel. Solid-fuel combustion is associated with household air pollution and unequal health burdens, and recent CFPS research documents the multidimensional character of energy poverty (World Health Organization 2025; Zhou et al. 2025b). However, the CFPS item does not measure stove technology, ventilation, fuel stacking or individual exposure. The result therefore supports attention to clean household energy as a living-condition domain, not an estimated health effect for each respondent.

4.3 Income, identification mismatch and social protection: different roles in multidimensional poverty

Relative household income poverty affected around one fifth of rural adults in 2022. The 50% weighted-median threshold follows a conventional relative-poverty logic, but the sensitivity analysis shows that moving the line to 40% or 60% changes H only moderately. This is because multidimensional identification requires joint deprivation: changing income status affects overall poverty only when it changes whether an adult crosses the combined cutoff. The result illustrates one value of the AF approach: it distinguishes the prevalence of low income from the extent to which low income overlaps with other disadvantages.

The classification-overlap analysis makes this distinction concrete. A relatively small income-only group reflects the fact that low income by itself does not cross the primary two-deprivation threshold, whereas the much larger MPI-only group experienced combinations of non-income disadvantages without meeting the relative-income criterion. Nearly half of the MPI-only group crossed the threshold with reported solid-fuel deprivation as the pivotal second deprivation, and the cross-wave similarity of this fraction suggests that the result is not a single-wave anomaly. This does not make multidimensional identification 'truer' than income poverty; it shows that the two rules operationalise different visibility criteria. The MPI-only group was also younger and more often currently employed than the concordant poor in both waves, indicating that the additional population made visible by the multidimensional rule is not simply a subset of the oldest or least economically active adults.

The social-protection result is also substantively different from a scheme-by-scheme interpretation. Only 7.41% of rural adults in the 2022 complete analytic sample lacked all listed public/basic medical coverage, compared with 9.19% in 2020. Integrated medical insurance has been associated with improved use of health services in rural China (Fan et al. 2021), and research on social security and transfers shows that pensions and other arrangements can reduce poverty or improve welfare (Huang and Zhang 2021; Wu 2024; Liao et al. 2026). Yet the present measure captures formal coverage, not benefit generosity, reimbursement quality, portability, unmet need or catastrophic expenditure. Its relatively small contribution to M0 therefore does not show that health financing is unimportant; it shows

that complete absence of basic public medical coverage is less common than the other deprivations represented here.

This distinction is important for multidimensional poverty research. A social-protection dimension should measure a welfare-relevant shortfall, not multiply deprivation counts simply because a welfare system contains several administratively distinct programmes. Collapsing substitutable medical schemes into functional coverage yields a more interpretable indicator and avoids treating institutional eligibility rules as separate welfare failures. Similar care would be required before incorporating pensions into a general adult index, because pension eligibility varies sharply across age and employment histories. Pension participation is consequently better analysed within age-eligible populations or as a separate social-policy outcome than imposed as a universal deprivation criterion for all adults.

4.4 Regional and age inequalities

The regional findings place multidimensional poverty within China's uneven geography of rural development. The paired Western-Eastern difference was 15.35 percentage points in 2022 and 14.57 points in 2020, with both confidence intervals excluding zero. Yet the profile analysis adds an important qualification. Paired component contrasts show the clearest cross-wave Western-Eastern differences for solid-fuel and education deprivation, whose confidence intervals excluded zero in both waves. Relative-income deprivation was also higher in the Western region at the point-estimate level in both waves, but its 2022 interval included zero; differences in poor self-rated health and no public/basic medical coverage were comparatively small and imprecise. The Northeast, by contrast, combined high solid-fuel prevalence with a higher burden of poor self-rated health. This accords with evidence of spatial differentiation in rural relative poverty (Huo et al. 2025), but also shows why policy should respond to local deprivation composition rather than region labels alone.

The 2020 Northeast estimate was high and its interval remained wide. The complete pairwise contrast table shows that not all regional differences are statistically resolved, and the intervals are not adjusted for multiple comparisons. The appropriate interpretation is therefore not a deterministic regional ranking but evidence of a replicated broad East-West gradient alongside year-specific uncertainty in the middle and Northeastern estimates. For social policy, this supports regionally differentiated monitoring while keeping attention on the dimensions responsible for disadvantage locally rather than on regional labels alone.

Age differences are equally important. Adults aged 60 years or older had more than three times the poverty incidence of adults aged 18–44 in both waves. Because education and health are index components, this is a profile of accumulated and cohort-specific disadvantage rather than a causal effect of ageing. The concentration is nevertheless consistent with studies of rural older adults and multidimensional poverty dynamics in China (Zeng et al. 2022; Wang et al. 2023). It complements evidence that rural pensions can affect income, work and health among eligible populations (Huang and Zhang 2021) and supports age-sensitive social-protection analysis.

4.5 Measurement robustness and substantive inference

The robustness analysis is subordinate to the substantive questions but central to measurement governance. Income-line changes generated small shifts, and removing survey weights produced modest changes. By contrast, unrestricted entropy weights sharply reduced H as they downweighted prevalent education and fuel deprivation while upweighting rare medical non-coverage. At the focal cutoff, the full-sample estimated weights imply that differences between the rules arise among adults with exactly two deprivations; Fig. 5c makes these combination-specific boundaries explicit. The resulting entropy-poor population is nested within the equal-weight population. Equal and entropy weights therefore answer different normative and statistical questions; neither transformation is neutral (Decancq and Lugo 2013; Greco et al. 2019).

The wider implication is that a composite indicator is also an institutional rule for visibility. Indicator definitions decide which shortfalls count; weights decide which combinations cross the threshold; and decomposition determines which patterns appear salient. A transparent index should therefore disclose three layers: the welfare meaning of each indicator, the normative weighting architecture and the empirical stability of conclusions under plausible alternatives. Here, education and reported household solid-fuel use remain prominent under sampling uncertainty, whereas the number classified as poor is specification-dependent. That distinction is more informative than treating one incidence value as invariant.

4.6 Limitations

Several limitations remain. First, the analyses are repeated cross-sections rather than a causal panel analysis. Many respondents may appear in both CFPS waves, but the present design does not model within-person transitions and does not estimate the effect of policy or time on poverty status. The descriptive difference between 2020 and 2022 therefore cannot be interpreted as a treatment effect or a clean secular trend. Both waves were also collected during years affected by the COVID-19 pandemic, which may have influenced income, health-care access and labour conditions.

Second, the index is intentionally parsimonious. It does not cover every dimension that could plausibly matter for rural well-being, such as assets, housing quality, digital access, transport, social participation, mental health or benefit adequacy. Adding dimensions may enrich substantive coverage but also changes the identification rule, as demonstrated by the water-source sensitivity analysis. Future research should add domains only when they can be measured comparably and interpreted directly.

Third, the health and social-protection indicators have limits. Self-rated health is subjective and may vary by expectations and reporting styles. Medical-insurance participation captures formal coverage but not service quality, effective reimbursement, catastrophic spending or unmet need. The study also does not include pension protection in the core adult index because of heterogeneous age and employment eligibility. Separate analyses focused on older adults could incorporate pension receipt and entitlement more directly.

Fourth, the primary analysis is complete-case. Among otherwise eligible adults with valid weights, any core-indicator missingness affected 8.76% of the 2022 sample and 5.50% of the 2020 sample; the corresponding weighted proportions were 9.58% and 6.32%. No single indicator had weighted missingness above 6% in 2022 or 4% in 2020, but excluded adults had lower weighted median household income than included adults. These observable differences raise concerns about selection, but do not determine the direction or magnitude of bias in multidimensional poverty. Indicator-specific missingness and the included-versus-excluded comparison are reported in Supplementary Tables S9 and S7 rather than assumed away. Multiple imputation could be explored in future work if defensible models can be specified for all indicator variables while respecting the survey design.

Fifth, the uncertainty analysis uses the released CFPS sampling-frame indicator (subpopulation), PSU identifier and person cross-sectional weights in a stratified PSU-cluster bootstrap. This is closer to the released survey design than an unstratified cluster bootstrap, but it cannot reconstruct the survey's full implicit within-frame stratification by administrative and socioeconomic ordering. The intervals should therefore be interpreted as design-informed approximations rather than exact replication-weight variance estimates. They also condition on the full-sample income thresholds and entropy weights, and do not incorporate uncertainty from re-estimating those rules in each resample. Regional estimates, particularly for smaller regional subsamples, should still be interpreted with their confidence intervals rather than as precise rank orderings.

5 CONCLUSIONS

Using harmonised CFPS 2022 and 2020 data, this study finds substantial overlapping disadvantage among rural adults and a consequential mismatch between income-only and multidimensional identification. Around one fifth of rural adults were multidimensionally poor without falling below the primary relative-income line, and reported household solid-fuel deprivation was pivotal to crossing the multidimensional threshold for roughly half of this MPI-only group. Education was the largest and most stable contributor to M0, reported household solid-fuel use was generally second, and the Western-Eastern incidence gap was about 15 percentage points in both waves. Regional profiles nevertheless show that similar incidence can reflect different combinations of education, fuel, income and health deprivation.

The policy implication is not a search for one definitive poverty rate. Monitoring should distinguish a common social protection floor from profile-sensitive responses to adult education, clean household energy, income insecurity, health and effective service access. Functional medical coverage is more interpretable than multiple scheme-specific non-participation indicators, while contribution shares should not be mistaken for causal returns to intervention.

For the next stage of rural poverty governance, every headline multidimensional rate should be accompanied by its identification overlap with conventional income screening, deprivation composition, uncertainty and sensitivity to reasonable design choices. This reporting discipline makes clear which

conclusions are robust - notably the prominence of education and household fuel conditions and the broad east-west gradient - and which depend on the chosen measurement architecture. The findings provide a transparent basis for describing and monitoring rural disadvantage, rather than establishing eligibility for specific assistance programmes or the effects of interventions.

DECLARATIONS

Competing interests

The authors declare no competing interests.

Author Contribution

L.W. conceived the study, curated the data, developed the methodology, conducted the investigation and formal analysis, developed the analysis code, administered and supervised the project, acquired funding, and drafted the original manuscript. C.W. contributed to the investigation, methodology, resources, and validation, and reviewed and edited the manuscript. X.J. contributed to the conceptualization, methodology, formal analysis, validation, visualization, resources, and project administration, and reviewed and edited the manuscript. F.Z. contributed to the methodology, resources, validation, visualization, and supervision. All authors reviewed and approved the manuscript.

Acknowledgements

Not applicable.

Data Availability

The study uses the 2020 and 2022 public-use China Family Panel Studies (CFPS) data maintained by the Institute of Social Science Survey, Peking University (dataset DOI: 10.18170/DVN/45LCSO). Dataset information and access links are available on the CFPS collection page of the Peking University Open Research Data Platform (https://opendata.pku.edu.cn/dataverse/CFPS). Access to respondent-level public-use microdata requires registration, approval by the data provider and acceptance of the provider's access conditions and Data User Agreement. Respondent-level records are not redistributed. The exact six input-file releases, cross-wave variable mappings and coding rules are documented in the Methods, Supplementary Information and the README accompanying Supplementary Code. Aggregate numerical results underlying the reported tables and statistical figures are supplied as Supplementary Data 1 and contain no respondent-level records.

Code availability

The statistical analysis code is supplied as Supplementary Code (Statistical Reproduction Package), containing the core-analysis, extended-diagnostic and identification-mismatch modules, a unified execution script, dependency versions, exact input-file requirements, output mappings and a result-verification script. The code reconstructs the analytic samples and deprivation indicators and reproduces survey-weighted estimates, design-informed stratified PSU-bootstrap intervals, rank probabilities, regional and specification contrasts, weighting diagnostics and income-MPI classification results. Users must obtain CFPS microdata independently under the provider's access conditions. The accompanying README gives the local execution and verification instructions; Supplementary Data 1 provides the aggregate reference results.

REFERENCES

1. Alkire S, Fang Y (2019) Dynamics of multidimensional poverty and uni-dimensional income poverty: an evidence of stability analysis from China. Soc Indic Res 142:25–64. https://doi.org/10.1007/s11205-018-1895-2
2. Alkire S, Foster J (2011a) Counting and multidimensional poverty measurement. J Public Econ 95:476–487. https://doi.org/10.1016/j.jpubeco.2010.11.006
3. Alkire S, Foster J (2011b) Understandings and misunderstandings of multidimensional poverty measurement. J Econ Inequal 9:289–314. https://doi.org/10.1007/s10888-011-9181-4
4. Alkire S, Foster JE, Seth S, Santos ME, Roche JM, Ballon P (2015) Multidimensional poverty measurement and analysis. Oxford University Press, Oxford. https://doi.org/10.1093/acprof:oso/9780199689491.001.0001
5. Decancq K, Lugo MA (2013) Weights in multidimensional indices of wellbeing: an overview. Econom Rev 32:7–34. https://doi.org/10.1080/07474938.2012.690641
6. Fan X, Su M, Si Y, Zhao Y, Zhou Z (2021) The benefits of an integrated social medical insurance for health services utilisation in rural China: evidence from the China Health and Retirement Longitudinal Study. Int J Equity Health 20:126. https://doi.org/10.1186/s12939-021-01457-8
7. Greco S, Ishizaka A, Tasiou M, Torrisi G (2019) On the methodological framework of composite indices: a review of the issues of weighting, aggregation, and robustness. Soc Indic Res 141:61–94. https://doi.org/10.1007/s11205-017-1832-9
8. He X, Xi H, Li X (2024) Multi-dimensional decomposition, measurement, and governance mechanism of relative poverty in Chinese households under the goal of common prosperity: empirical analysis based on CFPS2020 data. Sustainability 16:5181. https://doi.org/10.3390/su16125181
9. Huang W, Zhang C (2021) The power of social pensions: evidence from China's New Rural Pension Scheme. Am Econ J Appl Econ 13:179–205. https://doi.org/10.1257/app.20170789

10. Huo Z, Yang Y, Yang Y, Zhou J, Zhang M (2025) How livelihood strategies affect spatial differentiation of relative poverty of rural households: evidence of Chinese rural areas based on the GWR model. Front Sustain Food Syst 9:1540911. https://doi.org/10.3389/fsufs.2025.1540911
11. Institute of Social Science Survey, Peking University (2015) China Family Panel Studies (CFPS). Peking University Open Research Data Platform. https://doi.org/10.18170/DVN/45LCSO
12. Li N, He M (2024) Feminization of poverty: an analysis of multidimensional poverty among rural women in China. Humanit Soc Sci Commun 11:568. https://doi.org/10.1057/s41599-024-03006-4
13. Liao H, Liu H, Wang J (2026) Relative poverty and antipoverty effects of public and private transfers in China. Soc Indic Res 181:29. https://doi.org/10.1007/s11205-025-03791-8
14. Ministry of Education of the People's Republic of China (2009) Compulsory Education Law of the People's Republic of China. Ministry of Education, Beijing. https://en.moe.gov.cn/Resources/Laws_and_Policies/201506/t20150626_191391.html. Accessed 24 Sep 2026
15. Ravallion M (2011) On multidimensional indices of poverty. J Econ Inequal 9:235–248. https://doi.org/10.1007/s10888-011-9173-4
16. Wang Q, Shu L, Lu X (2023) Dynamics of multidimensional poverty and its determinants among the middle-aged and older adults in China. Humanit Soc Sci Commun 10:116. https://doi.org/10.1057/s41599-023-01601-5
17. World Health Organization (2025) Household air pollution. World Health Organization, Geneva. https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health. Accessed 23 Sep 2026
18. Wu T (2024) Digital divide, social security, and relative poverty in Chinese households. Int Rev Econ Financ 96:103716. https://doi.org/10.1016/j.iref.2024.103716
19. Xie Y, Hu J (2014) An introduction to the China Family Panel Studies (CFPS). Chin Sociol Rev 47:3–29. https://doi.org/10.2753/CSA2162-0555470101
20. Xie Y, Lu P (2015) The sampling design of the China Family Panel Studies (CFPS). Chin J Sociol 1:471–484. https://doi.org/10.1177/2057150X15614535
21. Xu L, Deng X, Jiang Q, Ma F (2021) Identification and alleviation pathways of multidimensional poverty and relative poverty in counties of China. J Geogr Sci 31:1715–1736. https://doi.org/10.1007/s11442-021-1919-8
22. Zeng W, Zhao P, Zhao Y, Saddique R (2022) The multidimensional relative poverty of rural older adults in China and the effect of the health poverty alleviation policy. Front Public Health 10:793673. https://doi.org/10.3389/fpubh.2022.793673
23. Zhong R, Xue J, Zheng X, Wei C, Sun Q (2026) Food-related energy consumption can help reveal poverty in rural Chinese households. Nat Commun 17:9086. https://doi.org/10.1038/s41467-026-76026-0
24. Zhou D, Chen T, Zhu Y, He Y, Li B, Wang W (2025a) A statistical evaluation of the effectiveness of multidimensional relative poverty alleviation efforts in China. J Econ Inequal 23:279–302.

https://doi.org/10.1007/s10888-024-09629-6

25. Zhou D, Zhang Z, Zheng X, Wang M (2025b) A chronic multidimensional measure of energy poverty and its impacts on physical and mental health. Humanit Soc Sci Commun 12:1725. https://doi.org/10.1057/s41599-025-05990-7
26. Zou W, Cheng X, Fan Z, Lin C (2023a) Measuring and decomposing relative poverty in China. Land 12:316. https://doi.org/10.3390/land12020316
27. Zou W, Cheng X, Fan Z, Yin W (2023b) Multidimensional relative poverty in China: identification and decomposition. Sustainability 15:4869. https://doi.org/10.3390/su15064869

Figures

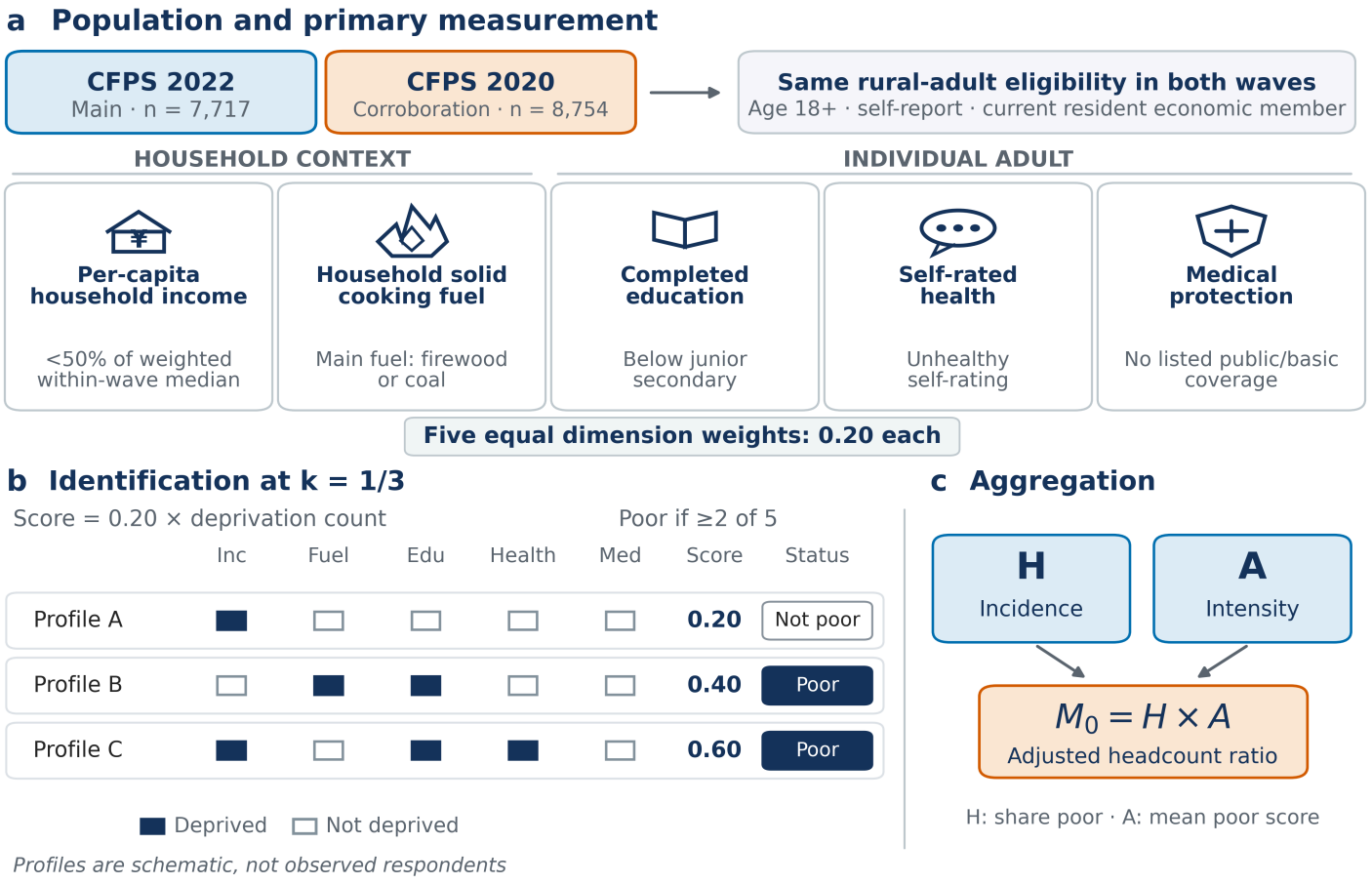
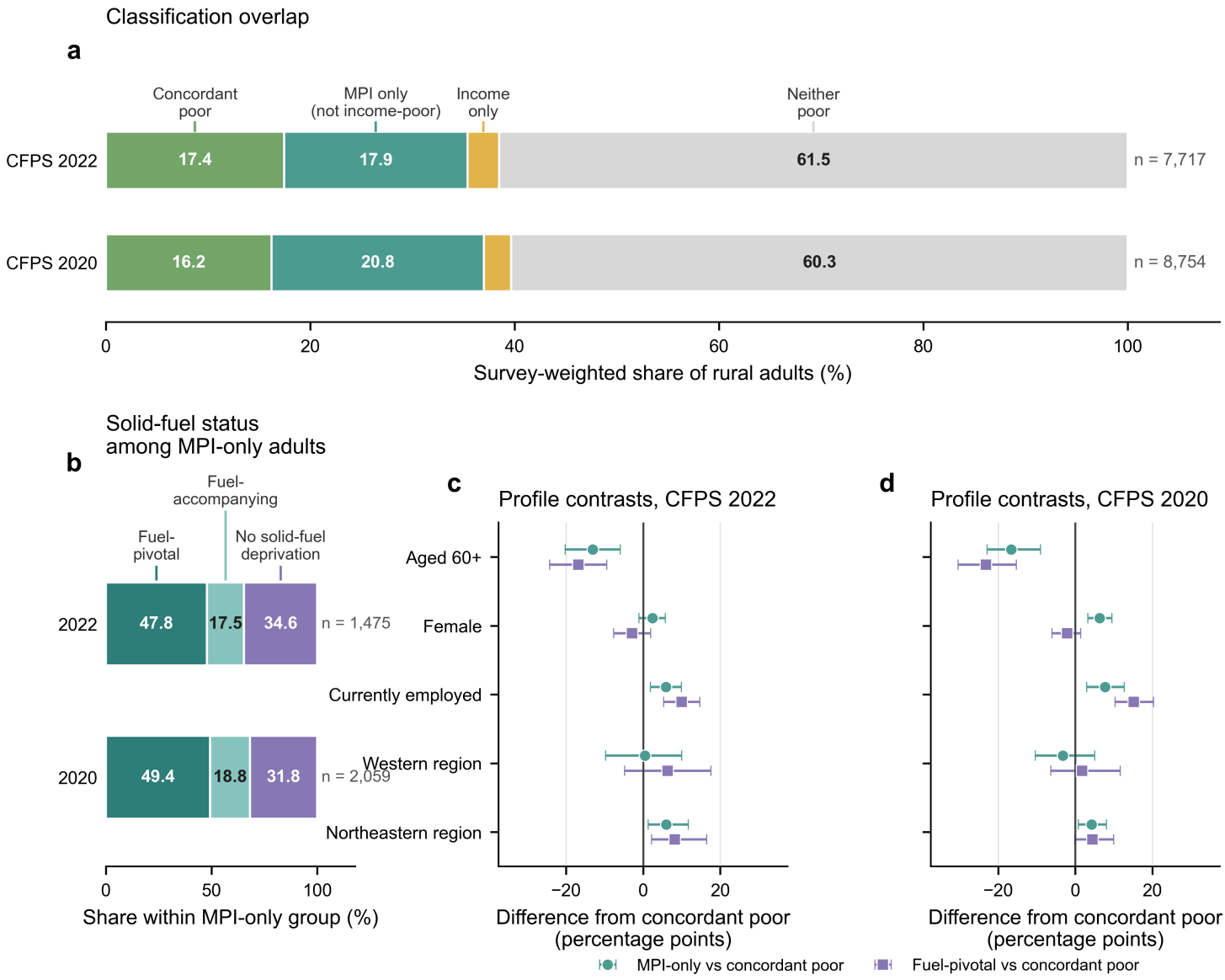


Figure 1

Primary multidimensional-poverty measurement architecture. (a) CFPS 2022 is the main repeated cross-section (n = 7,717); CFPS 2020 provides cross-wave corroboration (n = 8,754) under identical eligibility rules. The first two indicators describe household context, whereas education, self-rated health and medical coverage are measured for the adult respondent. Household cooking fuel is not a direct measure of individual exposure. The relative-income indicator is household per-capita income below 50% of the survey-

weighted within-wave rural-adult median. (b) Five equally weighted indicators give scores in 0.20 increments; k = 1/3 identifies adults deprived in at least two indicators. The three profiles are schematic, not observed respondents. (c) Poverty incidence H and average deprivation intensity A among identified adults form the adjusted headcount ratio M0 = H × A.



Fuel-pivotal means that the reported household solid-fuel condition is necessary for crossing the primary two-deprivation threshold. It is not a standalone measure of energy poverty or individual exposure.

Figure 2

Income-multidimensional poverty identification overlap. (a) Survey-weighted shares classified as poor under both rules, the multidimensional rule only, the relative-income rule only or neither rule. (b) Solid-fuel status among MPI-only adults: fuel-pivotal, fuel-accompanying or no solid-fuel deprivation. (c, d) Differences in selected characteristics relative to adults poor under both rules in 2022 and 2020; whiskers show paired design-informed stratified PSU-bootstrap 95% confidence intervals from 1,000 resamples. Income poverty is household per-capita income below 50% of the within-wave weighted median; MPI uses five equally

weighted indicators at k = 1/3. Employment uses valid released status. Classification differences are not error rates; fuel-pivotal status is rule-dependent, not causal.

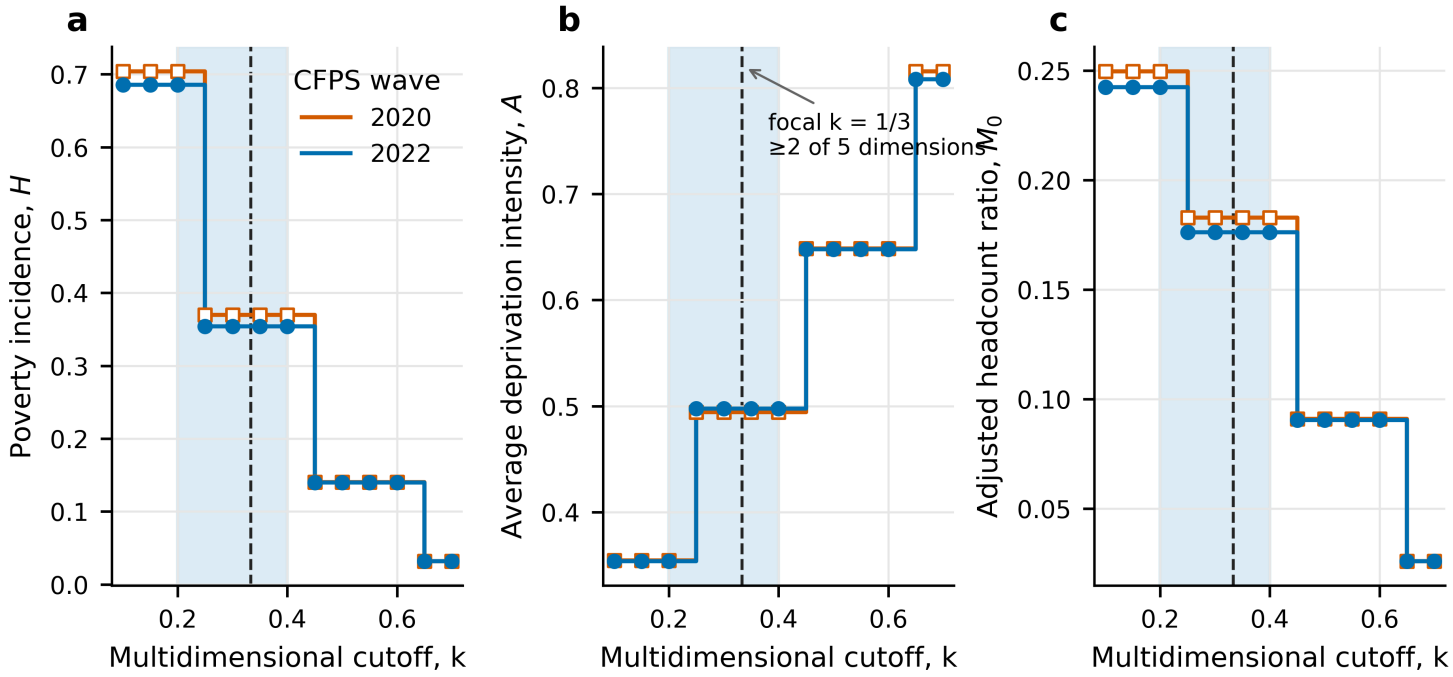


Figure 3

Sensitivity of multidimensional poverty identification to cutoff k. (a) Poverty incidence H, (b) average deprivation intensity A among identified adults and (c) adjusted headcount ratio M0. The dashed line marks the focal k = 1/3. The shaded interval (0.20, 0.40] identifies the same group - adults deprived in at least two of five equally weighted dimensions - because deprivation scores change in 0.20 increments.

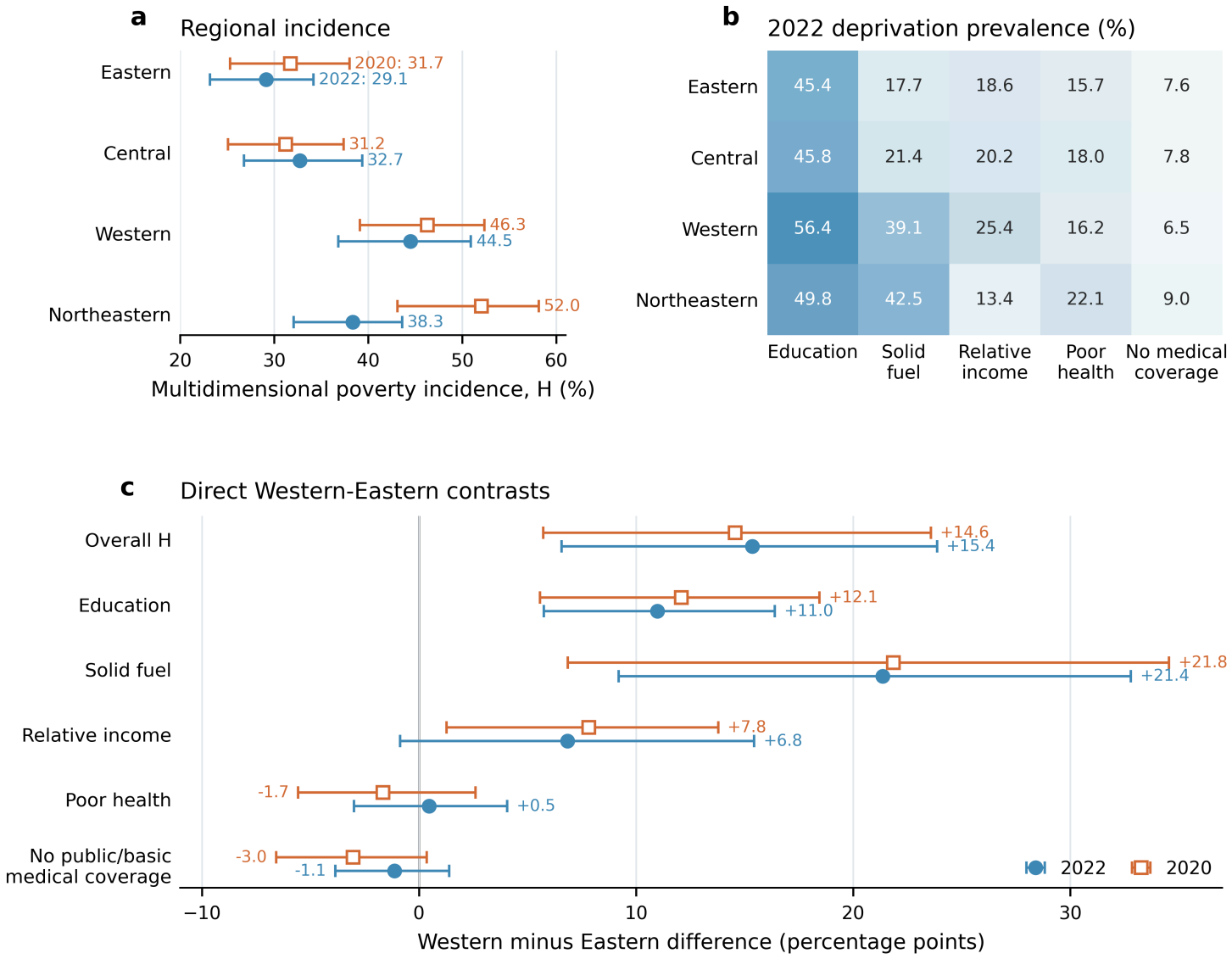


Figure 4

Macroregional heterogeneity in multidimensional poverty incidence and deprivation profiles. (a) Survey-weighted H across the four macroregions in CFPS 2022 and 2020; whiskers are design-informed stratified PSU-bootstrap 95% confidence intervals (1,000 resamples). (b) Survey-weighted prevalence of the five component deprivations across macroregions in 2022; cells show percentages. (c) Paired Western-minus-Eastern contrasts in H and each component-deprivation prevalence for both waves; positive values indicate higher Western prevalence. Whiskers are 95% confidence intervals for the paired difference, with both regions calculated within each bootstrap replicate. CFPS 2022 is the main assessment and CFPS 2020 provides cross-wave corroboration. Contrasts are descriptive, not causal decompositions of the regional poverty gap.

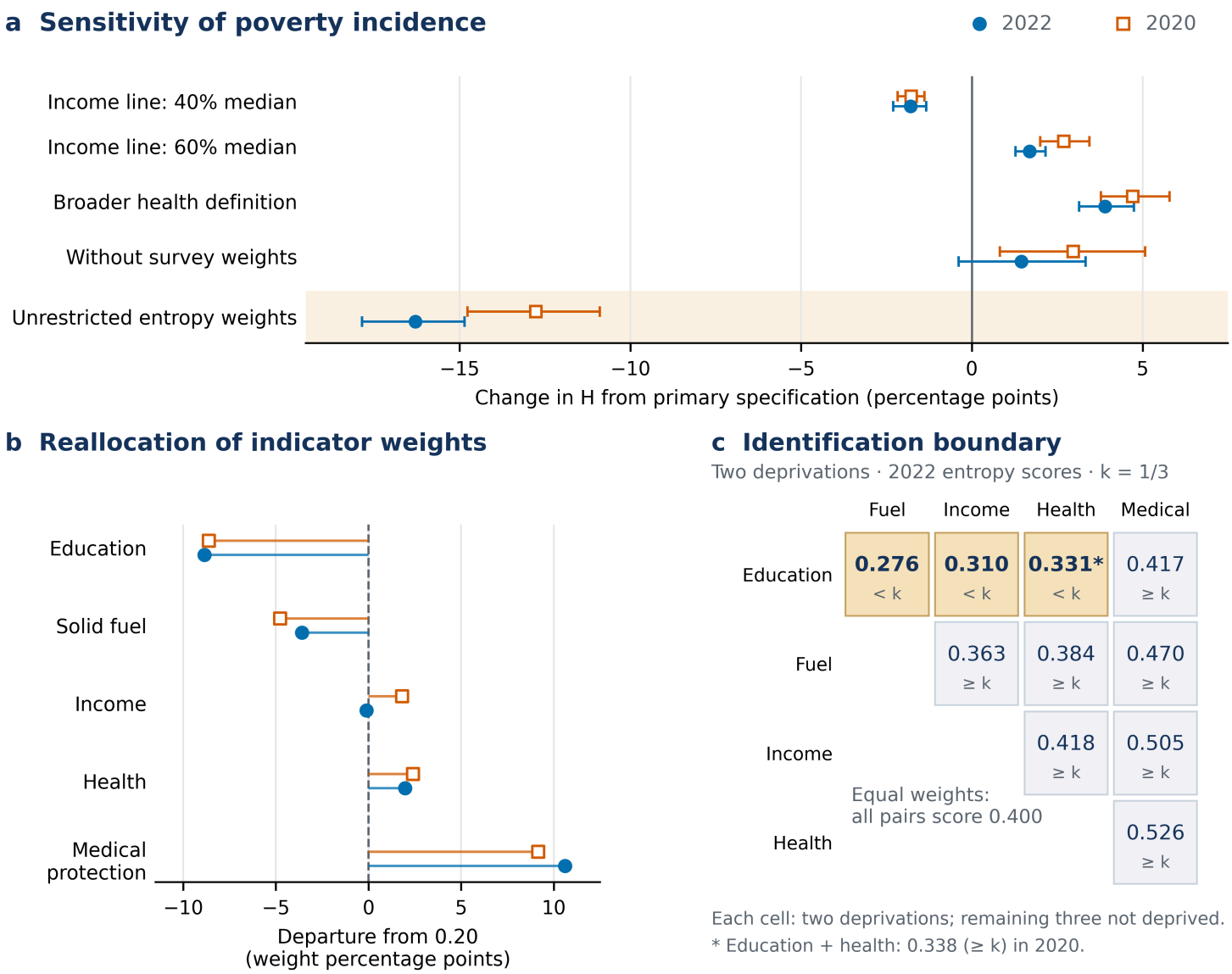


Figure 5

Measurement sensitivity and identification boundaries. (a) Paired changes in poverty incidence H relative to the primary specification; whiskers show design-informed stratified PSU-bootstrap 95% confidence intervals from 1,000 resamples. (b) Changes from equal weights of 0.20 to the full-sample estimated entropy weights, expressed as 100 × (entropy weight - 0.20). (c) Scores for the ten possible two-deprivation profiles under the 2022 entropy weights, with the other three indicators non-deprived. All these profiles score 0.400 under equal weights. Amber cells fall below k = 1/3; classifications use unrounded weights and the exact cutoff. The asterisk marks education plus health, the only pair whose classification differs in 2020 (score 0.338). Cells represent possible indicator combinations, not population frequencies. Full weights and classification shares appear in Supplementary Tables S5 and S15; the water-source test appears in Supplementary Table S11.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryCodeStatisticalReproductionPackage.zip
- SupplementaryData1AggregateResults.xlsx
- SupplementaryInformation.docx