Chronic and Transient Food Insecurity: Evidence from High-Frequency Panel Data in Sub-Saharan Africa

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Abstract

Global progress toward eliminating hunger has stalled, with more than 2.3 billion people experiencing food insecurity in 2024 (1). Standard monitoring approaches rely on cross-sectional snapshots, recording who is food insecure at a given moment, but not how long that condition persists. Using 59 rounds of high-frequency phone surveys conducted between 2020 and 2024 with approximately 13,000 households across six sub-Saharan African countries, we investigate the duration and dynamics of food insecurity within and across years. We show that the share of households experiencing food insecurity at any point during the year substantially exceeds standard point-in-time estimates, with a median gap of 24 percentage points relative to annual averages. Within a given year, 28% of households are chronically food insecure and 38% transiently so – the largest group among food-insecure households. Chronically and transiently food insecure households are largely indistinguishable on standard observable characteristics. Transient households frequently experience food insecurity episodes as severe as those of chronically food insecure households, meaning depth of food insecurity at a point in time is a poor proxy for its duration. They differ, however, in spatial distribution: chronic food insecurity clusters at district and village levels, while transient food insecurity is dispersed. Standard targeting instruments — whether area-based or household-level — reach the chronically food insecure with meaningful efficiency gains but offer no comparable advantage on the transient population. Transient food insecurity remains poorly understood; yet the longitudinal data needed to identify it is rarely available, leaving it largely invisible to both monitoring systems and research.

Significance Statement

Most food insecurity monitoring captures who is food insecure at a given moment but not how long that condition lasts. Using longitudinal data from nearly 100,000 household interviews across six Sub-Saharan African countries, we show that transient food insecurity is the most common form of food insecurity, yet is structurally overlooked in current monitoring systems and beyond the reach of standard humanitarian and social protection instruments. Transient food insecurity episodes can be as severe as chronic ones, linked with potentially lasting consequences for child nutrition and household assets. Distinguishing chronic from transient food insecurity requires longitudinal data that are rare, such that many food-insecure households remain beyond the reach of both research and policy response.

Main Text

Introduction

Ending hunger and ensuring food security all year round is the explicit target of Sustainable Development Goal (SDG) 2.1. Most food insecurity measures currently used in policy and monitoring, however, are based primarily on the intensity of food insecurity at a single point in time, which does not capture well the duration of the food insecurity experience. The distinction between one-off intensity and duration of food insecurity matters. Suffering food insecurity for a few weeks during the year is very different in experience and implications from being food insecure every month of the year. A single snapshot based on cross-sectional surveys, like those used for FAO's primary SDG indicator as well as for the International Phase Classification (IPC) acute food insecurity classifications, miss by design whether a food insecurity episode is chronic or transient.

Not all food insecurity is the same, and the difference has consequences for policy. The literature on poverty dynamics has long distinguished between transient poverty, driven by shocks pushing vulnerable households below the poverty line, and chronic poverty, rooted in structural deprivation (2). Barrett (2010) extends this framing to food insecurity arguing that most food insecurity is associated with structural deprivation and chronic poverty rather than shocks or catastrophes (3). These conditions require different interventions: long-run investments in human capital and productive assets for households facing chronic food insecurity; short-run, shock-responsive income or food assistance aimed at smoothing consumption and protecting assets for those affected by transient food insecurity (4–6). Transient food insecurity is not harmless because it is temporary. Acute episodes can be severe, which has been linked to lasting consequences for example through child undernutrition and health shocks (7, 8) and repeated transient spells may push households into chronic deprivation (4).

The ability to identify and delineate transient from chronic food insecurity is critical both for appropriate policy design and for more efficient targeting of programs. Yet despite the policy significance of this distinction, there is little systematic evidence testing it with longitudinal household data at scale. Identifying transient food insecurity requires tracking the same households repeatedly within the year, a data setup that remains rare in practice, leaving the transient population largely invisible to both research and policy (9).

Here, we offer such at-scale evidence, making use of a harmonized cross-country panel dataset containing 59 rounds of high-frequency food insecurity measurements for approximately 13,000 households in six Sub-Saharan African countries (Burkina Faso, Ethiopia, Malawi, Nigeria, Tanzania, Uganda), covering a period from 2020 to 2024. For each of the five years, our dataset consists of a nationally representative sample of households for which we have repeated measures, on average 3.4 per year, of the Food Insecurity Experience Scale (FIES). We examine different types of households based on within-year variation of food insecurity status and delineate households by whether their experience with food insecurity is transient or chronic.

Our paper is the first cross-country, high-frequency panel study of within-year food insecurity dynamics at scale. We show that food insecurity varies substantially over the course of the year, with implications for monitoring food insecurity prevalence and targeting food insecure populations. The share of households that are food insecure at any point during the year substantially exceeds cross-sectional point-in-time prevalence, with a median gap of 24 percentage points. Cross-sectional severity, as measured by the FIES score, provides little signal about whether food insecurity is chronic or transient, and the two types are not reliably distinguished on household observables available at monitoring scale. Chronic food insecurity clusters geographically while transient food insecurity does not, a difference that translates directly into targeting performance: geographic targeting reaches the chronically food insecure much more efficiently than it reaches the transiently food insecure. As chronically and transiently food insecure households look similar

on standard observables, proxy means tests do not allow to reliably adjust policy to a household's predicted food insecurity type. We argue that the chronic–transient distinction has direct operational consequences for how food security programming is designed and delivered.

Results

High frequency data changes our understanding of food insecurity prevalence and nature

Food insecurity (defined here as moderate or severe food insecurity following SDG 2.1.2) is a prevalent phenomenon in the study countries, with considerable variation across time, even within the same household. The high-frequency data indicate that around two thirds (66%) of the population of these six countries have experienced food insecurity as defined in our main specification at least once in a given year. Figure 1 shows the proportion of survey rounds within a calendar year that each household is classified as food insecure. Somewhat less than one third (28%) of the population was food insecure in all survey rounds within a year, which we define as chronically food insecure. In contrast, just over one third (34%) never experience food insecurity within the year. The largest group (38%), however, experienced food insecurity at one point during the year, but not throughout the entire year. This pattern of transient food insecurity represents the most common experience of food-insecure households in our study population, a pattern we confirm in a range of robustness checks (summarized in Table S29).

By design, the FIES instrument can only identify transient or chronic food insecurity through repeated measurements of the same household within a year. In any single-round assessment, a transiently food insecure household may appear as either food insecure or not. Figure 1, Panel B shows the single-round estimates of food insecurity prevalence in our sample, based on a 30-day recall FIES measure (grey dots). This is an operationally relevant measure, and figures among the tools used in International Phase Classification (IPC) assessments of acute food insecurity.

These single-round estimates vary substantially across time and countries (median within-year range of 15 percentage points), reflecting a combination of seasonal dynamics and shock-driven fluctuations. Tracking the same households repeatedly, however, allows us to go beyond what a single snapshot can tell us: the share of households observed to be food insecure at least once (in any survey round) during a calendar year (diamonds) substantially exceeds any single-round estimate (circles), with a median gap of 24 percentage points relative to the round average and 14 percentage points relative to even the peak round. This gap is necessarily driven by transiently food insecure households. It points to a meaningful degree of idiosyncrasy in the timing of food insecurity; not all within-year variation stems from seasonality or aggregate shocks at the national and subnational level. This finding is also consistent with an interpretation that the variation in FIES can result both from idiosyncratic changes in household access to food (e.g., stemming from household-specific economic or health shocks) as well as idiosyncratic variation in how households respond to questions about their experiences with food and behaviors correlated with food insecurity (e.g., worried about insufficient food). This means that no single survey round, however timed, can fully capture the population experiencing food insecurity within the year.

These findings identify a structural limitation of snapshot food insecurity assessments. A single round will capture all chronically food insecure households, but will always miss a share of the transiently food insecure, and it will not distinguish chronic and transient households. High-frequency panel data like the dataset analyzed here is what enables us to reveal this dimension of food insecurity. This matters in two distinct ways. First, single-round assessments — including the 30-day FIES-based snapshots used in IPC acute food insecurity classifications — will systematically undercount the food insecure, missing those transiently food insecure households whose episodes fall outside the assessment window. Second, even among households captured as food insecure in a given round, a snapshot cannot distinguish the chronic from the transient: a household observed as food insecure may be so permanently or only occasionally. These two groups likely require differentiated policy responses — sustained structural support and asset-

building for the chronically food insecure; timely, shock-responsive assistance for the transient (4, 5). Whether standard data and targeting tools can tell chronic and transient households apart and reach them differentially is the question the remainder of this paper addresses.

Depth and duration as distinct dimensions of food insecurity

The FIES scale is a measure of the severity of the food insecurity experience of a household at a point in time, based on a series of eight items of increasing severity (with a resulting score of 0-8). Here, we ask: How well does the severity of food insecurity measured at one point in time predict the duration and corresponding type of food insecurity (transiently food insecure, chronically food insecure)? If severity were a reliable proxy for duration, cross-sectional FIES data could partially compensate for the absence of panel observations.

Figure 2 relates severity and duration of food insecurity. In Panel A we plot, for each step (0-8) of the FIES raw score, the share of households of each food insecurity type (never food insecure, transiently food insecure, chronically food insecure). In Panel B, we plot the distribution of food insecurity episodes of transient and chronic households by FIES raw score. Never and always food insecure households are demarcated by construction at a raw score of 4; the share of always (never) food insecure households increases (decreases) with each step, suggesting that FIES score is a good proxy for these two states. However, transient households are present throughout. No single FIES score cleanly separates chronic and transient households, as there is a meaningful share of transient households at all points. Indeed, transient food insecurity does not mean mild food insecurity. Around 30% of food insecurity episodes of transient households are at the two most severe FIES raw scores of 7 and 8 – a finding that is qualitatively robust to enforcing a more stringent version of the FIES scale (see SI, Fig S29). Episodes of severe acute food insecurity are therefore not the exclusive experience of the chronically food insecure. This matters as temporary, yet severe episodes of food insecurity may have lasting consequences. Acute undernutrition during the first 1,000 days of life has been found to cause irreversible developmental damage, with effects on cognition, schooling, and adult productivity (7, 8).

To quantify how much information a single FIES score conveys about a household's food insecurity type, we regress the share of rounds a household is food insecure on its FIES raw score at different points in time (Table S4). This approach is conceptually similar to Gundersen (2008), who examines the extent, depth, and severity of food insecurity among American Indian families using a food insecurity score based on a Rasch model and depth-of-poverty methodology (10); here we ask instead whether increasing values indicate longer duration of food insecurity. We first restrict the sample to food insecure households (i.e. transient and chronic). The FIES score is a significant predictor of the share of rounds food insecure (with an increment in the FIES score associated with a 3.3 percentage point increase in the share of rounds food insecure), however, it has limited predictive power, explaining only 6% of the variation in time spent food insecure (R^2=0.061). Repeating this regression on the full sample, including the never food insecure households, the low predictive power of duration for those who are food insecure is not an artefact of a weak FIES instrument: when never-food-insecure households are included, the R^2 rises to 0.365. The signal therefore seems to come from low FIES scores being associated with households that are never food insecure. Some, but not all of this signal comes from FIES scores of exactly zero (Table S4). This indicates that snapshots carry some signal for identifying never food insecure households, but they do poorly in discerning a household that spends some of its time food insecure from a household that spends all of its time food insecure. These results suggest that depth and duration are empirically distinct dimensions of food insecurity. A single cross-sectional FIES score is a poor predictor for whether a household is chronically or transiently food insecure.

Chronically and transiently food insecure households share similar socioeconomic profiles

What characteristics distinguish chronically, transiently, and never food insecure households? Figure 3 addresses this question by comparing the household profiles of never, transiently, and

chronically food insecure households along socioeconomic dimensions commonly used to guide program targeting: wealth, education, sex and age of the household head, household size, and urban/rural location. Panel A shows unconditional means by type; Panel B estimates which characteristics predict type membership in a multinomial logit regression controlling for all dimensions jointly.

A clear pattern emerges across the two pieces of analysis: never food insecure households differ from the other two types in several dimensions. For example, they are 10 percentage points more likely than the transiently food insecure (13 percentage points more likely than the chronically food insecure) to belong to a higher wealth quintile, 7 percentage points less likely to live in urban areas and they are 6 percentage points more likely to have primary education. Overall, never food insecure households are wealthier, more educated, smaller, and less likely to live in urban areas and be female-headed than either food insecure group (Table S6).

In contrast, the chronically and transiently food insecure look much more similar across all of these dimensions, with no statistically significant differences on standard household socio-economic characteristics typically available for targeting. The implication is that household characteristics appear unsuited for targeting transiently and chronically food insecure households differentially.

Chronically food insecure households are clustered geographically

The analysis has established that neither cross sectional food insecurity severity nor household characteristics are reliable guides to distinguishing between chronic and transient food insecurity. Expanding our analysis of the urban indicator in Figure 3, here we explore geography as a potential differentiator in greater detail. This is directly relevant with area-based food insecurity assessments, prominently the IPC classification system, and geographic targeting, as a widely used targeting modality in humanitarian programming (11).

We assess the degree of geographic concentration of the different food insecurity types through the intra-cluster correlation coefficient (ICC) estimated from a multi-level model. This gives us a measure of how much variation in each food insecurity type is explained by clustering at different geographic levels (conditional on country-year fixed effects).

The first key finding from this analysis is that chronically food insecure households and never food insecure households display a high degree of geographic clustering, while transiently food insecure households are more dispersed (Figure 4). Specifically, for chronically and never food insecure households, geographic clustering at the district and village levels accounts for 24% (district: 14%; village: 10%) and 22% (district: 16%; village: 6%) of variation, compared to only 7% (district: 4%; village: 3%) for transiently food insecure households. A consistent interpretation of the geographic concentration of chronic food insecurity is that it's linked with structural poverty, which is itself geographically concentrated (12, 13) and persistent at the household level. The dispersion of transient food insecurity suggests a key role of idiosyncratic shocks whose timing and incidence vary across households within the same area (Tables S7, S8).

Further, the household-level ICC is high for both chronic and never food insecure households (chronic: 30%; never: 24%), indicating that these states are persistent across years. In other words, these households are likely to remain chronically (never) food insecure from one year to the next. In contrast, the household level ICC for transiently food insecure households is much lower at 9%, suggesting a lower degree of persistence across years, which means that transient households are more likely to become chronically food insecure – or stay out of food insecurity.

Taken together, household and geographic clustering explain over half of the variation (52%) in status for chronic food insecurity, compared to only 16% for transient food insecurity. This means that chronic food insecurity is more readily predictable based on where a household lives and its own history. Transient food insecurity is not, which is consistent with its more idiosyncratic nature.

The geographic concentration of chronic food insecurity suggests that area-based targeting can efficiently reach this group; the dispersion of transient food insecurity implies it may be insufficient for transient food insecurity – a contrast we will quantify directly through a targeting simulation.

Consequences for targeting

We now explore what these results imply for the delivery of food security assistance and the type of beneficiary population reached. We first simulate a geographical targeting exercise in which a policymaker selects those areas to receive food aid that are deemed the most food insecure. For a given calendar year, we assume that the policymaker has access to data from repeated snapshots of the food insecurity situation within each area. Based on this, the policymaker selects those areas for targeting that are, on average, the most food insecure over the year. Within each targeted area, all households receive food aid whereas in areas not selected for targeting, no household receives assistance. This scenario aligns with operational practice in which food security is monitored based on snapshots and aid targeted to the areas with greatest need. We conduct this exercise once at the admin-2 level and once at the admin-3 level and for varying program sizes (i.e., targeting between 5% and 80% of all areas).

Figure 5A demonstrates a key trade off. Geographic targeting reaches a substantial share of chronically food insecure far more efficiently than it reaches the transiently food insecure households (and more efficiently than random allocation). For example, targeting the 20% most food insecure areas reaches around 40% of chronically food insecure households while covering only around 5% never food insecure households (median across countries and years). Reaching at least two-thirds of chronically food insecure households takes targeting about 40% of admin-2 areas or 35% of admin-3 areas at the median and still includes only a small share of never food insecure households. This reflects the geographical clustering of chronically and never food insecure households in distinct areas. However, this is not the case for transiently food insecure households which are found to a similar extent across highly food insecure and relatively food secure areas: the share of transiently food insecure households that are reached is roughly proportional to the share of areas targeted. In a typical country-year, this results in less than 20% of transiently food insecure households receiving assistance as part of a program targeted at the bottom quintile of food insecure areas. Even a large program covering the bottom half of areas by food security usually misses between half (admin-2 level) to a third (admin-3) transiently food insecure households.

Area-based targeting derived from snapshots therefore provides useful, actionable information for reaching the chronically food insecure, but performs much less well for transient households, which are found in both very food insecure and relatively food insecure areas and are missed systematically. Targeting efficiency declines when less timely information is used, such as average food insecurity from the previous year (Figure S2) or average consumption expenditure from a previous LSMS-ISA household survey (Figure S3); chronic and transient households are selected at more similar rates in these cases.

Beyond geographic targeting, standard programs sometimes apply a second selection layer at the household level using proxy-means-test (PMT) scoring of household characteristics (demographics, assets, dwelling characteristics). We assess whether a PMT-style approach applied to food insecurity types, rather than the standard cross-sectional FIES depth or consumption, can preferentially reach the transient or chronic.

In Figure 5 B and C, we predict each household's food insecurity type using a multinomial logit model. In Panel B, we then rank households by their *predicted* probability to be chronically food insecure (highest to lowest) and ask whether this allows to preferentially target assistance to *truly* chronically food insecure households. We find this is possible at a meaningful rate. The chronic curve sits well above the 45-degree line at which predicted probabilities offer no targeting

advantage over random targeting. For example, we estimate that targeting the 30% of households predicted to be most likely chronically food insecure would allow to reach 50% of truly chronic households. At the same time, such a policy would also reach a meaningful share of transiently food insecure households at about the rate implied by random targeting (~30% coverage) and reduces inclusion errors by deprioritizing never food insecure households to a moderate extent (20% coverage, below 30% implied by random selection). In short, targeting chronic food insecurity based on a set of basic household characteristics is feasible yet imperfect. It comes at the cost of targeting a meaningful share of transiently food insecure households with the same policy and a much lower share of never food insecure households. This is consistent with static household characteristics proxying for chronic states of deprivation.

Results look much different in Panel C when attempting to single-out transiently food insecure households for targeting. Ranking households by their predicted probability to be transiently food insecure captures actual chronic and actual transient households at about the same rates. The exclusion of never-food-insecure households is broadly similar to the chronic-targeting case. This is a direct consequence of the patterns we found when comparing household profiles. On average, transiently food insecure households look somewhat more similar to chronically food insecure households on observables with the difference that they spent at least part of the year not food insecure. However, other transient households resemble never food insecure households. No combination of static information appears to isolate this group cleanly.

Combined with the geographic dispersion of transient food insecurity documented in the previous section, this implies that the failure to reach the transient is not a matter of model or data quality but is structural: standard targeting machinery – whether area-based, household-based, or a combination of the two – cannot reach the transient food insecure as a distinguishable group on available observables.

Discussion

This analysis leverages high-frequency, multi-year panel data on food insecurity experience from 13,000 households across six countries in Sub-Saharan Africa to generate new insights into the nature of food insecurity, with implications for policy and humanitarian programming.

The longitudinal, high-frequency nature of the data enables identifying two types of food insecurity experience: chronic food insecurity – households that are food insecure across all observed rounds throughout the year – and transient food insecurity – households that are food insecure in some rounds but not others. This distinction is grounded in an established empirical and theoretical literature on poverty related to chronic, structural deprivation versus transient poverty, typically driven by temporary shocks (3, 5, 13). Here we show that this distinction has operational implications in the food security domain: chronic and transient food insecurity differ not only in duration but in how visible they are to the instruments used to target assistance.

The temporal dimension of food insecurity has attracted some research attention, though the evidence base remains thin. One important example of within-year variation is Nord (2013) who uses data from the U.S. Current Population Survey Food Security Supplement (CPS-FSS) which includes substantially more detail than the FIES instrument, particularly concerning the frequency of food insecurity events. Based on classifications he constructs from the CPS-FSS data, he is able to document that slightly less than a quarter of the food insecure in the U.S. suffer from frequent or persistent food insecurity (15). Nord further notes that “almost all research and reporting on food security in the United States has used the … ever-during-year measures” (15, p.110), in essence ignoring the policy-relevant information about the frequency and duration of food insecure episodes. Several other recent studies document within-year variation in food-related outcomes at the household level: one uses three years of monthly panel survey data in Southern Malawi to

study the food insecurity effects of the COVID-19 pandemic (16); a related study uses earlier data from the same source and region to track monthly coping strategies among households (17); another follows child anthropometrics monthly across 23 districts in Kenya over more than a decade, drawing out implications for resilience and acute malnutrition prediction (18). Outside of LMICs, a study from the United States presents annual household level food insecurity dynamics from 2001 to 2017 (19). Beyond food insecurity, a recent study looks at poverty dynamics throughout the year in India (20).

With the exception of Nord (2013), the existing studies do not, however, classify households by the duration of their food insecurity experience at scale in LMICs or connect that classification to targeting performance. This analysis does both. Both types are prevalent in our sample, with a majority of food-insecure households experiencing transient food insecurity (53%). Accounting for both chronic and transient households over the course of a year, food insecurity is significantly more prevalent than at any given point in time, with a median gap of 24 percentage points across the six countries in the sample, and a 14 percentage points gap relative to even the highest single cross-sectional rounds.

The two types differ sharply in their spatial distribution: chronic food insecurity is geographically concentrated, while transient food insecurity is dispersed across communities. Moreover, food insecurity severity, as interpreted on the FIES scale, is not a good predictor of its duration. Transient households frequently experience food insecurity as acute as that of chronically food insecure households, so a single-round severity reading cannot reliably identify who is chronically deprived versus transiently food insecure. Even sophisticated cross-sectional measurements cannot substitute for longitudinal data structure.

The welfare costs of failing to reach this group are not trivial. Prior evidence shows that acute undernutrition during critical developmental windows can cause irreversible damage to child cognition and long-run productivity and that transient episodes can become chronic deprivation if productive assets are depleted to cope (7, 8).

Typical operational sequences in current humanitarian programming — geographic targeting followed by household-level selection based on proxy means tests or similar instruments (11, 21) — are better suited to chronic food insecurity, which is geographically concentrated and predictable on standard household observables available for monitoring. Area-based approaches can reach the chronically food insecure with meaningful efficiency gains over random selection. These approaches are, however, less well-suited for transient food insecurity (22): geographic targeting systematically excludes many dispersed transient households and household-level selection cannot compensate because singling out transiently food insecure household appears challenging. Even sophisticated adaptive and anticipatory systems (23), such as the multi-partner Joint Monitoring Reports, which use machine learning and high-frequency covariate data, especially on prices, to predict and respond to emerging food crises (24), are designed to be triggered by aggregate, covariate shocks detectable at higher administrative levels and thus cannot capture idiosyncratic household-level variation. These are not failures of design or implementation but represent structural limitations. Existing data and instruments are suited to chronic food insecurity, not to transient food insecurity.

The literature on targeting assistance typically identifies three mechanisms for directing resources to those who need them: individual assessment of household circumstances, the use of geographic or group indicators, and self-selection (11). The policy instruments examined here, that is, geographic targeting and proxy-means test for household selection, correspond to the first two mechanisms. Our results show that both are structurally ill-suited to the transient population. In contrast, self-selection mechanisms can, in principle, reach transient households whose need is time-varying and hard to predict ex ante. These mechanisms attach a cost accessing assistance, which is commonly referred to as an ‘ordeal’ such as time, travel, effort, or stigma. This induces

those in current need to identify themselves at the moment the episode occurs, matching the frequency of the response to the frequency of the problem (25, 26) . Food banks and walk-in food distribution points are examples of this mechanism. Self-targeting is not a substitute for geographic and household assessment based targeting, which reliably identify chronic households, but a complement to be employed where the other mechanisms fail to reach the transiently food insecure. Underlying the difficulty reaching the transient food insecure is a data problem. Repeated cross-sectional surveys however frequent and well-timed – including IPC Acute Food Insecurity assessments, which now incorporate 30-day referenced FIES data (27) – cannot capture all households that experience food insecurity at any point during the year or determine whether a households is transiently or chronically food insecure. That task requires either intensive month-by-month recall data, with the attendant risk of recall bias, or high-frequency longitudinal data, tracking household welfare often enough to capture within year variation.

Longitudinal tracking at census-level scale that would be required to directly target households is not operationally feasible or cost effective in most contexts. In contrast, nationally representative longitudinal and high-frequency data of the kind used here can provide diagnostic insights, such as the chronic-transient ratio in a given context, whether geographic and socioeconomic characteristics are good proxies for targeting, and whether existing response systems are likely to reach all households in current need. The contribution of longitudinal data to this challenge is therefore one of calibration rather than targeting. A national longitudinal food security panel can tell policymakers what kind of food insecurity problem they are dealing with before they commit to a response architecture. In contexts where the transient share is large and idiosyncratic – as in the six countries studied here – a substantial part of the food-insecure population lies beyond the reach of administrative targeting. This determines the right mix of instruments for a given context. The operationally relevant ratio is context-specific and shifts over time and must be re-estimated periodically using longitudinal data.

Our study faces several limitations. A first set relates to our empirical strategy. This is a descriptive analysis, which allows us to classify households, but we are not well equipped to show causal drivers of this typology or of food insecurity experience more broadly. A second set of limitations relates to the data. The intervals between survey rounds are not always the same length of time and we do not have a balanced panel, which somewhat complicates drawing inferences about the precise duration of food insecurity spells. A case in point, more observations on the same household in one year make it likelier that its food insecurity status changes (from food insecure to food secure or vice versa), and therefore that it is classified as transiently food insecure. It is not obvious what would be the natural or preferable data collection interval for this kind of data, and may depend on a range of context-specific factors (e.g. seasonality, exposure to shocks). As with all data, our data are subject to measurement error. The data is collected via telephone surveys, which comes with a degree of sample selection and some evidence suggests this survey mode may be particularly susceptible to reporting error (26–28).
Reweighting corrects observable composition but not potential selection on unobservables. The reliability and consistency of different measures of food insecurity, in particular the FIES measure, remains an area of active debate (30). A case in point, the binary response format of the FIES, which compresses variation at the highest raw score, may limit the predictive power of food insecurity depth for duration. Other scales, such as the Household Food Security Survey Module (HFSSM) (15) or the Food Consumption Score (FCS), capture the frequency of occurrence within individual questions, enabling richer frequency-based analysis.

We address several of these concerns through a wide range of robustness checks which reinforce our main conclusions. First, our results hold across different severity cut-offs to classify households as food insecure. We replicate our analysis using the IPC's reference methodology for acute food insecurity measurement (31) (Tables S9-S12, Figures S4-S9). This aligns our methodological choices --- including survey instrument, recall periods and severity cut-offs --- with what is used in operational practice to inform IPC Phase 3 ("Crisis") classification and stipulates a relatively higher

threshold for food insecurity classification (roughly corresponding to a FIES raw score of 6). We also replicate our analysis of time spent food insecure using an even more stringent cutoff of 7 on the FIES scale (Figure S36). This corresponds to 'severely food insecure' in FAO's reference approach. Second, we show that our conclusions hold when harmonizing the number of data points per household to two and three observations per year, respectively (Tables S13-S18, Figures S10-S21). While the ability to detect dynamics in a household's food insecurity situation naturally increases with the time it is under observation during a year, the robustness check offers strong evidence that such variation does not drive our core findings. Third, we account for possible measurement errors in classifying households as food (in)secure and therefore in the assignment to food insecurity types. Both probabilistic assignment to types instead of hard classification (Tables S19-S21, Figures S22-S26) and dropping observations with internally inconsistent response patterns (affirming a higher severity item while leaving a lower severity item unaffirmed) (Tables S22-S26, Figures S27-S32) leave our conclusions qualitatively unchanged. Lastly, and bearing on the reliability of the FIES measure specifically, we replicate our analysis using the Food Consumption Score (with the cutoff defined as in the IPC for Phase 3 using FCS), limited in our data to a single year (2023) and three countries. This independent and conceptually distinct measure of food insecurity confirms the same patterns regarding the prevalence of transient food insecurity and the distinction of duration and cross-sectional food insecurity depth (Tables S27-S28, Figures S33-S35).

Transient food insecurity remains common across these robustness checks and describes the experience of 43% - 75% of food insecure households over the course of a year (Table S29). This pattern also holds qualitatively across all six countries although we note that differences in data collection schedules (timing, number of rounds, coverage across years) complicates a clean comparison of country-level variation (Figure S36). Even with just two rounds of panel data per year (the arguably coarse minimum requirement to measure intra-year food security dynamics), a quarter of total households and 43% of food insecure households are transiently food insecure. *Any* intra-year panel data therefore represents a significant improvement in the information content of food insecurity data over the single snapshots common in policy and monitoring.

Materials and Methods

High-Frequency Phone Surveys

Our data is from 59 rounds of High-Frequency Phone Surveys (HFPS) in six Sub-Saharan African countries (Burkina Faso, Ethiopia, Malawi, Nigeria, Tanzania, Uganda). The HFPS are a series of panel surveys that were implemented by countries' national statistical offices with support from the World Bank's Living Standards Measurement Study (LSMS) team (32). The data were collected between May 2020 and July 2024 (Figure A1).

The HFPS are re-contact surveys, taking their sampling frames from the most recent, nationally representative LSMS-ISA household survey in each country. The LSMS-ISA surveys are longitudinal in-person surveys with national coverage. Each LSMS-ISA survey collected information on the phone number(s) of the household's members or, where a phone was unavailable, from a reference contact such as a neighbor. The list of households with at least one phone number (from a member or reference contact), or a random subset thereof, formed the list of households that the HFPS aimed to interview.

The HFPS used in this paper have three key advantages regarding their representativeness compared to other phone surveys in Sub-Saharan Africa. First, collecting phone numbers from all household members or a reference contact allowed the HFPS to have relatively broad coverage of the population, including where phone ownership is non-universal. The list of households with at least one phone contact comprised between 73% (Malawi) and 99% (Nigeria) of the full, in-person

sample. Second, as a re-contact survey, the HFPS have non-response rates that compare favorably to phone surveys using alternative approaches such as random digit dialing (28). Third, the direct link between the HFPS sample and the full, nationally representative LSMS-ISA sample facilitated the use of re-weighting techniques to attenuate coverage biases. This has been shown to effectively mitigate issues of sample representativeness in the phone data relative to a fully nationally representative sample (33). Further, the weights adjust for attrition over time. Throughout our analysis, we use these adjusted survey weights.

The main respondent for each HFPS interview is an adult household member (older than 15 years) who was selected to be broadly knowledgeable of the household's affairs. This meant that the respondent was more likely to be the household head, male, better educated, and older than the average adult.(34)

In total, our data is comprised of 93,081 interviews with 13,126 unique households across the six countries.

Food Insecurity Experience Scale data

We measure households' experiences with food security over the last 30 days through the FAO's Food Insecurity Experience Scale (FIES). The FIES comprises of a series of eight questions that capture access to adequate food at the household level. These questions are

During the last 30 days, was there a time when

1. You or others in your household were worried about not having enough food to eat because of lack of money or other resources?
2. You, or others in your household, were unable to eat healthy and nutritious/ preferred foods because of a lack of money or other resources?
3. You, or others in your household, only ate a few kinds of food because of a lack of money or other resources?
4. You, or any other adult in your household, had to skip a meal because there was not enough money or other resources to get food?
5. You, or any other adult in your household, ate less than you thought you should because of a lack of money or other resources?
6. Your household ran out of food because of a lack of money or other resources?
7. You, or any other adult in your household, were hungry but did not eat because there was not enough money or other resources for food?
8. You, or any other adult in your household, went without eating for a whole day because of a lack of money or other resources?

The eight questions are ordered on a scale reflecting increasing severity of food insecurity, from worrying about having sufficient food to going an entire day without eating. The FIES has undergone extensive benchmarking across countries to create a global reference scale that can be used for calibrating the FIES for cross-country comparability. Summing affirmative responses across these eight items yields the FIES raw score which consequently ranges between 0 (least food insecure) to 8 (most food insecure).

To turn FIES raw scores into a standardized, cross-country comparable probability to be food insecure for each household, we follow the FAO's reference methodology via the Rasch model that is also employed to calculate the prevalence of food insecurity for Sustainable Development Goal (SDG) 2.1.2 (35, 36). In a robustness check, we follow the IPC reference methodology for 30-day FIES recall instead. This is methodologically equivalent but stipulates a higher threshold for food insecurity based on a validation study specifically for the IPC Phase 3 ("crisis") threshold (30).

We use different transformations of the FIES for our respective analytical purposes.

Food Consumption Score (FCS)

In Burkina Faso, Tanzania, and Uganda, we also have repeated observations (two per household) on the Food Consumption Score (FCS) for one calendar year (2023). The FCS is a standard dietary diversity and nutrition indicator proposed by the World Food Program (WFP). It is calculated by asking households about how often they consumed items belonging to eight different food groups over the last 7 days, weighting each group according to their nutritional content, and calculating the weighted sum across all groups. Lower FCS scores therefore reflect higher food insecurity. The IPC's reference methodology (37) stipulates a threshold of 28 or lower to indicate "borderline" food consumption and as the cutoff for IPC Phase 3 classification ("crisis").

Estimating food insecurity prevalence

To estimate the share of the population that is food insecure, we calculate the weighted average of household's individual food insecurity probabilities. This follows the same approach as SDG 2.1.2.

We estimate the (weighted) share of households who were ever food insecure over the course of a year as follows

$$P(ever\ FI) = \frac{1}{H}\sum_{h=1}^{H}\left(1 - \prod_{r=1}^{R_h}(1 - P_{hr}^{FI})\right) \quad (1)$$

where P_{hr}^{FI} is the probability that household h is food insecure in round r, R_h is the total number of rounds (i.e. months) for which a household was observed during that year, and H is the total number of households. That is, for each household, we calculate the probability to be food insecure in at least one round (one minus the probability that the household is always food secure) and average across all households. We exclude households with fewer than two data points within a given calendar year for this calculation.

Food insecurity depth

To contrast the temporal dimension of food insecurity with a measure of cross-sectional food insecurity depth, we rely on the FIES raw score. Higher values represent more severe food insecurity. As the FAO's methodology for calculating food insecurity probabilities from FIES raw scores weights each of the eight items on the FIES equally, this closely corresponds to using food insecurity probabilities as a measure of depth instead. In the case of FCS, we use the total score as a measure of cross-sectional depth.

Classifying households into food secure or insecure

Much of our analysis relies on classifying individual households as either food secure or insecure. To do so, our main specification takes a FIES raw score of 4 and above to indicate food insecurity. This corresponds to the threshold suggested by the FAO based on cross-country validation of the FIES that showed a discrete jump in the probability of food insecurity at this cutoff (36). This is also the case for each country in our data. As food insecurity probabilities are directly calculated from FIES raw scores and therefore equally discrete, this closely corresponds to choosing a probability cutoff (of around 70%) to classify households instead.

We conduct two robustness checks for this approach to food insecurity classification. First, we calibrate our data on the thresholds proposed in the IPC's reference methodology for 30-day FIES recall (31) which are relatively higher than those for 12-month recall. This corresponds to a cutoff of 6 on the FIES raw score scale (except Burkina Faso and Tanzania where calibration results in a cutoff at a raw score of 5). Cafiero et al. (2024) provide details on the standard methodology for calibration of 30-day FIES recall data to their thresholds which we follow (31). Second, we do not rely on hard classification at all and instead assign households a probability to be food insecure or not. This probability is a direct output of the standard FIES methodology and meant to account for potential measurement error in FIES raw scores.

Food insecurity types

For each calendar year, we classify households into discrete food insecurity types: those who are never food insecure over the period we observe them during that year, those who are sometimes, but not always, food insecure (or transiently food insecure), and those who are always (or chronically) food insecure.

We also verify the robustness of our results using an alternative method where we calculate the probability of a household to be never food insecure as the complementary probability to equation (1); the probability to be always food insecure as the product of round-specific food insecurity probabilities; and the probability to be sometimes food insecure as one minus the probability to be always or never food insecure. We then treat each household's type membership as fractional with weights for each type corresponding to the estimated probability to belong to this type. This allows us to account for potential measurement error inherent in deterministic classification. As type membership probabilities must sum to one, this analysis maintains the same weighting scheme across households as our main analysis but distributes any given household's weight across the three food insecurity types.

Irrespective of the method, we only classify households with at least two observations within a calendar year into food insecurity types. As the number of data points per household differs between countries, years, and households, we conduct a robustness check harmonizing the number of observations per household to K = 2 per year and to K = 3 per year, respectively. We do this by calculating all possible combinations of K rounds for each household-year. In each case, we note the food insecurity type that this particular combination of rounds would suggest for the household in that year. From this, we calculate the probability that the household is assigned to each of the three food insecurity types when drawing eiher K = 2 or K = 3 rounds at random. Therefore, instead of deterministically classifying each household as belonging to a single type per year, we account for the variation in what rounds get sampled by assigning a fractional weight to each type for each household-year. The weights correspond to the type-specific probabilities and sum to one. As a result, we are able to replicate our analysis with harmonized numbers of data points per year without discarding information or being arbitrary in our selection of data points to retain.

Predictive power of cross-sectional depth for food insecurity duration

As a formal test of the predictive power of a household's cross-sectional depth of food insecurity for the amount of time the household is food insecure in that year, we run the following regression

$$s_{hy}^{(-r)} = \beta_0 + \beta_1 fies_rawscore_r + \varepsilon_{hy}$$

where $s_{hy}^{(-r)}$ is the share of rounds a household is food insecure excluding round *r,* and $fies_rawscore_r$ is the FIES raw score in round *r* of the household. We are interested in the R^2

which gives the variation in time spent food insecure in the remaining year that is explained by a proxy of cross-sectional food insecurity depth.

Food insecurity profiles

To characterize the profiles of each food insecurity type, we first calculate simple, unadjusted weighted means among households belonging to each type. We do so across the following variables: dummy variables indicating whether the household belonged to the top or bottom wealth quintile; gender, age, and education (at least primary or not) of the household head; household size; the household's ratio of members aged 0 – 14 or above 65 to members aged 14 – 64; and a dummy for whether the household resided in an urban area. In each country, wealth quintiles reflect a household's position in the national wealth distribution based on an index calculated from household asset ownership and dwelling characteristics (from the in-person LSMS-ISA that served as sampling frames). Specifically, we use the list of assets included in each country's LSMS-ISA survey's asset module. In addition, we use the material of the dwelling's roof, outer walls, and floor; the number of rooms of the dwelling; drinking water source; and toilet type (see Supplementary Appendix for a full list per country). We construct the wealth index separately for each country as the first principal component of the correlation matrix of these variables. Scores are standardized to mean zero and unit variance so that higher values indicate higher wealth. We then classify households into wealth quintiles based on the index (this step includes survey weights).

Subsequently, we use a multinomial logit model to estimate each variable's marginal effect on the probability of a household to belong to a specific type. As our classification into food insecurity types is mutually exclusive and collectively exhaustive, an increase in the marginal probability to belong to one type will always be offset with an equivalent decrease in the marginal probability to belong to another type. Which types become more or less likely based on different household characteristics and by how much is the empirical question that we are analyzing.

Clustering of food insecurity types

We analyze the degree to which households of the same food insecurity types cluster in the same geographical areas, and the degree to which a household's type is stable across years, using multilevel mixed effects logistic regressions of the form

$$logit\left(P_{yhva}^{j}\right) = \boldsymbol{\delta_{cy}} + u_a + u_{v(a)} + u_{h(v,a)} \quad (2)$$

where P_{yhva}^{j} is the probability that household h in geographic region a and village v is classified as belonging to type j in year y, as opposed to one of the remaining two types; $\boldsymbol{\delta_{cy}}$ is a country-year fixed effect and u_a, $u_{v(a)}$ and $u_{h(v,a)}$ are random intercepts for geographic area (small administrative units, corresponding to either the second or the third level of the Nomenclature of Territorial Units for Statistics, or NUTS-2/3), village (i.e., the primary sampling unit or enumeration areas within the household surveys, typically a small cluster of neighboring households) and household (nested within geographic area a and village v). We estimate equation (2) once for each food insecurity type versus the remaining two types, respectively. In each case, we estimate the intra-cluster correlation of food insecurity type j (i) within geographic areas, (ii) within villages, and (iii) within households. That is, for each type j, we compute the share of total latent variance, conditional on country-year fixed effects, attributable to geographic areas, villages within areas, and households within villages. The household-year residual variance is fixed at $\pi^2/3$ as implied by the logistic distribution. The remaining share captures changes in a household's type across years net of country-wide shocks, along with any error in classifying households into types. This allows us to determine to what extent geographic areas, villages, and households differ in the prevalence of the different food insecurity types. For tractable estimation and in contrast to our remaining analysis, this analysis is not survey-weighted.

Targeting performance

We simulate two targeting exercises. First, we simulate geographical targeting in which we rank areas according to their estimated food insecurity prevalence in the year in question. We then ask what share of all never/transient/chronic food insecure households would be covered by a program targeting the *x%* most food insecure households in a given country and year, assuming that within selected areas all households are targeted. As a robustness check, we also conduct the area ranking using less contemporaneous information: food insecurity prevalence in the previous year or average consumption expenditure as calculated from the baseline LSMS-ISA household surveys.

Second, we conduct a targeting exercise in the style of a proxy-means test (PMT), but estimated on food insecurity types. We run a multinomial logit regression of food insecurity types on a set of household characteristics commonly used in the operational practice: a durable assets index, dwelling characteristics (all countries except TZA: material of roof, floor, and walls; the number of rooms; source of drinking water; toilet type; in addition: electricity access in BFA and NGA; internet access in BFA), and household demographics (household size, dependency ratio, a female headship dummy, and an urban/rural dummy). From this regression, we predict --- for each type --- a household's probability to belong to this food insecurity type. We then simulate a scenario for targeting chronically food insecure households and one targeting transiently food insecure households. In the scenario targeting chronically food insecure households, we rank households by their predicted probability to be chronically food insecure and target the *x%* households with highest predicted probability. For the households selected to be targeted in this way, we calculate the share of each food insecurity type covered according to households' *true* type instead of their *predicted* type. We conduct an equivalent exercise targeting transiently food insecure households.

Measurement error in FIES data and classification

One concern with identifying transient food insecurity is measurement error near the food insecurity cut-off that could manufacture spurious transient food insecurity classifications. Our strategy for addressing this is two-pronged.

First, we use food insecurity probabilities instead of deterministic classification. This follows the canonical, model-based way in which measurement error is handled within the standard FIES methodology. We explain this approach in Section *Classifying households into food secure or insecure.*

Second, we conduct a robustness checked premised on dropping observations with internally inconsistent response patterns. As our primary measure of inconsistency, we first rank the eight FIES items by pooled affirmation rates and cut them into four tiers that are each clearly distinct in their affirmation rates: Items 1-3, items 4-5, items 6-7, and item 8. We flag an observation as presenting an apparent inconsistency if the household affirms an item from a higher tier but does not affirm all items in the lower tiers. We drop observations flagged in this way and re-run our analysis using the remaining observations. In Table S26, we show this represents an intermediate case (labeled "L2") between dropping logical contradictions only (L1) which drops fewer observations and imposing the ordering of items strictly which is vulnerable to differences in interpretation between similarly severe items (L3). As dropping observations reduces the number of data points, the share of transiently food insecure households will drop mechanically. Table S26 therefore also reports a placebo comparison in which we drop the same number of rounds at random, providing a better comparison for the effect of potential *measurement errors* on the share

of transiently food insecure households rather than the effect of dropping observations more generally.

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Figures and Tables

A: Share of rounds food insecure within a year

B: Prevalence of food insecurity by round and ever within a year

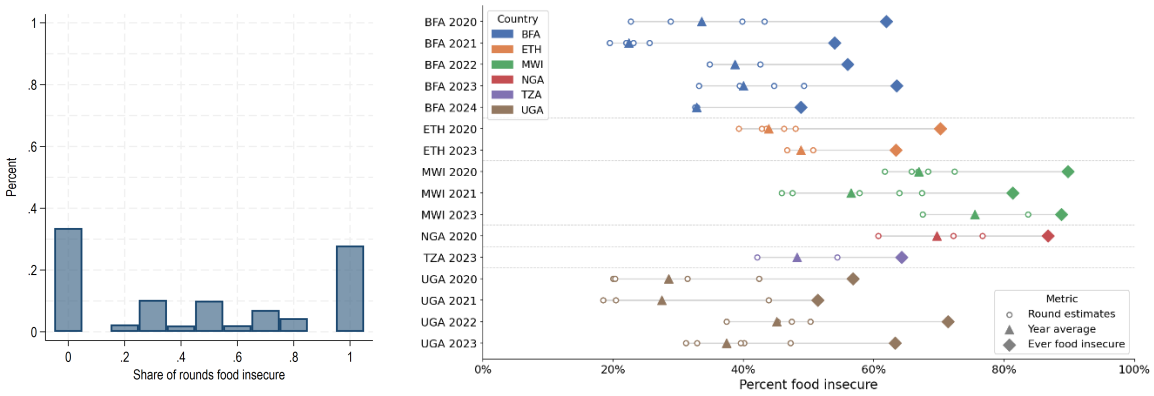


Fig 1: Intra-year variation in food insecurity prevalence. Panel A shows the share of rounds that a household was food insecure within a calendar year (N = 27,004 household-years). Panel B shows the prevalence of food insecurity by round (dots), the average food insecurity in the year (triangles) and the share of households that were food insecure at least once within the year (diamonds). N = 93,081 observations.

A: Food insecurity types at different FIES scores

B: Percent of transient and chronically food insecure households by FIES score

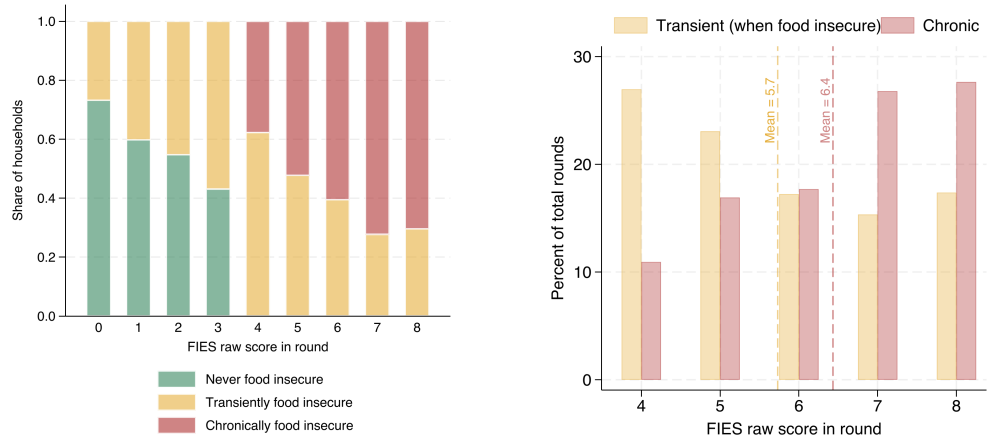


Fig 2: Cross-sectional food insecurity depth vs. longitudinal food insecurity types. Panel A shows, for each FIES raw score, the share of households by food insecurity type (N = 93,081). Panel B focuses on transient and chronically food insecure households and shows the distribution of their FIES raw scores when food insecure (N = 34,636).

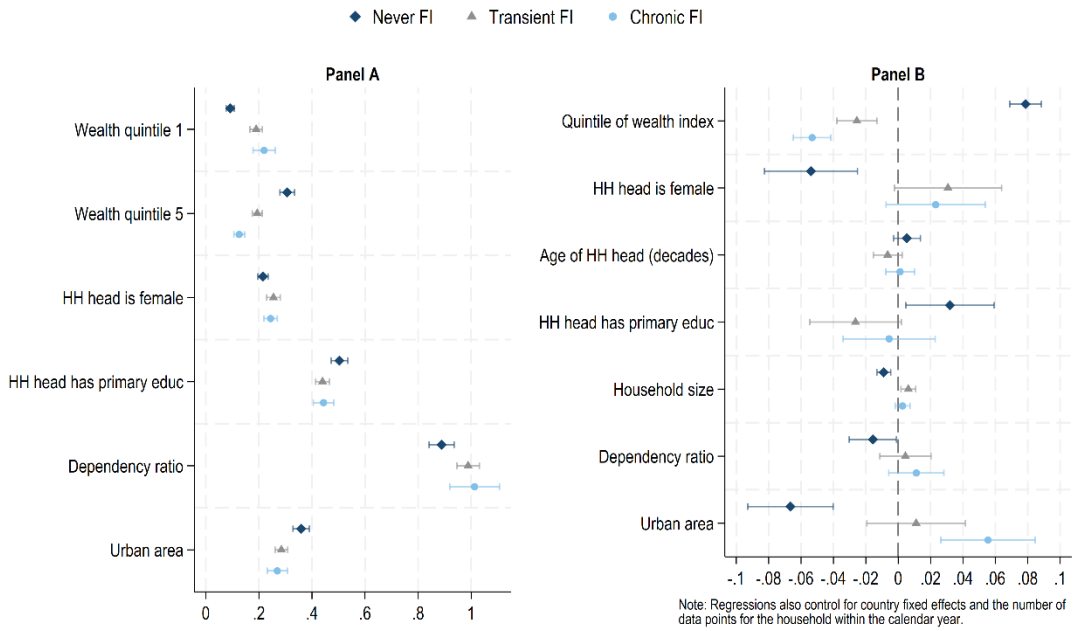


Fig 3: Profiles of households by food insecurity types. Panel A shows unconditional means. Panel B shows marginal probabilities from a multinomial logit regression controlling for country fixed effects and the number of data points for the household within the same calendar year. N = 25,213.

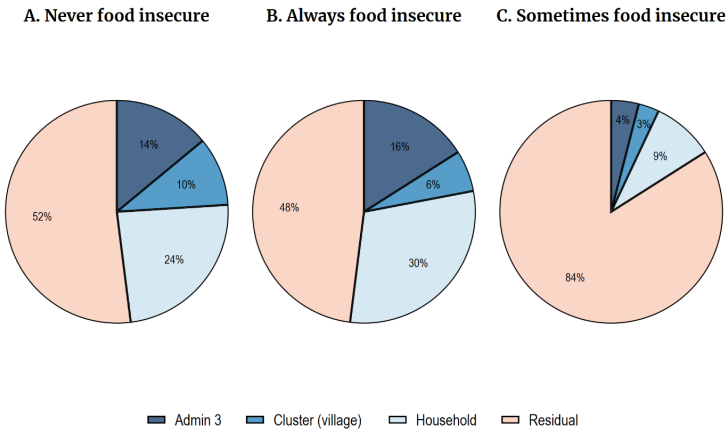
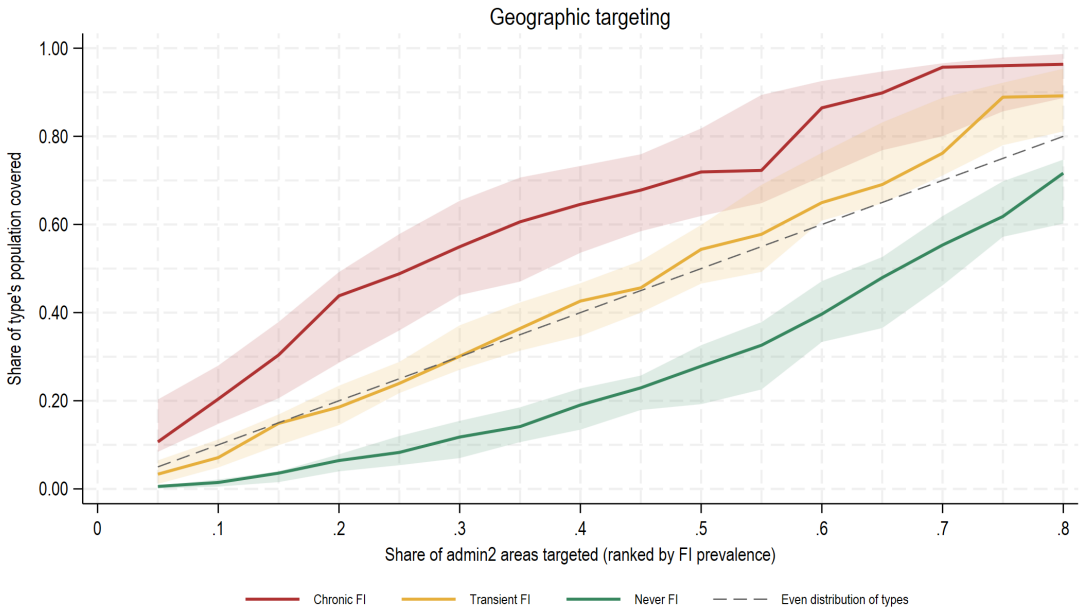
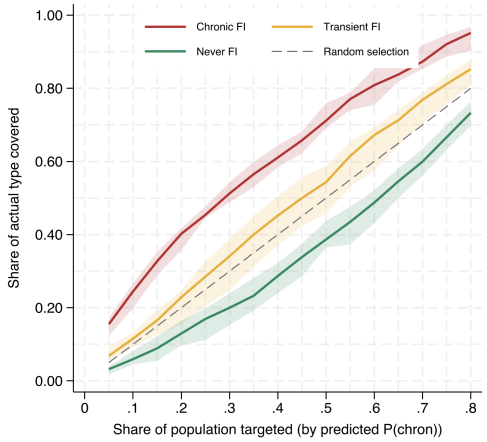


Fig 4: Intra-cluster correlation (ICC) for food insecurity types at admin 3, village, and household levels from mixed effects logistic regression. Panel A compares never food insecure households to households that were food insecure at least once in the year. Panel B compares chronically food insecure households to those who were food secure at least once in the year. Panel C compares transiently food insecure households to those that were either chronically or never food insecure. N = 26,320.

A: Geographic targeting exercise at admin 2 level



B: Share of each food insecurity type covered when targeting chronically food insecure households



C: Share of each food insecurity type covered when targeting transiently food insecure households

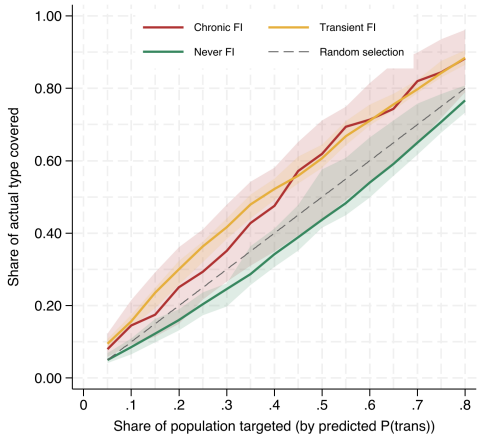


Fig 5: Share of each food insecurity type covered by different targeting modes. Panel A shows geographical targeting, ranking areas by average food insecurity prevalence and targeting the most food insecure areas. Within targeted areas, it is assumed that all households are targeted (N = 26,666). Panels B and C show proxy-means-test style targeting. Panel B targets chronic food insecurity and Panel C targets transient food insecurity (N = 26,185). Lines show median coverage across country-years; shaded bands show interquartile range.