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## **Food Security at High Frequency: Evidence from One Hundred Thousand Panel Interviews in Sub-Saharan Africa**

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## **Food Security at High Frequency: Evidence from One Hundred Thousand Panel Interviews in Sub-Saharan Africa**

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## **Abstract**

Global progress toward eliminating hunger (SDG 2) has stalled, with more than 2.3 billion people experiencing food insecurity in 2024. Yet standard monitoring approaches typically rely on cross-sectional, annual averages that obscure how households experience food insecurity over time. Using 72 rounds of high-frequency phone surveys conducted between 2020 and 2024 with more than 17,000 households across six Sub-Saharan African countries (Burkina Faso, Ethiopia, Malawi, Nigeria, Tanzania, and Uganda), we investigate the duration and dynamics of food insecurity. We contrast three measures of prevalence—point-in-time, annual average, and longitudinal “ever food insecure”—and show that the latter substantially exceeds standard estimates, with median gaps of 24 percentage points relative to annual averages. Household-level dynamics are critical: one third of households are never food insecure in a given year, 28% are chronically food insecure, and 38% experience transient food insecurity. Transient households are particularly important to identify, as they are neither adequately captured by point-in-time nor annual prevalence statistics. Socioeconomic profiling reveals clear differences between food secure and ever-insecure households—driven largely by wealth, rural residence, and demographics—but weaker distinctions between chronic and transient insecurity. Geographic clustering analysis shows that chronic and never-insecure households are spatially concentrated, while transiently food insecure households are dispersed, complicating program targeting. Our findings underscore that food insecurity is not only widespread but also dynamic, and that cross-sectional monitoring underestimates both its prevalence and complexity. High-frequency, longitudinal data are essential for designing more effective and context-specific food security interventions.

## Introduction

Ending hunger and ensuring food security all year round is at the core of the second Sustainable Development Goal (SDG). Achieving this goal by 2030 will not occur with a “business as usual” approach. In 2024, 2.3 billion people worldwide were food insecure, including almost two-thirds of the population of Sub-Saharan Africa, according to recent estimates by the Food and Agriculture Organisation of the United Nations (FAO) (1). The situation is particularly severe in several countries afflicted by acute conflicts, including Gaza, Democratic Republic of Congo, Sudan, South Sudan, and Yemen (2), and is compounded by climate shocks (3) and rising global food prices (1). These overlapping crises are unfolding at a time when global development and humanitarian assistance is contracting, and the gap between needs and available financing is widening (4).

In this context of shrinking budgets and increasing economic and climate volatility, accelerating progress towards the goal of year-round food security will require better evidence and data. Improved policies and programs will rest on better information about those who are food insecure. Barrett notes that “Although the most severe food insecurity is typically associated with disasters such as drought, floods, war, or earthquakes, most food insecurity is associated not with catastrophes, but rather with chronic poverty” (5). An inference from this is that there are important differences in the ways in which people experience food insecurity. Research on poverty policy has a long history of distinguishing the duration of experiencing poverty (6). Similarly, the ability to identify people who are food insecure and delineate those who are chronically or transitorily food insecure can help both conceptually in terms of appropriate policy design and empirically, in terms of more efficient targeting of programs. The aim of this paper is to shed light on both of these points.

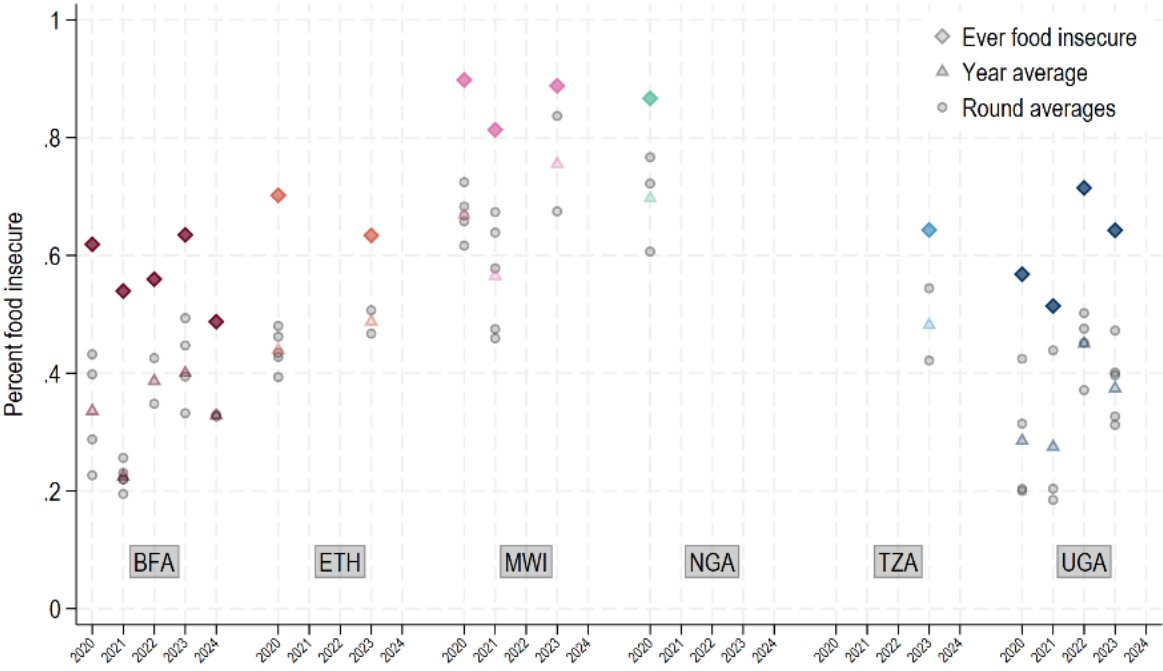
We make use of a harmonized cross-country panel dataset containing 72 rounds of high-frequency food insecurity measurements for 17,000 households in six Sub-Saharan African countries (Burkina Faso, Ethiopia, Malawi, Nigeria, Tanzania, Uganda), covering a period from 2020 to 2024. Our dataset contains for each household repeated measures within the year of the Food Insecurity Experience Scale (FIES) and we examine different types of households based on the duration of their food insecurity experiences. We first show that who is considered food insecure and the nature of food insecurity they experience depends critically on measurement, and specifically on accounting for household level dynamics throughout the year: the number of households experiencing food insecurity at any point during the year is much higher than the average food insecurity prevalence at any point during the year – but the duration of food insecurity spells differs between households.

We then contrast households based on whether they are food insecure in all rounds during the year (suggesting chronic food insecurity), in some rounds (suggesting transitory food

insecurity), or in none (suggesting stable food security) in terms of socioeconomic attributes and geographic location.

**Results**

Figure 1. Food insecurity prevalence point-in-time, annual average, and longitudinal (at any point)

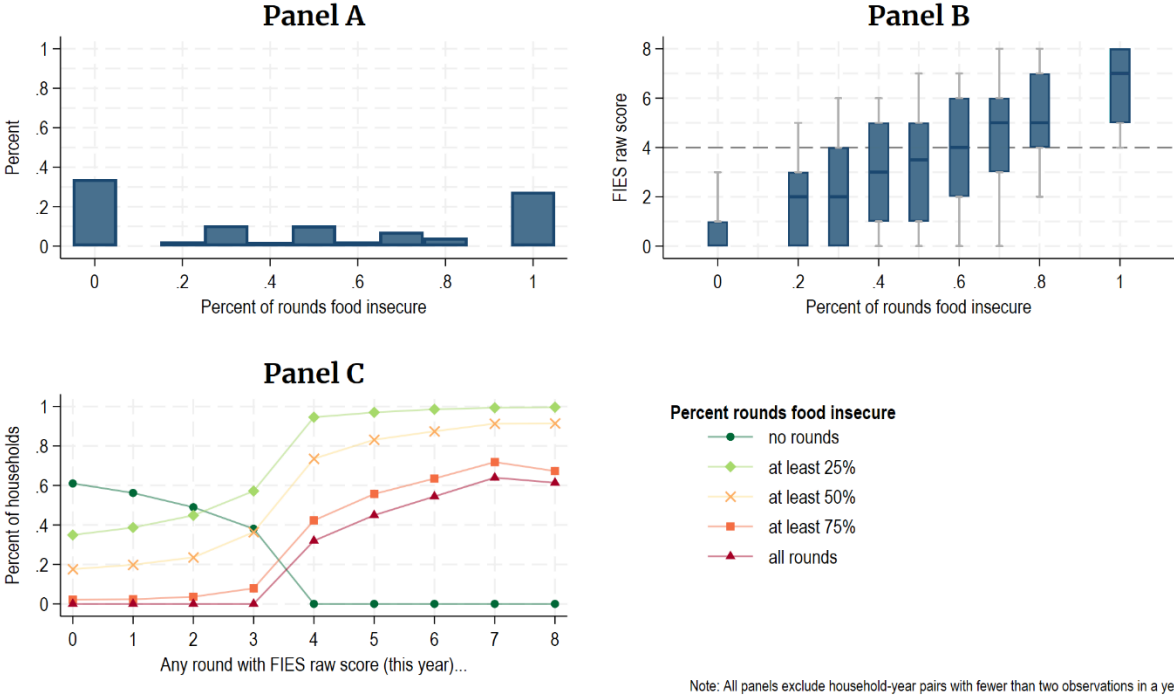


In a first step, we aim to show that country- and household-level dynamics matter for understanding and interpreting the nature and prevalence of food insecurity. We construct three estimates of the prevalence of moderate food insecurity (SDG 2.1.2) based on the Food Insecurity Experience Scale (FIES) in our study countries for several years between 2020 and 2024 (Figure 1). The first is the point-in-time prevalence which reflects round-specific cross-sectional estimates (circles in Figure 1). The second is the annual average prevalence, defined as the weighted mean of these round estimates within a given year (triangles in Figure 1). This measure mimics the standard reporting format for the prevalence of food insecurity, for example in the Sustainable Development Goals (1). The third is a longitudinal measure, defined as the share of households that experience food insecurity at least once during the year (diamonds).

Contrasting these measures shows that both within-year country-level variation and household-level dynamics matter for understanding the prevalence and nature of food insecurity. Point-in-time prevalence estimates vary widely, reflecting seasonality and

shocks. The median gap between minimum and maximum prevalence is 15 percentage points, ranging from 6 percentage points in Ethiopia to 19 percentage points in Uganda. Annual averages mask this intra-annual variation. In contrast, the longitudinal prevalence (ever food insecure in a given year) is, by construction, at least as large as the highest point-in-time prevalence, but in practice it exceeds both the annual average and the maximum round by substantial margins: the median gap relative to the annual average is 24 percentage points, and the median gap relative to the maximum round-specific point-in-time estimate is 14 percentage points. These differences indicate that many households experience food insecurity outside of the timing of aggregate peaks. The extent of this divergence varies across settings: in Ethiopia, point-in-time prevalence is relatively stable across rounds, yet the at-least-once prevalence is much higher, suggesting considerable household-level cycling. By contrast, in Malawi (2023) and Uganda (2021), household and country-level variation are more closely aligned.

Figure 2: Intra-year variation in food insecurity prevalence and depth of households



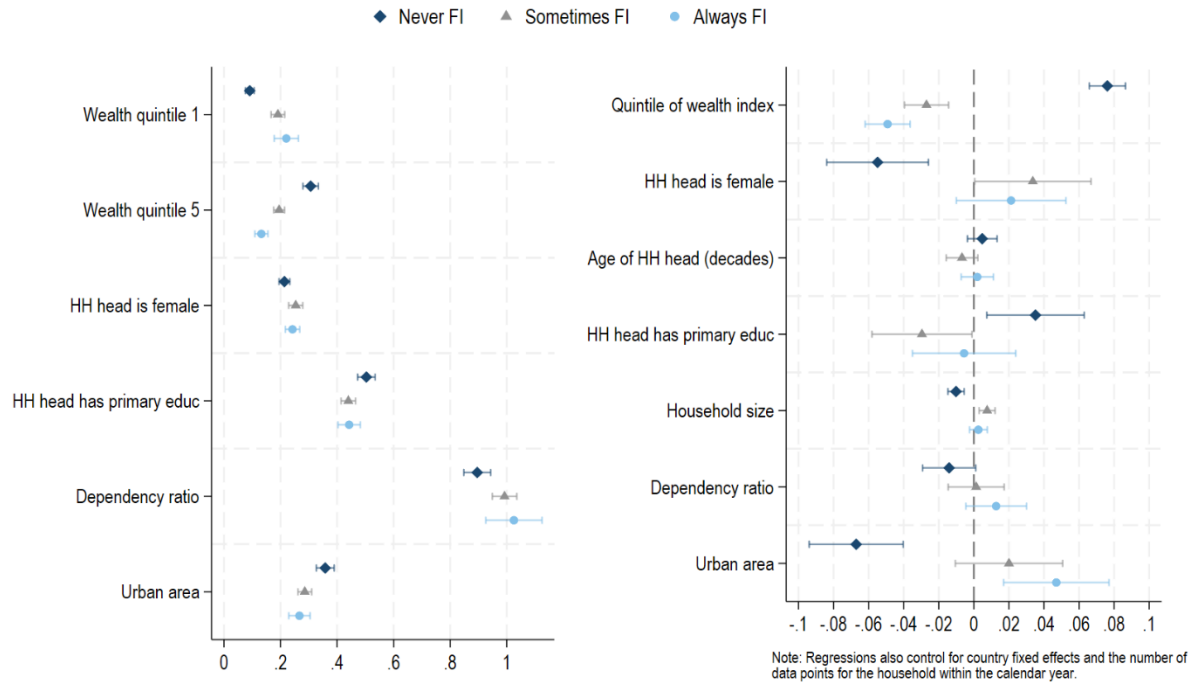
Underlying this aggregate variation in food insecurity are ups and downs in the food security of a given household within the same calendar year (Figure 2). Panel A demonstrates that there is a large group of households for which food insecurity is transient, that is, they are sometimes but not always food insecure of the course of a year. A histogram of the share of

rounds within the same year that households were food insecure separates three groups. About one third (34%) of households are never classified as food insecure, while the rest experiences at least one bout of food insecurity. Among households that experience any food insecurity, less than half (42%; 28% of total households) are chronically food insecure, that is, food insecure over the full period that we observe them within a calendar year. Conversely, 38% of total households (58% of ever food-insecure households) are transiently food insecure. These households are not adequately characterized as 'food secure' or 'food insecure'. Rather, their food security situation changes over the course of the same calendar year.

Panel B shows that even households who are food secure over much of the period covered within a year can experience relatively severe bouts of food insecurity and vice versa. We bin households together that spent a similar share of rounds in food insecurity over a given calendar year and visualize the 10<sup>th</sup> (lower whisker), 25<sup>th</sup> (lower box boundary), 50<sup>th</sup> (line within box), 75<sup>th</sup> (upper box boundary), and 90<sup>th</sup> percentile (upper whisker) of FIES raw scores within each bin. Households that are food insecure for a larger share of the period under observation within a calendar year also tend to have a higher depth of food insecurity, proxied by their FIES raw score. Median FIES scores increase from zero (never food insecure group) to seven (always food insecure group). At the same time, food security for most of a year can still go with times of relative food insecurity. Households who were food insecure for just 30% of the time we observe them within a year still had FIES raw scores peaking at seven or eight in about 10% of rounds. Similarly, 10% of FIES raw scores are zero among the group of households that were food insecure in 70% of rounds.

Because a household's food security can change drastically over the course of the same year, a single snapshot is often not enough to capture how much time a household spends food secure or insecure (Panel C). Even among households who experience a bout of severe food insecurity (raw score of 8), only 61% are food insecure over the whole study period of that year. About 9% of households in this group are food *secure* for more than half of the time observed. Among households appearing to be very food secure at a given point in time (raw score of 0), 39% still experience some food insecurity in the same year. A single raw score sitting in the middle of the range (i.e., four) can belong to a household that is chronically food insecure (32% of cases); or, in a quarter of cases (26%), it belongs to a household that is food insecure for less than half the time we track them in that year. This highlights the value of high-frequency panel data when characterizing household's food security profile.

Figure 3: Profiles of households with different food insecurity types



What characteristics distinguish chronically, transiently, and never food insecure households? In Figure 3, we compare the household profiles of these three groups. In Panel A, we present unadjusted means and find that, intuitively, households that are always food insecure are much more likely to be among the least wealthy 20% of the national population than households that are never food insecure (22% vs. 9%) and much less likely to be among the wealthiest quintile (13% vs. 31%). Conversely, there is no discernible wealth gradient among the transiently food insecure group. Chronically food insecure households are also more often found in rural areas than never food insecure households and have a relatively larger share of household members outside working age. The transiently food insecure group also tends to present an intermediate case in between the never and always food insecure groups regarding their household profile.

In Panel B, we move to multinomial logit regressions that allow us to analyze different factors in conjunction and to estimate how the probability of a household belonging to either group changes with their household characteristics. This allows for two main observations. First, the group of never-food-insecure households is often distinctly different from those households that are food insecure within a year (always or sometimes). This goes for wealth, which is positively correlated with a household being never food insecure, as well as female headship, household size, and urbanicity which are negatively correlated. The second observation is that distinguishing between households that are always or just sometimes

food insecure is much harder based on readily observable household socio-economic characteristics.

Despite the inability to delineate between the chronically and transiently food insecure in terms of socio-economic characteristics, Figure 4 suggests that there are some important geographic distinctions between these two types of food insecure households. The estimates underlying this figure are measures of the intra-group, or intra-cluster correlation coefficient (ICC). Higher ICCs indicate greater homogeneity of the variable within the grouping, relative to the overall observed variation of the variable. The highest geography level examined is the 3<sup>rd</sup> administrative unit, or NUTS-3 (Nomenclature of Territorial Units for Statistics). This identifies different political boundaries in each country but is a policy-relevant geography. For example, in Burkina Faso, this corresponds to departments; Uganda, counties; and Ethiopia, woredas (or districts). The ICC at this geographic level for households that are never food insecure within the calendar year is at about the same level as for households who are always food insecure within the year; while the ICC at the NUTS-3 level for households who are sometimes food insecure within the year is much lower. An inference of this difference in the ICCs is that geography does explain a substantial amount of the overall variation in the likelihood that someone will either never or always be food insecure (within a year). In contrast, NUTS-3 provides very little information about the likelihood that someone will sometimes be food insecure.

Another noteworthy element of Figure 4 is the high level of intra-household correlation for those who are never, or always food insecure (within a year), while the ICC is about 1/3 the size for individuals who are transiently food insecure. We mark a household as being never, always or sometimes food insecure within the year, so any observed variation in these attributes is across years. A relatively higher ICC at the household level – as Figure 4 indicates for never and always food insecure – indicates that households in either of those two states within the year are likely to be in those states from one year to the next.

Finally, the relatively larger cumulative ICC for the combined effect of NUTS-3, neighborhood, and household for never and always food insecure indicates that about half of the overall variation in these two typologies is explained by these three variables. In contrast, for those experiencing shorter bouts of food insecurity – the transient food insecure – geography and household only explain about 15 percent of the overall variation.

Figure 4. Intra-cluster correlation (ICC) of food insecurity types at NUTS-3, village, and household levels

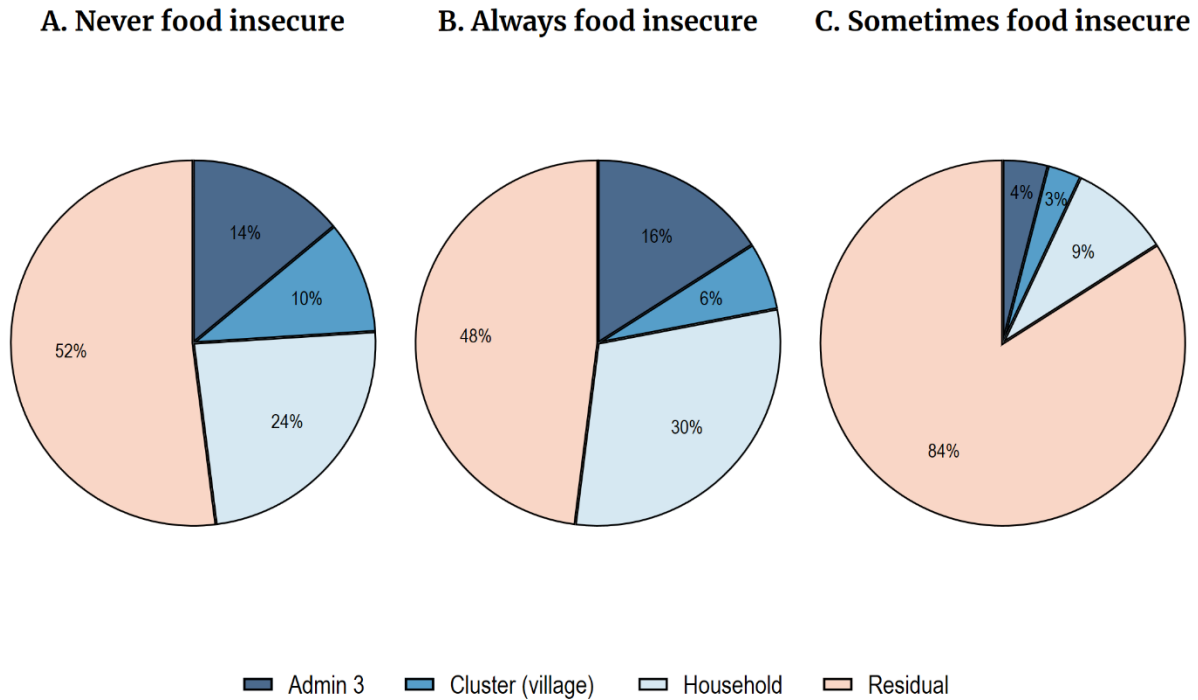


Table 1. Intra-cluster correlation (ICC) of food insecurity types at NUTS-3, village, and household levels

	Never vs. ever	Always vs. ever not	Sometimes vs. always/never
ICC Admin 3	0.142 (0.014)	0.155 (0.016)	0.036 (0.005)
ICC Admin3-Cluster	0.236 (0.014)	0.218 (0.015)	0.070 (0.007)
ICC Admin3-Cluster-HH	0.479 (0.015)	0.520 (0.018)	0.163 (0.014)
Observations	26,320	26,315	26,320

## Discussion

The challenge of eradicating food insecurity is massive. Failing to recognize distinctions in how and why people experience food insecurity will result in programs and policies premised on an assumption of “one size fits all.” A household that remains food insecure throughout the year, and over years, differs from households that transition in and out of food insecurity within the year. The existing evidence on household food insecurity dynamics, and in particular within-year dynamics, is very limited. Two recent studies present evidence on

monthly household coping strategies index data for a sample of households in district of Southern Malawi over 12 months (8); and monthly child anthropometrics in 23 countries in Kenya covering a period from 2006 to 2020 (9), drawing out important implications for resilience and acute malnutrition prediction. Another study presents annual household level food insecurity dynamics in the United States from 2001 to 2017 (10).

In this paper, we leverage high-frequency, multi-year panel data on food insecurity experience from 17,000 households across six countries in Sub-Saharan Africa to move beyond cross-sectional annual estimates and capture household food insecurity dynamics and duration. We show that there is a substantial number of people who experience food insecurity at some point in time during the year but who will not typically be observed as food insecure. For example, in 2023 Burkina Faso, the average rate of food insecurity over several rounds was 40 percent (i.e., at any point in time during the year, the expected rate of food insecurity in Burkina Faso was about 40 percent) while about 62 percent of the population experienced food insecurity at some point during the year (Figure 1). In our set of six countries from Sub-Saharan Africa, the typical gap between the average level food insecurity measure (i.e., on expectation, who is food insecure at a point in time) and the prevalence of those who experienced food insecurity at any point during the year was about one-fourth of the entire population (Figure 1).

The depth or intensity of food insecurity as proxied by the value of the FIES score will not capture well this distinction. About half of the households with a FIES score of 8 (the highest possible score) will transition out of food insecurity status within the year; this is about the same proportion as for households with a FIES score of 6 (Figure 2, panel B). The finding that there is a strong wealth gradient, particularly for the top and bottom 20 percent of the wealth distribution, in the duration (always, sometimes, never) of food insecurity status (Figure 3), suggests that those who are chronically food insecure are in need of longer-run investments in human capital that improve their ability to earn income and then use savings to buffer against shocks that induce food insecurity. Temporary assistance programs will provide temporary help but once the assistance ends, those households who were chronically food insecure will likely revert back to this status. In contrast, for those who transit in and out of food insecurity, well-timed, temporary assistance can help mitigate the harm caused by adverse shocks.

While this narrative suggests that a typology based on duration of exposure to food insecurity can help improve the efficiency of programs and policies, the empirical evidence on socio-economic correlates of this distinction seems to indicate that it is not easy to delineate the chronic from the transient food insecure. The main observable difference comes either from measures of wealth or repeated measures of food insecurity. Wealth is challenging to

estimate, particularly in those countries where food insecurity prevalence rates are the highest. Across the world though, wealth is a strong factor affecting where people live. Many public policies and programs that target geography (such as communities, villages, districts) rather than individuals are premised on this empirical regularity. Location of residence is easy to measure and our findings suggest that it is also a signal to target the chronically food insecure. The combined findings on the wealth gradient and the high ICC for the geography of the chronically (and never) food insecure suggest that the chronically food insecure tend to live in poorer communities consisting of other individuals who are also chronically food insecure. In contrast, the transiently food insecure are not clustered in terms of their residence suggesting that the shocks that force people into food insecurity are largely not localized, covariate shocks affecting specific communities.

This idea of using intra-cluster correlations as a tool for tailoring policy draws from the public health literature that will frequently aim to identify geographic areas for community based interventions such as vaccination campaigns or WASH interventions (7).

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, having more observations on the same household in one year make it likelier that food its insecurity status changes (from food insecure to not food insecure 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, and some evidence suggests this survey mode may be particularly susceptible to reporting error (11–13).

## **Materials and Methods:**

### High-Frequency Phone Surveys

Our data is from 72 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. 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 (11). 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 (14). Throughout our analysis, we use these weights but verify the robustness of our results to calculating unweighted sample statistics instead.

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.(15)

In total, our data comprises of 115,225 interviews with 17,233 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, were unable to eat healthy and nutritious/ preferred foods 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 can be 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 (16, 17).

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

#### 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

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

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 measure the depth of a household's food insecurity, we rely on the FIES raw score with higher values representing 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.

#### Classifying households into food secure or insecure

Some of our analysis relies on classifying individual households as either food secure or insecure. To do so, we take 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 (17). 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.

#### 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 assign households to their most probable type based on this calculation. Irrespective of the method, we only classify households with at least two observations within a calendar year into food insecurity types.

### 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).

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

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

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;  $\delta_{cy}$  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 the third level of the Nomenclature of Territorial Units for Statistics, or NUTS-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 calculate the intra-cluster correlation of food insecurity type  $j$  (i) within geographic areas, (ii) within villages, and (iii) within households. That is, we calculate the share of the total variation in the prevalence of type  $j$  that is explained by variation between geographic areas, between villages nested under geographic areas, and between households nested under geographic areas and villages. The residual variation not explained by the model is temporal variation in the food security type of a household across years. This allows us to determine to what extent geographic areas, villages, and households differ in the prevalence of the different food insecurity types.

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**Competing Interests:**

The authors declare no competing interests.

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## Appendix Figures

Figure 5: Data collection schedule



## Appendix Tables

Table 2: Average food insecurity prevalence by country and year

	Mean/se	[95% CI]
BFA 2020	0.336 (0.013)	[0.310,0.361]
BFA 2021	0.224 (0.010)	[0.204,0.244]
BFA 2022	0.387 (0.016)	[0.356,0.417]
BFA 2023	0.400 (0.032)	[0.337,0.463]
BFA 2024	0.328 (0.026)	[0.278,0.378]
ETH 2020	0.439 (0.020)	[0.400,0.479]
ETH 2023	0.488 (0.036)	[0.418,0.557]
MWI 2020	0.669 (0.016)	[0.637,0.701]

MWI 2021	0.565 (0.016)	[0.533,0.597]
MWI 2023	0.755 (0.018)	[0.720,0.791]
NGA 2020	0.697 (0.013)	[0.672,0.723]
TZA 2023	0.482 (0.016)	[0.449,0.514]
UGA 2020	0.285 (0.010)	[0.265,0.305]
UGA 2021	0.275 (0.009)	[0.257,0.293]
UGA 2022	0.450 (0.013)	[0.425,0.475]
UGA 2023	0.374 (0.011)	[0.353,0.395]
UGA 2024	0.548 (0.091)	[0.369,0.728]
Observations	93,017	

Table 3: Share of population that is ever food insecure in a year

	Mean/se	[95% CI]
BFA 2020	0.619 (0.016)	[0.588,0.650]
BFA 2021	0.540 (0.018)	[0.504,0.575]
BFA 2022	0.560 (0.019)	[0.523,0.597]
BFA 2023	0.635 (0.017)	[0.601,0.669]
BFA 2024	0.488 (0.033)	[0.423,0.552]
ETH 2020	0.702 (0.020)	[0.663,0.742]
ETH 2023	0.634 (0.039)	[0.557,0.710]
MWI 2020	0.898 (0.011)	[0.877,0.919]
MWI 2021	0.813 (0.015)	[0.783,0.843]
MWI 2023	0.888 (0.015)	[0.859,0.917]
NGA 2020	0.867 (0.011)	[0.845,0.888]
TZA 2023	0.643 (0.021)	[0.602,0.684]
UGA 2020	0.568 (0.014)	[0.540,0.596]
UGA 2021	0.514 (0.014)	[0.486,0.542]
UGA 2022	0.715 (0.014)	[0.688,0.742]
UGA 2023	0.643 (0.014)	[0.614,0.671]
UGA 2024	0.900 (0.076)	[0.751,1.048]
Observations	26,924	

Table 4: Estimated food insecurity prevalence by country and survey round

	Mean/se	[95% CI]
BFA 2020-11	0.288 (0.015)	[0.259,0.316]
BFA 2020-12	0.227 (0.013)	[0.201,0.252]
BFA 2020-7	0.432 (0.019)	[0.395,0.469]
BFA 2020-9	0.398 (0.017)	[0.364,0.432]
BFA 2021-1	0.195 (0.012)	[0.172,0.218]
BFA 2021-2	0.231 (0.013)	[0.205,0.256]
BFA 2021-4	0.220 (0.013)	[0.194,0.245]
BFA 2021-6	0.220 (0.014)	[0.193,0.246]
BFA 2021-7	0.256 (0.014)	[0.228,0.284]
BFA 2022-11	0.348 (0.016)	[0.318,0.379]
BFA 2022-6	0.426 (0.019)	[0.388,0.463]
BFA 2023-11	0.394 (0.063)	[0.272,0.517]
BFA 2023-3	0.332 (0.018)	[0.297,0.368]
BFA 2023-7	0.447 (0.026)	[0.396,0.498]
BFA 2023-9	0.493 (0.055)	[0.385,0.602]
BFA 2024-2	0.326 (0.030)	[0.268,0.385]
BFA 2024-6	0.329 (0.023)	[0.284,0.375]
ETH 2020-10	0.393 (0.023)	[0.348,0.438]
ETH 2020-5	0.480 (0.022)	[0.438,0.523]
ETH 2020-6	0.462 (0.022)	[0.419,0.505]
ETH 2020-8	0.435 (0.022)	[0.391,0.478]
ETH 2020-9	0.428 (0.023)	[0.382,0.473]

ETH 2023-10	0.507 (0.043)	[0.423,0.590]
ETH 2023-3	0.467 (0.038)	[0.392,0.542]
MWI 2020-11	0.617 (0.021)	[0.575,0.659]
MWI 2020-12	0.658 (0.020)	[0.618,0.698]
MWI 2020-5	0.724 (0.015)	[0.694,0.754]
MWI 2020-7	0.683 (0.019)	[0.647,0.719]
MWI 2020-8	0.668 (0.020)	[0.629,0.707]
MWI 2021-1	0.639 (0.019)	[0.601,0.676]
MWI 2021-3	0.674 (0.019)	[0.636,0.711]
MWI 2021-4	0.578 (0.020)	[0.539,0.617]
MWI 2021-5	0.475 (0.017)	[0.441,0.508]
MWI 2021-6	0.459 (0.018)	[0.424,0.494]
MWI 2023-12	0.837 (0.017)	[0.804,0.870]
MWI 2023-6	0.675 (0.026)	[0.624,0.725]
NGA 2020-11	0.607 (0.016)	[0.575,0.638]
NGA 2020-6	0.767 (0.013)	[0.742,0.792]
NGA 2020-8	0.722 (0.015)	[0.692,0.752]
TZA 2023-11	0.421 (0.023)	[0.376,0.467]
TZA 2023-6	0.544 (0.022)	[0.501,0.588]
UGA 2020-11	0.200 (0.012)	[0.177,0.223]
UGA 2020-6	0.424 (0.015)	[0.396,0.453]
UGA 2020-8	0.314 (0.014)	[0.288,0.341]
UGA 2020-9	0.203 (0.011)	[0.182,0.225]

UGA 2021-10	0.439 (0.015)	[0.409,0.469]
UGA 2021-2	0.185 (0.011)	[0.163,0.207]
UGA 2021-3	0.204 (0.012)	[0.181,0.227]
UGA 2022-10	0.502 (0.018)	[0.467,0.537]
UGA 2022-12	0.371 (0.017)	[0.337,0.405]
UGA 2022-6	0.476 (0.016)	[0.445,0.507]
UGA 2022-8	0.452 (0.015)	[0.421,0.482]
UGA 2023-10	0.312 (0.019)	[0.275,0.349]
UGA 2023-12	0.472 (0.021)	[0.432,0.513]
UGA 2023-2	0.326 (0.016)	[0.296,0.357]
UGA 2023-7	0.401 (0.022)	[0.358,0.444]
UGA 2023-9	0.396 (0.020)	[0.357,0.436]
UGA 2024-2	0.903 (0.075)	[0.757,1.050]
UGA 2024-3	0.218 (0.078)	[0.065,0.371]
Observations	93017	

Table 5: Intra-cluster correlations using administrative 2 divisions

	Never vs. ever	Always vs. ever not	Sometimes vs. always/never
ICC Admin 2	0.146 (0.017)	0.152 (0.018)	0.034 (0.005)
ICC Admin 2 - Village	0.252 (0.017)	0.232 (0.018)	0.068 (0.007)
ICC Admin 2 – Village - Household	0.492 (0.021)	0.533 (0.020)	0.163 (0.015)
Observations	26,664	26,659	26,664

Note: Intra-cluster correlations at the admin 2 area level, admin2-cluster level and household-within-cluster-within-admin2-area level from multilevel mixed effects logistic regressions. All models include country-year fixed effects.