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# Inside the crowd: Assessing the suitability of SMS-based surveys to monitor the food security situation in Uganda

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**Abstract**

SMS-enabled surveys are gaining traction as a rapid, low-cost means of monitoring food security situations as part of early warning systems. However, such surveys run the risk of yielding biased results, given that mobile phones are more prevalent among young, urban and wealthier populations. To assess the suitability of SMS-enabled surveys for food security monitoring, we conducted monthly surveys of 2000 respondents across Uganda over the course of one year. A filtering approach was used to ensure a representative sample. We evaluate the validity of the data by triangulating the responses with high-frequency data from our own face-to-face household surveys as well as externally collected phone survey data. The analysis suggests that SMS-based surveys can be a promising tool to measure changes in food security status over time, but they perform less well with regard to measuring the actual food security status. Responses related to the general food situation (rather than dietary diversity, food consumption or market prices) emerged as the most reliable indicator. Using different scenarios, we assess implications of changes in the sample composition and size for the results. Even biased samples, e.g. in terms of gender, location or age, show comparable trends, but a minimum sample size is required to obtain valid results.

**JEL Codes:** C83, H12, O13.

# 1 Introduction

The global food crises in 2007/2008 and 2011 sparked extensive monetary and technical investment into monitoring of national and global food supply and demand for early detection of food emergencies worldwide. Both the Food and Agricultural Organization (FAO) and the World Food Program (WFP) use remote sensing information and food price data for their early warning systems to detect abnormalities. These systems are of great help to international and non-governmental organizations to make provisions for food aid distributions, in particular in remote locations where they cannot conduct food security monitoring themselves.

The major challenges of early warning systems are related to data accuracy, usability and timeliness (Morrow et al., 2016). In lower-income countries, food price inflation data may be used as a political instrument and could be downward biased. Furthermore, price data is often missing for remote and conflict prone areas. There is also a time lag between price data collection and publishing as can be seen in the price tools of the FAO Global Information and Early Warning System on Food and Agriculture (GIEWS) and the WFP's Vulnerability Analysis and Mapping (VAM). Some of these shortcomings of using price data can be overcome by remote sensing-based early warnings systems, which use information about the biophysical state of vegetation at high spatial resolution and timeliness. The downside of this approach, however, is that the resulting food supply forecasts represent only one indicator of the food security situation. As an example, food imports can overcome production shortfalls without consequence for the local food security situation.

The rapid spread of mobile phones to even remote areas has opened up new opportunities to collect food security data rapidly. Among the most extensive effort to use mobile phones in food security monitoring is the Mobile Vulnerability Analysis and Mapping (mVAM) tool developed and operated by the WFP (Morrow et al., 2016). Following pilots in the Democratic Republic of Congo and Somalia in 2013, mVAM was deployed to track food security conditions in Guinea, Sierra Leone and Liberia during and after the Ebola epidemic. Application was expanded to other deployment contexts and countries in Africa. Short surveys were conducted by SMS, interactive voice response (IVR) and/or Computer Assisted Telephone Interviews (CATI) usually on a monthly basis to collect data on food consumption and coping strategies as well as occasionally price data.

Mobile phone-based survey approaches to data collection are argued to hold great potential for food security and disaster monitoring (Ballivan et al., 2015; Cinnamon et al., 2016; Dillon, 2012; Morrow et al., 2016; Van der Windt & Humphreys, 2016).[1] The technology enables near real-time access to high-frequency data to assist decision makers in targeting interventions. Data can be collected even from remote areas that may be difficult or unsafe to access in person. In particular SMS is thought to be a promising tool due to low costs, quick response collection and high response rates (Alam et al., 2014; Ballivan et al., 2015; Bauer et al., 2015; Lau et al., 2019). Respondents can answer in their own time and with greater privacy than in the case of phone calls (Dillon, 2012; Firchow & Mac Ginty, 2020; Gibson et al., 2017). SMS surveys have also been shown to be useful in creating panel data (Broich, 2015).

Mobile phone-based survey approaches are subject to various challenges, however, in particular with regard to their representativeness and the validity of the results. As will be discussed in detail below, mobile phone access and use and hence survey participation tends to be more prevalent among young, male, more educated and urban-based respondents. This bias may hinder data collection on

[1] This article focuses on modes that do not require an internet connection, given low internet uptake and smartphone use in lower income countries, in particular among vulnerable communities who would be the main target of food security monitoring (ITU, 2023).

food security precisely from those population groups that are most severely affected (Mock et al., 2015). Various authors have used weighting approaches to address possible biases in the data which runs the risk of distorting the results. The validity of the responses has also been called into question (Cinnamon et al., 2016; Mock et al., 2015). Without the presence of interviewers, it is not possible to collect additional contextual data or verify the responses through observation. Understanding how these limitations play out in practice is important to be able to take advantage of these survey tools while minimizing risks of incorrect information (Cinnamon et al., 2016).

While the potential shortfalls of mobile phone-based survey approaches have been widely recognized, systematic research to quantify and address these constraints remains scarce. To close this knowledge gap, this study assesses the validity of food security data crowdsourced through monthly SMS surveys conducted over the course of one year in Uganda. It then evaluates whether the size and characteristics of the sample influence the validity of the results. The study adds to the existing literature in a number of ways. First, we use triangulation to assess the validity of mobile phone-sourced food security data by comparing SMS data to data collected through our own face-to-face household surveys as well as data collected by the Uganda Bureau of Statistic (UBOS, 2021a). Second, we use systematic demographic filtering to avoid biases often found in SMS surveys that rely on mobile phone lists from mobile network operators. Third, by using demographic filtering to obtain a representative sample, we are able to apply weighting to emulate different scenarios of bias and assess related implications for the validity of the results.

The remaining article is structured as follows. Section 2 provides an overview of the literature related to mobile phone-based surveys in general and related to food security monitoring in particular. Section 3 outlines the data collection process and analytical methods used. Section 4 presents the results of the data analysis while Section 5 concludes with a discussion of the findings.

# 2 Literature review

A sizeable body of literature has shown that the use of mobile phones to collect data via SMS, IVR or CATI can result in a biased sample. First, there may be mismatch between the sampling frame and the target population (Brubaker et al., 2021; Firchow & Mac Ginty, 2020; Gourlay et al., 2021; Lau et al., 2019). Target respondents may not have access to mobile networks or phones or to electricity to recharge their phones (Ballivan et al., 2015; Croke et al., 2012; Dillon, 2012; Firchow & Mac Ginty, 2020; Lau et al., 2019). Network coverage and electricity access tends to be particularly low in rural areas of lower income countries (ITU, 2023). In emergency situations, infrastructure may be destroyed, malfunctioning or overburdened (Cinnamon et al., 2016; Morrow et al., 2016). Bias can also arise due to patterns in mobile phone ownership and use, which are associated with certain factors, such as level of education (higher formal education), sex (men), location (urban), income (higher), age (lower), and technological capacities (higher) (Cinnamon et al., 2016; Dillon, 2012; Firchow & Mac Ginty, 2020; Gibson et al., 2017; Giroux et al., 2019; Lau et al., 2018, 2019; Leo et al., 2015; Mock et al., 2015; Morrow et al., 2016). Many of these factors are also often associated with food insecurity, thus making sample selection a particularly important potential source of bias in this context (Mock et al., 2015).

Another potential source of bias is due to possible self-selection, that is who actually decides to respond initially and over time. Mobile phone-based surveys generally suffer from low response rates (Broich, 2015; Lau et al., 2019). Factors that influence response rates are similar to those that determine mobile phone ownership and use in general (Broich, 2015; Croke et al., 2012; Demombynes et al., 2013; Lau et al., 2019). For instance, Lau et al. (2019), who compared IVR, SMS and CATI with face-to-face (F2F) data collection in Nigeria, find that only around a third or less of CATI, SMS and IVR respondents were female while the share of female respondents in F2F interviews was representative.

They found similar biases with regard to education levels and location (rural / urban). Regarding income levels, however, Brubaker et al. (2021) find that wealthier households were less likely to respond to a telephone survey assessing impacts of the Covid-19 pandemic, possibly due to higher opportunity cost of their time.

In addition to potential biases in initial response rates, attrition rates and periodic non-responses can also lead to bias in repeat surveys (Gourlay et al., 2021). Response rates are often found to decrease over time (Ballivan et al., 2015; Demombynes et al., 2013; Hoe & Grunwald, 2015). Respondents who do not complete the study may be different from those who continue to participate. Ballivan et al. (2015), for instance, find that attrition rates tend to be higher among older, less educated and less affluent respondents and among households living in rural areas in Peru and Honduras. Attrition rates also differed by survey mode, with the highest rates recorded for IVR and SMS and the lowest for CATI surveys. The effect of sex is not clear-cut. One study using a call centre in South Sudan finds that while women were less likely to be part of the sample, they were more likely to complete the survey rounds. Leo et al. (2015) also observed different rates of survey completion across the selected languages, possibly because of poor translation or correlation of some languages with other characteristics such as education or income. Periodic non-response can also be observed where respondents participate in some rounds but not others. In a repeated SMS survey of farmers in Zambia, Giroux et al. (2019) observed a stable response rate of 40-65%, but hardly any farmers responded every week. Reasons for attrition or periodic non-responses are diverse, including, among others, being too busy, not understanding the purpose or topic, forgetting to respond, lack of phone credit, (accidentally) deleting SMS, phone malfunction, network problems or lack of ability or help to send SMS (Giroux et al., 2019; Hoe & Grunwald, 2015).

Bias may also arise when frequently re-surveying individuals if repeated participation in the survey affects individuals' responses over time, referred to as panel conditioning (Sun et al., 2019). On the one hand, panel conditioning could improve the quality of data as participants learn what is expected of them. On the other hand, it may also reduce data quality, for instance if respondents change their behaviour or attitudes over time as a result of participating in the survey (Cornesse et al., 2023). The occurrence of panel conditioning has not been assessed in the context of mobile-phone enabled food security monitoring.

Several studies have used incentives to increase response rates and reduce attrition (Ballivan et al., 2015; Broich, 2015; Leo et al., 2015). They find that incentives help to solicit initial responses and increase completion rates, in particular financial incentives. Leo et al. (2015), for instance, offered three types of incentives to respondents in Mozambique, Afghanistan and Ethiopia, including a pro-social or intrinsic incentive about the purpose of the data, an airtime raffle where 2 participants per country could win two hours of airtime, and transfer of 4 minutes of airtime upon completing the survey. They find that both the raffle and the transfer conditions increased completion rates. Whether the amount of the compensation matters is somewhat unclear, but in most study contexts, the incentive amount did not have a discernible impact on response rates (Ballivan et al., 2015; Croke et al., 2012).

Another approach to reducing possible biases used in the literature is to artificially change the composition of the sample either during data collection (through filtering) or data analysis (through weighting). Filtering with demographic quotas was employed by Leo et al. (2015). On some days, males, urban respondents or urban males were filtered in Afghanistan and Zimbabwe to achieve a more representative sample. However, since the filtering was not carried out systematically throughout the survey, it is difficult to draw conclusions on selection bias. More commonly, weighting is applied to the data to conform the sample to population parameters (Gourlay et al., 2021; Leo et al., 2015). Lau et al. (2019), for instance, weighted the sample of the phone-based data collection so as to align it with population totals from F2F surveys related to age, gender, education and village residence. Weighting bears certain risks, however. As Croke et al. (2012) notes, weighting can be challenging where they are associated with unobservable characteristics. Brubaker et al. (2021), for instance, find that individual-level reweighting applied in the Covid-19 telephone survey reduced selection biases, but could not eliminate all statistically significant differences.

It is important to note that lack of representativeness of the sample does not automatically invalidate the results. Rather, it is necessary to determine which degree of bias may be admissible in certain study contexts to yield valid results. Little research has been carried out in this regard. Lau et al. (2019) compare voting responses in Nigeria collected via SMS and IVR surveys with officially reported actual voting behaviour. They find substantial bias in the mobile phone-sourced data. Weighting by demographic characteristics did not improve the results. They do not offer a possible explanation for the differences. Other studies shed some light on possible pathways. For instance, validity may be impacted by mobile survey mode. In some contexts, SMS produced more reliable results than IVR or CATI. Bauer et al. (2015), for instance, conclude that the data quality of SMS data with regard to coping strategies was better than IVR and close to F2F data. Food price data collected via SMS also showed fewer outliers than IVR data. The type of information collected may also matter. Ballivan et al. (2015) finds that mobile phone-sourced responses to factual questions such as on household infrastructure, were more reliable (i.e. closer to F2F data) than responses related to the perception of poverty. Finally, validity may be influenced by other factors than the sample characteristics. For instance, the implementers of mVAM reported concerns over possible 'gaming' behaviour where respondents deliberately underreport their food consumption to increase the likelihood of food distribution by WFP (Mock et al., 2015; Morrow et al., 2016).

# 3 Methods and Data

## 3.1 Data

Data was collected using an SMS-based survey tool. As argued in the previous section, existing research suggests that SMS are more cost-effective, less prone to temporary network unavailability and yield comparably or more reliable results than other mobile phone modes. Thus, rather than assessing 'mode effects', we opted for an in-depth analysis of SMS as a suitable survey mode. Since the limit to 160 characters and lack of multimedia content do not allow for posing complex questions, SMS are suitable for basic closed-answer questions (Cinnamon et al., 2016). We employ single- and multiple-choice questions as well as simple numerical responses. The whole set of questions can be found in Appendix A1. Four different measures to assess food security status were included in the survey:

- number of food groups consumed by the respondent (**Dietary Diversity Score**, DDS), i.e. cereals, vegetables, fruits, groundnut/beans/peas/oil, meat/fish/eggs, milk products
- change in the availability of food in the market over the past seven days (**Food Market**), i.e. no change, less food is available, more food is available, don't know
- change in the household's level of food consumption over the past seven days (**Food Consumption**), i.e. better access to food, difficulties in obtaining food, no change
- food situation in the household (**Food Situation**) i.e. very good, good, poor or very poor

The survey was implemented by the private company GeoPoll which has access to a large set of mobile phone numbers via contracts with telecommunication companies. Usually, a subset of these mobile subscribers are active participants in SMS surveys of the provider. GeoPoll implemented the same 13 question SMS survey monthly between February 2020 and April 2021. The SMS survey was targeted at the general population. Several filtering criteria were used to avoid the bias towards urban, male, and wealthier respondents observed in the literature:

- Maximum income thresholds to make our sample representative or close to representative for the poor and lower middle class. We use a monthly income threshold of Ugandan Shillings 753,000 (roughly $200 in Jan 2020) for rural households and Ugandan Shillings 1,130,000 (roughly $300 in Jan 2020) for urban households. The thresholds roughly coincide with the World Bank poverty lines.
- Respondents from Metropolitan districts were excluded. In districts with both rural and urban areas, a threshold of 75% completion by self-identified rural respondents was applied.
- 50% split of men and women.

Based on regional stunting figures obtained from the Uganda Demographic and Health Survey, we identified seven sub-regions of Uganda, namely Central Region, Eastern Region, North-West, Karamoja and Mount Elgon (Eastern border of Uganda), Eastern (part) of Northern Region, Western Region, and South-West. Then, we apply population weights to determine the proportion of the total target of 2000 respondents from the different sub-regions.[2] The details are shown in table A2.1 in the appendix.

Next to its active subscribers, GeoPoll did recruit additional subscribers in regions with lower coverage prior to the start of the survey. From this, a respondent repository was created during the first wave of the SMS survey which was retargeted during subsequent rounds. After the first survey round was completed in February 2020, those who participated in the first round and new respondents could participate in the subsequent rounds of the survey. This also yields an unbalanced panel of repeated respondents, i.e., respondents who participate in more than one survey round over the 12-months period. The survey tool was available in English and Luganda (similar to Lau et al., 2018).. Luganda is the most widely spoken indigenous language and the most widely spoken second language alongside English (Nakayiza & Ssentanda, 2015). The questionnaire was initially translated by GeoPoll. The translation was then cross-checked by a food security expert in Uganda.

During the same period as the SMS survey[3], we conducted a face-to-face High Frequency Panel Survey (HFPS) in collaboration with the College of Agriculture and Environmental Science at Makerere University in Kampala.[4] In this survey, the same questions on the food security status were asked as in the SMS survey alongside the standard household demographics. There is an overlap of four out of the six rounds of the HFPS with the SMS survey period, namely in June 2020, August/September 2020, December 2020, and April 2021. The food security-related questions were answered by the (self-reported) caretaker in the household.

The third source of data for this study is the UBOS' High Frequency Telephone Survey (HFTS) collected between June 2020 and April 2021 using CATI technology (UBOS, 2021a). The HFTS interviewed respondents of households from the Uganda National Panel Survey. The initial survey is nationally representative but the HFTS only includes households that stated their telephone number and who could be reached during June 2020 when the first round was conducted. The HFTS reports the food insecurity experience scale (FIES) an indicator based on eight questions about the household's food insecurity situation (FAO, 2018). Moderate and severe food insecurity are determined by the answers

[2] We use this approach instead of sampling from the four official regions because we want to avoid an overrepresentation of areas with better food security status whose inhabitants are also more likely to participate in the survey.
[3] The time plan of the face-to-face survey was interrupted by the Covid-19 pandemic. While the SMS survey could be implemented as planned, the timing of the face-to-face survey was postponed and it was conducted between Jun 2020 and July 2021.
[4] Ethical approval the HFPS was granted by the review board of Makerere University.

to specific of the eight questions. The questions were answered by different members of the household, including the household head, spouse or a child (Brubaker et al., 2021).

### 3.2 Analytical methods

The data analysis is conducted in several steps focussing on two research questions: (1) Are results from the SMS survey valid? And (2) Do the size and characteristics of the sample influence validity? To do so, we compare responses from our SMS survey to our HFPS and the UBOS' HFTS.

For research question 1, we test the validity of the SMS survey by comparing the levels and variances of questions on the respondents' food security status. This was done by statistically testing if the means and variance of two different data are equal by applying the t-test and the variance f-test. However, as we do not know which data constitute the true level of food security, we also focus on the correlates of food security. This includes the temporal progression of average food security during the period June 2020 and April 2021 and covariates of the food security status, such as household characteristics. This was examined by running multi-variate regressions with selected counterfactuals and testing the equality of two t-student distributed coefficients. The difference of two t-student distributions is chi2 distributed, and therefore, the chi2 difference test is used.

For research question 2, we follow suggestions in the literature and look at the response accuracy of answers to supposedly invariant variables and the reliability by testing the consistency across different food security indicators. We test the representativeness of the dataset by comparing the characteristics of our SMS sample to nationally representative data and by performing statistical tests with the SMS sample data, changing the characteristics of the SMS sample, for instance by using survey weights that replicate the mean characteristics of nationally representative data. Finally, we investigate the importance of the survey composition. On the one hand, we compare results from the cross-sectional SMS data with the subset of repeated respondents. On the other hand, we draw random samples (out of the 2000 respondents per wave) to examine the sensitivity of the results to the sample size.

Among the 26,000 (13 x 2,000) completed surveys, 45% are from single respondents who only participate in one survey round. The remainder comes from repeated respondents, i.e. respondents that participate at least twice. Among the repeated respondents, 25% of the responses come from respondents who participate twice, 13% from respondents who participate three times, 7% from respondents who participated four times, 4% from respondents who participated five times, and 6% from respondents to participated six and more times. The details for each round are presented in Figure A1 in the Appendix. There are few differences between one-time and repeated respondents. While the age structure is the same between the two groups on average, urban and male respondents are more likely to participate multiple times in the survey. Besides, multiple participation is more common in three of our regional zones (North-West, Karamoja/Mount Elgon, and Eastern/Northern) than in the remaining regions.

## 4 Results

### 4.1 Food security status level

Table 1 shows the mean difference between the SMS survey, the HFPS and the HFTS, the ratio of standard deviations and the respective t-statistics and f-statistics for overlapping survey periods and regions as well as to rural respondents. In both cases, the null hypothesis is that there is no difference in the means or the standard deviations between the data sets. In all cases, we reject the null hypothesis of mean equality and in three cases we also reject the null hypothesis of equality of the standard deviations.

Table 1: Mean and variance difference between SMS and HFPS/HFTS data

| | diff. mean | t-mean | sd ratio | f-sd |
|---|---|---|---|---|
| Panel A: Comparison with HFPS | | | | |
| DDS | 1.181*** | (21.36) | 0.83*** | (0.67) |
| Food Consumption | 0.110*** | (3.40) | 0.97 | (0.95) |
| Market Food | -0.148*** | (-4.16) | 0.98 | (0.97) |
| Food Price | -0.0812** | (-2.29) | 1.02 | (1.05) |
| Food Situation (1,2,3,4) | 0.139*** | (4.50) | 0.91*** | (0.84) |
| Food Situation is poor (=1) | 0.129*** | (5.97) | 1.08 | (1.02) |
| Food Situation is very poor (=1) | -0.0119 | (-1.04) | 0.80*** | (0.64) |
| Panel B: Comparison with HFTS | | | | |
| Food Situation is poor (=1) | 0.118*** | (11.01) | 1.06*** | (1.13) |
| Food Situation is very poor (=1) | 0.0255*** | (4.71) | 1.21*** | (1.44) |

*t* statistics and f statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: UBOS (2021a); Kornher and Baumüller (2024)

Columns (1)-(4) in Table 2 show the mean differences and t-statistics for all four periods in the Eastern Region. The results for the remaining regions can be found in A3: supplementary tables and figures. For all regions, we find statistical differences between the means of the SMS survey and the HFPS consistently for DDS, Market Food and Food Price across all regions. For Food Consumption, about half of the mean difference tests reveal statistical differences between the SMS survey and the HFPS. On the other hand, the majority of the mean differences of Food Situation are not statistically different. This reveals already a pattern across the food security variables as some questions could be more suitable for SMS surveys than others. In particular, the mean difference of DDS appears to be substantial, suggesting that the SMS survey systematically underestimates the DDS.

Table 2: Mean difference t-test for Eastern Region

| | June 2020 | Aug/Sep 2020 | December 2020 | April 2021 |
|---|---|---|---|---|
| DDS | 0.949*** | 1.134*** | 0.868*** | 0.943*** |
| | (0.123) | (0.104) | (0.117) | (0.107) |
| Food Consumption | -0.0912 | -0.210*** | -0.102 | -0.105 |
| | (0.0678) | (0.0702) | (0.0806) | (0.0843) |
| Market Food | -0.101 | -0.311*** | -0.421*** | -0.610*** |
| | (0.0800) | (0.0746) | (0.0836) | (0.0795) |
| Food Price | -0.325*** | -0.355*** | -0.0723 | -0.507*** |
| | (0.0780) | (0.0744) | (0.0843) | (0.0824) |
| Food Situation | -0.245*** | -0.0903 | -0.0878 | -0.128* |
| | (0.0717) | (0.0654) | (0.0684) | (0.0730) |
| Food Situation is poor (=1) | -0.130*** | -0.0868* | -0.0531 | -0.0683 |
| | (0.0497) | (0.0450) | (0.0509) | (0.0503) |

| | | | | |
|---|---|---|---|---|
| Food Situation is very poor (=1) | -0.0958*** (0.0296) | -0.0313 (0.0231) | -0.0603** (0.0260) | -0.0371 (0.0225) |
| Observations | 433 | 658 | 411 | 413 |

Standard errors statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: Kornher and Baumüller (2024)

## 4.2 Socio-economic and spatial determinants of food security status

We examine the validity of the SMS survey by running several multivariate regressions and testing if socio-economic and spatial variables have equal effects on food security status between the SMS survey and the HFPS. In doing so, we run both ordinary least square regressions (OLS) and poisson regressions (Poisson) and test for the equality of the coefficients across different regression models, one regression using the SMS survey data and one regression using the HFPS data. The poisson regression model may fit the data better because the dependent variables are categorical and not continuous, and therefore, may be better described by a poisson distribution.

Table 3: Difference in socio-economic drivers of Food Situation between SMS and HFPS

| | OLS | | | Poisson | | |
|---|---|---|---|---|---|---|
| | (1) SMS | (2) HFPS | Chi2(1) | (3) SMS | (4) HFPS | Chi2(1) |
| Age | -0.00255 (0.00323) | -0.00515 (0.00497) | 0.19 | -0.00103 (0.00297) | -0.00204 (0.00472) | .0.18 |
| Age^2 | 0.00000754 (0.0000444) | 0.0000638 (0.0000486) | 0.71 | 0.00000296 (0.0000408) | 0.0000253 (0.0000460) | 0.69 |
| Gender | -0.0362*** (0.0101) | 0.0387 (0.0251) | 7.90*** | -0.0148 (0.00927) | 0.0155 (0.0239) | 8.08*** |
| Household size | 0.0457*** (0.00475) | 0.0239 (0.0148) | 1.38 | 0.0195*** (0.00435) | 0.00990 (0.0144) | 1.55 |
| Household size^2 | -0.000817*** (0.000265) | -0.00186** (0.000899) | 0.75 | -0.000396* (0.000239) | -0.000773 (0.000881) | 0.55 |
| _cons | -0.00255 (0.00323) | -0.00515 (0.00497) | | -0.00103 (0.00297) | -0.00204 (0.00472) | |
| Observations | 19490 | 3763 | | 19490 | 3763 | |

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: Kornher and Baumüller (2024).

In these regressions, we focus on two distinct food security indicators for the sake of space. The indicators are DDS and Food Situation. These two variables were chosen because the mean values of DDS appeared to be very different between the SMS survey and the HFPS, while Food Situation was relatively similar between the two (i.e. means were rejected only for four combinations of periods and sub-regions). The regression results for the socio-economic drivers are shown in Tables 3 and 4. We can see that, apart from the variable gender, the signs of the coefficient estimates are the same for SMS and HFPS and no statistical difference between the coefficients can be detected. We find that a quadratic relationship is the best fit for both age and household size. Accordingly, food security improves with higher age but at a decreasing rate. Food Situation worsens with household size (at a decreasing rate) but DDS increases with household size (at a decreasing rate).[5] Gender appears insignificant in the HFPS regression. In contrast, female respondents in the SMS survey report a better Food Situation and higher DDS as compared to male respondents.

Table 4: Difference in socio-economic drivers of Dietary Diversity Score between SMS and HFPS

| | OLS | | | Poisson | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | | (3) | (4) | |
| | SMS | HFPS | Chi2(1) | SMS | HFPS | Chi2(1) |
| main | | | | | | |
| Age | 0.0178$^{***}$ | 0.00845 | 1.15 | 0.00932$^{***}$ | 0.00306 | 2.79$^{*}$ |
| | (0.00546) | (0.00718) | | (0.00340) | (0.00460) | |
| Age^2 | -0.000183$^{**}$ | -0.000100 | 0.74 | -0.0000963$^{**}$ | -0.0000362 | 1.82 |
| | (0.0000751) | (0.0000701) | | (0.0000468) | (0.0000450) | |
| Gender | 0.0995$^{***}$ | -0.0219 | 7.60$^{***}$ | 0.0513$^{***}$ | -0.00764 | 12.34$^{***}$ |
| | (0.0171) | (0.0379) | | (0.0104) | (0.0240) | |
| Household size | 0.00225 | 0.0226 | 0.67 | 0.00183 | 0.00896 | 0.62 |
| | (0.00803) | (0.0215) | | (0.00499) | (0.0134) | |
| Household size^2 | -0.000927$^{**}$ | 0.000571 | 0.89 | -0.000534$^{*}$ | 0.000123 | 1.40 |
| | (0.000449) | (0.00130) | | (0.000284) | (0.000798) | |
| Observations | 19490 | 3618 | | 19490 | 3618 | |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$
Data sources: Kornher and Baumüller (2024).

## 4.3 Temporal variations in food security status

The most important aspect of food security monitoring is to detect abrupt worsening of the food security status. Therefore, we lastly, perform a comparison between the SMS and HFPS surveys over the temporal variation of food security status. For this purpose, we use the four overlapping waves in June 2020 (base category), August/September 2020, December 2020, and April 2021 and compare the

[5] We interpret the coefficient estimate here and not the level of significance.

average differences across survey rounds controlling for socio-economic and spatial variables. The results shown in Table 5 indicate that the SMS and HFPS surveys do not exhibit statistically significant differences for the dependent variable Food Situation and only statistically significant differences in December 2020 for the dependent variable DDS. For Food Situation, data from both surveys show the highest level of food insecurity for June 2020, just after the first national lockdown in Uganda, and the lowest level of food insecurity for April 2021. Moreover, for both datasets, the variation between August/September 2020, December 2020, and April 2021 is relatively small. By contrast, DDS is found to be highest in June 2020 in both datasets. On the other hand, the lowest DDS is reported for December 2020 by the HFPS and in August/September by the SMS survey.

Table 5: Difference in temporal variation of Food Situation and Dietary Diversity Score between SMS and HFPS

| | OLS | | | Poisson | | |
|---|---|---|---|---|---|---|
| | (1) SMS | (2) HFPS | Chi2(1) | (3) SMS | (4) HFPS | Chi2(1) |
| **Panel A: Food Situation** | | | | | | |
| Aug/Sep 2020 (=1) | $-0.107^{***}$ | $-0.158^{***}$ | 0.98 | -0.0429 | $-0.0627^{*}$ | 0.93 |
| | (0.0349) | (0.0367) | | (0.0311) | (0.0356) | |
| December 2020 (=1) | $-0.0867^{**}$ | $-0.136^{***}$ | 0.84 | -0.0347 | -0.0540 | 0.80 |
| | (0.0401) | (0.0368) | | (0.0357) | (0.0356) | |
| April 2021 (=1) | $-0.112^{***}$ | $-0.175^{***}$ | 1.27 | -0.0453 | $-0.0698^{*}$ | 1.22 |
| | (0.0402) | (0.0366) | | (0.0360) | (0.0356) | |
| Socio-economic variables | Yes | Yes | | Yes | Yes | |
| Region FE | Yes | Yes | | Yes | Yes | |
| Observations | 3100 | 2503 | | 3100 | 2503 | |
| **Panel B: Dietary Diversity** | | | | | | |
| Aug/Sep 2020 (=1) | $-0.133^{**}$ | $-0.131^{**}$ | 0.00 | $-0.0687^{*}$ | -0.0429 | 0.52 |
| | (0.0572) | (0.0588) | | (0.0352) | (0.0357) | |
| December 2020 (=1) | -0.0258 | $-0.325^{***}$ | $11.11^{***}$ | -0.0132 | $-0.110^{***}$ | $6.02^{**}$ |
| | (0.0656) | (0.0579) | | (0.0400) | (0.0357) | |
| April 2021 (=1) | $-0.112^{*}$ | $-0.159^{***}$ | 0.28 | -0.0576 | -0.0524 | 0.02 |
| | (0.0658) | (0.0582) | | (0.0406) | (0.0354) | |
| Socio-economic variables | Yes | Yes | | Yes | Yes | |
| Region FE | Yes | Yes | | Yes | Yes | |
| Observations | 4120 | 2359 | | 4120 | 2359 | |

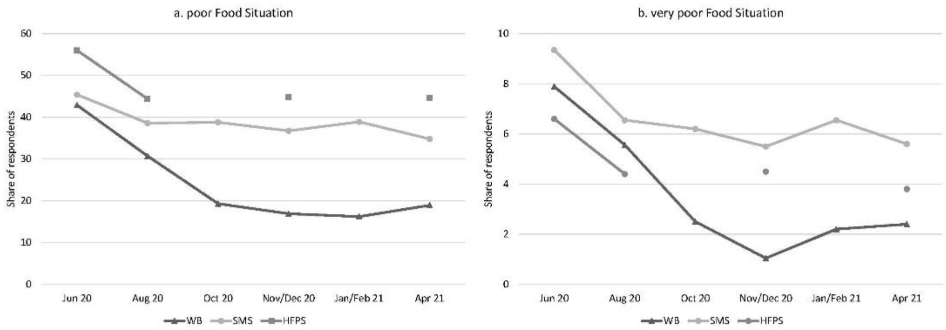
Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Data sources: Kornher and Baumüller (2024).

We also compare the food security status of our preferred indicator Food Situation with the food security data reported by the UBOS' HFTS. Figure 1 shows the prevalence of moderate and severe food insecurity over the period from June 2020 to April 2021 next to the prevalence of a poor (very poor) Food Situation reported by respondents of the SMS survey. In both cases, the trends are similar with the highest level of food insecurity reported in June 2020 and a declining trend thereafter. Notably, the HFTS reports a much faster recovery of Ugandan households after the first national lockdown in Uganda than what the SMS data suggests. Nevertheless, the HFTS confirms the trend of responses to the Food Situation and questions the validity of the DDS responses, which suggested an increasing trend in food insecurity after April 2020.

Figure 1: Percentage of respondents with poor (left panel) and very poor (right panel) Food Situation (moderate and severe FIES)




Data sources: UBOS (2021a); Kornher and Baumüller (2024)

## 4.4 Measurement error in the SMS survey

We cannot be conclusive about the validity based on the above comparison due to the fact that we have two samples. Therefore, Mock et al. (2015) propose to test validity through the survey's response accuracy. For instance, several variables, such as age, gender, and ethnicity, are not supposed to change between different survey waves. On the other hand, response accuracy is not sufficient to receive a reliable response. Reliability refers to the consistency of the responses across different questions.

The results show that the accuracy of the response is above 90% for all variables examined. The highest share of inaccurate responses was found for responses related to urban-rural location with 8.6%, followed by age (5.6%), region (5.3% and gender (2.9%). This level of accuracy is probably a bit lower than in usual face-to-face surveys with the possibility of probing if the reply seems incorrect. However, it is important to note that more than one person may use one mobile phone and the selected mobile phone number. In this case, the responses naturally would differ between the different mobile phone users.

The reliability of responses is tested by comparing the replies of the respondents to three food security monitoring questions, namely the Food Security Situation, the availability of food in the market (Food Market), and the change in the household's level of food consumption (Food Consumption). There may be reasons that the Food Situation is still poor or very poor despite positive changes in the level of food consumption or the availability in the market, however, this is unlikely. We report the percentages in Table 6. As shown in column 3, only about 1% of the respondents state that their Food Situation is poor, but they give positive responses on both the food availability in the market and the change in the household's level of food consumption. Individually, for Food Market and Food

Consumption, the share of these possibly inconsistent replies is higher, but not concerning given that the food availability can well improve if respondents consider themselves as having a poor or very poor Food Situation.

Table 6: Percentage of implausible responses on the Food Situation in the SMS survey

| Variable | % of respondents who stated "more food is available" | % of respondents who stated "better access to food" | % of respondents who stated both column (1) and (2) |
|---|---|---|---|
| FoodSituation Poor=1 | 10% | 4% | 1% |
| FoodSituation very Poor=1 | 7% | 3% | 1% |

Data source: Kornher and Baumüller (2024)

## 4.5 Scenarios for changes in sample composition

To assess whether the composition of the sample would affect the validity of the results, we applied a number of scenarios to artificially bias the sample, either by emulating a specific sample distribution or by comparing responses of sub-samples to assess how the results would have changed had we limited ourselves to specific sub-groups (e.g. only urban respondents):

**Scenario 1: Emulate a nationally representative sample (by gender, location and age)**

We consult the Uganda National Household Survey (UNHS) 2019/2020 to extract representative values (UBOS, 2021b). The UNHS is representative of the country as a whole, rural vs. urban areas, Uganda's four regions and 15 sub-regions. We removed the districts Kampala and Wakiso, as we did for the SMS survey, and calculate the survey means of the sample. Accordingly, 21% of the households live in urban areas (25% in the SMS sample), the average household size is 4.95 (6 in the SMS sample), and the average age of household is 45 (41 in the SMS sample). The regional distribution is as follows: 15% of the households live in the Central Region (19% in the SMS sample), 22% live in Northern Region (26% in the SMS sample), 28% live in the Western Region (26% in the SMS sample) and 30% live in the Eastern Region (32% in the SMS sample). This indicates that the SMS survey, with the exemption household size, broadly represents the overall Uganda population. Differences can be observed with regard to the distribution of gender among the respondents. Since the UNHS primarily targeted household heads, 68% of the respondents are male (50% of the respondents in the SMS sample). In the comparison, we replicate the survey characteristics of the UNHS in terms of location (rural vs. urban), gender (of the respondent) and age group composition[6].

**Scenario 2: Emulate the unfiltered sample**

We limit the sample to 500 early responders, representing respondents that are more likely to participate in the survey if no conditions on the characteristics are imposed. The comparison with the SMS survey respondents shows that the early respondents are comparable to the full sample regarding gender and age. There are minor differences in the location and the proportion of urban respondents among the early respondents is substantially higher.

**Scenario 3: Emulate an unfiltered sample of a previous GeoPoll survey (by gender and age)**

We weight the full sample using the gender and age weights of the survey by Lau et al. (2018) who did not apply filtering conditions in their GeoPoll-run survey (see Table 7).

[6] Age groups are the following: (1) 15-24, (2) 25-34, (3) 35+. We use the Stata command sreweight to compute the new survey weights.

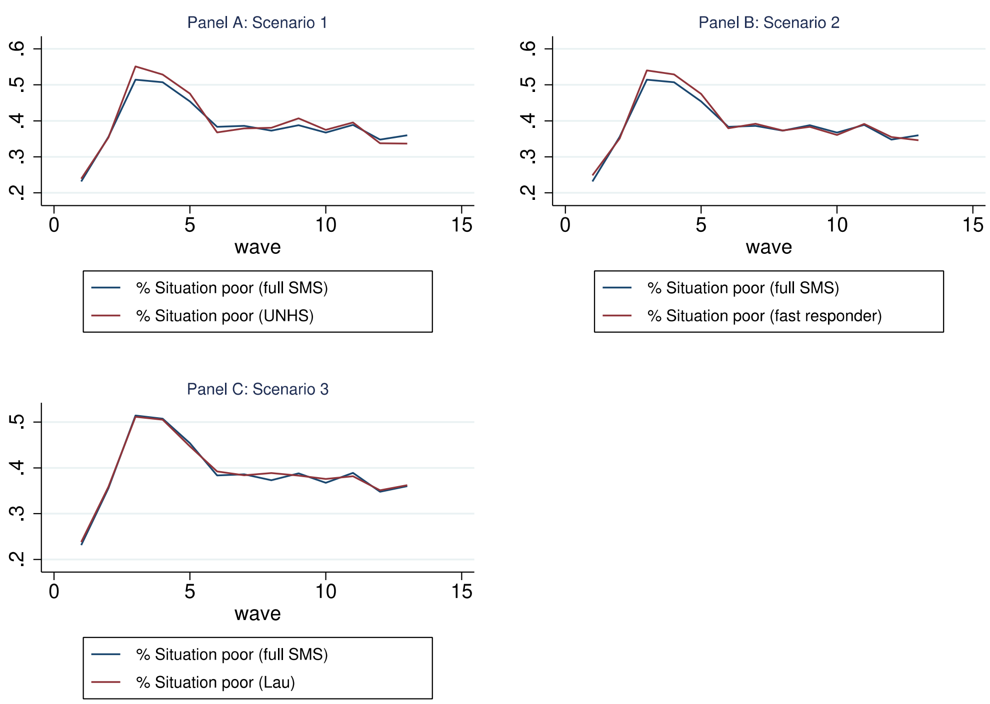
Table 7: Age and gender distribution in Lau et al. (2018) and SMS survey

| | | Lau et al. (2018) | SMS survey |
|---|---|---|---|
| Male | 18-24 | 40.6% | 35.4% |
| | 25-34 | 26.7% | 51.9% |
| | >34 | 7.7% | 12.8% |
| Female | 18-24 | 15.3% | 27.6% |
| | 25-34 | 7.7% | 55.6% |
| | >34 | 2.1% | 16.8% |

Data sources: Lau et al. (2018); Kornher and Baumüller (2024)

The results for Scenarios 1-3 are shown in Figure 2 which presents the prevalence of households that report a poor Food Situation across all waves from February 2020 until April 2021. The percentage shown is the conditional prevalence accounting for all other socio-economic and spatial covariates obtained from different OLS regressions, which are omitted for the sake of space. In the first panel, we present the results of the unweighted full SMS data compared with the full SMS data with the UNHS-related survey weights (Scenario 1). The second panel presents the results of the unweighted full SMS data in comparison to the 500 early respondents (Scenarios 2) and a full SMS sample weighted using the gender and age weights of the survey by Lau et al. (2018) (Scenario 3). The differences in the prevalence of a poor Food Situation appear to be very marginal. The same is true for prevalence of a very poor Food Situation reported in Figure A2 in the appendix. The results indicate that weighting has barely an effect on the coefficient estimates for the individual survey waves.

Figure 2: Conditional prevalence of Food Situation poor across Scenarios 1-3

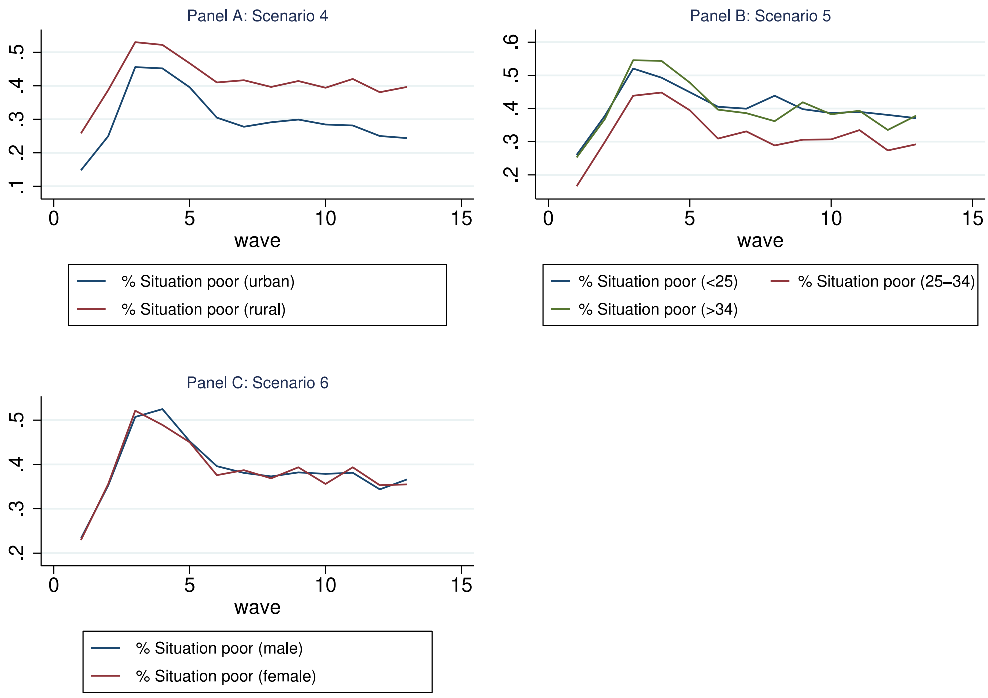



Data sources: UBOS (2021b); Lau et al. (2018); Kornher and Baumüller (2024)

**Scenarios 4-6: Comparison of responses from different sub-groups within the SMS survey (by location, age, gender)**

In addition, we compare responses by location (urban/rural, Scenario 4), age groups (<25, 25-34, >34; Scenario 5) and gender (male/female, Scenario 6) Panel A of Figure 3 shows the results from the unweighted sample of urban and rural respondents compared with the full sample (Scenario 4) while Panel B shows the results from the regressions for different age groups (Scenario 5). These two panels indicate mainly differences in the level but not so much in the trend of food insecurity related to age and location. The differences between males and females (Scenario 6) are shown in Panel C of Figure 3, but they appear to be minimal for both trend and prevalence.

Figure 3: Conditional prevalence of Food Situation poor across Scenarios 4-6




Data source: Kornher and Baumüller (2024)

**Scenario 7: Comparison of responses from repeated respondents and the full sample**

Next, in Table 8, we show the results of the regressions of the full sample (columns (1) and (3)) and a reduced sample using only repeated respondents using panel data estimator that controls household characteristics and location. We do not find significant differences in the coefficient estimates between the full and the restricted sample consisting of repeated respondents only.

To test for the possible occurrence of panel conditioning, we also compare responses from repeated respondents with those of one-time respondents (Figure A3 in the appendix). Again, we do not find notable differences. However, we are not able to draw strong conclusions since the number of repeated respondents, in particular across several survey rounds, was relatively small.

Table 8: Temporal variation in Food Situation comparing the full sample with repeated respondents

| | Food Situation | | Food Situation very poor=1 | |
|---|---|---|---|---|
| | OLS (full sample) | FE (repeat respondents) | Logit (full sample) | FE-Logit (repeat respondents) |
| March 2020 (=1) | 0.183*** | 0.144*** | 0.394** | 0.411 |
| | (0.0216) | (0.0279) | (0.159) | (0.295) |
| April 2020 (=1) | 0.397*** | 0.339*** | 1.034*** | 1.159*** |
| | (0.0216) | (0.0277) | (0.144) | (0.275) |
| May 2020 (=1) | 0.384*** | 0.337*** | 1.012*** | 1.211*** |
| | (0.0216) | (0.0277) | (0.144) | (0.289) |
| June 2020 (=1) | 0.317*** | 0.238*** | 1.023*** | 1.142*** |
| | (0.0216) | (0.0280) | (0.144) | (0.283) |
| July 2020 (=1) | 0.215*** | 0.197*** | 0.720*** | 0.674** |
| | (0.0216) | (0.0275) | (0.150) | (0.293) |
| August 2020 (=1) | 0.207*** | 0.150*** | 0.647*** | 0.908*** |
| | (0.0216) | (0.0278) | (0.152) | (0.295) |
| September 2020 (=1) | 0.200*** | 0.115*** | 0.420*** | 0.430 |
| | (0.0216) | (0.0273) | (0.158) | (0.291) |
| October 2020 (=1) | 0.215*** | 0.148*** | 0.580*** | 0.425 |
| | (0.0216) | (0.0277) | (0.153) | (0.291) |
| November 2020 (=1) | 0.188*** | 0.109*** | 0.463*** | 0.262 |
| | (0.0216) | (0.0278) | (0.157) | (0.301) |
| December 2020 (=1) | 0.219*** | 0.122*** | 0.638*** | 0.647** |
| | (0.0216) | (0.0284) | (0.152) | (0.296) |
| January 2021 (=1) | 0.144*** | 0.0898*** | 0.453*** | 0.450 |
| | (0.0216) | (0.0285) | (0.156) | (0.295) |
| April 2021 (=1) | 0.178*** | 0.104*** | 0.505*** | 0.464 |
| | (0.0216) | (0.0287) | (0.156) | (0.312) |
| Socio-economic variables | Yes | Yes | Yes | Yes |
| Region FE | Yes | n.a. | Yes | n.a. |
| Urban (=1) | Yes | n.a. | Yes | n.a. |
| Observations | 26000 | 14180 | 26000 | 1842 |

Standard errors in parentheses

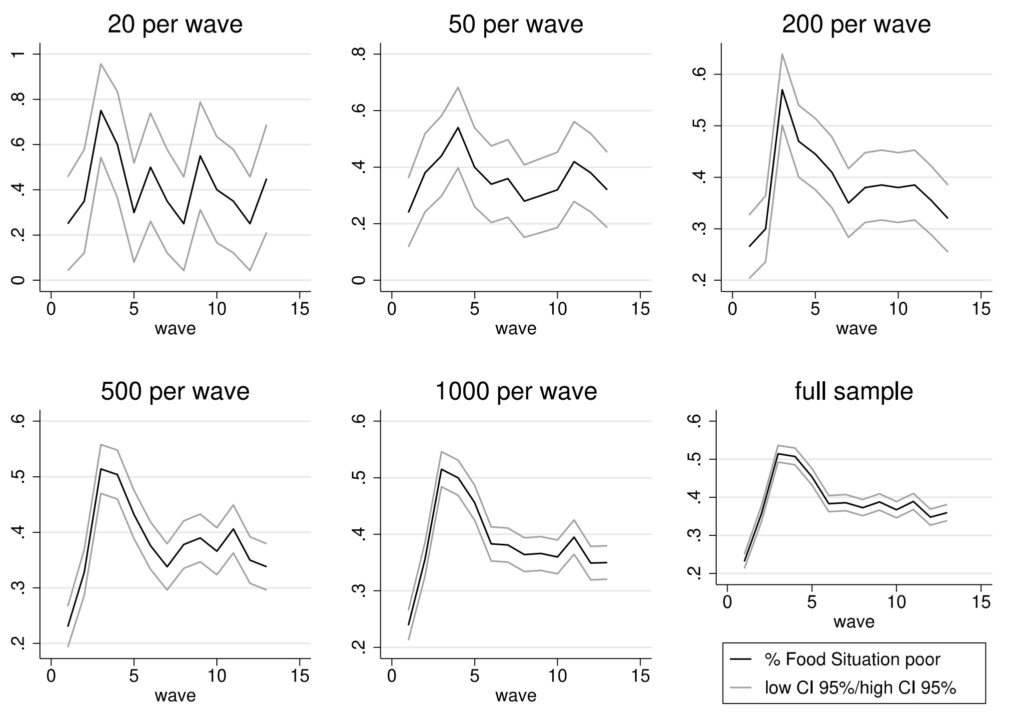
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data source: Kornher and Baumüller (2024).

**Scenario 8: Comparison of responses for different sample sizes**

Finally, we examine the relevance of the sample size by drawing random samples from the full SMS sample of 2000 respondents per wave. We randomly draw 20, 50, 200, 500 and 1000 households per wave. The prevalence of poor Food Situation per wave and the respective confidence interval are illustrated in Figure 4. Below 200 respondents per wave, the trend appears to be random as compared to the “true” trend in the full sample. While the trend for 500 respondents per wave looks similar to the full sample, a minimum of 1000 respondents seems necessary to replicate the trend of the full sample.

Figure 4: Prevalence of Food Situation poor and 95% confidence interval with different sample sizes




Data source: Kornher and Baumüller (2024)

# 5 Discussion

This study set out to assess the suitability of crowdsourcing information from the general public using SMS-based surveys to monitor the food security situation in Uganda. To this end, we examine to what extent data collected on a monthly basis over the course of one year reflects changes in the food security situation across the country. We further investigate how the representativeness and size of the sample may influence the results.

While most of the literature on SMS-based data collection commonly focuses on the sample characteristics and response rates, we assessed the validity of the results by comparing our data with data collected thorough two other surveys. To this end, we used different food security indicators (i.e. dietary diversity, availability of food in the market, food consumption and food situation) to determine the most reliable measure with regard to actual values and changes over time. Among the four possible indicators of food security status, the general food situation in the household appears to provide the most reliable measure. Questions related to the diversity of food items consumed by the respondents (DDS) showed the least promising results, possibly due to the complexity of the multiple-choice question. Moreover, the survey was targeted at the general population rather than food decision-makers in the households who may be more aware of this information.

Regarding the general food situation of the household, the SMS-collected data were more reliable in revealing changes over time than absolute estimates. A comparison with externally collected data from the Uganda Bureau of Statistics showed similar trends in the responses over time, but generally higher estimates of food insecurity in the SMS data. SMS surveys could therefore present a suitable data collection tool for food security early warning systems which focus on real-time monitoring of the food situation to detect changes that can then trigger more detailed assessments and targeted actions.

Much of the existing research on SMS-based data collection applies weighting to the collected data to reduce biases in the sample. In contrast, we systematically applied filtering to avoid selection biases commonly found in SMS-survey samples (i.e. prevalence of male, urban and higher-income respondents). We also provided incentives for participation (airtime) which the literature has shown to reduce selection biases, attrition and periodic non-response. The large sample size then allowed us to create scenarios that emulate certain sample biases found in the literature to assess how they may influence the validity of the results.

Applying weights to the sample to emulate either a nationally representative survey or biases found in the literature did not substantially change the results with regard to the food situation reported by the respondents over time. Comparable results were also obtained through from both repeated and single respondents. It is also noteworthy that responses provided by men and women was on average almost identical in levels and for the trend. While responses between rural and urban respondents and between different age groups followed a similar trend, the food situation among rural respondents and older youth (25-34) were generally worse.

These findings suggest that the composition of the sample may be less important for early warning systems that focus on changing trends rather than absolute values. Panel data is also not required. However, a minimum sample size is needed to obtain reliable results (at least 500 respondents in the case of Uganda). In surveys where information on the actual food security situation is required, the sampling strategy will need to ensure that a sufficiently large number of respondents from rural areas and different age groups are included.

This research is subject to a number of limitations that point to areas for future research. SMS surveys limit the number and length of questions that can be answered which did not allow us to collect additional socioeconomic data that could help to explain the variations. Further research could accompany SMS surveys with detailed baseline surveys of potential respondents to gather the relevant data. Due to the filtering approach, completing the quotas took a long time in some regions. As a result, the gap between the monthly survey rounds was only small in some cases. In future research, filtering criteria could be relaxed to increase the speed and reduce the cost of data collection. Finally, additional language should be offered in future surveys to minimize risks of bias due to differing language skills.

# Acknowledgments

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# Appendix

## A1. Questionnaire and submission form

| Q # | Q Name | English | Q Type | Skip Pattern |
|---|---|---|---|---|
| **NA** | Opt In Credit | You have been selected to take a GeoPoll survey. Reply 1 to answer questions and earn #TOPUP#! No cost to reply. For help reply HELP. | Single Choice | 1 = Language<br>HELP = HELP |
| **NA** | HELP | GeoPoll is a global network of people shaping their community by answering short surveys. Free to respond. Reply 1 to answer questions. Reply STOP to Opt-Out. | Single Choice | 1 = Language<br>STOP = Refusal |
| **NA** | Language | Which language do you wish to proceed with?<br>1)English<br>2)Luganda | Single Choice | 1 = BirthYear[English]<br>2 = BirthYear[Luganda] |
| **NA** | Refusal | Thank you for your time, you will be removed from today's survey. For more information or to register for future surveys please visit http://gpl.cc/co | NA | End poll declined |
| **NA** | Ineligible | You are ineligible for this survey. Thank you for your time and please look out for future GeoPoll surveys! For more information visit http://gpl.cc/co | NA | End poll ineligible |
| **1** | BirthYear | In what year were you born? Reply with a four-digit number like 1980. | Range | 1900-1918 = Ineligible<br>1919-2004 = Gender<br>2005-2019 = Ineligible |
| **2** | Gender | Are you male or female? Reply with 1 or 2.<br>1)Male<br>2)Female | Single Choice | 1-2 = Admin2-EN-Uganda |
| **3** | Admin2-EN-Uganda | What District do you currently live in? Reply with the name of your District, like: Kayunga. | Single Choice | Central Kampala, Central Wakiso = Ineligible<br>Any Other = Urban/Rural |
| **4** | Urban/Rural | Do you live in a city/town or village/countryside? Reply with 1 or 2. | Single Choice | 1 = EarnUrban<br>2 = EarnRural |

| | | | | |
|---|---|---|---|---|
| | | 1)City/town<br>2)Village/countryside | | |
| **5** | EarnUrban | How much does your household earn per month in UGX? Reply with 1 or 2 or 3<br>1)0-753000<br>2)753001-1130000<br>3)More than 1130000 | Single Choice | 1-2 = HouseHold<br>3 = Ineligible |
| **6** | EarnRural | How much does your household earn per month in UGX?<br>1)0-753000<br>2)753001-1130000<br>3)More than 1130000 | Single Choice | 1 = HouseHold<br>2-3 = Ineligible |
| **7** | HouseHold | How many people live in your household? Reply with a numerical value. | Range | 1-100 = Farming |
| **8** | Farming | Does your household engage in any farming? Reply with 1 or 2.<br>1)Yes<br>2)No | Single Choice | 1 = Locusts<br>2 = Locusts2 |
| **9** | FoodSituation | What is the current food situation in your household? Reply with 1 or 2 or 3 or 4.<br>1)Very good<br>2)Good<br>3)Poor<br>4)Very poor | Single Choice | 1-4 = FoodItems1 |
| **10** | FoodItems1 | Did you eat something other than cereals (other than for example rice/cassava/potato/matoke/bread/maize) yesterday? Reply with 1 or 2.<br>1)Yes<br>2)No | Single Choice | 1 = FoodItems2<br>2 = FoodConsumption |
| **11** | FoodItems2 | Which of the following foods did you eat? Include all in one message (e.g.145)<br>1)Vegetables<br>2)Fruits<br>3)Groundnut/beans/peas/oil<br>4)Meat/fish/eggs<br>5)Milk products | Select All That Apply | 1-5 = FoodConsumption |

| | | | | |
|---|---|---|---|---|
| **12** | FoodConsumption | Has the food consumption of your household changed over the past 7 days?<br>1)Better access to food<br>2)Difficulties in obtaining food<br>3)No change | Single Choice | 1-3 = MarketFood |
| **13** | MarketFood | Has the amount of food available in the local market changed over the past 7 days?<br>1)No change<br>2)Less food is available<br>3)More food is available<br>4)Don't know | Single Choice | 1-4 = FoodPrice |
| **14** | FoodPrice | Has the price of food available in the local market changed over the past 7 days?<br>1)No change<br>2)Food is more expensive<br>3)Food is cheaper<br>4)Don't know | Single Choice | 1-4 = HaveProblems |
| **15** | HaveProblems | Did others in your community have problems obtaining food over the last 7 days? Reply with a number.<br>1)Yes<br>2)No<br>3)Don't know | Single Choice | 1-3 = Cope1 |
| **16** | Cope1 | How did you cope with difficulties in obtaining food? If more than 1 option, include all in one message (e.g. 146). Reply with 1 to see choice of answers. | Single Choice | 1 = Cope2 |
| **17** | Cope2 | Pick from:<br>1)Reduced meals/portion size<br>2)Changed to cheaper food<br>3)Used savings to buy food<br>4)Friends/family assistance<br>5)Government/NGO assistance<br>6)Other | Select All That Apply | 1-6 = Close Out Credit |
| **NA** | Close Out Credit | Survey complete, you will receive #TOPUP# airtime credit within 2 days. For more info and to register friends/family visit http://gpl.cc/co | NA | NA |

## A2. Targets by geographical areas within the countries

Table A2.1: Definition of sub-regions and sample size.

| Name of the sub-region | Districts within sub-region | Estimated population in 2020 | Sample size |
|---|---|---|---|
| Central Region (without Kampala and Wakiso) | Region 1: Buikwe, Bukomansimbi, Butambala, Buvuma, Gomba, Kalangala, Kalungu, Kayunga, Kiboga, Kyankwanzi, Luweero, Lwengo, Lyantonde, Masaka, Mityana, Mpigi, Mubende, Mukono, Nakaseke, Nakasongola, Rakai, Ssembabule Districts | 6,024,729 | 388 |
| Eastern | Region 2: Bugiri, Bukedea, Busia, Butaleja, Buyende, Iganga, Jinja, Kaliro, Kamuli, Kibuku, Luuka, Mayuge, Namayingo, Namutumba, Pallisa, Tororo Districts | 5,440,620 | 348 |
| Northern-West | Region 3: Adjumani, Amuru, Arua, Gulu, Koboko, Maracha, Moyo, Nebbi, Nwoya, Yumbe, Zombo Districts | 3,885,399 | 248 |
| Karamoja/Mount Elgon | Region 4: Abim, Agago, Bududa, Amudat, Bulambuli, Bukwa, Kaabong, Kitgum, Kapchorwa, Kotido, Lamwo, Kween, Moroto, Manafwa, Nakapiripirit, Napak, Mbale, Pader, Sironko Districts | 3,417,214 | 220 |
| Northern-East | Region 5: Amuria, Budaka, Alebtong, Amolatar, Apac, Dokolo, Kaberamaido, Kole, Katakwi, Lira, Kumi, Soroti, Serere, Ngora, Otuke, Oyam Districts | 3,467,328 | 224 |
| Western | Region 6: Buliisa, Bundibugyo, Bushenyi, Hoima, Kabarole, Kamwenge, Kasese, Kibaale, Kiryandongo, Kyegegwa, Kyenjojo, Masindi, Ntoroko, Rubirizi Districts | 3,908,813 | 252 |
| Western-South | Region 7: Buhweju, Ibanda, Isingiro, Kabale, Kanungu, Kiruhura, Kisoro, Mbarara, Mitooma, Ntungamo, Rukungiri, Sheema Districts | 4,966,049 | 320 |

Note: The Geopoll panel in January 2020 had estimated numbers per sub-region of: (1) 28,000, (2) 16,000, (3) 12,800, (4) 11,200, (5) 9,600, (6) 12,800, (7) 16,000.

## A3. Supplementary tables and figures

Table A3.1: Mean difference t-test for Eastern/Northern Region

| | June 2020 | Aug/Sep 2020 | December 2020 | April 2021 |
|---|---|---|---|---|
| DDS | 1.217*** | 0.911*** | 0.745*** | 0.943*** |
| | (10.41) | (12.10) | (8.43) | (9.60) |
| Food Consumption | 0.0266 | -0.440*** | -0.290*** | -0.270*** |
| | (0.39) | (-7.60) | (-4.32) | (-3.54) |
| Market Food | -0.438*** | -0.579*** | -0.362*** | -0.471*** |
| | (-5.99) | (-9.18) | (-4.49) | (-5.84) |
| Food Price | -0.205*** | -0.628*** | -0.460*** | -0.535*** |
| | (-2.70) | (-9.99) | (-5.74) | (-7.02) |
| Food Situation | 0.180*** | -0.0338 | 0.0142 | 0.0916 |
| | (2.77) | (-0.62) | (0.23) | (1.39) |
| Food Situation is poor (=1) | 0.166*** | -0.0514 | 0.0505 | 0.0544 |
| | (3.55) | (-1.34) | (1.08) | (1.13) |
| FoodSituatio is very poor (=1) | -0.0318 | -0.00872 | -0.0305 | 0.0164 |
| | (-1.15) | (-0.47) | (-1.43) | (0.75) |
| Observations | 476 | 674 | 495 | 481 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

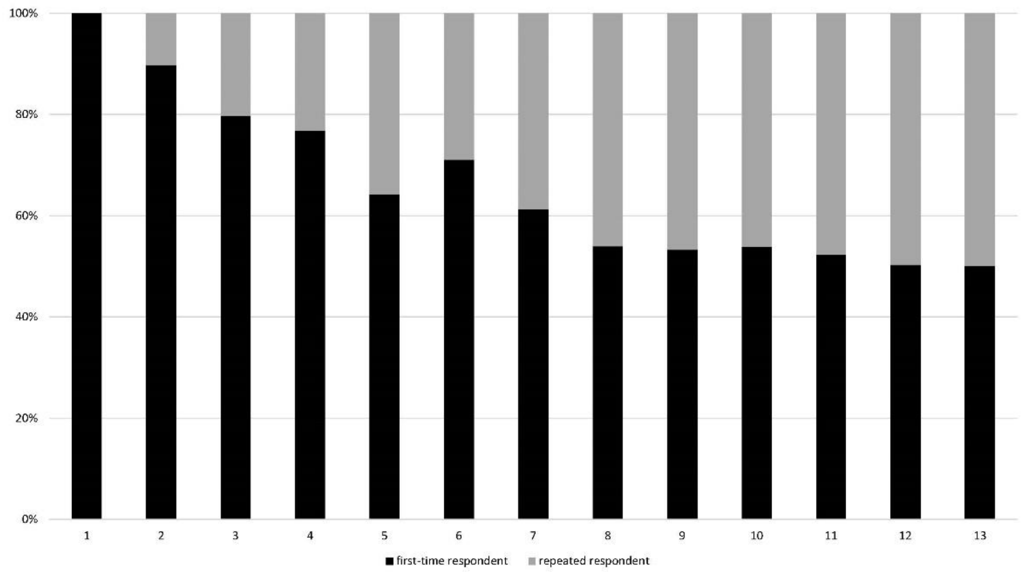
Source: Kornher and Baumüller (2024).

Table A3.2: Mean difference t-test for Western Region

| | June 2020 | Aug/Sep 2020 | December 2020 | April 2021 |
|---|---|---|---|---|
| DDS | 0.790*** | 1.417*** | 0.952*** | 1.260*** |
| | (6.33) | (13.29) | (8.24) | (11.14) |
| Food Consumption | 0.00339 | 0.193*** | -0.0148 | -0.174** |
| | (0.04) | (2.85) | (-0.19) | (-2.20) |
| Market Food | -0.286*** | 0.144* | -0.318*** | -0.214** |
| | (-3.16) | (1.83) | (-3.76) | (-2.51) |
| Food Price | -0.0251 | 0.351*** | -0.228** | -0.0998 |
| | (-0.26) | (4.67) | (-2.54) | (-1.18) |
| Food Situation | 0.0805 | 0.225*** | 0.101 | -0.0764 |
| | (1.02) | (3.68) | (1.42) | (-1.08) |
| Food Situation is poor (=1) | 0.0893* | 0.236*** | 0.0895* | 0.0271 |
| | (1.70) | (5.12) | (1.72) | (0.52) |
| FoodSituation is very poor (=1) | -0.0217 | -0.0420** | 0.0229 | -0.0808*** |
| | (-0.75) | (-2.08) | (0.98) | (-3.47) |
| Observations | 359 | 522 | 356 | 352 |

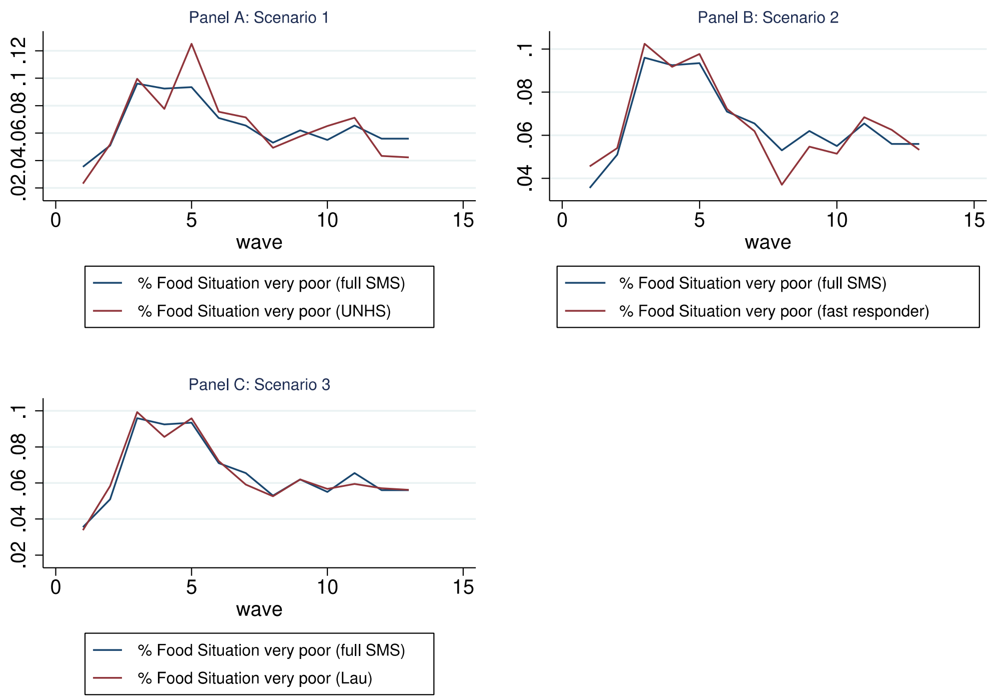
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Kornher and Baumüller (2024).

Figure A1: First-time and repeated participation across survey waves



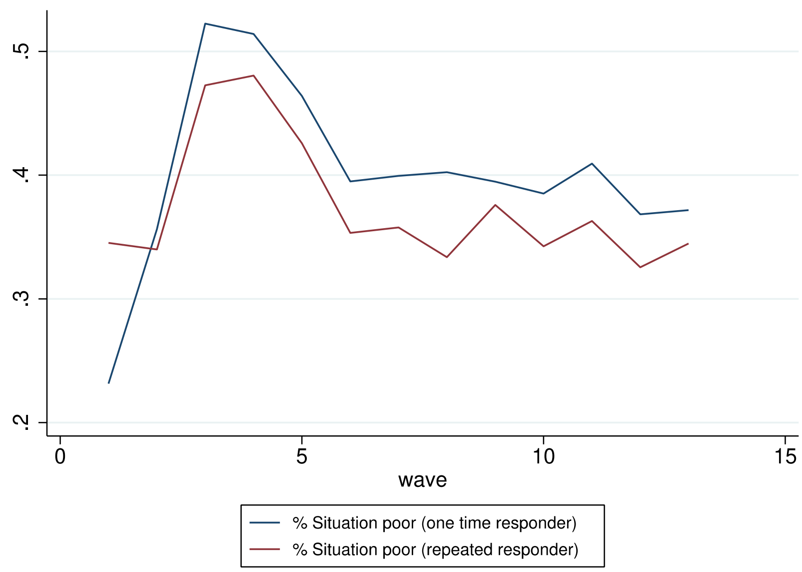

Source: Kornher and Baumüller (2024).

Figure A2: Food Situation of different sub-samples in Scenarios 1-3 over time




Source: Kornher and Baumüller (2024).

Figure A3: Food Situation of first-time and repeated respondents over time




Source: Kornher and Baumüller (2024).