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The State of Food Insecurity Measurement

A Mix of Methods, and a Mix of Messages

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Abstract

Robust food insecurity indicators are needed for monitoring development targets, humanitarian advocacy efforts, and rationally allocating foreign aid. Longstanding dissatisfaction with the FAO's undernourishment indicator prompted the development of new metrics in recent decades, including the FAO's Food Insecurity Experience Scale (FIES) and the unaffordability of healthy diets. However, no previous research has assessed whether food insecurity and poverty indicators are in broad agreement on which countries are insecure/ poor, and whether global food insecurity is rising or falling. Unfortunately, this new mix of methods produces mixed messages. At the country level, FIES severe food insecurity is often higher in Latin America and the Caribbean than in Niger and other extremely poor African countries. On global trends, the FAO reports increasing undernourishment and FIES food insecurity over 2014-2022, whereas the World Bank reports monetary poverty declining and healthy diets becoming more affordable. Moreover, trends in FAO food security indicators are not statistically explained by hypothesized factors cited in FAO reports, such as conflict or climate change, and increases in the FAO's calorie consumption inequality metric are inconsistent with declining income inequality reported by the World Bank. We provide four concrete suggestions to improve food security measurement and monitoring: (1) the FAO should cease modelling undernourishment; (2) new independent studies should re-evaluate the FIES and test new metrics; (3) international agencies should implement coordinated, high-frequency, multi-purpose, open-access surveys; and (4) researchers should further improve the "nowcasting" of poverty and food insecurity for data-scarce crisis contexts.

Keywords: Food insecurity; undernourishment; poverty; stunting; malnutrition

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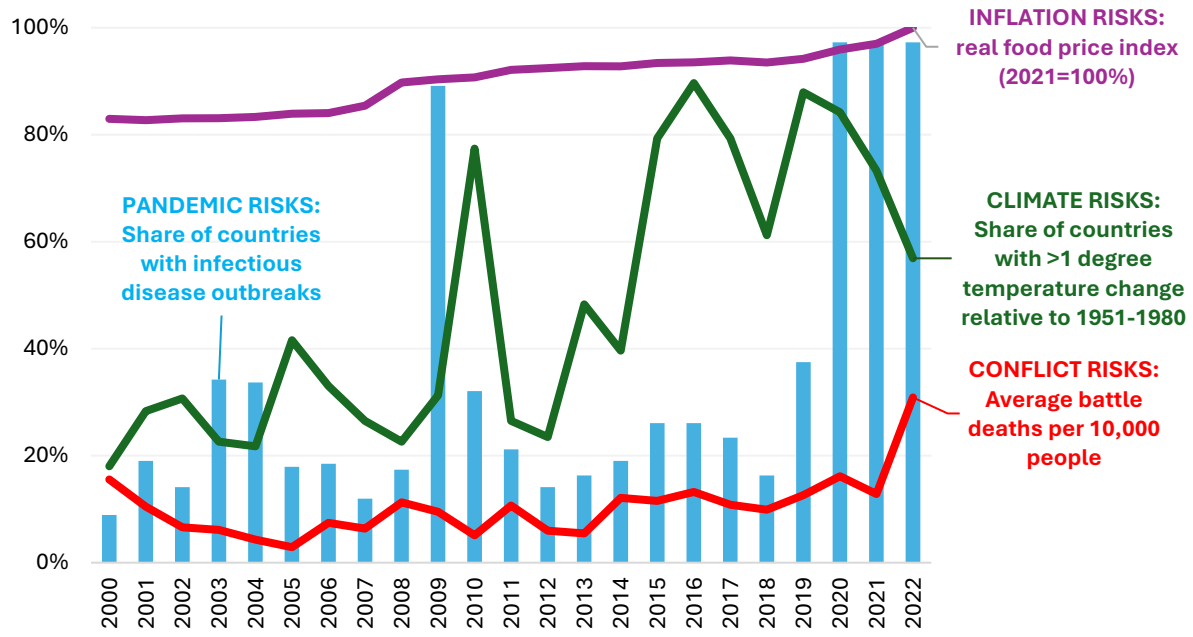
1. Introduction

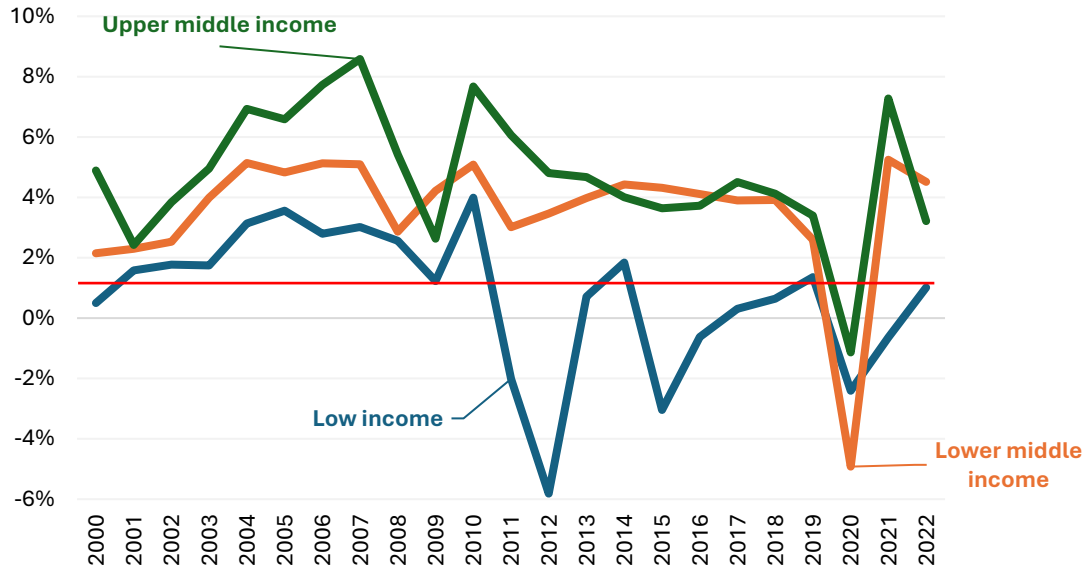
In the 21st Century, conflict, climate change, pandemics, food inflation, and slower economic growth have all emerged as serious barriers to achieving the Sustainable Development Goals of ending poverty (SDG 1) and hunger in all its forms (SDG 2) by 2030. Figure 1 graphically illustrates these rising risks for a large sample of low- and middle-income countries (LMICs). Real food prices have risen rapidly, outpacing non-food price increases by 18% over 2000-2022 in the average LMIC, with sharp spikes in the 2007-08 and 2021-22 global food price crises. The share of LMICs experiencing more than 1 degree Celsius of warming on land relative to the 1951-1980 average rose from around 40% in the first decade of the Century to around 75% over 2015-2022. Large scale outbreaks of diseases, like SARS, Ebola, Swine Flu, COVID-19 and Monkey Pox, appear to be increasing in frequency and severity. Conflict has intensified in sub-Saharan Africa (Sudan, Ethiopia, the Sahel), Eastern Europe (Ukraine), the Middle East (Yemen, Syria, Gaza, Lebanon) and Asia (Myanmar, Afghanistan). Growth in per capita Gross Domestic Product (GDP) in LMICs – reported in Panel B of Figure 1 – was relatively strong over 2000-2008 but slowed noticeably over 2010 to 2019 before plummeting drastically during the COVID-19 pandemic.

Figure 1. Converging risks to food security and poverty eradication: 2000-2022

Panel A. Conflict, climate, pandemic and inflationary risks in LMICs



Panel B. Average economic growth rates in LMICs



Sources: Panel A. Inflationary risks are a real food price index constructed by the authors as the ratio of the food consumer price index (CPI) to the total CPI, with 2022=100. Climate risks are the share of countries in any given year with land temperature greater than 1 degree above their 195-1980 average. Both the climate risk and inflationary risk indicators are sourced from the FAO (FAO, 2024). Conflict risks are average of country level data on battle deaths per 10,000 people (World Bank, 2024d). Pandemic risks are the share of countries with sizable infectious disease outbreaks, and sourced from (Torres Munguía et al., 2022). Panel B. Economic growth rates are percentage changes in GDP per capita for low-income, lower middle income and upper income groups as defined by and estimated by The World Bank (World Bank, 2024d).

Yet despite presumably strong interlinkages between poverty, food insecurity and malnutrition, global indicators of these phenomenon have been moving in opposite directions since 2014 (Figure 2). The World Bank estimates that global poverty prevalence at the $3.65/day poverty line fell throughout 2000 to 2022, including an 8-point decline from 30% to 22% over 2014-2022 despite the COVID-19 pandemic (panel A of Figure 2). In contrast, the United Nations Food and Agriculture Organisation (FAO) reports rising food insecurity since 2014, according to two very different types of indicators. The first is the FAO's modelled estimates of caloric undernourishment derived from aggregate data and imputation methods, while the second consists of survey-based indicators of household's reported food insecurity experiences such as being "unable to eat healthy and nutritious food" (a moderate food insecurity experience) and "going to bed hungry" (a severe experience). As Panel B of Figure 2 shows, both types of FAO indicators have trended upwards since 2014, and sharply so in the case of moderate/severe food insecurity, which increased from 21% in 2014 to 29% in 2022. To further muddy the waters, a new indicator of the share of people unable to afford a healthy diet (Herforth et al., 2022) declined from 40% in 2017 to 35% in 2022, closely in keeping with poverty trends.[1]

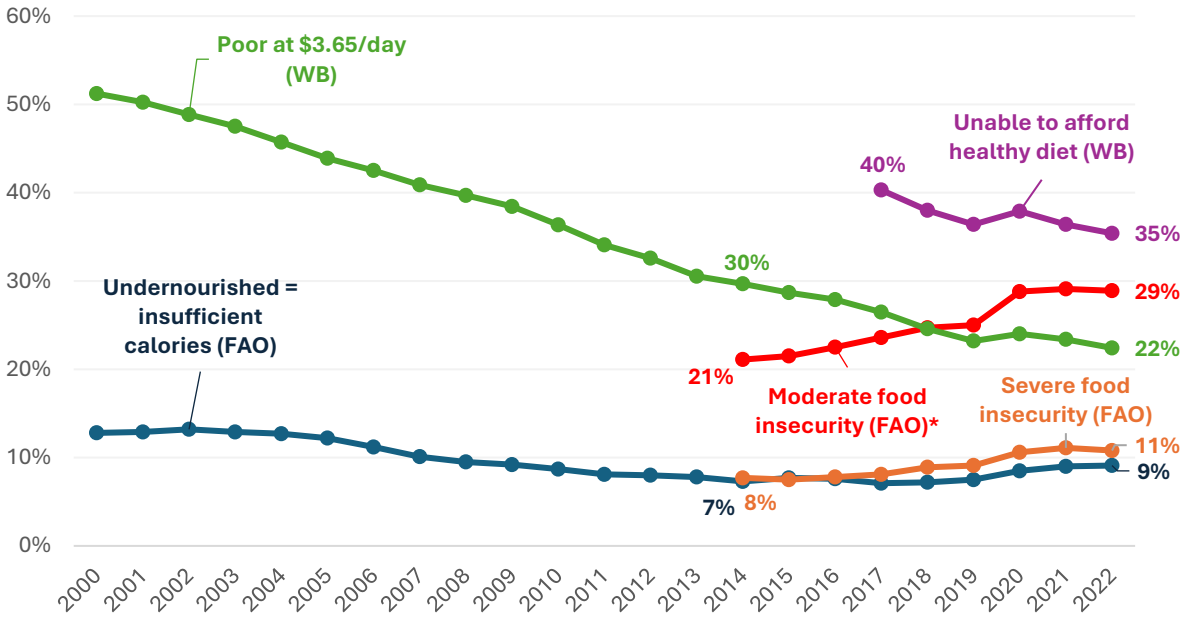
Why should poverty and malnutrition be falling, and food insecurity rising? This divergence is deeply troubling given the conceptual interlinkages between these indicators, including the reasonable presumption that they share common drivers. This divergence in trends also begs the question of whether different indicators even agree on which countries are in greatest need: how should international agencies respond if a country is not monetarily poor, but its population frequently report food insecurity experiences?

In light of these concerns, the objective of the present study is to re-assess the methodological weaknesses of these indicators, including their basic methodological validity and the critical issue of cross-country and inter-temporal validity, but also critical gaps in survey coverage and the under-discussed issue of whether the imputation and extrapolation methods used to derive regional and global trends are appropriate and unbiased. Our conclusions are quite pessimistic insofar as we find some fault in all these indicators, or at least in their regional and global trend estimates. Given how important these indicators are, we urge international institutions to rely less on questionable imputation/extrapolation methods, and instead invest in survey systems that are more rigorous, more timely and more transparent.

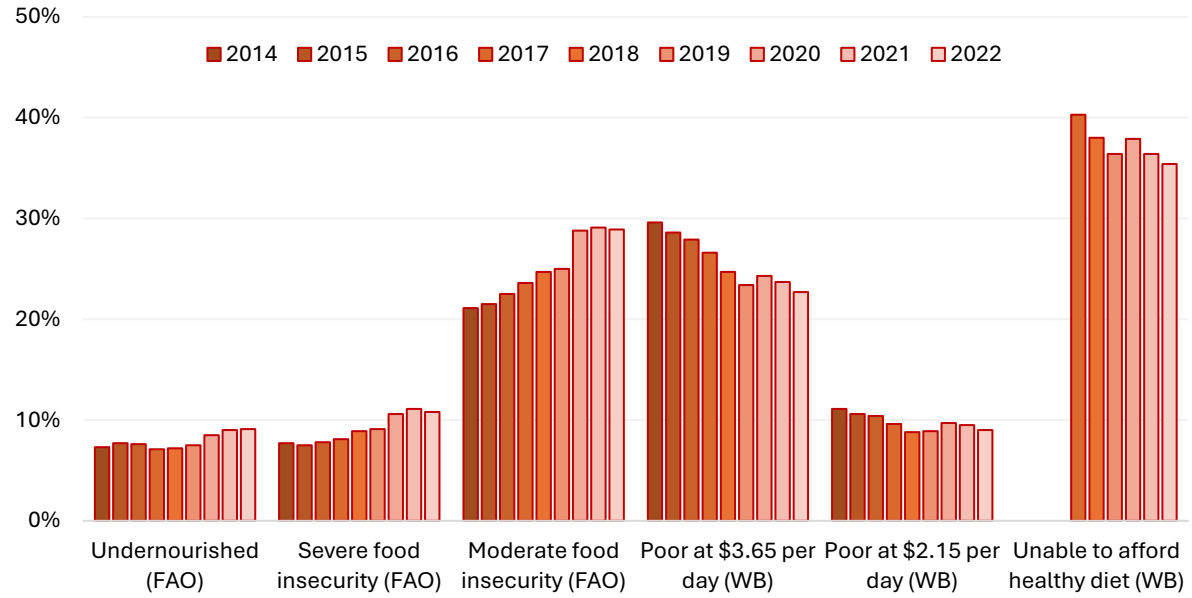
[1] Still another discrepancy in food security and nutrition monitoring comes from the World Bank-UNICEF-WHO Joint Modelled Estimates (JME) for stunting among children under 5 years of age (a marker of chronic undernutrition in early childhood), which shows continuous decline throughout 2000-2022, including during the COVID-19 pandemic. The authors have a separate study on the problems with the JME methods, which are serious indeed.

Figure 2. Divergent trends in poverty and food insecurity indicators

Panel A. Divergent trends in food and nutrition insecurity indicators over 2000-2022



Panel B. Divergent trends in food insecurity and poverty indicators over 2014-2022



Source: Insufficient calories and severe food insecurity experiences are sourced from the FAO's FAOSTAT database (FAO, 2024), while people who are $3.65/day poor or $2.15/poor or unable to afford a healthy diet are sourced from the World Bank (World Bank, 2024d). All three measures compare expenditures to poverty lines that are measured in in 2017 purchasing power parity dollars. *Moderate food insecurity refers to moderate or severe food insecurity.

2. The FAO's modelled undernourishment indicator: Is "hunger" really increasing?

The FAO's headline indicator of food insecurity aims to measure the share of people who are undernourished in caloric terms and is often referred to as a "hunger" estimate. This modelled indicator has been subject to significant criticism for several decades on both conceptual and methodological grounds (Barrett, 2010; Headey and Ecker, 2013; Masset, 2011; Svedberg, 1999).

First, conceptually, the FAO undernourishment indicator tries to measure an inherently individual-level construct – whether an individual is consuming enough calories relative to specific individual needs – using national level data on aggregate calories supplies from FAO food balance sheets. Yet individual calorie requirements vary substantially depending on physical activity, sex, age, height and existing body mass. Even though FAO analysts make some adjustments for demographic differences at any given time, physical activity levels (and hence calorie requirements) can decline systematically over the course of development as manual production becomes mechanized, or arduous collection of firewood and water is replaced by electricity, gas and water infrastructure in the home itself (Deaton and Dreze, 2008). This leads to the possibility that calorie consumption is declining in a country not because people are more food insecure, but because the country's population requires fewer calories for their reduced physical activity. Indeed, this decline in physical activity associated with manual labor is one contributing factor to rising obesity in LMICs (Popkin, 2001; Popkin, Corvalan and Grummer-Strawn, 2020).

Second, empirically, the FAO relies on two highly problematic sources of data: (i) the FAO national level food balance sheet data providing an aggregate of the total supply of calories in a country from all foods, net of waste and storage; and (ii) scarce household-level food consumption data (not individual consumption data) used to compute the inequality in calorie availability across households in a country.

To start with (i), the FAO food balance sheet data is often of very low quality and highly incomplete in terms of its raw data inputs, especially in countries likely to have the highest rates of undernutrition, such as those affected by conflict, political instability or natural disasters. No one could claim that there is any reliable basis for estimating annual aggregate production, imports, exports, storage or waste for all the foods consumed in a fragile and low-capacity state like the Democratic Republic of Congo (DRC), where large swathes of the country live outside national government control, borders are porous and statistical systems extremely weak. The World Bank (2024d) gives the DRC a statistical capacity score of 43 out of 100, compared to 84 for a country like Indonesia. Yet the DRC is not an exceptional case; it is hard to imagine any low-income country being able to report sufficiently high quality and timely data on production of the full range of foods consumed in a country, while parameters like food waste and storage are always imputed or extrapolated rather than observed, since there are no representative data on food waste in LMICs (UNEP, 2021). In summary, the FAO's food balance sheet estimates of calorie consumption are constructed from low quality

national input data to begin with, combined with vast amounts of imputation and conjecture from FAO statisticians. There is no easy solution to this problem, and the problem is more severe in precisely those countries likely to have the highest rates of undernourishment.

As for step (ii), calorie inequality estimation, FAO statisticians need to somehow distribute this national supply of calories - 213,000,000,000 kilocalories per day in the DRC in 2022 - across all the individuals in a country. To do so, they use household food consumption surveys to provide some empirical basis for the potential variation in calorie consumption across the population. At this point, one may well ask why the FAO does not simply estimate caloric undernourishment directly from household surveys. The answer likely lies in the fact that since FAO statisticians are mandated to produce undernourishment estimates for all countries in all years, there is an insufficient supply of timely food consumption surveys to estimate calorie consumption through this more bottom-up process. Instead, the FAO uses what surveys they do have access to for estimating calorie inequality for those specific survey years, before interpolating and extrapolating inequality of calorie consumption for all other years.

The FAOSTAT website describes the reality of the situation:

> "When appropriate data for directly estimating the variability of food consumption are not readily available, indirect procedures are used by FAO to estimate a suitable value for this parameter."

So how do FAO statisticians derive a "suitable value for this parameter" for countries like Afghanistan, where the World Bank reports that no nationally representative household survey has ever been conducted? Or in a less extreme case, how does the FAO derive a "suitable value" in Rwanda in 2022, where the last household income and expenditure survey was conducted in 2016?

Why.is.undernourishment.rising.while.poverty.is.falling?

Deterministically, increases in the modelled FAO undernourishment estimates must stem from decreases in calorie availability for consumption or increases in the inequality of calorie consumption.[2] In Table 1 we therefore report trends over 2014-2022 in FAO estimates of mean calories per capita as well as a calorie inequality proxy, the coefficient of variation in calories, stratified by World Bank income levels. However, we also report trends in World Bank estimates of median income/expenditure and the Gini coefficient of income/expenditure, since changes in poverty must analogously be a function of changes in mean income and changes in the income inequality (Bourguignon, 2002).

Should the FAO undernourishment "input indicators" and World Bank poverty "input indicators" be correlated with each other? Calorie consumption is expected to rise with

[2] FAO calorie requirements only change slowly according to demographic shifts, so changing calorie requirements are not likely to explain rising undernutrition in the short run.

income/expenditure, albeit at a diminishing rate (Engel's law). A corollary of this is that one would expect the changes in the Gini coefficient of income inequality to be positively correlated with the coefficient of variation in calorie consumption, especially if the FAO are using the same kinds of income/expenditure surveys to estimate the coefficient of variation in calories as the World Bank uses to estimate income/expenditure inequality.[3]

A first key takeaway from Table 1 is that the supply of household surveys for modelling undernourishment for low-income countries – where hunger and extreme food insecurity are most prevalent – is highly problematic. The FAO produced undernourishment estimates for 23 LMICs in every year over 2014-2022, even though the maximum number of surveys used by the World Bank to estimate incomes, inequality and poverty was never more than 7 surveys in a given year, while in 2017 there were no LMIC income/expenditure surveys. Yemen, Madagascar, Somalia and Afghanistan had no surveys conducted over 2014-2022, while many low-income countries had only one survey in this period.

[3] It should be noted, though, that there is no easy way of knowing exactly which surveys the FAO uses to estimate calorie inequality, as this is not described in any publicly available documents or websites that we are aware of.

Table 1. Gaps and trends in undernourishment and poverty "inputs": 2014-2022

	FAO undernourishment inputs[2]			World Bank (WB) poverty inputs[3]			
LOW-INCOME COUNTRIES: Statistical capacity score[1] = 55%							
	N (FAO)	**Mean Calories**	**Calorie inequality**	**N (WB)**	**Median income**	**Income inequality**	**WB surveys as % of FAO estimates**
2014	23	2,323	0.31	6	$2.72	0.38	26%
2015	23	2,306	0.31	3	$2.98	0.38	13%
2016	23	2,288	0.32	4	$2.31	0.42	17%
2017	23	2,307	0.32	0	NA	NA	0%
2018	23	2,299	0.32	7	$3.02	0.38	30%
2019	23	2,312	0.33	3	$1.77	0.44	13%
2020	23	2,329	0.34	2	$2.50	0.42	9%
2021	23	2,327	0.34	6	$2.75	0.37	26%
2022	23	2,329	0.34	2	$3.03	0.32	9%
% Change		6¡9↘	❺¦❷↘		77¡0↘	_7❶¦❸↘	
LOWER MIDDLE-INCOME COUNTRIES: Statistical capacity score[1] = 66%							
	N (FAO)	**Mean Calories**	**Calorie inequality**	**N (WB)**	**Median income**	**Income inequality**	**WB surveys as % of FAO**
2014	42	2,603	0.27	9	$6.55	0.40	21%
2015	42	2,611	0.27	16	$5.26	0.40	38%
2016	42	2,623	0.27	9	$6.20	0.40	21%
2017	42	2,637	0.28	9	$5.67	0.38	21%
2018	42	2,655	0.28	15	$5.34	0.38	36%
2019	42	2,669	0.28	8	$6.47	0.38	19%
2020	42	2,681	0.29	5	$7.56	0.36	12%
2021	42	2,689	0.30	10	$6.10	0.36	24%
2022	42	2,683	0.30	4	$7.44	0.38	10%
% Change		9¡7↘	❹¦7↘		79¡❷↘	_0¡❶↘	
UPPER MIDDLE-INCOME COUNTRIES: Statistical capacity score[1] = 71%							
	N (FAO)	**Mean Calories**	**Calorie variation**	**N (WB)**	**Median income**	**Income Gini**	**WB surveys as % of FAO**
2014	45	2,950	0.25	26	$9.99	0.40	58%
2015	45	2,966	0.25	25	$10.56	0.40	56%
2016	45	2,969	0.25	23	$10.42	0.39	51%
2017	45	2,981	0.25	23	$10.86	0.38	51%
2018	45	3,002	0.25	26	$11.76	0.38	58%
2019	45	3,028	0.25	22	$11.46	0.37	49%
2020	45	3,038	0.26	18	$10.50	0.38	40%
2021	45	3,050	0.26	17	$11.38	0.39	38%
2022	45	3,064	0.26	14	$10.81	0.41	31%
% Change		9¡❹↘	0¡❺↘		❹¦8↘	8¡❺↘	

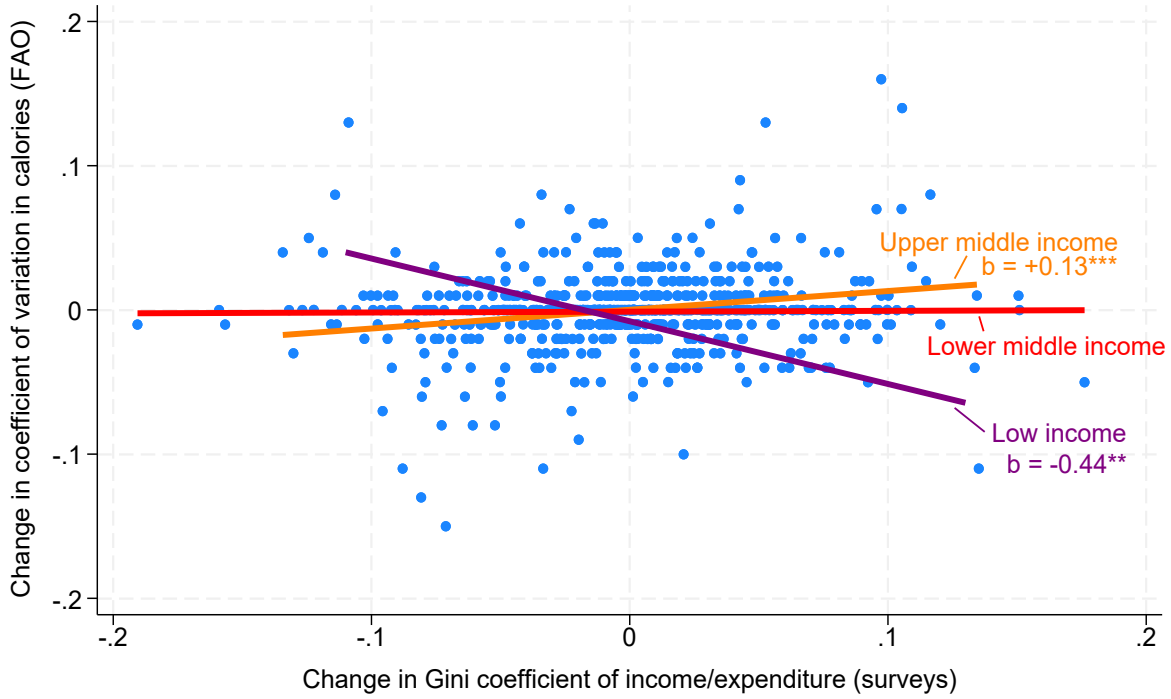
Source: 1. World Bank's index of overall statistical capacity. 2. FAO (2024) input indicators into the calculation of undernourishment as defined in the text. 3. World Bank input indicators into monetary poverty measures are sourced from the Poverty and Inequality Platform (World Bank, 2024a).

Despite such a limited availability of consumption surveys, the FAO estimates that inequality in calorie consumption increased by 9.6% over 2014-2022 in low-income countries. To dig into this divergence further, we plot changes in the coefficient of variation in calorie consumption reported by the FAO against changes in the Gini coefficient of income/expenditure reported by the World Bank across common country-specific time periods (Figure 3). In addition to the scatterplot, we also fit linear regressions separately for upper middle, lower middle and low-income countries, since survey availability is dramatically different for each income group (Table 2).

The scatterplot in Figure 3 suggests little correlation between the two inequality measures, but the linear regression fits suggest that the associations do indeed vary by income groups. In the sample of upper middle-income countries – who have much higher statistical capacity and more frequent income/expenditure surveys (Table 2) – the correlation between the calorie and income/expenditure inequality indicators is positive and significant, as expected, but modest in magnitude (a slope coefficient of 0.13 significant at the 1% level). In lower middle-income countries, the slope coefficient is close to zero and statistically insignificant. However, in low-income countries the correlation between the two inequality indicators is counterintuitively negative and statistically significant at the 5% level, with a very steep slope coefficient of -0.44. This is remarkable in that it implies that in countries where the World Bank is reporting declining income/expenditure inequality, the FAO is typically reporting increasing calorie consumption inequality.

In conclusion, it is difficult to know what the empirical basis is for the FAO's estimation that undernourishment is generally increasing in LMICs, especially low and lower middle-income countries. On top of the conceptual and empirical problems discussed at the beginning of this section, the development community should be additionally concerned that trends in undernourishment are not adequately reliable or transparent enough to draw any firm conclusions on global or region trends in caloric deprivation.

Figure 3. Associations between the FAO's estimates of changes in the coefficient of variation in calorie consumption against changes in the Gini coefficient of income or expenditure, stratified by World Bank income levels



Notes: The y-axis reports changes in the coefficient of variation in calorie consumption used by the FAO (FAO, 2024) for estimating levels and trends in its undernourishment indicator, but which includes imputed values. The x-axis reports changes in the Gini coefficient of income or expenditure from the Poverty and Inequality Platform (World Bank, 2024a). The timeframe for changes in both inequality indicators is country-specific, depending on the availability of World Bank Gini coefficient estimates. The low-income sample includes 61 observations. The lower middle-income sample includes 193 observations. The upper middle-income sample includes 467 observations.

3. The World Bank's monetary poverty estimates: Is poverty really declining?

Conceptually, monetary poverty ought to be a strong predictor of food insecurity, and arguably should be more widely thought of as a food insecurity indicator in its own right.

Why?

First, since the inception of poverty measurement in the 19th Century, poverty lines have always aimed to consider basic nutritional needs, although these have all too often been defined as sufficient calorie availability at the household level (Ravallion, 2000). As a result, standard food poverty lines have a conceptual affiliation with calorie-based undernourishment measures. Second, a household's ability to purchase or "access" sufficient food also depends on its non-food expenditure needs. For example, increases in the price of electricity – a non-food basic need – could lead to a significant reduction in food expenditures, i.e. rising food insecurity. Hence, measuring income relative to a combined food and non-food poverty line seems conceptually more relevant to food insecurity status than food poverty status alone.

That said, measuring poverty across countries in a timely fashion is challenging. Household income/expenditure surveys are not highly standardized (Ravallion, 2020), and some countries use income to measure poverty while others use expenditures. Perhaps most importantly in the current context, we saw in Table 2 that there are simply not enough surveys conducted in poorer countries. To their credit, however, the World Bank Poverty and Inequality Platform (PIP) at least offers detailed documentation of its method and online tools for replicating their official poverty estimates, as well as information on their global and regional poverty nowcasts and forecasts (World Bank, 2024b).

For the latter, the PIP uses an extrapolation method based on regression-based elasticities between poverty and economic growth from historical data, which is then combined with recent or forecast growth rates in GDP per capita or household consumption per capita to predict changes in poverty for recent years when no survey estimates exist. A published World Bank study shows that this simple approach performs nearly as well as models using statistical learning on 1,000+ variables (Mahler, Castañeda Aguilar and Newhouse, 2022).

The World Bank also has clear decision rules for whether or not to report trends that are at least partially derived from poverty predictions: a country is only considered to have sufficiently recent data for extrapolation if it has a survey-based poverty estimate at most three years from the reference interpolation year; regional estimates are only reported for a given year if survey data cover 50 percent of the population in the region; and global estimates are only reported if data are representative of at least 50 percent of the global LMIC population. A published study by World Bank authors provides a statistical rationale for this decision rule (Mahler, Serajuddin and Maeda, 2023), though they also note the more stringent decisions rules would be advisable for assessing trends over time, and that "rather than

conditioning on data being present for populous countries, it would be better to increase the coverage threshold" (e.g. beyond 50%).

Whether these rules are sufficiently conservative or not is open to debate, though they are at least transparent. Hypothetically, covering 50% of the global LMIC population could be achieved by having access to recent surveys in India and a few other large countries, whilst still having gaps for many less populous LMICs, especially poor low-income countries in sub-Saharan Africa.[4] In fact, this hypothetical scenario is not far off the actual data situation over the 2020 to 2022 period (admittedly unusual because of COVID-19 disruptions), when just one third of the 48 countries in sub-Saharan Africa had conducted a suitable survey, and none of the three largest countries in Africa had done so (Nigeria, Ethiopia and the DRC). A related problem is that the World Bank's extrapolation method assumes there is no change in inequality in a country. As the World Bank (2024b) itself notes, such an assumption is likely invalid in some contexts, especially during the COVID-19 pandemic,[5] though there are many other shocks likely to affect inequality. Indeed, World Bank staff also report potential discrepancies between simple growth elasticity-based poverty projections and more sophisticated microsimulations that model growth shocks in particular sectors and occupational categories.[6]

A further concern in global poverty estimation is the under-recognized problem of selection bias: countries in various forms of crisis are less likely to have conducted recent income/expenditure surveys, and more likely to experience rising poverty rates. Political or economic crises have delayed the regular implementation of income/expenditure surveys in crisis countries like Sri Lanka, Ethiopia and Myanmar, to name just a few. No less worrying is the possibility that political leaders may delay or cancel surveys if they feel the results of the survey will yield unfavourable poverty trends. The World Bank's extrapolation methods account for economic growth's predictive influence on poverty – and the growth rate may. absorb most of the information needed to predict changes in income distributions – but there remains much greater uncertainty regarding poverty trends in LMICs where poverty may be highest, and statistical capacity or political commitment to poverty monitoring are lowest.

Bearing in mind selection biases, Figure 4 reports the most recent trends in poverty at the $3.65/day poverty line for 17 low and lower middle-income countries in which the most recent survey round was conducted in 2021 or 2022. This approach will potentially cover

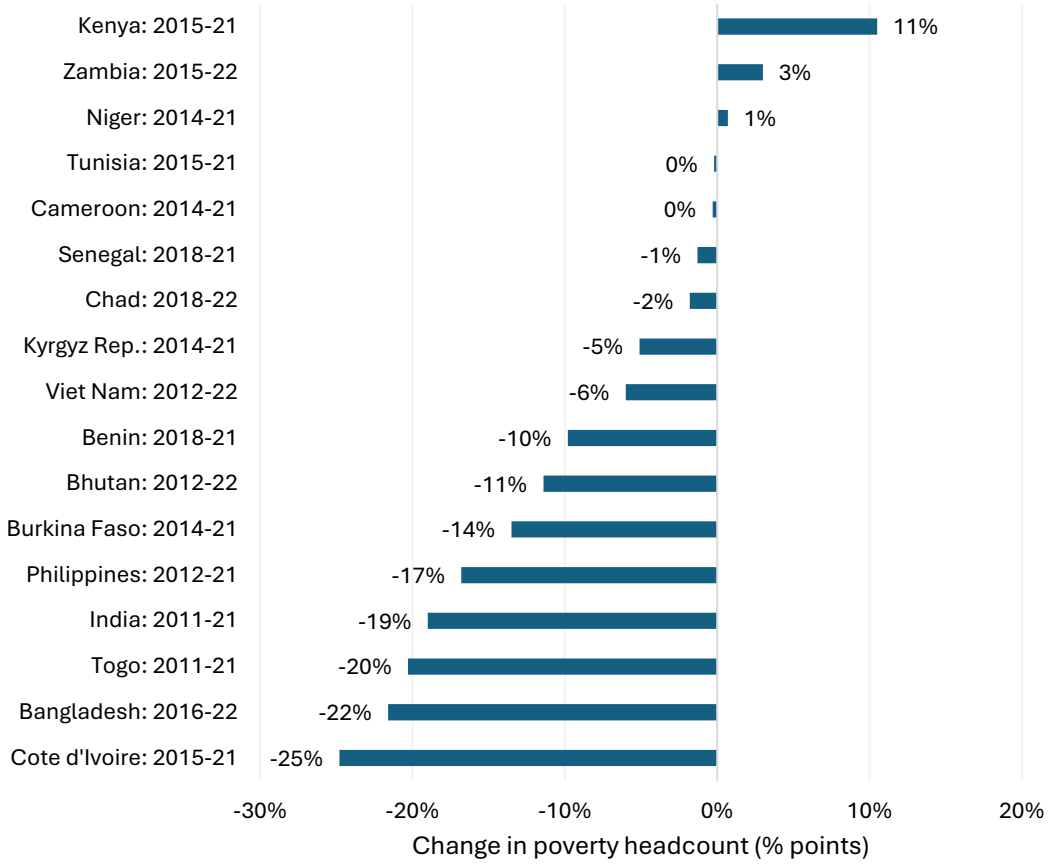
[4] Moreover, poverty trends in India are quite uncertain. India had a remarkable 11-year gap in the production of official poverty statistics under the current government, leading the World Bank to start using a privately implemented national survey, but one that required special corrections for its under-sampling of poorer households (Roy and van der Weide, 2022). Their conclusion is that poverty has declined in India, but not by as much as was previously estimated.

[5] Indeed, in its most recent global poverty estimates, The World Bank refrained from using its standard 3-year rule for poverty projections from 2020 onwards, and instead relied entirely on actual survey-based estimates for recent years.

[6] This point was made during a personal communication with Dr. Marta Schoch, an Economist in the Poverty and Equity Global Practice of the World Bank. She cited the example of microsimulations in the Sri Lankan economic crisis (2022-2024), where more sophisticated microsimulation results yielded a larger increase in the estimated poverty rate than the standard growth-poverty elasticity.

periods of some poverty reduction prior to COVID-19, and some increase in poverty during COVID-19. Bearing that in mind, only three countries saw a net increase in poverty, most notably Kenya (an 11-percentage point increase over 2015-2021). Two countries saw no change (Tunisia, Cameroon), while the remaining 12 saw decreases in poverty, sometimes quite large. Interestingly, these 12 countries are not confined to any single region. In summary, we can at least conclude that poverty rates have declined in most LMICs where surveys have recently been conducted, though the World Bank's most recent poverty report concludes that poverty reduction has stalled since the COVID-19 pandemic, including in sub-Saharan Africa (World Bank, 2024c).

Figure 4. The most recent changes in poverty headcounts in 17 low and lower middle-income countries at the $3.65/day poverty line



Source: Author's estimates from the Poverty and Inequality Platform (World Bank, 2024a)

A final point to note is that the $3.65/day poverty rate shares a common downward trend over 2017-2024 with a new food insecurity measure, the share of people unable to afford a healthy diet, as defined by nutritional standards of dietary balance across a range of nutrient-dense foods (Herforth et al., 2022). Here, we do not dig deep into explaining the declining share of people unable to afford a healthy diet, because there is no puzzle to explain: the inability to

afford a healthy diet is.a type of poverty metric, but one with a food poverty line set at the cost of a healthy diet. Its chief difference to the $3.65/day poverty line is that the cost of a healthy diet is country-specific rather than fixed, and the healthy diet poverty line is generally a much higher cost than the $3.65/day poverty line because healthy foods are often relatively expensive (and of course, the $3.65 line is designed to cover food and non-food basic needs).

Since the inability to afford a healthy diet is a type of monetary poverty indicator, it follows that the dearth of surveys that are problematic for poverty measurement are equally problematic for healthy diet affordability measurement, but with the additional step taken by its analysts to extrapolating trends in healthy diet costs via changes in national consumer food price indices (Herforth et al., 2022).[7] Moreover, we note that the FAO does not follow the more conservative decision rules on missing data in the context of global and regional poverty that the World Bank PIP follows. Instead, the FAO FAOSTAT website and SOFI report provide diet unaffordability estimates for a large swathe of countries on an annual basis over 2017 to 2023, even if a country, region or income group has little or no survey data over this timeframe. Some caution should therefore be used when inferring trends in this metric over time.

4. The Food Insecurity Experience Scale: do FIES-based indicators provide valid comparisons across countries and over time?

Acknowledgement of the limitations of its undernourishment indicator prompted the FAO to invest in developing and testing experiential indicators of food insecurity, building on indicators developed in North and South America in previous decades. In this section we review the origins of the FIES, two new independent studies on its validity and comparability across African populations and provide new and more global comparisons of FIES-based extreme food insecurity and World Bank estimates of extreme poverty.

The.construction.and.validation.of.the.FIES

The FIES builds on research conducted in the US in the 1980s (Radimer, Olson and Campbell, 1990), which first categorized different kinds of food insecurity experiences, and then scaled different experience by their intensity. Through the Voices of the Hungry project, the FAO team followed this approach by asking individual respondents eight questions about whether any member of their household had either moderate food insecurity experiences (e.g. worrying about insufficient food to eat, reducing the quality of the diet) or severe experiences (skipping meals, going hungry, or having to go for a whole day without eating) because of a lack of money or other resources over the past 12 months (Table 2).

[7] We do not discussion the question of whether the cost of a healthy diet can accurately be projected using the food CPI, but this could certainly be problematic because the CPI's food items are weighted by prevailing consumption patterns from household surveys, whereas the healthy diet food groups are weighted by nutrition guidelines. There are likely many instances where the two indices do not follow similar trends. For one thing, governments often try to stabilize the price of staple foods for welfare reasons and political reasons, whereas they very rarely intervene to stabilize the prices of fruits, vegetables or animal-sourced foods.

Table 2. The Food Insecurity Experience Scale (FIES) questions and aggregate classifications into moderately or severely food insecure

Score value	During the last 12 MONTHS, was there a time when because of a lack of money or other resources? (YES–NO)
1	1. You were worried you would not have enough food to eat
1	2. You were unable to eat healthy and nutritious food
1	3. You ate only a few kinds of foods
1	4. You had to skip a meal
1	5. You ate less than you thought you should
1	6. You ran out of food
1	7. You were hungry but did not eat
1	8. You went without eating for a whole day
	Food insecurity classification
6_9	Not.food.insecure.or.mild.food.insecurity
0_❷	Moderately.food.insecure
❸_❹	Severely.food.insecure

Source: Ballard, Kepple and Cafiero (2013).

Proponents of experience-based food insecurity indicators argue that they are specifically defined and generally valid and comparable across populations, cheaply and easily measured and analysed, and suitable for use in high frequency surveys, allowing policymakers to respond more proactively to food crises (Cafiero, Viviani and Nord, 2018; Saint Ville et al., 2019). For global monitoring, the FAO contracted the Gallup World Poll (GWP) to add the FIES module to the standard GWP survey instrument.

Clearly, a key goal in the development of FIES was the pursuit of cross-country comparability but also cross-cultural comparability given the high degree of ethnic heterogeneity in many LMICs. To date, validity has largely been assessed through Rasch models in which it is expected that responses to each insecurity question should become increasingly infrequent as the experience becomes more severe, while responses to each question should also be relatively independent of responses to other items. Initial evidence from the Voices of the Hungry project suggested the FIES performed well on the Rasch scale (Cafiero et al., 2018), while comparative evidence for three countries suggested that more extreme experiences (e.g. going a whole day without eating) have greater comparability across cultures and countries, while more moderate experiences do not (Deitchler et al., 2011).

While those initial Voices of the Hungry studies were promising – albeit from relatively small subsets of countries – two independent studies of FIES data in sub-Saharan Africa raise serious concerns on the validity of the FIES measures (Lain, Tandon and Vishwanath, 2023; Wambogo et al., 2018).

First, Wambogo et al. (2018) analyzed a cross-section of FIES data collected through the GWP in 37 sub-Saharan African countries. They find that the expected ordering for questions 1–5 (based on severity of the types of experiences) was often different from their actual order of ranked prevalence. In other words, the Rasch tests were not passed. Moreover, although the most severe experience – "whole day without eating" – was indeed the least widely reported, as expected, even this indicator had erratic or unexpected responses in 12 countries of the 37 countries (32% of the sample), most prominently in Madagascar. Finally, in the Republic of Congo, the DRC and Somalia, the FIES performed poorly, and the authors conclude that the FIES questions in these countries "may be understood differently and may measure different severity levels of food insecurity compared with the rest of SSA".

Second, Lain et al. (2023) use household surveys from 10 West African countries, all of which collected the FIES, the WFP's Food Consumption Score (FCS) and standard expenditure-based poverty measures. They find that in 4 out of 10 countries, there is a similar prevalence of FIES-based food insecurity among segments of the population that are likely undernourished and segments likely not undernourished. In 5 of the 10 countries, there is a surprisingly large prevalence of FIES-based food insecurity in the segments of the population that are least likely to be undernourished. And in their Nigerian survey the FIES metrics suggest that food insecurity is more prevalent in the south of the country, whereas FCS and poverty-based metrics clearly suggest more food insecurity and poverty in the north (as do many other surveys in Nigeria).

Both of these studies analyzed a cross-section of FIES data and uncovered serious concerns regarding the validity and reliability of the FIES module for cross-country comparability, as well as comparability across regions within Africa's most populous country, Nigeria. However, neither study examined the plausibility of FIES trends over time. However, an earlier review did raise the concern that more moderate forms of food insecurity may be overly reactive to small shocks or changes in contextual factors (Headey and Ecker, 2013), which FAO experts also acknowledge (Cafiero et al., 2018). Furthermore, that review concluded that experience-based indicators have only been subject to specific types of validity tests, mostly Rasch tests. In contrast, other types of self-reported wellbeing indicators outside the food security literature have been subjected to a much wider range of tests, especially measure of subjective wellbeing (happiness, life satisfaction, emotions). This literature has uncovered serious cause for concern, including high degrees of sensitivity to test-retest (Krueger and Schkade, 2008), and to contextual factors such as the weather (Feddersen, Metcalfe and Wooden, 2016), module placement and framing effects (Deaton, 2012), a respondent's mood

(Diener, 2013) and subtle translation issues (Oishi, 2010).[8] So far, no analogous literature exists for experienced-based food insecurity indicators.

Do.FIES_based.food.insecurity.indicators.identify.food.insecure.populations?

Given the concerns raised about the validity, comparability and sensitivity of FIES indicators, it is important to ask whether these indicators provide an accurate identification of food-insecure countries. Cross-country correlations reported in Appendix Table A2 show that moderate and severe food insecurity are relatively strongly correlated with the FAO's modelled undernourishment estimates and monetary poverty (with correlation coefficients ranging from 0.67 to 0.82). FIES indicators are somewhat less strongly correlated with stunting (0.60 for moderate food insecurity and 0.46 for severe food insecurity), whereas the $3.65/day poverty rate has a 0.83 correlation with stunting and much stronger correlations with child wasting, a measure of severe acute malnutrition. Indeed, the FIES-based severe food insecurity indicator has no significant correlation with wasting, despite the a.priori expectation that severe food insecurity is a major cause of wasting.

Correlation coefficients are only broadly indicative of whether different indicators classify countries in the same way. Figure 5 therefore compares the FIES severe food insecurity measure – since more severe food insecurity experiences ought to be more comparable across countries than moderate food insecurity (Deitchler et al., 2011) – to the $2.15/day World Bank indicator of extreme poverty. For illustrative purposes, we arbitrarily choose a cut-off prevalence of 20% for identifying countries as severely food insecure and extremely poor (though inferences are not sensitive to this threshold). These countries are reported in Quadrant 3, while countries that are severely food insecure but not extremely poor are reported in Quadrant 4, and poor but not food insecure are in Quadrant 2, while Quadrant 1 includes countries where prevalence rates for both indicators are below 20%. We also report a regression fit. Finally, we note that Figure 5 does not include FIES results for India, since the Indian government does not permit the FAO to report FIES-based indicators in its SOFI reports or FAOSTAT database.[9]

Despite a statistically significant slope coefficient of 1.11 and an R-squared of 0.65, Figure 5 identifies a number of countries that are reported to be extremely poor but not severely food insecure according the FIES-based indicator, or severely food insecure but not extremely poor. Surprisingly, and worryingly, a number of countries in sub-Saharan Africa have FIES-based severe food insecurity rates below 20% but poverty rates well above 20%. The most striking

[8] From the authors' own experiences with implementing the FIES and HHS in several LMICs, translation of these modules from English to local languages in LMICs is by no means a trivial task, and there is ample scope for quite subtle translation errors.

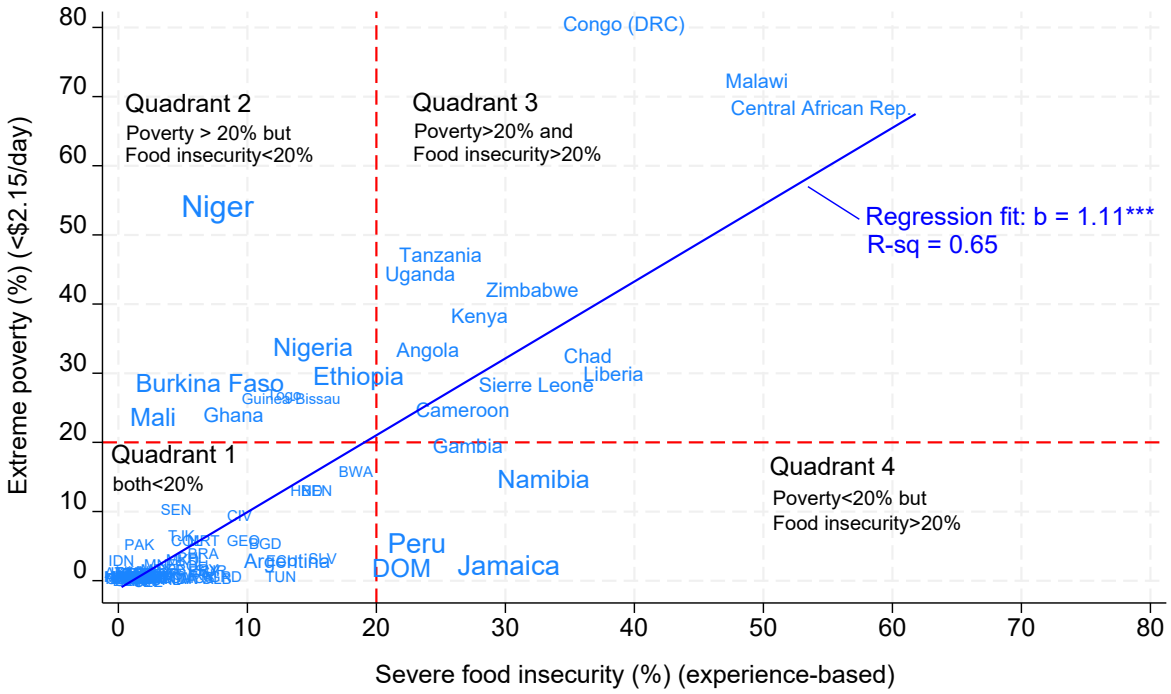
[9] However, we know from a 2016 FAO report (FAO, 2016) that severe food insecurity in India in 2014 was estimated to be 12.4%, while the World Bank estimates that extreme poverty was around 18.8%. However, these estimates are now 10 years out of date and were not reported during COVID-19, for example, which had major effects on India's GDP growth and poverty rates.

outlier is Niger, surely one of the poorest and.most food insecure countries in the world, and indeed the country that the UNDP's multi-dimensional poverty index classifies as the poorest in the world (UNDP, 2023). Despite the strong prior that Niger is highly food-insecure, the FIES suggests severe food insecurity was just 7.7% in 2021. In contrast, the World Bank estimates that extreme poverty in Niger was 50.6% in 2021: in other words, one in two people were classified as extremely poor versus one in thirteen people classified as severely food insecure. Niger is an extreme case, but many other African countries also have lower rates of severe food insecurity experiences than one would expect from the regression fit.

Conversely, there are several countries in Quadrant 4 that have unexpectedly high rates of severe food insecurity given their poverty levels, notably Jamaica, Peru and the Dominican Republic. The 2021 GWP survey for Jamaica reports 25.6 percent of respondents as severely food insecure, more than three times the rate for Niger. In contrast, just 0.3% of Jamaicans were poor at the $2.15/day poverty line.[10] For Peru in 2022, the GWP estimates that 20.3% of people were severely food insecure, whereas just 2.7% were extremely poor. The Dominican Republic has similar discrepancies: between 2015 and 2022 its prevalence of severe food insecurity varied between 24.3% in 2015 and 19% in 2022, while its poverty rate was varied between 2.5% and 0.8%.

[10] This is not a result of the COVID-19 pandemic: the GWP estimates severe food insecurity in Jamaica varying between 23 and 26 percent every year over 2015-2022.

Figure 5. Do the FIES-based severe food insecurity indicator and the World Bank extreme poverty indicator identify the same countries as food-insecure?



Notes: Poverty and severe food insecurity pertain to the most recent year in which poverty is measured. The x-axis reports severe food insecurity prevalence based on the FIES module implemented through the Gallup World Poll and reported by FAO (FAO, 2024). The y-axis reports extreme poverty prevalence at the $2.15/day poverty line as reported by the Poverty and Inequality Platform (World Bank, 2024a). The data pertain to the most recent year for which poverty estimates are available.

It is surely implausible that "true" levels of severe food insecurity are so much higher in Jamaica, Peru or the Dominican Republic than they are in Niger, Burkina Faso or Mali. In addition to the analyses of FIES indicators in sub-Saharan Africa by (Wambogo et al., 2018) and (Lain et al., 2023), the more global cross-country comparisons in Figure 5 cast further doubt on the cross-country comparability of the FIES-based indicators. We conclude that a great deal more independent and varied validation studies – or invalidation studies – are needed to re-assess the validity and reliability of FIES metrics.

5. Can rising food insecurity be explained?

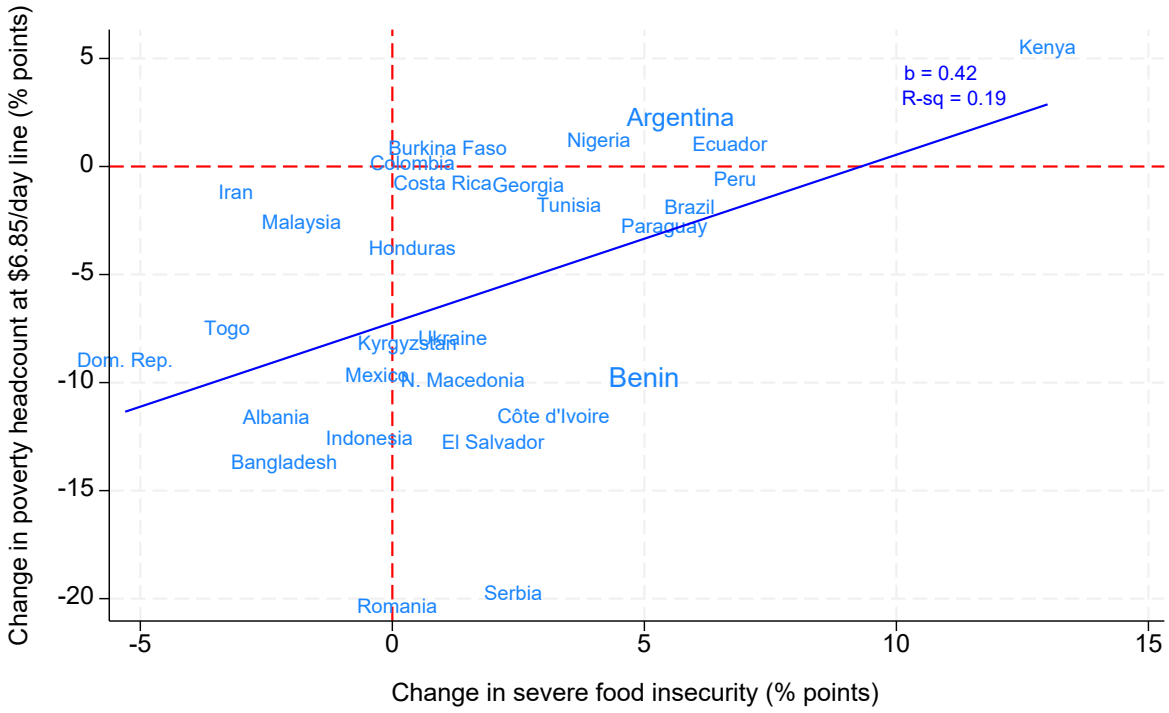
Where the previous section cast further doubt on the cross-country comparability of FIES-based indicators and poverty, it did not explore why FIES-based food insecurity indicators are rising at the global and regional level. In this section we first examine FIES trends more closely, examine trends in an alternative source of experiential food insecurity indicators from Afrobarometer, and use regression analysis to explore whether widely hypothesized drivers of rising food insecurity can statistically explain increases in FIES indicators.

Comparing.trends.in.FIES_based.food.insecurity.to.changes.in.poverty

In Figure 6 we replicate the scatterplot and regression fit for poverty-FIES comparisons from Figure 5 above, but with each indicator expressed as percentage point changes over the maximum possible timeframe for each country. However, because most of the countries in Figure 6 with recent income/expenditure surveys are upper middle income, we use the $6.85/day poverty line deemed appropriate for these countries.

Figure 6 shows a positive and statistically significant slope coefficient of 0.42, but a rather low R-squared of just 0.19, suggesting statistical agreement on poverty and FIES trends is rather weak. Moreover, the y-intercept is -7.3, indicating that when a country has had no change in severe food insecurity, its expected change in poverty was a reduction of 7.3 percentage points. Also striking is that there are number of upper middle-income countries – where one would expect severe food insecurity to be quite rare – which report large increases in severe food insecurity (Paraguay, Brazil, Peru, Ecuador and Argentina) but no change in poverty. In Appendix Figure A1 we repeat this exercise with moderate food insecurity with similar results, and we again observe a cluster of Latin American countries seeing marked increases in food insecurity in the range of 10-18 percentage points over various recent timeframes.

Figure 6. The association between changes in the poverty headcount at the $6.85/day headcount and changes in FIES-based severe food insecurity within the 2014-2022 window



Notes: Poverty and severe food insecurity pertain to the most recent year in which poverty is measured. The x-axis reports changes in severe food insecurity based on the FIES module implemented through the Gallup World Poll and reported by FAO (FAO, 2024). The y-axis reports extreme poverty headcount at the $6.85/day poverty line as reported by the Poverty and Inequality Platform (World Bank, 2024a). The data changes in both indicators are country-specific, as determined by the availability of poverty estimates, but all periods of change fall in the 2014-2022 window.

Is.food.insecurity.increasing.in.Africa?.Comparisons.to.Afrobarometer

While this disconnect between trends in the FIES-based food insecurity and poverty rates is surprising, Afrobarometer (2024) – a multi-thematic survey of African countries that is somewhat similar to the GWP – also reports increases in an alternative experience-based food insecurity indicator. Unlike the FIES, Afrobarometer only asks a single food security question: "Over the past year, how often, if ever, have you or anyone in your family gone without enough food to eat?" with response options being never, just once or twice, several times, many times or always. Here we use these classifications to construct a distinct severe food insecurity indicator based on "Many times or always without enough food".

Table 3 compares changes in this Afrobarometer-based indicator from 2014-15 to 2021-23 to the FIES-based severe food insecurity rates from the GWP surveys over similar timeframes. Like the GWP, Afrobarometer reports some dramatic increases in severe food insecurity, including in Africa's largest country, Nigeria (+21.5 points), with large increases also observed in Niger, Zimbabwe, Madagascar and Kenya. Moreover, population-weighted changes in

regional food insecurity from both sources – albeit with different countries sampled – increase by similar margins: +7.2 points in Afrobarometer and +7.5 points in the GWP. Hence, an independent source of self-reported food insecurity data seems to contradict the more positive conclusions drawn from the World Bank's limited poverty estimates for sub-Saharan Africa (Figure 4).

Table 3. Comparing trends in Afrobarometer's severe food insecurity indicator to the GWP FIES severe food insecurity for Sub-Saharan Africa: 2014-15 to 2021-23

	Afrobarometer severe food insecurity[1] (many times or always not enough food)			**GWP FIES-based severe food insecurity[2]** (hungry but did not eat, all day no food)		
	2014-15	**2021-23**	Change	**2014-15**	**2021-23**	Change
All countries[3]	11.5%	18.7%	+7.2 points	15.9%	23.4%	+7.5 points
Burkina Faso	13.6%	15.3%	+1.7 points	6.0%	7.2%	+1.2 points
Cameroon	15.2%	24.2%	+9.0 points	22.3%	26.1%	+3.8 points
Côte d´Ivoire	14.1%	13.2%	-0.9 points	6.2%	9.2%	+3.0 points
Ghana	6.6%	9.2%	+2.6 points	5.1%	7.6%	+2.5 points
Kenya	7.3%	17.6%	+10.3 points	15.0%	28.0%	+13.0 points
Madagascar	23.8%	34.3%	+10.5 points	9.5%	13.6%	+4.1 points
Malawi	29.5%	34.7%	+5.2 points	47.7%	52.9%	+5.1 points
Mali	14.3%	23.0%	+8.7 points	3.1%	2.7%	-0.4 points
Mozambique	17.6%	20.7%	+3.1 points			
Niger	24.6%	39.6%	+15.0 points	9.7%	7.6%	-2.1 points
Nigeria	7.4%	28.9%	+21.5 points	11.0%	22.0%	+11.0 points
South Africa	5.7%	13.5%	+7.8 points	6.9%	8.4%	+1.5 points
Sudan	6.7%	13.4%	+6.7 points			
Tanzania	10.3%	11.0%	+0.7 points	20.6%	25.9%	+5.3 points
Zambia	10.1%	14.3%	+4.2 points			
Zimbabwe	11.0%	21.6%	+10.6 points	35.5%	27.3%	-8.2 points
Correlations with FIES indicator[4]	0.41	0.28	0.17			

Source: These are changes in a severe food insecurity indicator based on Afrobarometer (Afrobarometer, 2024) respondents answering "many times" or "always" to a single food security question: "Over the past year, how often, if ever, have you or anyone in your family gone without enough food to eat?". 2. These are changes in severe food insecurity based on the FIES module implemented through the Gallup World Poll and reported by the FAO (2024).

Less encouragingly, there are still contradictions between Afrobarometer and GWP, and between both of these sources of food insecurity trends and World Bank poverty trends. For example, Afrobarometer reports that severe food insecurity has risen by 15 points Niger, while the GWP FIES data suggest food insecurity has fallen by 2.1 points. Zimbabwe also has opposing trends across Afrobarometer and GWP (Table 3). Both Afrobarometer and GWP concluded food insecurity has risen modestly in Burkina Faso, but the World Bank estimates that poverty in Burkina Faso fell by 14 percentage points over 2014-2021. There is a similar discrepancy for Cote d'Ivoire where poverty is estimated to have fallen by 25 percentage points over 2015-2021. So, while Afrobarometer offers some corroboration that Africans may indeed be feeling more food insecure, it is hard to reconcile this with the few observations on poverty trends observed in this continent, and there is not a close country-level agreement between the FIES and Afrobarometer indicators.

Can.rising.food.insecurity.be.explained.in.cross_country.regression.models?.

There could be many reasons why respondents in the GWP more frequently report food insecurity experiences, some real and some potentially artefactual or methodological in nature. On the former, various SOFI reports (FAO et al., 2022) cite several possible drivers of increasing food insecurity:

(1) Slower economic growth;
(2) The COVID-19 pandemic;
(3) Rising conflict and political instability; and
(4) Climate change.

In Table 4 we use population-weighted cross-country panel regressions for LMICs to explore whether indicators of these potential factors can statistically explain the marked increases in the FIES-base food insecurity indicator. For each FIES indicator we first estimate a simple fixed effects time trends model, which only includes a full set of annual dummy variables to capture population-weighted LMIC time trends relative to 2015 as a base year. We then add variables representing the potential drivers listed above, to assess whether: (1) these factors do indeed predict variation in FIES-based food insecurity; and (2) whether the inclusion of these factors attenuates or removes the upwards trends in FIES-based food security (i.e. coefficients on the annual dummy variables). Note, also, that with country fixed effects in the model, the coefficients on the explanatory variables can be thought of as the effect of changes or deviations in these drivers relative to long-run (multi-year) country averages (e.g. 2014-2022). Finally, standard errors are clustered at the country level and are reported in Appendix Tables A3 and A4.

In regression (1) in Table 4 we observe that severe food insecurity is significantly higher in every year relative to 2015. By 2022, for example, severe food insecurity was 2.82 percentage points higher than 2015. In regression (2) the addition of various "drivers" does not attenuate these time trends for severe food insecurity, and the only explanatory variable with a

significant coefficient is that of the log of GDP per capita, which is negatively correlated with severe food insecurity, as expected.

In regression (3) we observe an even stronger upwards trends for moderate food insecurity, which rose every year from 2015 to 2022, by which time it was 7.48 percentage points higher than in 2015. Adding control variables leads to only a very modest attenuation of these time trends. The coefficient on the log of GDP per capita is negative and large in absolute magnitude, and statistically significant. The coefficient on the real food price index – the ratio of the food consumer price index (CPI) to the total CPI – is positive, suggesting that real food price increases leave respondents more likely to report moderate forms of food insecurity. We also tested whether nominal food inflation or total inflation explain rising food insecurity, but they do not (results available on request). Finally, the coefficient on a political instability index is counterintuitively negative and statistically significant. Measures of disease outbreaks, country-specific COVID-19 containment policies and exposure to natural disasters do not significantly explain variation in FIES-based food insecurity indicators, although the effects of COVID-19 may be substantially picked up by the 2020 and 2021 time dummies.

Appendix Table A5 reports a similar situation with undernourishment as the dependent variable: undernourishment is explained by economic growth, but not by any of the other drivers. Moreover, once those drivers are added to the model, the unexplained upward trend effects in undernourishment actually increase in magnitude, making these trends more inexplicable, not less.

Finally, regressions (5) and (6) utilize the same model to explain variation in poverty at the $2.15/day and $3.65/day poverty lines, to test whether poverty trends have similar or different drivers. Note, however, that the less frequent implementation of income/expenditure surveys in LMICs means that the trend effects are less meaningful because the panel is highly unbalanced across years; for example, there were very few such surveys conducted during the COVID-19 pandemic. However, what is intriguing in these results is that increases in poverty are not only negatively associated with economic growth (deviations in the log of GDP per capita) but also temperature increases and the incidence of natural disasters. So while climate change is slowing down progress against poverty and stunting (Dang, Hallegatte and Trinh, 2024), there is no indication that it explains the rising prevalence of FIES-based food insecurity or undernourishment.

Table 4. Panel fixed effects regressions of the predictors of food insecurity, poverty and stunting in low- and middle-income countries

Dependent variable	(1) Severe food insecurity	(2) Severe food insecurity	(3) Moderate food insecurity	(4) Moderate food insecurity	(5) Extreme poverty ($2.15/day	(6) Moderate poverty ($3.65/day)
Time trends						
Year 2016 vs 2015	0.75***	0.87***	1.74***	2.07***	-0.26	-0.14
Year 2017 vs 2015	1.33***	1.61***	3.42***	4.13***	-0.23	-0.04
Year 2018 vs 2015	1.28***	1.83***	3.61***	5.23***	-3.65**	-2.45*
Year 2019 vs 2015	1.79***	2.45***	4.76***	6.70***	-1.04	-1.90
Year 2020 vs 2015	2.30***	1.95**	6.18***	4.54**	-5.12*	-3.77*
Year 2021 vs 2015	2.85***	2.59**	7.46***	5.85***	-4.75	-2.56
Year 2022 vs 2015	2.82***	2.89***	7.48***	6.77***	0.64	0.06
Hypothesized drivers						
Log GDP per capita		-6.93**		-20.02***	-11.43***	-29.06***
Real food price index (2015 = 1.00)		-0.33		3.55***	-5.23	-5.60
Political instability Z-score (SDs)		-1.47		-5.38**	0.84	0.58
Major disease outbreak = 1		-0.14		-0.49	-0.57	-0.19
C19 stringency index (0-1)		-0.01		-0.02	0.17	0.12
C19 containment index (0-1)		0.02		0.08	-0.09	-0.12
Temperature rise of >1 degree = 1		-0.03		-0.23	1.36*	1.74**
Log of disaster- affected population		0.05		0.18	0.27*	0.32*
R-squared within	0.18	0.23	0.28	0.41	0.53	0.71
Observations	627	627	627	627	800	800
Countries	94	94	94	94	104	104

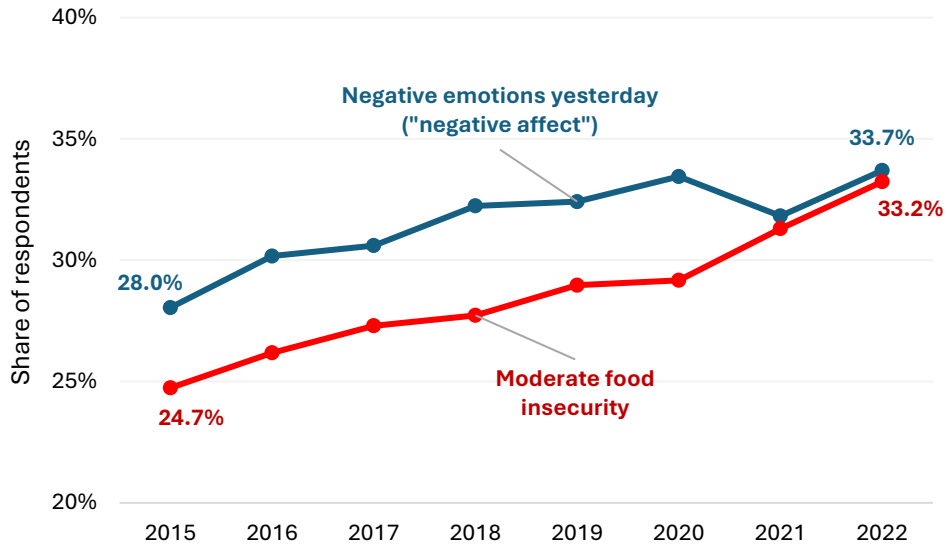
Notes: Robust standard errors in parentheses, clustered at the country level. See Appendix Tables A3 and A4 for standard errors. Statistical significance is as follows: *** p<0.01, ** p<0.05, * p<0.1. Details of data sources are provided in Figure 1, with the following exceptions. First, C-19 stringency and containment indices are from the Oxford Covid-19Government Response Tracker (Hale et al., 2024). Second, the share of the population affected by natural disasters is sourced from (EM-DAT, 2024). Note that the sample excludes high income countries as defined by The World Bank, since these tend to have very low food insecurity, which has not risen significantly over 2015-2022.

Could.rising.food.insecurity.be.associated.with.deteriorating.mental.health?

The 2024 World Happiness Report (Helliwell et al., 2024) – which largely utilized GWP data – reports declining levels of subjective wellbeing in a number of South Asian, sub-Saharan African and Middle Eastern and Northern African countries over 2006-2010 to 2021-2023, as well as in many high income countries. COVID-19 also had severe adverse impacts on mental health, with one study estimating an additional 53.2 million cases of major depressive disorder globally and 76.2 million cases of anxiety disorders (Santomauro et al., 2021). Is it possible that rising rates of self-reported food insecurity are at least partially an artefact of deterioration in life satisfaction and mental health?

To explore this, we use a GWP indicator of whether respondents reported experiencing at least one of three negative emotions in the day before the survey (worry, sadness, anger). Trends in this indicator – often called "negative affect" – are reported in Figure 6 along with moderate food insecurity in LMICs. Interestingly, reporting of negative emotions trends upwards similarly to food insecurity over most of 2015-2022.

Figure 6. Population-weighted trends for moderate food insecurity and the share of respondents who experienced negative emotions yesterday in LMICs



Notes: Moderate food insecurity experiences are sourced from the FAO (FAO, 2024), with underlying data from the Gallup World Poll. Gallup World Poll data on negative emotions yesterday are sourced from The World Happiness Report (Helliwell et al., 2024). Negative.emotions.yesterday. Negative affect is given by the average of individual yes or no answers about three emotions: worry, sadness, and anger. Note that the panel is unbalanced, with 27 countries in 2015, 26 in 2016, 34 in 2017, 36 in 2018, 40 in 2019, 27 in 2020, 32 in 2021 and 43 in 2022.

However, since the data in Figure 6 come from an unbalanced panel, Appendix Table A6 provides more rigorous tests of whether negative emotions in the previous day explain variation in FIES-based food insecurity measures in panel fixed effects regressions similar to those reported in Table 4. The results consistently suggest that in GWP rounds where negative emotions are more widely reported in the day before the survey, we can expect higher reporting of both severe and moderate food insecurity. Without any controls, negative emotions explain 10-11% of the within-country variation in food insecurity. Interestingly, the share of respondents reporting that they have no social support is also positively associated with food insecurity, suggesting the potential importance of social capital for reducing food insecurity.

These associations between FIES-based food insecurity and recent negative emotions are not necessarily indicative of a bias in the GWP FIES trends, because it is certainly possible that genuine food insecurity stressors increase the risk of food insecurity in the past 12 months and also increase the risk of recent negative emotions. Nevertheless, the results in Figure 6 and Table A6 indicate an intriguing correlation, and more research is clearly needed on the sensitivity of FIES-based indicators to negative affect, mood, weather, question ordering, linguistic translation, and survey modalities such as phone-based versus face-to-face surveys.

6. Conclusions

Since a comprehensive review of food security indicators by Barrett (2010) over a decade ago, significant advancements have been made in measuring and monitoring food security. Yet, despite progress, old challenges for food security measurement have persisted, and new ones have emerged.

The most persistent problem is that the FAO continues to estimate and highlight its modelled undernourishment indicator, despite fundamental conceptual flaws and insurmountable problems of poor-quality input data on national calorie supplies and calorie consumption inequality between households, as well as the absence of any suitable methods for gauging the impacts of economic crises (Headey and Ecker, 2013; Masset, 2011; Svedberg, 1999). In this study we also show that the recent increase in inequality of calorie consumption reported by the FAO for low-income countries is negatively correlated with changes in income/expenditure inequality estimated by the World Bank.

The widespread reporting that calorie deprivation is increasing in the world, without any transparent explanation of rising caloric inequality or any rigorous survey-based data to support such a conclusion, is highly problematic for two reasons. First, the promotion of indicators that are seriously flawed, non-transparent and essentially impossible to independently replicate, reduces confidence in official statistics in a global context where scientific credibility is already under widespread attack (Philipp-Muller, Lee and Petty, 2022; Rosenstock and Lee, 2002). A particular concern is that the FAO has no rigorous means of

nowcasting undernourishment rates during national or global economic crises; indeed, the FAO chose to retract the inflated global estimates it produced during the 2008-09 food and financial crises. Second, the persistent reporting of headline undernourishment statistics arguably diverts attention away from more serious malnutrition problems (stunting, wasting, obesity, micronutrient deficiencies and poor child feeding practices), as well as more serious food insecurity indicators.[11] Indeed, it becomes difficult to explain how caloric deprivation is increasing in a context where obesity in LMICs is rising rapidly, including in poorer rural areas (Bixby et al., 2019). In our view, the FAO should simply abandon efforts to model undernourishment from national food supply data, and instead focus efforts on improving measurement of survey-based metrics.

As for new problems, the efforts by the FAO and others to measure food insecurity more directly through experience-based indicators in nationally representative has been an important new development. However, the adaptation and scaling up of experience-based food insecurity measures developed in the US and Latin America to a global level through the GWP appears to have been problematic. Two published studies on FIES measurement in sub-Saharan Africa cast major doubt on the validity and cross-country comparability of FIES-based indicators (Lain et al., 2023; Wambogo et al., 2018). In the present study we show more global evidence of some of the problems with FIES indicators collected through the GWP, with food insecurity prevalence in highly impoverished countries like Niger being much lower than in upper middle-income countries in Latin America and the Caribbean. Hence, the FAO's claim that the FIES-based severe food insecurity indicator is valid and comparable across all countries (Cafiero et al., 2018; Deitchler et al., 2011) seems far too strong an assertion.

We also showed that the sharp increases in FIES-based food insecurity since 2015 are at odds with declining poverty, and difficult to explain in regression models that encapsulate the postulated drivers of rising food insecurity cited by the FAO and other UN organizations (FAO et al., 2024). That said, Afrobarometer respondents also report rising food insecurity using a different indicator, although country-level agreement between GWP and Afrobarometer food insecurity trends is poor. We also found that GWP respondents have become somewhat more likely to say they experienced negative emotions in the day before the survey (negative affect), but it is not clear whether this constitutes a bias for FIES measurement or common causes of deteriorating mental health and deteriorating food insecurity.

What can be done to improve experienced-based food insecurity indicators? First, more independent evaluation of the FIES indicators collected through the GWP is needed, as well as more in-depth experimental work on experienced-based indicators to assess whether responses are affected by contextual factors like negative affect (mood) and weather, as well as frame of reference effects, translation issues, survey methods (including questionnaire ordering and placement), survey modalities (e.g. phone vs face-to-face surveys), as well as

[11] Moreover, it becomes difficult to explain how caloric deprivation is increasing in a context where obesity in LMICs is rising rapidly, including in poorer rural areas (Bixby et al., 2019).

the important question of whether experience-based indicators have test-retest reliability. Such research may have much to learn and emulate from the more mature and extensive literature on subjective wellbeing measurement (Diener, 2013; Kahneman and Krueger, 2006; Krueger and Stone, 2014).

What can be done to improve poverty measurement, and better integrate poverty measures into food insecurity assessments? First, the FAO's reporting on food insecurity via FAOSTAT and its SOFI reports could include poverty estimates, particularly since they already include unaffordability of a healthy diet – which is, in effect, a new type of poverty indicator (Mahrt et al., 2022). Second, the World Bank and other institutions could scale up microsimulation approaches to nowcasting and forecasting poverty rates, including poverty metrics that incorporate healthy diet poverty lines. Such an expansion would be timely given the extensive use of poverty microsimulations during the COVID-19 context (Arndt et al., 2023; Brum and De Rosa, 2021; Cereda, Rubiao and Sousa, 2020; Pauw, Smart and Thurlow, 2021; Tekleselassie et al., 2024), and presumably the extensive learning that comes from these applications.[12] Likewise, COVID-19 demonstrated the potential for more extensive use of high frequency phone surveys for poverty and food security measurement (Gourlay et al., 2021; Lambrecht et al., 2023).

Is the world getting more food insecure or less food insecure? Unfortunately, the jury is out, awaiting stronger evidence one way or the other.

[12] Nowcasting and forecasting microsimulation models also have the virtue that they can be back-checked against historical poverty estimates from household surveys (Caruso et al., 2017; Ferreira et al., 2004; Habib et al., 2010). They also have the added virtue of being a useful tool for simulating alternative poverty reduction interventions (Bourguignon and Spadaro, 2006). And potentially, microsimulation studies could be used to model impacts on other welfare indicators, such as malnutrition or child mortality (Rasella et al., 2018)

Appendix Table A1. Definitions of alternative indicators of food insecurity and poverty

Indicator	Description	Limitations
Insufficient calories (undernourishment)	An estimate of the probability that a randomly selected individual has an insufficient calorie supply to meet her/his energy requirement for an active and healthy life. The indicator is computed from food balance sheet estimates of national calorie supplies, from which a distribution of calories (inequality) is modelled from household survey data, and then compared against a set minimum dietary energy requirement.	Calorie requirements are an inherently individual-level construct, but this indicator uses national-level food balance sheets rather than individual or household survey data. Food balance sheet data is often low quality in LMICs. There are insufficient surveys to provide updated evidence on inequality in calorie consumption. Calorie requirements may change over time. Significant imputation and extrapolation.
Severe and moderate food insecurity (FIES)	A household is classified as severely food insecure when at least one adult has reported several of the most severe experiences, such as reducing the quantity of the food, skipping meals, going hungry, or having to go for a whole day without eating because of a lack of money or other resources. Moderate food insecure is when at least one adult in the household has reported to have been exposed to low quality diets and/or forced to also reduce the quantity of food they would normally eat because of a lack of money or other resources. Data collected annually via Gallup World Poll.	Cross-country comparability of moderate forms of food insecurity experiences may be low because of context-specific definitions of the quality of diets or adequate quantities of food. In theory, severe insecurity experiences should be more comparable across countries. Gallup World Poll has small sample sizes and uses phone surveys and face-to-face. No data reported for India or China.
Monetary poverty	People living on less than the chosen poverty line in 2017 purchasing power parity prices. $2.15/day is often referred to as extreme poverty and used for low-income countries, while $3.65/day is used for lower middle-income countries and $6.85/day for upper middle-income countries. These poverty lines were originally drawn from averages of various national poverty lines for different World Bank income categories. Surveys come from different national sources and World Bank LSMS surveys.	A common international poverty line is used, which may not reflect welfare or food security conditions in every country. Different countries use different survey methods, and some use income instead of expenditure to estimate poverty. Household surveys often infrequent in LMICs.
Unable to afford healthy diet	A healthy diet is considered unaffordable in a country when its cost exceeds 52% of household income. Income data provided by the World Bank's Poverty and Inequality Platform, while price data are for 2017 or 2021 from the International Comparison Program.	Food & non-food expenditure imputed. Cross-country price data may not be fully comparable. Does not measure what people eat, only whether they can afford nutritious foods. Data on income/expenditure and prices infrequent for LMICs.

Source: Definitions from FAO (www.fao.org/faostat/en/#data) and World Bank websites (https://databank.worldbank.org/), and author's own assessments.

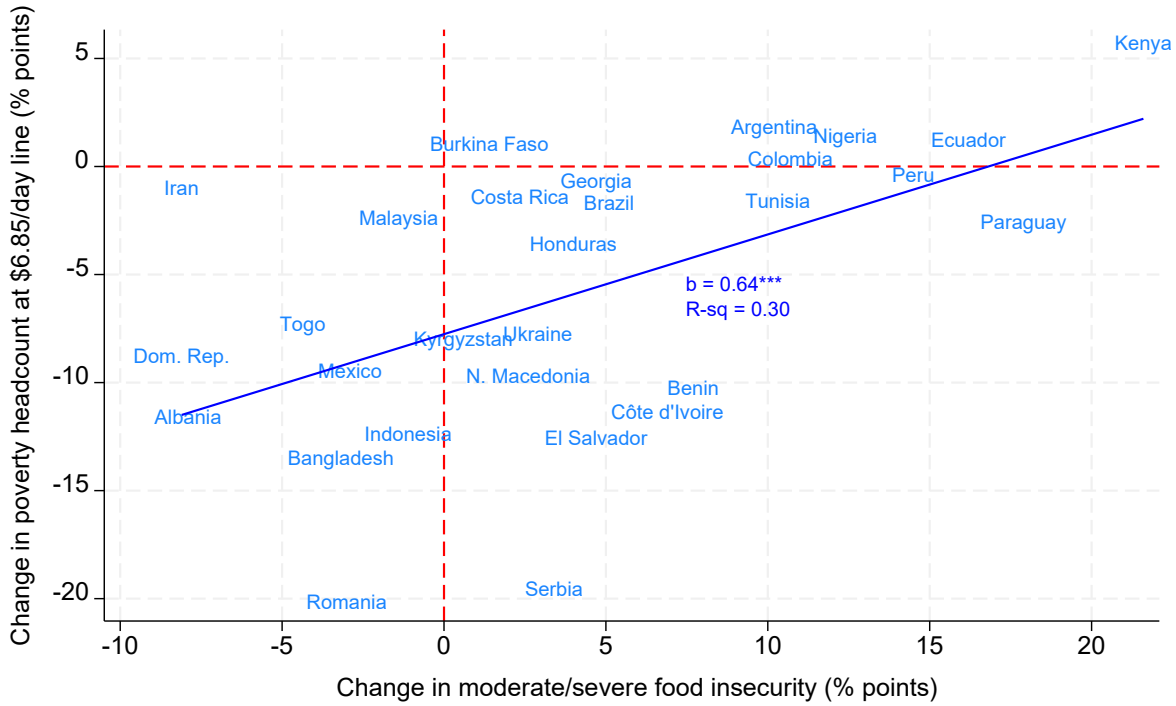
Appendix Table A2. Pairwise correlations between food insecurity, poverty and nutrition indicators (all available years)

	Under-nourishment	Moderate or severe food insecurity	Severe food insecurity	Unable to afford healthy diet	Extreme poverty ($2.15/day)	Moderate poverty ($3.65/day)	Stunting (under-5s)	Wasting (under-5s)
Undernourishment	1.00							
Moderate/severe food insecurity	0.82	1.00						
Severe food insecurity	0.78	0.89	1.00					
Unable to afford healthy diet	0.75	0.81	0.69	1.00				
Extreme poverty ($2.15/day)	0.74	0.70	0.70	0.74	1.00			
Moderate poverty ($3.65/day)	0.78	0.74	0.67	0.84	0.94	1.00		
Stunting (under-5s)	0.65	0.60	0.46	0.79	0.73	0.83	1.00	
Wasting (under-5s)	0.30	0.14	0.01^{NS}	0.31	0.41	0.56	0.57	1.00

Notes: NS= not significant at the 10% level. All other correlation coefficients are significant at the 5% level or higher.

Source: Undernourishment and severe food insecurity experiences are sourced from the FAO's FAOSTAT database (FAO, 2024), while people who are $3.65/day poor or $2.15/poor or unable to afford a healthy diet are sourced from the World Bank, as are stunting and wasting estimates (World Bank, 2024d). All three measures compare expenditures to poverty lines that are measured in in 2017 purchasing power parity dollars.

Appendix Figure A1. The association between changes in the poverty headcount at the $6.85/day headcount and changes in moderate food insecurity over 2014 to 2022 (or latest year)



Notes: Poverty and severe food insecurity pertain to the most recent year in which poverty is measured. The x-axis reports changes in moderate food insecurity based on the FIES module implemented through the Gallup World Poll and reported by FAO (2024). The y-axis reports extreme poverty headcount at the $6.85/day poverty line as reported by the Poverty and Inequality Platform (World Bank, 2024a). The data changes in both indicators are country-specific, as determined by the availability of poverty estimates, but all periods of change fall in the 2014-2022 window.

Appendix Table A3. Panel fixed effects regressions of the predictors of the FAO experienced-based food insecurity indicators in low- and middle-income countries: results with standard errors included

	(1)	(2)	(3)	(4)
Dependent variable	Severe food insecurity	Severe food insecurity	Moderate food insecurity	Moderate food insecurity
Time trends				
Year 2016 vs 2015	0.75***	0.87***	1.74***	2.07***
	(0.20)	(0.21)	(0.35)	(0.40)
Year 2017 vs 2015	1.33***	1.61***	3.42***	4.13***
	(0.33)	(0.38)	(0.63)	(0.74)
Year 2018 vs 2015	1.28***	1.83***	3.61***	5.23***
	(0.39)	(0.50)	(0.78)	(0.98)
Year 2019 vs 2015	1.79***	2.45***	4.76***	6.70***
	(0.44)	(0.59)	(0.89)	(1.19)
Year 2020 vs 2015	2.30***	1.95**	6.18***	4.54**
	(0.50)	(0.81)	(1.05)	(1.83)
Year 2021 vs 2015	2.85***	2.59**	7.46***	5.85***
	(0.57)	(1.01)	(1.21)	(2.10)
Year 2022 vs 2015	2.82***	2.89***	7.48***	6.77***
	(0.62)	(0.97)	(1.29)	(1.97)
Hypothesized drivers				
Log GDP per capita		-6.93**		-20.02***
		(3.38)		(6.26)
Real food price index (2015 = 1.00)		-0.33		3.55***
		(1.71)		(1.30)
Political instability Z-score (SDs)		-1.47		-5.38**
		(1.11)		(2.17)
Major disease outbreak = 1		-0.14		-0.49
		(0.28)		(0.73)
C19 stringency index (0-1)		-0.01		-0.02
		(0.03)		(0.06)
C19 containment index (0-1)		0.02		0.08
		(0.04)		(0.07)
Temperature rise > 1 degree		-0.03		-0.23
		(0.32)		(0.35)
Log of disaster- affected population		0.05		0.18
		(0.06)		(0.13)
R-squared within	0.18	0.23	0.28	0.41
Observations	627	627	627	627
Countries	94	94	94	94

Notes: Robust standard errors in parentheses, clustered at the country level. Statistical significance is as follows: *** p<0.01, ** p<0.05, * p<0.1. Details of data sources are provided in Figure 1, with the following exceptions. First, C-19 stringency and containment indices are from the Oxford Covid-19 Government Response Tracker (Hale et al., 2024). Second, the share of the population affected by natural disasters is sourced from (EM-DAT, 2024). Note that the sample excludes high income countries as defined by The World Bank, since these tend to have very low food insecurity, which has not risen significantly over 2015-2022.

Appendix Table A4. Panel fixed effects regressions of the predictors of World Bank poverty headcounts in low- and middle-income countries: results with standard errors included

	(1)	(2)
Dependent variable	Extreme poverty ($2.15/day	Moderate poverty ($3.65/day)
Hypothesized drivers		
Log GDP per capita	-11.43***	-29.06***
	(3.92)	(4.26)
Real food price index (2015 = 1.00)	-5.23	-5.60
	(6.42)	(7.82)
Political instability Z-score (SDs)	0.84	0.58
	(1.29)	(1.16)
Major disease outbreak = 1	-0.57	-0.19
	(0.51)	(0.67)
C19 stringency index (0-1)	0.17	0.12
	(0.23)	(0.22)
C19 containment index (0-1)	-0.09	-0.12
	(0.29)	(0.27)
Temperature rise > 1 degree	1.36*	1.74**
	(0.69)	(0.76)
Log of disaster- affected population	0.27*	0.32*
	(0.16)	(0.19)
Annual time dummies included?	Yes	Yes
R-squared within	0.53	0.71
Observations	800	800
Countries	104	104

Notes: Robust standard errors in parentheses, clustered at the country level. Statistical significance is as follows: *** p<0.01, ** p<0.05, * p<0.1. Details of data sources are provided in Figure 1, with the following exceptions. First, C-19 stringency and containment indices are from the Oxford Covid-19 Government Response Tracker (Hale et al., 2024). Second, the share of the population affected by natural disasters is sourced from (EM-DAT, 2024). Note that the sample excludes high income countries as defined by The World Bank, since these tend to have very low food insecurity, which has not risen significantly over 2015-2022.

Appendix Table A5. Panel fixed effects regressions of the predictors of the FAO undernourishment indicator in low- and middle-income countries (LMICs)

	(1) LMICs	(2) LMICs	(3) Low & lower middle income	(4) Low & lower middle income
Time trends				
Year 2016 vs 2015	-0.24	0.33	-0.29	0.35
	(0.15)	(0.22)	(0.20)	(0.30)
Year 2017 vs 2015	-0.57	0.28	-0.71	0.45
	(0.37)	(0.32)	(0.46)	(0.41)
Year 2018 vs 2015	-0.65	0.45	-0.79	0.70
	(0.42)	(0.47)	(0.54)	(0.67)
Year 2019 vs 2015	-0.01	1.39**	0.08	1.99**
	(0.34)	(0.55)	(0.49)	(0.76)
Year 2020 vs 2015	0.86**	0.53	1.23**	0.80
	(0.39)	(1.81)	(0.53)	(1.95)
Year 2021 vs 2015	1.49***	1.51	2.00***	2.64
	(0.51)	(2.25)	(0.66)	(2.38)
Year 2022 vs 2015	1.65***	2.58	2.21***	4.24**
	(0.56)	(1.88)	(0.80)	(2.09)
Hypothesized drivers				
Log GDP per capita		-11.38***		-12.80***
		(3.14)		(4.67)
Real food price index (2015 = 1.00)		-4.25		-3.10
		(2.67)		(3.54)
Political instability Z-score (SDs)		0.91		0.80
		(0.72)		(1.15)
Major disease outbreak = 1		0.22		0.01
		(0.28)		(0.36)
C19 stringency index (0-1)		-0.01		0.05
		(0.08)		(0.12)
C19 containment index (0-1)		0.03		-0.03
		(0.10)		(0.13)
Temperature rise > 1 degree		-0.45		-0.59
		(0.46)		(0.84)
Log of disaster-affected population		0.01		-0.03
		(0.09)		(0.09)
R-squared within	0.39	0.50	0.41	0.50
Observations	2,256	2,256	1,354	1,354
Countries	106	106	64	64

Notes: Robust standard errors in parentheses, clustered at the country level. Statistical significance is as follows: *** p<0.01, ** p<0.05, * p<0.1. Details of data sources are provided in Figure 1, with the following exceptions. First, C-19 stringency and containment indices are from the Oxford Covid-19 Government Response Tracker (Hale et al., 2024). Second, the share of the population affected by natural disasters is sourced from (EM-DAT, 2024). Note that the sample excludes high income countries as defined by The World Bank, since these tend to have very low food insecurity, which has not risen significantly over 2015-2022.

Appendix Table A6. Is FIES-based food insecurity over the past 12 months associated with positive or negative emotions in the previous day?

	Severe food insecurity experiences in past 12 months			Moderate food insecurity experiences in past 12 months		
	(2)	(3)	(4)	(6)	(7)	(8)
Negative emotions yesterday	0.16***	0.12***	0.08**	0.38***	0.28***	0.15**
	(0.05)	(0.04)	(0.04)	(0.11)	(0.09)	(0.07)
Limited social support		0.08***	0.05**		0.20***	0.13**
		(0.03)	(0.02)		(0.07)	(0.06)
Log GDP per capita		1.51	-6.35*		-0.45	-23.75***
		(3.14)	(3.54)		(6.30)	(6.58)
2016 vs 2015			0.91***			2.18***
			(0.22)			(0.39)
2017 vs 2015			1.75***			4.72***
			(0.33)			(0.63)
2018 vs 2015			1.94***			5.72***
			(0.45)			(0.84)
2019 vs 2015			2.47***			7.32***
			(0.54)			(1.01)
2020 vs 2015			2.32***			6.55***
			(0.55)			(1.08)
2021 vs 2015			3.32***			9.26***
			(0.69)			(1.31)
2022 vs 2015			3.36***			9.64***
			(0.74)			(1.41)
R-squared within	0.10	0.12	0.29	0.11	0.15	0.45
Observations	503	503	503	503	503	503
Number of ctry	79	79	79	79	79	79

Notes: Sample of LMICs only. Robust standard errors in parentheses, clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1 Negative.emotions.yesterday is given by the average of individual yes or no answers about three emotions: worry, sadness, and anger. Limited.social.support is the national average of the share of people who responded negatively to the question “If you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?”

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