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The impacts of exposure to COVID-19 on food security and diet diversity in Africa

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Abstract

We study the impact of exposure to COVID-19 on food security and diet diversity in four African countries (Uganda, Tanzania, Sierra Leone and Mozambique), using phone-based survey data collected throughout 2021. We find that in 2021, one in two households faced moderate-to-severe food insecurity and one in three households had borderline to poor diet diversity score. Food insecurity and poor diet diversity are particularly pronounced among certain groups of households, who characterize with large family sizes, low access to public services, own fewer assets, and mostly have a female, younger, and less educated person as household head. Both food insecurity and poor diet diversity are positively associated with exposure to COVID-19 – either through individual experience of having a virus or having people in their surroundings who had the virus. We show that tighter movement restrictions and a more drastic decline in household income in COVID-19-exposed areas were the main reasons for worsened food insecurity and poorer diet diversity. Vulnerable households rarely received financial support from governments, forcing many of them to use harmful food- related coping strategies and to borrow from other households.

JEL Codes: Q18, I18, O15

1 Introduction

Risks of poverty and food insecurity in less developed countries exacerbated with the onset of the COVID-19 pandemic. The fear of contracting the virus and the restrictions imposed by the governments to contain the spread of the virus had profound economic impacts, such as job and income losses and disruptions of food supply chains, which put additional stress on already fragile food security outcomes in low and middle-income countries (Bundervoet et al., 2022; Devereux et al., 2020; Laborde et al., 2021).

In this paper, we study the status and drivers of food insecurity and diet diversity in Africa during the COVID-19 pandemic. We use micro-level survey data on four African countries from the Life with Corona – Africa (LwC-A) research project. The survey collected continuous cross-sectional phone-based household survey data throughout 2021 in Uganda, Tanzania, Sierra Leone, and Mozambique, resulting in an overall sample of 24,000 responses. We spatially and temporally matched the survey data with external data on government-imposed restrictions, food prices, and agro-ecological variables. We use Food Insecurity Experience Scale (FIES) and Food Consumption Score (FCS) to respectively measure food insecurity and diet diversity.

Overall, we find that food insecurity is highly prevalent in the survey countries when measured by FIES. About half of households were moderately or severely food insecure on average, ranging from 28% of households in Tanzania to 78% in Sierra Leone. In general, food-insecure households are larger in size, have poorer access to services and lower asset endowments, and are more likely to be headed by female, younger, and less educated individuals. Poor diet diversity, measured with FCS, is prevalent among 14% of households on average. While 11-13% households in Uganda, Tanzania, and Sierra Leone are classified as having a poor diet diversity, the share is about 22% in Mozambique. Both food insecurity and poor diet diversity outcomes are strongly associated with households' degree of exposure to COVID-19, which we define as an individual experience of having a virus or having people in surroundings who had the virus. Key correlates of poor welfare outcomes are movement restrictions, declines in household income, and increases in food prices.

Our research contributes to understanding how the COVID-19 pandemic affects food insecurity in low and middle-income countries. A large body of evidence documents worsening food security globally due to the COVID-19 pandemic, particularly in low-income countries (Bundervoet et al., 2022; Devereux et al., 2020; Jr. Tabe-Ojong et al., 2023; Laborde et al., 2021). However, the evidence is mixed in some aspects, such as in terms of the resilience of food systems and agricultural systems to provide food supply, but also in terms of the resilience of households to shift diets to overcome food shortages and rising food prices (Mkupete et al., 2023). Differences in evidence are also defined by a variety of data sources and definitions of food insecurity, timing of data collection, and the respondents' sample heterogeneity. Our study contributes to the literature by using large-scale survey data that is collected continuously throughout 2021 in four countries, and by analyzing two indicators for measuring food insecurity and diet diversity. In our estimations, we control for confounding factors and apply an instrumental variables (IV) approach to address endogeneity concerns. Finally, we show how individual exposure to COVID-19, public health and social measures (PHSMs), income losses, and rising food prices are related to food insecurity.

This paper is structured as follows: Section 2 presents a summary of the literature on the link between the COVID-19 pandemic and food security, focusing on sub-Saharan African countries. Section 3 describes the data, measurement of the key variables and the econometric approach. Section 4 presents the main results and the underlying mechanisms. In Section 5, we assess the robustness of the main findings. We discuss the results in Section 6 before we conclude the paper.

2 Background to food insecurity and countries of study

2.1 Evidence on COVID-19 and food insecurity

The outlook of worsening global food insecurity was abundant as soon as the implications of the pandemic on physical restrictions became clear (Laborde et al., 2020). Over the subsequent months and years, a detrimental impact of the pandemic on food security has realized itself to a substantial degree. Indeed, a large number of studies have shown that since the start of the pandemic crisis, levels of food insecurity increased not only in low- and middle-income countries but also in developed countries (Bundervoet et al., 2022; Ismail et al., 2023; Laborde et al., 2021; Milovanska-Farrington, 2022; Swinnen and Vos, 2021). Vulnerable and poor households in low- and middle-income countries, who already were at substantial risk of food insecurity before the start of the pandemic, were hit hardest since the start of the crisis. Women, children, and migrants are particularly affected by the food insecurity implications of the pandemic (Akalu and Wang, 2023; Swinnen and McDermott, 2020).

COVID-19 undermines food security and dietary diversity On the supply-side by disrupting food systems and trade, and on the demand-side, through the impacts of lockdowns on income and job losses, and increasing food prices (Devereux et al., 2020). The rise in food insecurity and poor diet diversity is consistently shown to be driven by a loss of income and jobs, which in turn is a consequence of the mobility restrictions imposed by governments (Balana et al., 2023; Egger et al., 2021; Josephson et al., 2021). Using household data from 31 low- and middle- income countries, Bundervoet et al. (2022) found that food insecurity is closely related to job and income losses at the peak of the first waves of the pandemic. They show that pandemic-induced job and income losses translated into heightened food insecurity at the household level with about 15% of the total sample experiencing a severe form of food insecurity. In country-specific studies in developing countries, a larger share of female, young, less educated, and urban workers are found to have stopped working, which led to a large real income shock and jeopardized household food security (Agamile, 2022; Arndt et al., 2020; Kugler et al., 2021; Mandal et al., 2021).

Reduced physical access to food due to closed roads and markets is another channel through which the pandemic affects food insecurity. The evidence seems to point to a much more strenuous situation for urban poor households who tend to be residing in informal densely populated areas and who obtain most of their daily food in small markets (Chirisa et al., 2022; Montoya et al., 2021). The closure of small markets is likely to worsen the availability of fresh food, turn the consumers to buy more expensive food from supermarkets, and eventually, worsen the quality of household nutrition (Devereux et al., 2020). In the city of Dhaka in Bangladesh, the pre-COVID-19 share of households who bought fish from wet markets dropped from 80% to 45% during the pandemic. Many households substituted fish and meat with poultry, eggs, and dried fish (Mandal et al., 2021). Such closures of markets also may affect the input markets, such as seeds and fertilizers, thus affecting the food value chain. The mobility restrictions also affect people's ability to help each other as this type of inter-household support is prevalent in times of shocks (Balana et al., 2023; Palma and Araos, 2021).

In the early phases of the pandemic, food prices remained relatively stable, and in some cases even dropped due by the decline in the demand from the hospitality industry and low oil prices that reduced transportation costs (Beckman et al., 2021). At this stage, agri-food trade demonstrated its resilience to the pandemic, though short-term trade disruptions were unavoidable, especially at the heights of policy stringency and mobility reductions (Engemann and Jafari, 2022). The adverse price effects on food security started to be noticeable in import-dependent and integrated markets around the end of 2020, owing to the effect of mobility restrictions on higher food prices (Dietrich et al., 2022). On the demand-side, evidence from country studies shows that pandemic-related government cash transfers in addition to stockpiling practices contributed to increases in staple food prices (Bairagi et al., 2022).

Policy responses to limit the social and economic impact of the COVID-19 pandemic included income

Table 1: Key demographic, economic, and Covid-19 related indicators

Country	Mozambique	Sierra Leone	Tanzania	Uganda
Population, mln	31.3	8	59.7	45.7
Rural population, % to total	63	57	65	75
Real GDP growth in 2017-19, %	3.1	4.2	6.9	6.7
Real GDP growth, %	-1.2	-2	4.8	-1.4
GDP per capita, USD	449	509	1076	822
Agriculture, % to GDP	26	59	27	24
Stringency index, average during 2020-21	52	39	18	62
Fiscal measures in response to COVID-19, in % to GDP since 2020	4.9	7.6	...	2.1

Sources: World Development Indicators, World Bank (2022); IMF (2022); Oxford University (2022). Note: the indicators are for the year 2020 unless indicated otherwise

support to households and tax reliefs on top of the existing public transfers which proved to remain extremely effective tool in easing food insecurity pressures for beneficiary households (Abay et al., 2023a; Ahmed et al., 2023). In addition, the governments in sub-Saharan African countries minimized restrictions related to agriculture and food systems (Devereux et al., 2020; Ismail et al., 2023), beyond a few cases of closure of enterprises in food production that saw the workers getting ill with COVID-19. As a result, the food value chains remained resilient to the shock associated with the pandemic (Engemann and Jafari, 2022; Hale et al., 2020; Hirvonen et al., 2021). However, with the persistent restrictions and the rising food prices, the adverse effects of the pandemic on food insecurity became more apparent. Worryingly, the risk to food security persisted longer due to a combined effect of economic slowdown and increase in poverty, limiting food supply and access beyond the COVID-19 pandemic period (Udmale et al., 2020), especially in the light of the war in Ukraine against Russia that limited the global supply of grains from both countries in the first year of the war (Abay et al., 2023b). This had major implications for the international community, as food insecurity remains a challenge globally, with negative consequences for welfare of households and individuals and inducing, among other, push factors for migration, displacement, and conflicts (Sadiddin et al., 2019; Smith and Floro, 2020; Smith and Wesselbaum, 2020).

2.2 Study countries

The four countries under analysis, Uganda, Tanzania, Sierra Leone, and Mozambique belong to low and lower-middle-income countries in Africa. Tanzania had the highest level of income with around 1076 USD of per capita GDP in 2020, and Mozambique's per capita GDP stood at 449 US dollars (Table 1). Both countries are also the largest and smallest in terms of population size. Rural population is predominant in all four countries with Uganda having the highest level with three-quarters of rural population. However, the contribution of agriculture to GDP mirrors the rural population ratio only in Sierra Leone, while in the other three countries agriculture contributes about a quarter to GDP. The pre-pandemic economic growth was solid in these countries, however, all of them, besides Tanzania, reported negative real GDP growth in 2020.

Like most countries in the world, all four countries imposed certain levels of economic and mobility restrictions since the onset of the pandemic. The pandemic-related restrictions included limitations to domestic and international travel; bans on large gatherings; and closure of schools, shops, and restaurants. The restrictions were put in place first around March-May 2020 and were eased or imposed back depending on the dynamics of COVID-19 cases. Tanzania had the shortest time in such restrictions, opening up the country within four months; other countries kept restrictions in a varying degree throughout 2021.

The Stringency Index by Oxford University (Hale et al., 2020) usefully summarizes the levels and duration of these restrictions. Besides Tanzania, the other three countries imposed a relatively high level of restrictions, ranging from 39 to 62 in average (out of the maximum possible score of 100). The governments in these countries have also intervened to provide income support to the population and businesses which is estimated by the IMF as high as 7.6% of GDP in Sierra Leone and 2.1% of GDP in Uganda (IMF, 2021)[1].

Even before the COVID-19 pandemic, these four countries had significant food insecurity. By FAO's estimates, the level of undernourishment in these countries ranged from 26% of the population in Sierra Leone to 41% in Uganda in 2017 which was higher than the average of 20% in Africa (WHO, 2020). The food security in these countries has been negatively affected by staple food price shocks, weather shocks, and regional conflicts (FAO, 2019; Gebre et al., 2021; Rudolf, 2019). The Covid-19 pandemic has exacerbated existing factors in these countries and added more pressure on food security, especially when the rise in global food prices since end-2020 became evident.

3 Data and Methods

3.1 Data

We use survey data collected as part of the "Life with Corona - Africa" (LwC-A) project[2]. The LwC-A survey is a large phone survey conducted in four African countries of Uganda, Tanzania, Sierra Leone, and Mozambique between January and December 2021. Using repeated cross-sections, the survey collected data from 500 new random respondents per month per country. In total, the dataset contains information from about 24,000 households collected continuously throughout 2021 across these four countries.

In all four countries, the respondents for the LwC-A survey were chosen randomly from large databases which were generated in the past decade through Random Digit Dialing (RDD) and/or face-to-face interviews. In Mozambique, the data were collected by Intercampus, a survey firm, where they drew the sample from a large database of about 600,000 mobile phone contacts. In Uganda, Tanzania, and Sierra Leone, data were collected by BRAC International. BRAC relied on the Independent Evaluation and Research Cell (IERC) database, which consists of more than 10,000 beneficiaries per country selected from their current and previous programs. While these databases are large and cover respondents from across all regions, they are not nationally representative. Therefore, in each round, we followed a stratified random sampling method to generate a sample the distribution of which reflects the national population by gender, age group, and location. However, we could not reach this goal fully due to two limitations. First, mobile phone subscriptions are not universal in any of these countries. There are about 80 subscriptions per 100 people in Sierra Leone and Tanzania. The subscription rate is much lower in Uganda and Mozambique (61 and 49 subscriptions per 100 people, respectively). Second, given the large sample size of the study, the databases did not contain enough respondents to maintain the sampling balance at the national level (e.g., many of the BRAC projects focus on women). Nevertheless, although the results cannot be generalized to the country level, the large sample size and uniformity of the survey time and structure across the four countries provide novel insights into the understanding of the pattern in and the response to COVID-19 exposure of food insecurity and dietary diversity across African countries and beyond.

The LwC-A survey questionnaire includes information on basic socio-demographic characteristics, housing, and basic assets ownership, as well as on the economic well-being of the households such as food insecurity and food consumption. Moreover, it includes questions on personal coronavirus exposure, testing and vaccination experiences, social life, mental health and well-being, and assistance received since the start of the pandemic. The modules were short to suit phone interviews and most of the questions and the answer choices were simplified (e.g., yes or no).

[1]Data on Tanzania were not available from IMF.
[2]For details of the LwC-A project, see https://lifewithcorona.org/africa/

3.2 Main variables

We use food insecurity and poor diet diversity score as the main outcome variables. We measure food insecurity by using the Food Insecurity Experience Scale (FIES), which is an experience-based measure of food insecurity developed by the United Nations Food and Agriculture Organization (FAO). FIES provides an internationally comparable estimate of the prevalence and severity of food insecurity at the individual and household levels. FIES has been validated for cross-cultural use and is one of the main indicators used for monitoring Sustainable Development Goal (SDG) indicator 2.1 'Prevalence of moderate or severe food insecurity in the population' (Ballard et al., 2013; Cafiero et al., 2018).

The FIES module includes eight questions related to households' access to food (see Table A1 in the appendix). These questions are designed to capture a range of severity of food insecurity (Nord, 2014), and inquire a respondent about the anxiety not to find enough food, compromises on food variety, quantity, and quality, insufficient food intake, and experience of hunger due to lack of money or other resources (FAO, 2016). Table A1 in the appendix shows that 18% of respondents indicated that over the four weeks prior to the interview, there was at least one instance when members of their households went a whole day without eating because of lack of money or other resources. More than half of the respondents also reported that members of their household had to reduce the frequency, diversity, quality or quantity of the food items due to lack of resources.

Commonly, an aggregated food insecurity score is used in empirical analysis, rather than the individual items in Table A1. The first step in the construction of such a score involves statistical validation and standardization of the data using the Rasch model. The Rasch model assumes that the FIES questions and respondents are on the same continuum of food insecurity. We conducted statistical validation of the data for each country separately based on the suggested values of infit and outfit statistics[3], and overall reliability score (Nord, 2014). Following FAO (2016), we use raw scores to finally classify households into one of the three categories of food (in)security experience: food secure, moderately food insecure, and severely food insecure[4].

Figure 1 presents the share of households in these food insecurity categories in the four countries. Overall, about half of households were moderately or severely food insecure. Figure 1 also indicates significant variation in food security status across the four countries. The share of (moderately and severely) food insecure households is relatively lower in Uganda (35%) and Tanzania (24%). In contrast, Sierra Leone has the worst status with more than 75% of food-insecure households. In Mozambique the share of food insecure households is 56%.

The second outcome variable is the diet diversity score, which we measure using Food Consumption Score (FCS). Compared to the traditional household diet diversity indicator, FCS accounts not only for the diversity in consumption but also considers the frequency and relative caloric contribution of different food groups. Validation studies conducted in different settings indicate that FCS is strongly associated with caloric intake (Leroy et al., 2015; Wiesmann et al., 2009). The data for FCS is collected based on the survey questions on the type and frequency of food intake over seven days before the survey. The FCS is calculated as a weighted sum of the number of days per week different food groups are consumed with weights representing the relative caloric contribution of the consumed food groups (Wiesmann et al., 2009)[5]. For each household, this leads to a score ranging from 0 to 112. Based on this score, households are then grouped into three categories: poor consumption (FCS:0-28), borderline consumption (FCS:28-42), and acceptable consumption (FCS: 42-112).

Figure 2 presents the share of households with borderline and poor diet intake in the four surveyed

[3]Infit statistics assesses the assumption of equal relation to food security, while outfit statistics is used to flag outliers and unexpected response patterns. Appendix A1 presents technical details of these steps.

[4]Some studies identify four food insecurity categories by splitting food secure households into food secure (zero FIES score) and mildly food insecure households.

[5]The specific weight for the food group are: starch staples (2), pulses (3), vegetables (1), fruits (1), fats (0.5), sugars (0.5), meat/fish/eggs (4), milk/dairy (4), condiments (0).

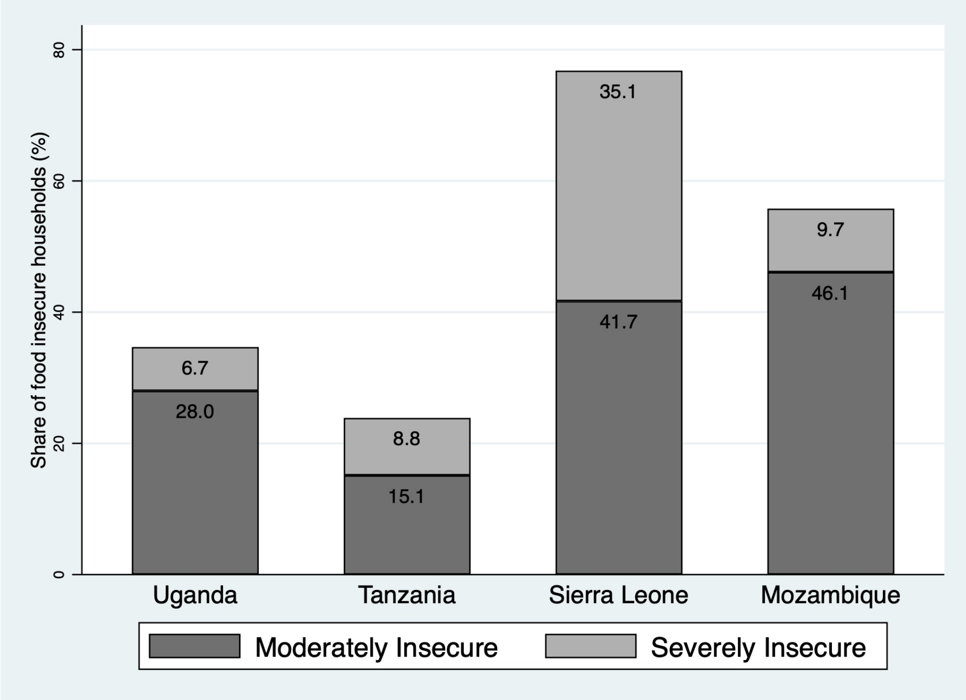


Figure 1: Food insecurity status by country

Note: Food insecurity indicators (food secure, moderately & severely food insecure) are generated from FIES.

countries. It shows that 22% and 14% of households in our sample fall within borderline and poor FCS categories. There are, however, considerable spatial differences across and within countries. Across the four countries, the percentage of households with poor diet diversity is the highest in Mozambique (21%) with the other three countries having comparable shares (11-13%). Despite the food insecurity status, the diet quality in Sierra Leone is relatively good due to the higher consumption of meat/fish/egg/milk in the country, the food categories with higher weight in the FCS calculation (see Table A2 in the appendix).

Our main explanatory variable is the COVID-19 exposure indicator. We generated this indicator from four questions included in the survey with dichotomous (yes/no) responses. The questions asked were: 1) "Have you ever had, or do you believe that you have ever had, the coronavirus?"; 2) "In the last 14 days, do you think you have met (seen) anyone who you think had the coronavirus when you met them?"; 3) "Do you think your area has a high incidence of coronavirus?"; and 4) "Do you personally know someone who has died from the coronavirus in your area?". The main indicator used in the basic analysis was created as a binary variable that takes a value of one if the respondent answers affirmatively to any of these four questions and zero, if otherwise. We also constructed an alternative indicator - a COVID-19 exposure index - by combining the four variables using principal component analysis (PCA). While the latter approach generates a continuous indicator that differentiates the intensity of exposure, the basic result produced using the two approaches remained qualitatively the same. Therefore, owing to its ease of interpretation, we report the basic results using the binary COVID-19 exposure indicator. The result using the COVID-19 exposure index is presented and discussed in section 5.

3.3 Econometric approach

We model the outcome variables (F_{it}) - food insecurity and poor diet diversity - reported by household i at time t as a function of COVID-19 exposure (C_{it}), and specify the basic econometric model as:

$$F_{it} = \alpha + \beta_1 C_{it} + \beta_2 T_i + \beta_3 X_{it} + \epsilon_{it} \qquad (1)$$

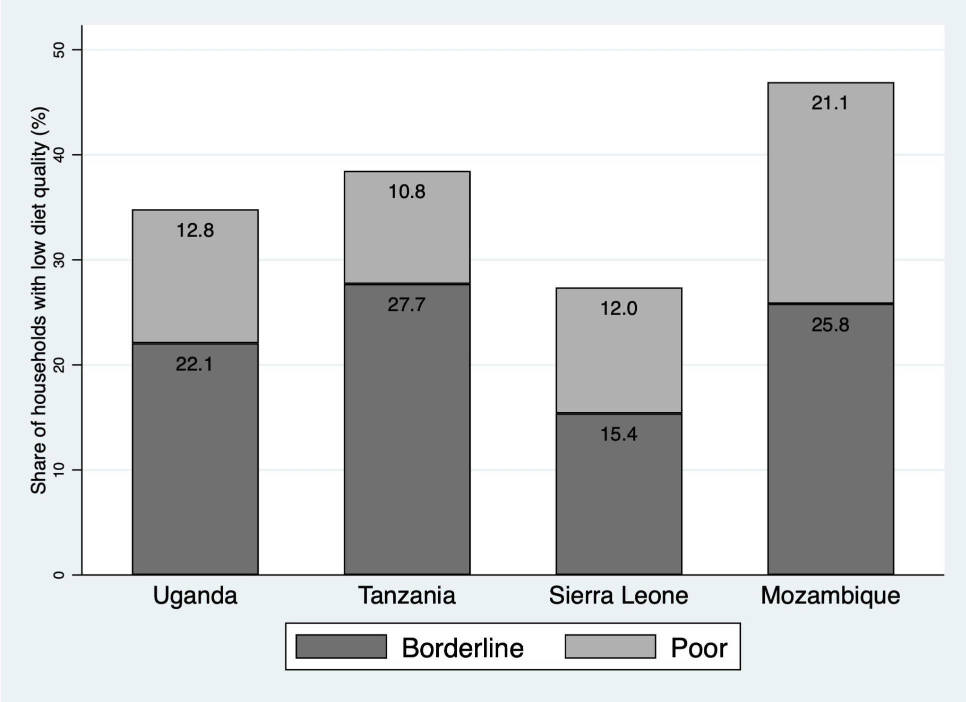


Figure 2: Food Consumption Score by country
Note: Diet intake indicators (acceptable, borderline & poor) are derived from the food consumption Score(FCS).

where X_{it} is a vector of household and location characteristics. Household-level characteristics include household size and composition, age, gender and education level of the respondent and value of durable assets. Location characteristics cover urbanization of place of residence, road density, distance to the nearest market, and a variety of agro-ecological variables including precipitation z-score, soil terrain, and stringency score. X_{it} also include country and regional dummies which are added in to control for additional observed and unobserved economic, demographic, agro-ecological, and other characteristics associated with each country and the regions within countries. T_i represents indicators of survey rounds. It may capture aggregate shifts in the outcome variables or correlated shifts in the right-hand side variables. The last term in the equation, ϵ_{it}, is the random error term. Standard errors are clustered at the district level.

In equation 1, β_1 captures the main relationship of interest: the effect of COVID-19 exposure on food insecurity and poor diet diversity. Our central hypothesis is that COVID-19 exposure leads to or worsens food insecurity and the prevalence of poor diet diversity score as fear of the virus or the physical restrictions imposed to contain it or the decline in income due to job loss leads to lower food consumption and, hence, β_1 is positive. However, as indicated before, COVID-19 exposure might be endogenous due to potential reverse causality and omitted variables that could drive both COVID-19 exposure and the outcome variables.

When the indicator of COVID-19 exposure is endogenous, $corr(C_{it}, \epsilon_{it}) \neq 0$ and β_1 would be inconsistent. Typically, the instrumental variables (IV) method that relies on exclusion restriction is used to address such endogeneity concerns with (non-experimental) cross-section data. In our case, however, this method is not feasible since it proved difficult to find appropriate instrument(s) for COVID-19 exposure. Instead, we employ a heteroscedasticity-based identification strategy proposed by Lewbel (2012). This approach allows identification where other traditional sources of identification, such as standard instrumental variables approach or panel data method, are not available or unable to credibly address the problem.

To intuitively expound the approach based on equation 1, let's suppose that Z_{it} represents the vector of exogenous variables and C_{it}, representing COVID-19 exposure, is endogenous. In the first stage, the endogenous variable, C_{it}, is regressed on the exogenous variables, Z, and the vector of residuals $\bar{\epsilon}$ is retrieved. Next, the instruments are obtained as $(Z - E(Z))\bar{\epsilon}$, where $E(Z)$ is the expected value of Z. The basic requirement of the model is that there is heteroscedasticity in the residual, $\bar{\epsilon}$, (i.e.,$cov(\bar{\epsilon}^2, Z_{it}) \neq 0$). Based on this relationship, internally generated instruments are used in estimation without imposing any exclusion restrictions (Lewbel, 2012). This approach has recently been used in a growing number of empirical literature (Mallick, 2012; Tran et al., 2020; Zeng et al., 2018).

In our study, we first run separate regressions of COVID-19 exposure on a set of exogenous variables (Z) and then retrieved the residuals ($\bar{\epsilon}$). The included exogenous variables include location level characteristics (urban/rural indicator, road density, distance to the nearest market, and a variety of agro-ecological variables including precipitation z-score, soil terrain, and stringency score). The Breusch–Pagan test rejects the null of homoscedasticity at the 1% level for COVID-19 exposure. As per the literature, we selected the exogenous variables so that the residuals become heteroskedastic. Further, IV-diagnostics tests reported with the results in Section 4 support the validity of the approach. The critical values of the Cragg-Donald test statistic reject the null hypothesis that the endogenous regressor (COVID-19 exposure) is weakly identified. The Kleibergen-Paap test also rejects the hypothesis of under-identification, i.e. the minimal canonical correlation between the endogenous variable and the instruments is statistically different from zero. The Hansen test statistics of over-identification fail to reject the null hypothesis that our over-identifying restrictions are valid across the different IV regressions, i.e. we cannot reject the null hypothesis of zero correlation between the instruments and the error term.

4 Results

4.1 Descriptive statistics

Table 2 describes household characteristics by food insecurity status. The last column shows the P-values of mean difference tests. Panel A provides information on the average value of the food consumption score and the share of households with poor diet diversity. The first row shows that the average FCS of the whole sample is 51.4 (out of the possible 112) and the score is, on average, higher for food secure households (57.3) than for food insecure households (45.1). In terms of FCS categories, 6.1% of food secure households have poor diet diversity which is significantly lower than the share of food insecure households with poor diet diversity (23%). From these statistics, two points are worth noting. First, our food insecurity and diet diversity indicators are strongly correlated. Second, the prevalence of poor diet diversity among food secure households and the prevalence of acceptable diet diversity among food insecure households suggests that diet diversity and food insecurity measures are complementary indicators of welfare.

Panel B of Table 2 presents information on covariates related to individual and household characteristics. The mean comparison tests show that the distributions of most of these covariates vary significantly based on food security status. In general, food insecurity is more prevalent among households with large family sizes, low access to services (drinking water, electricity), low asset ownership (TV, radio), and those with women, younger, less educated household heads/respondents. The distribution of asset index - index of durable assets generated using PCA from individual asset items owned by households - indicates that food insecurity is more prevalent among the poor, the less asset-endowed. The share of food secure households that reported exposure to COVID-19 is slightly higher (21% Vs. 17%).

Panel C presents information on location characteristics. Column 1 shows the share of households from the different locations to the total sample pool. Of the total sample, the share of households from rural areas, the capital city, small urban centers, and peri-urban areas is respectively 34%, 16%, 30%, and 21%. Similarly, columns 2 and 3 present the shares of households from the different locations in the

Table 2: Descriptive statistics by food security status

Variables	Total	Food Secure	Food Insecure	Mean Diff.
Panel A: Alternative welfare indicators				
Food Consumption Score (0-112)	51.4	57.3	45.1	0.00
Poor diet diversity (%)	14.1	6.10	22.8	0.00
Panel B: Individual and household characteristics				
Respondent is female	0.55	0.51	0.59	0.00
Age of respondent in years	36.6	37.8	35.4	0.00
Education of respondent in years	9.54	10.13	8.90	0.00
Number of HH members under 18	2.70	2.55	2.87	0.00
Number of HH members over 60	0.33	0.27	0.40	0.00
Number of HH members, 18-60	3.09	2.90	3.30	0.00
Access to drinking water	0.22	0.30	0.13	0.00
Access to electricity	0.74	0.81	0.65	0.00
Household owns radio	0.72	0.79	0.65	0.00
Household owns TV	0.59	0.69	0.49	0.00
Asset index (PCA)*	0.00	0.46	-0.50	0.00
Exposure to COVID-19	0.19	0.21	0.17	0.03
Panel C: Location characteristics				
Rural household	0.34	0.33	0.34	0.00
Capital city household	0.16	0.18	0.14	0.00
Other urban household	0.30	0.29	0.30	0.00
Peri-urban households	0.21	0.20	0.22	0.00
Rainfall quantity (z-score)	-0.15	-0.15	-0.14	0.90
Soil terrain (z-score)	0.00	0.01	-0.01	0.13
Log(road density)	5.40	5.05	5.73	0.00
Log(distance to market in km)	3.02	3.01	3.03	0.46
Stringency index	42.6	40.3	45.1	0.00
Uganda	0.25	0.31	0.18	0.00
Tanzania	0.25	0.36	0.12	0.00
Sierra Leone	0.26	0.12	0.41	0.00
Mozambique	0.25	0.21	0.29	0.00
Observations	24,041	11,562	12,479	

Note: Food insecurity indicators (food secure, moderately & severely food insecure) are generated from FIES. *We generated the assets index using principal component analysis (PCA) from individual asset items owned by households two food security categories. For example, column 2 shows that households from the capital city account for 18% of food secure households - disproportionately more than their contribution to the total sample pool. Overall, we note that there is a systematic spatial variation with households residing in small towns and peri-urban areas significantly more likely to be food insecure than households from the capital city. Similarly, the distribution across the survey countries shows that the proportion of food insecure households is much larger in Sierra Leone and Mozambique compared to that in Uganda and Tanzania.

These differences in household and location characteristics point to the need to control for a set of household and community-level variables in the analysis to attenuate potential sources of selection biases (see below). That is, while the mean difference test results of the outcome variables presented in this subsection are informative, they cannot be used to make causal inferences regarding the effect of COVID-19 exposure on food insecurity and diet diversity, since they do not account for potential confounding factors. We employ a heteroscedasticity-based identification strategy to account for potential endogeneity concerns.

4.2 COVID-19 exposure, food insecurity, and diet diversity

To set the stage, we first estimate the association between COVID-19 exposure, food insecurity, and poor diet diversity using a simple Linear Probability Model (LPM) model [6]. Results presented in Columns 1 and 3 of Table 3 indicate that COVID-19 exposure is positively associated with both food insecurity and poor diet diversity.

However, as discussed earlier, COVID-19 exposure may be endogenous in the models explaining both food insecurity and diet diversity. To attenuate this concern, we employ a heteroscedasticity-based identification strategy (IV-2SLS) using relatively exogenous variables to instrument internally for the measure of COVID-19 exposure (Lewbel, 2012). Columns 2 and 4 in Table 3 present the regression results of the food insecurity and poor diet diversity based on the IV-2SLS estimates, respectively. The results show that exposure to COVID-19 has causally contributed to the increasing propensity of household food insecurity and poor diet diversity score. Specifically, on average, a household exposed to COVID-19 is 7.5 and 7.3 percentage points more likely to be food insecure (Column 2) and have a poor diet diversity (column 4) than its counterpart.

While the results of the OLS regressions and the IV estimations are largely consistent, the coefficients of the COVID-19 exposure are generally higher for the IV estimates than their corresponding values from the OLS regressions. Such differences are consistent with measurement error, as expected in retrospective data from household surveys. While measurement errors can lead to an attenuation bias towards zero in OLS and linear probability model coefficients (Theil, 1971), instrumental variable approaches often mitigate such problems (Gujarati, 2008).

Overall, we posit that COVID-19 exposure increases the likelihood of food insecurity and poorer diet diversity across the surveyed countries. The fear of catching the virus and/or the physical restrictions imposed by countries to contain the virus has led to a significant decline in food security and dietary diversity. These results are consistent with previous studies. Kansiime et al. (2021) reported a substantial decline in food security and the quality of diets consumed in Uganda and Kenya due to COVID-19. Mueller et al. (2022) find a positive correlation between an acquaintance of the respondents with COVID-19 infected persons with more food insecurity in their households in a multi-country study that included Bangladesh, Kenya, and Nigeria.

The results presented in Table 3 also reveal that both food insecurity and poor diet diversity are significantly correlated with many other covariates. Younger and less educated respondents are more likely to experience food insecurity compared to their respective counterparts. As expected, food insecurity is

[6] *Despite the nature of our outcome variable (binary variables), we report here the Linear Probability Model (LPM) to be consistent with the result based on IV-2SLS. However, our results remain qualitatively the same when probit/logit models are used (see Section 5).*

Table 3: COVID exposure and food insecurity

	Food Insecurity		Poor diet diversity	
	OLS	IV (2SLS)	OLS	IV (2SLS)
COVID exposure indicator	0.033***	0.075***	0.027***	0.073**
	(0.010)	(0.030)	(0.010)	(0.032)
Respondent is female, yes=1	0.013	0.014*	0.008	0.009
	(0.008)	(0.008)	(0.007)	(0.007)
Age of respondent in years	-0.003***	-0.003***	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Education of respondent in years	-0.009***	-0.009***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Number of household members, under 18	0.021***	0.021***	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Number of household members, over 60	0.027***	0.027***	0.031***	0.031***
	(0.005)	(0.005)	(0.006)	(0.006)
Number of household members, 18-60	0.012***	0.012***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Asset index(PCA)	-0.079***	-0.080***	-0.044***	-0.045***
	(0.005)	(0.005)	(0.003)	(0.003)
Rural household, yes=1	-0.036***	-0.036***	-0.029***	-0.029***
	(0.013)	(0.013)	(0.009)	(0.009)
stringency index 30-day average	0.035	0.035	-0.063	-0.063
	(0.025)	(0.025)	(0.044)	(0.044)
Rainfall quantity (z-score)	-0.003	-0.003	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Soil terrain (z-score)	-0.006	-0.006	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)
Log(road density)	-0.005	0.006	0.006	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Log(distance to market in km)	-0.002	-0.002	-0.009***	-0.009***
	(0.004)	(0.004)	(0.003)	(0.003)
Tanzania	0.065	0.076	0.003	0.015
	(0.053)	(0.053)	(0.078)	(0.078)
Sierra Leone	0.334***	0.373***	-0.108*	-0.107***
	(0.063)	(0.045)	(0.061)	(0.039)
Mozambique	0.389***	0.402***	0.230***	0.234***
	(0.033)	(0.032)	(0.019)	(0.019)
Regional & Survey FE	yes	yes	yes	yes
Constant	0.267	0.132	0.389**	0.359*
	(0.106)	(0.133)	(0.171)	(0.186)
Observations	23,898	24,014	24,241	24,241
R2	0.270	0.254	0.122	0.119
Adjusted R2	0.268	0.253	0.120	0.118
IV DIAGNOSTICS:				
Kleibergen-Paap LM statistic		16.21		16.21
Kleibergen-Paap p-value		0.00		0.00
Cragg-Donald test		536		536
Hansen-J test		0.924		6.027
Hansen-J p-value		0.968		0.304

*Note: .01 - ***; .05 - **; .1 - *. Food insecurity indicator is a binary variable generated from Food insecurity Experience Scale (FIES). The variable takes a value of 1 if a household is moderately or severely food insecure, zero otherwise; Diet quality indicator is a binary variable derived from the food consumption Score (FCS). The variable takes a value of 1 if household's food consumption is below acceptable level, zero otherwise; Estimates of Regional and survey fixed effects are not reported for brevity.*

Table 4: Change in income since the start of the pandemic by type of employment

Activity	Drastically decreased	Moderately decreased	Did not change	Increased	Observation
Wage worker or public employee	11.5	18.9	62.2	7.4	4,806
Casual laborer	48.2	35.4	14.8	1.6	1,513
Self-employed	36.5	53.8	7.4	2.3	12,603
Farmer	36.5	49.7	10.6	3.2	5,164
Did not work but have a job	23.9	25.7	45.1	5.3	340
Unemployed/Inactive	54.4	3.7	32.9	8.95	1,064
Total	32.6	44.7	19.2	3.4	25,491

more prevalent among urban households with larger family sizes and lower asset endowments. Moreover, an average household from Sierra Leone and Mozambique is more likely to be food insecure compared to that from Uganda or Tanzania. However, households from Sierra Leone tend to have more diversified diet score than households from the reference country, Uganda.

The governments in the four countries had some role to play in supporting their population during the pandemic, but not to the degree seen in higher-middle and higher-income countries (Life with Corona Project, 2021). As we reported in Section 2.1, the governments' additional spending or liquidity support in response to COVID-19 since January 2020 were not large, averaging about 5% of GDP (excluding Tanzania), while the global average was at around 10% of GDP. Per our data, some form of government assistance was received by 10% of households. The pro-poor targeting seems worked well since about 9% of food insecure report some form of aid from the government, and about 20% from all formal sources, such as charitable organizations. A more important source of economic support has been inter-household transfers including overseas remittances. As we see, these channels were more effective as evidenced by the LwC-A data which states that about 21% of households received inter-household remittances, mostly from within countries (see Tables A3 and A4). This channel, especially in food transfers between households, also was likely affected by government mobility restrictions, a finding documented in other studies (Palma and Araos, 2021).

Furthermore, Figure 3 indicates that food insecure households are more likely to adopt harmful livelihood coping strategies such as drawing down savings, falling into debt, selling productive assets, and reducing essential non-food expenditure, to deal with income shortages and increased prices resulting from COVID-19 exposure. This is consistent with the covariate nature of the COVID-19 pandemic, which has disrupted formal and informal capital and insurance institutions. This is also consistent with other studies conducted in similar settings (Janssens et al., 2021; Mahmud and Riley, 2021; Schotte et al., 2021).

4.3 Transmission mechanisms

The main result shows that exposure to COVID-19 increases the likelihood of food insecurity and poorer diet diversity. In this section, we highlight two major mechanisms that are likely to underlie this basic finding - a decline in income, and the physical mobility restriction imposed by governments to curb the spread of the virus.

In our survey, we asked respondents whether their income had declined since the onset of COVID-19. Table 4 indicates that the income of more than three-quarters of the households has declined since COVID-19. While households from all employment categories were adversely affected, the decline was particularly drastic among farmers, the self-employed, and informal/casual workers. Wage employees in the formal sector are less affected. Similar effects of the pandemic on household income in the survey countries were reported in other studies (Kansiime et al., 2021; Mueller et al., 2022).

Another potential underlying mechanism of our basic result is the mobility restriction that countries

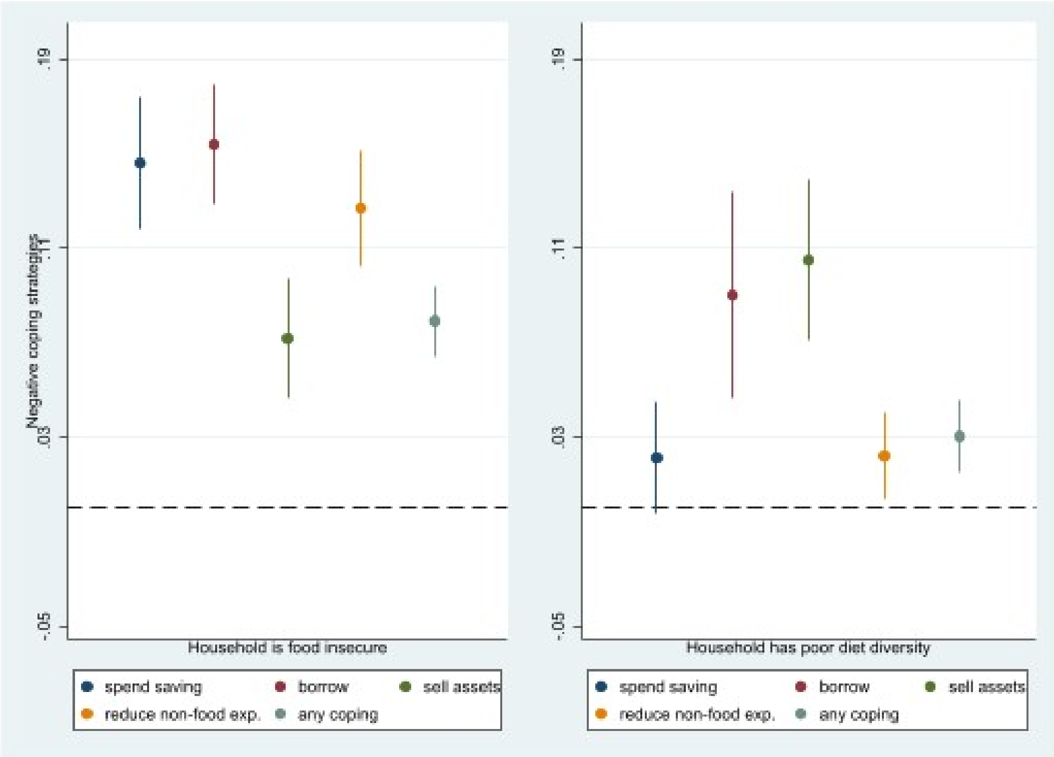


Figure 3: Adoption of negative Coping strategies by food insecure households
Note: Food insecurity indicator is generated from FIES and poor diet diversity score is generated from FCS

imposed to limit the spread of the virus. To measure the intensity of the COVID-19 related restrictions, we use data on policy stringency from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2020). OxCGRT collects information on policy measures implemented by governments to curb the spread of the pandemic. Based on this information, OxCGRT constructs the stringency index, which measures the strictness of the policies. The index is based on nine indicators: school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns and restrictions on nationwide and international movements, each of which are scored between 0 and 100 (100 representing the strictest restrictions). The overall stringency index is calculated as the mean score of these nine indicators. The stringency index is calculated at the country level and is updated daily. Figure 4 shows that there is a strong positive correlation between our measure of COVID-19 exposure and OxCGRT's stringency index.

To further examine the link between our measures of COVID-19 exposure, the outcome variables, and the two underlying mechanisms (income decline and stringency measure), we conduct a simple statistical mediation analysis. This method involves quantifying the indirect effect of an independent variable (e.g. exposure to COVID-19) on the dependent variable (e.g. food insecurity) through a third variable called the mediator (e.g. decline in income). This analysis would reveal to us whether the adverse impact of the pandemic on food insecurity and poor dietary intake could indeed be (partly) due to the indirect influence of income shock and the stringency index. We perform a mediation analysis using the structural equation modeling (SEM) framework and the Stata package medsem (Mehmetoglu, 2018). Income decline is constructed as a binary variable which takes a value of 1 if a household reported a moderate or drastic decline in income, zero otherwise. The log-transformed version of the 30-day average stringency index is used to measure the physical mobility restrictions[7].

[7] *We used the 30 day aggregation to be consistent with our measure of the food insecurity. However, our results*

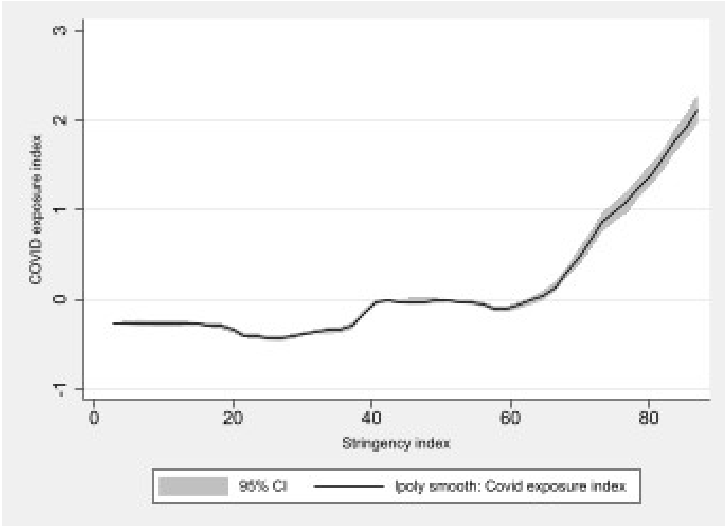


Figure 4: Association between COVID exposure and stringency index

The result of the mediation analysis presented in Table 5 shows that both the mediator variables (decline in income and the stringency measures), as well as the independent variable (COVID-19 exposure), are associated positively with the outcome variables. It also shows that COVID exposure is positively correlated with both mediator variables. Furthermore, the ratio of Indirect to Total effect (RIT, %) indicates that 12-13% of the effect of COVID exposure on the outcome variables are mediated by the income shock and the physical mobility restrictions. Indeed, this corroborates the findings from other studies that found that pandemic-related interruptions in supply chains, as well as shop and market closures, substantially impede physical as well as economic access to food in most low-income countries (Devereux et al., 2020; Mandal et al., 2021). Similarly, Josephson et al. (2021) argue that the COVID-19 related income losses have led to the worsening of other elements of the household economy, particularly, food insecurity.

Table 5: Results from mediation analysis

	Food insecurity	Poor diet diversity
Income shock on outcome	0.153***	0.062***
	0.006	0.005
Stringency index on outcome	0.111***	-0.064***
	0.012	0.009
COVID exposure on outcome	0.064***	0.032***
	0.008	0.006
COVID exposure on income shock	0.028***	0.027***
	0.008	0.008
COVID exposure on stringency index	0.041***	0.040***
	0.004	0.004
RIT - Income shock	6.2%	5.0%
RIT - Stringency index	6.6%	8.8%
Controls?	yes	yes
Observation	22,319	22,524

Note: .01 - ***; .05 - **; .1 - *; (Indirect effect / Total effect)

remain qualitatively the same when other aggregation levels are use.

5 Sensitivity analyses

We assess the robustness of the basic results in several ways. First, the main explanatory variable used in the basic analysis is a binary COVID-19 exposure variable. While this variable has an advantage owing to its ease of interpretation, it does not differentiate households based on the intensity of exposure. To partially address this, we alternatively used a COVID-19 exposure index – a variable generated by combining the four individual COVID-19 exposure variables using principal component analysis (PCA). The results presented in Panel A of Table 6 using IV-2SLS indicate that the COVID-19 exposure index increases both the propensity of food insecurity and poor diet diversity - consistent with the result in Table 3.

Table 6: Alternative measurements of COVID exposure and food security indicators

	Panel A		Panel B	
	Food Insecurity	Poor Diet	Food Insecurity	Poor Diet
COVID exposure index (PCA)[a]	0.017***	0.022***	0.314***	-0.066***
	(0.006)	(0.007)	(0.105)	(0.022)
Household controls?	yes	yes	yes	yes
Regional FE?	yes	yes	yes	yes
Survey FE?	yes	yes	yes	yes
Constant	0.270**	0.428**	0.202	3.420***
	0.108	0.201	0.464	0.058
Observations	20,434	20,434	23,898	20,898
R2	0.280	0.124	0.313	0.165
Adjusted R2	0.278	0.123	0.312	0.164
IV DIAGNOSTICS:				
Kleibergen-Paap LM statistic	26.87	26.87	16.21	829.31
Kleibergen-Paap p-value	0.00	0.00	0.01	0.00
Cragg-Donald test	1,133.3	1,133.3	536.08	526.93
Hansen-J test	5,937	4,089	7,390	21,291
Hansen-J p-value	0.312	0.537	0.193	0.001

*Note: .01 - ***; .05 - **; .1 - *;* [a] *COVID exposure index is generated by combining the four individual COVID-19 exposure variables using principal component analysis (PCA)*

Second, the binary outcome variables used for the basic result are each generated from non-binary indicators. In this part, we test the sensitivity of our basic result using the non-binary versions of the outcome variables. For food insecurity, we use a reparameterized raw FIES score, which is generated from the original raw score by applying Item Response Theory (IRT) models to better reflect the probability of experiencing food insecurity given the respondent's answers (see Appendix A1 for detailed description). For diet diversity, we use the Food Consumption Score (FCS), which ranges from 0-112 depending on the type and frequency of food groups consumed by the households. Panel B of Table 6 shows that exposure to COVID-19 increases the probability of experiencing food insecurity. For FCS, the COVID-19 exposure index appears with negative and statistically significant coefficients indicating that exposure to COVID-19 reduces the FCS of households, which is consistent with our main results.

Third, the basic results assumed the outcome variables as linear variables. However, since both used outcome variables - food insecurity and poor diet diversity - are binary variables, using a linear model may not be unequivocally appropriate. Linear models are preferable due to their simplicity, interpretability, and because they provide a host of specification tests to assess the validity of the IV strategy (Angrist and Pischke, 2009; Caudill et al., 1988). However, for limited dependent outcomes, a linear model may be unreliable (Wooldridge, 2002). Therefore, we assess the robustness of the basic findings using logit model regressions. The results presented in Panel A of Table 7 from using logit model regression indicates that the basic result remain robust and do not seem to be driven by the non-linear nature of the outcome variables.

Panel B of Table 7 reports the results from the categorical versions of the outcome variables. For food insecurity, these categories are: cat. 1 = food secure; cat.2 = moderately food insecure; and cat.3 = severely food insecure. Similarly, the FCS categories are: cat.1 = acceptable diet diversity; cat.2 = borderline diet diversity; and cat.3 = poor diet diversity. Due to the ordered nature of both variables (larger numbers represent worse welfare), the reported results are based on ordered logit model. The coefficient estimates for both outcome variables are positive and significant indicating that COVID-19 exposure increases log odds of being in a higher level of food insecurity and poor diet diversity by 0.2 and 0.1 respectively, given all of the other variables in the model are held constant at mean values.

Table 7: Result from using limited depended variables model

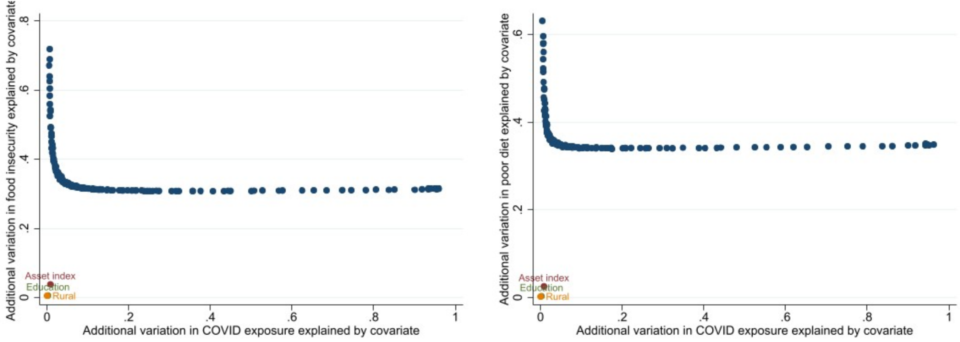
	Panel A		Panel B		Panel C	
	Food Insecurity	Poor Diet	Food Insecurity	Poor Diet	Food Insecurity	Poor Diet
COVID exposure indicator	0.182***	0.259***	0.171***	0.089**	0.185***	0.275***
	(0.049)	(0.079)	(0.043)	(0.038)	(0.040)	(0.051)
Household control?	yes	yes	yes	yes	yes	yes
Regional FE?	yes	yes	yes	yes	yes	yes
Survey FE?	yes	yes	yes	yes	yes	yes
Constant	-1.230**	0.192			-1.548***	0.209
	(0.613)	1.73			0.330	0.424
Observations	23,898	23,898	23,898	23,898	23,898	23,898
Pseudo R2	0.220	0.149	0.176	0.106		

Note: .01 - ***; .05 - **; .1 - *;

Fourth, given the nested structure of our data, the assumption of independent errors is likely violated. Instead, it is plausible to assume that individual responses are highly correlated within one country-survey round than they are across country-survey rounds. Individuals interviewed within one country at a one-time point are more likely to be exposed to a similar set of factors (e.g., severity of COVID incidence, government policies and social safety net programs) compared to individuals interviewed in a different country at a different time point. The linear regression model used for the basic model assumes that one intercept is common to all individuals in our sample. However, in our context – where individuals are clustered together in countries and survey rounds – it is likely that the conditional mean of the dependent variable is different across clusters. We attempted to address this by controlling for country and survey round fixed effects as well as clustering the standard errors at the district level. However, this might not be sufficient as it does not introduce cluster-specific intercepts (Hedeker, 2003). Therefore, in this part, as a sensitivity analysis, we fit a random intercept logistic regression model (melogit). The result presented in Panel C of Table 7 shows that the effect of COVID exposure on the outcome variables is qualitatively similar to the result from the basic model.

Finally, omitted variables could remain a concern with our estimation of the effect of COVID exposure on the outcome variables if the omitted variables are significantly correlated with both dependent and independent variables. To attenuate this concern, we control for country-fixed effects and regional dummies throughout our regressions that could partially account for observed and unobserved location-specific characteristics. Despite this, omitted variables bias could remain a concern, given the observational nature of the data. For example, it is plausible that food secure households are better in terms of immunity to the virus and hence they are less exposed to the pandemic. We formally assess the degree of omitted variable bias using the sensitivity analysis proposed by Imbens (2003). The test helps us examine whether our results are appreciably affected by omitted variable bias by estimating the degree of correlation a missing variable should have with both the outcome and explanatory variables to substantially change the estimated effect.

To implement this procedure, we start with our preferred specifications (the IV results in Table 3)



(a) (b)

Figure 5: Sensitivity of estimated effect to omitted variable bias

and consider the correlation between COVID exposure and unobserved covariates that are also correlated with the outcome variables – food insecurity and poor diet diversity. By generating pseudo-observables over 200 iterations, Figure 5 shows a series of points representing the combination of R-squared values that would lead to a reduction of the size of the effect coefficient by half. On the vertical axis, we plot the marginal increase in R-squared that results when an unobserved covariate is added to a regression of the outcome variables on our full set of significant controls. The horizontal axis plots the marginal increase in R-squared from adding the covariate to a regression of COVID exposure on our full set of controls. Panel A and Panel B present this analysis separately for food insecurity and poor diet diversity, respectively.

From the figure, we can see that a correlation between COVID exposure and an omitted variable would only be problematic if the correlation between the same omitted variable and the outcome variables was very high. To illustrate this finding made by a hypothetical omitted covariate, we also plot the partial correlation between the COVID exposure and the outcome variables for three significant control variables (rural/urban indicator, household asset index, and education level of the household head). The results show that none of the three controls even approaches the threshold that reduces our estimated effect of credit on the outcome variables by half. Therefore, an omitted variable would have to be much more important than our existing controls to invalidate our results. This gives us confidence that our main result, i.e. COVID exposure leads to or worsens food insecurity and poor dietary intake, is unlikely to have been driven by omitted variable bias.

6 Discussion and conclusion

A large body of evidence documents the negative effects of the COVID-19 pandemic on food security not only in developing countries but also in developed nations. In this study, we contribute to this literature by quantifying the effect of exposure to COVID-19 on food insecurity and diet diversity in four low- and middle-income countries in Africa using phone-based survey data with a sample of 24,000 responses collected monthly throughout 2021. A key question in the topic of food insecurity and the COVID-19 pandemics is the degree to which the pandemic affected food insecurity. The countries under this study had episodes of food insecurity before the pandemic and it is clear that the adverse welfare effects of COVID-19 have been dramatic.

We find that all four countries feature an alarming degree of food insecurity when measured by FIES which focuses on the aspect of access to food. We find that every second household experiences some degree of moderate to severe food insecurity; however, the difference in the food insecurity for individual countries ranged from 24% to 75%. We find that the degree of diet diversity is below the acceptable level for about 36% of the sample. Our analysis shows that exposure to COVID-19 - either through individual experience of having a virus or having people in surroundings who had the virus - had a profound effect on the probability of being food insecure. We show that the decline of household incomes (which partly relates to the loss of jobs or reduced earnings) and mobility restrictions are the mechanisms through which the pandemic leads to worsening food insecurity in these four African countries.

We find that the government played a rather limited role in providing financial and social assistance to households hit by the pandemics, though the pro-poor targeting seems to be in place. We also find that food-insecure households are more likely to use harmful coping strategies such as drawing down savings, falling into debt, selling productive assets, and reducing essential non-food expenditure, implying adverse effect of the pandemic on food and nutrition security beyond 2021.

Our key finding that the COVID-19 exposure had a strong adverse impact on food insecurity and diet diversity has two important implications. First, since households typically resort to reduction of food consumption after social transfers, inter-household remittances, and other coping mechanisms are exhausted (Janssens et al., 2021), the impact of the COVID-19 exposure on food security we report is likely to be on a lower bound of the welfare implication of the pandemic. Second, the higher propensity of adoption of the negative coping strategies by poor and food insecure households could mean that the adverse effect of the pandemic will continue in medium-term horizon, at least. The pandemic-induced sale of productive assets, lower expenditure on education and health, and the depletion of current saving are likely to lock poor households in poverty traps in the long term (Dercon and Christiaensen, 2011). Finally, the disproportionately stronger effect of the pandemic on vulnerable groups implies that COVID-19 risks is reinforcing pre-existing socioeconomic disparities within and across countries.

7 References

References

Abay, K. A., Berhane, G., Hoddinott, J., and Tafere, K. (2023a). Covid-19 and food security in ethiopia: do social protection programs protect? *Economic Development and Cultural Change*, 71(2):373–402.

Abay, K. A., Breisinger, C., Glauber, J., Kurdi, S., Laborde, D., and Siddig, K. (2023b). The russia-ukraine war: Implications for global and regional food security and potential policy responses. *Global Food Security*, 36:100675.

Agamile, P. (2022). Covid-19 lockdown and exposure of households to food insecurity in uganda: insights from a national high frequency phone survey. *The European Journal of Development Research*, 34(6):3050–3075.

Ahmed, A., Bakhtiar, M. M., Gilligan, D. O., Hoddinott, J., and Roy, S. (2023). Private transfers, public transfers, and food insecurity during the time of covid-19: Evidence from bangladesh. *Applied Economic Perspectives and Policy*, 45(4):1901–1921.

Akalu, L. S. and Wang, H. (2023). Does the female-headed household suffer more than the male-headed from covid-19 impact on food security? evidence from ethiopia. *Journal of Agriculture and Food Research*, 12:100563.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Arndt, C., Davies, R., Gabriel, S., Harris, L., Makrelov, K., Robinson, S., Levy, S., Simbanegavi, W., van Seventer, D., and Anderson, L. (2020). Covid-19 lockdowns, income distribution, and food security: An analysis for south africa. *Global food security*, 26:100410.

Bairagi, S., Mishra, A. K., and Mottaleb, K. A. (2022). Impacts of the covid-19 pandemic on food prices: Evidence from storable and perishable commodities in india. *PloS one*, 17(3):e0264355.

Balana, B. B., Ogunniyi, A., Oyeyemi, M., Fasoranti, A., Edeh, H., and Andam, K. (2023). Covid-19, food insecurity and dietary diversity of households: Survey evidence from nigeria. *Food Security*, 15(1):219–241.

Ballard, T., Kepple, A., and Cafiero, C. (2013). The food insecurity experience scale: development of a global standard for monitoring hunger worldwide. *Technical Paper*, (October):1–16.

Beckman, J., Baquedano, F., and Countryman, A. (2021). The impacts of covid-19 on gdp, food prices, and food security. *Q Open*, 1(1):qoab005.

Bundervoet, T., Dávalos, M. E., and Garcia, N. (2022). The short-term impacts of covid-19 on households in developing countries: an overview based on a harmonized dataset of high-frequency surveys. *World development*, page 105844.

Cafiero, C., Viviani, S., and Nord, M. (2018). Food security measurement in a global context: The food insecurity experience scale. *Measurement*, 116(November):146–152.

Caudill, S. B. et al. (1988). An advantage of the linear probability model over probit or logit. *Oxford Bulletin of Economics and Statistics*, 50(4):425–427.

Chirisa, I., Mutambisi, T., Chivenge, M., Mabaso, E., Matamanda, A. R., and Ncube, R. (2022). The urban penalty of covid-19 lockdowns across the globe: manifestations and lessons for anglophone sub-saharan africa. *GeoJournal*, 87(2):815–828.

Dercon, S. and Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from ethiopia. *Journal of development economics*, 96(2):159–173.

Devereux, S., Béné, C., and Hoddinott, J. (2020). Conceptualising covid-19's impacts on household food security. *Food Security*, 12(4):769–772.

Dietrich, S., Giuffrida, V., Martorano, B., and Schmerzeck, G. (2022). Covid-19 policy responses, mobility, and food prices. *American Journal of Agricultural Economics*, 104(2):569–588.

Egger, D., Miguel, E., Warren, S. S., Shenoy, A., Collins, E., Karlan, D., Parkerson, D., Mobarak, A. M., Fink, G., Udry, C., et al. (2021). Falling living standards during the covid-19 crisis: Quantitative evidence from nine developing countries. *Science advances*, 7(6):eabe0997.

Engemann, H. and Jafari, Y. (2022). Covid-19 and changes in global agri-food trade. *Q Open*, 2(1):qoac013.

FAO (2016). *Methods for estimating comparable rates of food insecurity experienced by adults throughout the world*, volume 2016. FAO, Rome.

FAO, IFAD, U. W. W. (2019). The state of food security and nutrition in the world 2019. safeguarding against economic slowdowns and downturns.

Gebre, G. G. et al. (2021). Prevalence of household food insecurity in east africa: Linking food access with climate vulnerability. *Climate Risk Management*, 33:100333.

Gujarati, D. (2008). N.(2003). basic econometrics. *New York: MeGraw-Hill*, pages 363–369.

Hale, T., Webster, S., Petherick, A., Phillips, T., and Kira, B. (2020). Oxford covid-19 government response tracker (oxcgrt). *Last updated*, 8:30.

Hedeker, D. (2003). A mixed-effects multinomial logistic regression model. *Statistics in Medicine*, 22(9):1433–1446.

Hirvonen, K., Minten, B., Mohammed, B., and Tamru, S. (2021). Food prices and marketing margins during the covid-19 pandemic: Evidence from vegetable value chains in ethiopia. *Agricultural Economics*, 52(3):407–421.

Imbens, G. W. (2003). Sensitivity to exogeneity assumptions in program evaluation. *American Economic Review*, 93(2):126–132.

IMF (2021). Fiscal monitor: Database of country fiscal measures in response to the covid-19 pandemic.

Ismail, A., Madzorera, I., Apraku, E. A., Tinkasimile, A., Dasmane, D., Zabre, P., Ourohire, M., Assefa, N., Chukwu, A., Workneh, F., et al. (2023). The covid-19 pandemic and its impacts on diet quality and food prices in sub-saharan africa. *PLoS One*, 18(6):e0279610.

Janssens, W., Pradhan, M., de Groot, R., Sidze, E., Donfouet, H. P. P., and Abajobir, A. (2021). The short-term economic effects of covid-19 on low-income households in rural kenya: An analysis using weekly financial household data. *World Development*, 138:105280.

Josephson, A., Kilic, T., and Michler, J. D. (2021). Socioeconomic impacts of covid-19 in low-income countries. *Nature Human Behaviour*, 5(5):557–565.

Jr. Tabe-Ojong, M. P., Nshakira-Rukundo, E., and Haile Gebrekidan, B. (2023). Covid-19 and food insecurity in africa: A review of the emerging empirical evidence. *European Review of Agricultural Economics*, 50(3):853–878.

Kansiime, M. K., Tambo, J. A., Mugambi, I., Bundi, M., Kara, A., and Owuor, C. (2021). Covid-19 implications on household income and food security in kenya and uganda: Findings from a rapid assessment. *World development*, 137:105199.

Kugler, M., Viollaz, M., Duque, D., Gaddis, I., Newhouse, D. L., Palacios-Lopez, A., and Weber, M. (2021). How did the covid-19 crisis affect different types of workers in the developing world?

Laborde, D., Martin, W., Swinnen, J., and Vos, R. (2020). Covid-19 risks to global food security. *Science*, 369(6503):500–502.

Laborde, D., Martin, W., and Vos, R. (2021). Impacts of covid-19 on global poverty, food security, and diets: Insights from global model scenario analysis. *Agricultural Economics*, 52(3):375–390.

Leroy, J. L., Ruel, M., Frongillo, E. A., Harris, J., and Ballard, T. J. (2015). Measuring the food access dimension of food security: A critical review and mapping of indicators. *Food and Nutrition Bulletin*, 36(2):167–195.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business and Economic Statistics*, 30(1):67–80.

Mahmud, M. and Riley, E. (2021). Household response to an extreme shock: Evidence on the immediate impact of the covid-19 lockdown on economic outcomes and well-being in rural uganda. *World Development*, 140:105318.

Mallick, D. (2012). Microfinance and Moneylender Interest Rate: Evidence from Bangladesh. *World Development*, 40(6):1181–1189.

Mandal, S. C., Boidya, P., Haque, M. I.-M., Hossain, A., Shams, Z., and Mamun, A.-A. (2021). The impact of the covid-19 pandemic on fish consumption and household food security in dhaka city, bangladesh. *Global Food Security*, 29:100526.

Mehmetoglu, M. (2018). Medsem: A stata package for statistical mediation analysis.

Milovanska-Farrington, S. (2022). Job loss and food insecurity during the covid-19 pandemic. *Journal of Economic Studies*.

Mkupete, M. J., Donath, L. T., and Mugizi, F. M. (2023). Household resilience to food and nutrition insecurity during covid-19 in tanzania. *GeoJournal*, 88(2):1721–1735.

Montoya, M. A., Krstikj, A., Rehner, J., and Lemus-Delgado, D. (2021). Covid-19 and cities: Experiences, responses, and uncertainties.

Mueller, V., Grépin, K. A., Rabbani, A., Navia, B., Ngunjiri, A. S., and Wu, N. (2022). Food insecurity and covid-19 risk in low-and middle-income countries. *Applied Economic Perspectives and Policy*, 44(1):92–109.

Nord, M. (2014). Introduction to item response theory applied to food security measurement: Basic concepts, parameters, and statistics. *Technical Paper. Rome: FAO*, 2014.

Palma, J. and Araos, C. (2021). Household coping strategies during the covid-19 pandemic in chile. *Frontiers in Sociology*, page 162.

Rudolf, R. (2019). The impact of maize price shocks on household food security: Panel evidence from tanzania. *Food Policy*, 85:40–54.

Sadiddin, A., Cattaneo, A., Cirillo, M., and Miller, M. (2019). Food insecurity as a determinant of international migration: evidence from sub-saharan africa. *Food Security*, 11(3):515–530.

Schotte, S., Danquah, M., Osei, R. D., and Sen, K. (2021). The labour market impact of covid-19 lockdowns: Evidence from ghana.

Smith, M. D. and Floro, M. S. (2020). Food insecurity, gender, and international migration in low-and middle-income countries. *Food Policy*, 91:101837.

Smith, M. D. and Wesselbaum, D. (2020). Covid-19, food insecurity, and migration. *The Journal of nutrition*, 150(11):2855–2858.

Swinnen, J. and McDermott, J. (2020). Covid-19 and global food security. *EuroChoices*, 19(3):26–33.

Swinnen, J. and Vos, R. (2021). Covid-19 and impacts on global food systems and household welfare: Introduction to a special issue. *Agricultural Economics*, 52(3):365–374.

Theil, H. (1971). Principles of econometrics.

Tran, V. T., Walle, Y. M., and Herwartz, H. (2020). The impact of local financial development on firm growth in Vietnam: Does the level of corruption matter? *European Journal of Political Economy*, 62(January):101858.

Udmale, P., Pal, I., Szabo, S., Pramanik, M., and Large, A. (2020). Global food security in the context of covid-19: A scenario-based exploratory analysis. *Progress in Disaster Science*, 7:100120.

WHO (2020). *The state of food security and nutrition in the world 2020: transforming food systems for affordable healthy diets*, volume 2020. Food & Agriculture Org.

Wiesmann, D., Bassett, L., Benson, T., and Hoddinott, J. (2009). *Validation of the world food programme s food consumption score and alternative indicators of household food security.* Intl Food Policy Res Inst.

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data mit press. *Cambridge, MA*, 108(2):245–254.

Zeng, D., Alwang, J., Norton, G., Jaleta, M., Shiferaw, B., and Yirga, C. (2018). Land ownership and technology adoption revisited: Improved maize varieties in Ethiopia. *Land Use Policy*, 72(October 2017):270–279.

8 Appendix

8.1 Appendix A: Methodological details of Food Insecurity Experience Scale (FIES)

Food Insecurity Experience Scale (FIES) is an experience-based measure of food insecurity developed by the United Nations Food and Agriculture Organization (FAO). FIES provides an internationally comparable estimate of the prevalence and severity of food insecurity at the individual and household levels. FIES has been validated for cross-cultural use and is one of the main indicators used for monitoring Sustainable Development Goal (SDG) indicator 2.1 'Prevalence of moderate or severe food insecurity in the population' (Ballard et al., 2013; Cafiero et al., 2018).

The FIES module includes eight questions related to households' access to food (see A1). Specifically, respondents were asked if because of lack of money or other resources – they or any member of their households:

1. ... were worried they would not have enough food to eat (WORRIED)?
2. ... were unable to eat healthy and nutritious food (HEALTHY)?
3. ... ate only a few kinds of foods (FEWFOOD)?
4. ... had to skip a meal (SKIPPED?
5. ... ate less than they thought they should(ATELESS?
6. ... household ran out of food(RUNOUT)?
7. ... were hungry but did not eat(HUNGRY)?
8. ... went a whole day without eating(WHDAY)?

The questions were asked for periods over 4 weeks prior to the survey. These questions are designed to capture a range of severity of food insecurity (Nord, 2014), and inquire a respondent about the anxiety not to find enough food, compromises on food variety, quantity, and quality, insufficient food intake, and experience of hunger due to lack of money or other resources (FAO, 2016).

Once the data is collected, the construction of the score involves a series of steps starting from the statistical validation of the data, performed with the official R-package "RM.weights" provided by the FAO. After calculating the Rasch-model, problematic items (questions) with an infit-statistic exceeding 1.3 are dropped from the scale after additional examination of their standard error and number of affirmative responses. Once the model is validated, the number of positive responses given to the 8 items (or the number of remaining items in case some of the items are excluded during cleaning) by an individual is used to classify the household of the respondent into one of the three categories of food (in)security experience: food secure, moderately food insecure and severely food insecure.

For the four "Life with Corona - Africa" countries, the statistical validation processes led to dropping one item for the Uganda data - HEALTHY - and two items for Mozambique - HEALTHY and FEWFOOD. All eight original items endured the statistical tests for the scale calculation in Tanzania and Sierra Leone. After the statistical validation process, the selected items for each country are used to perform an equating to make the results internationally comparable by inserting them into the official Excel template of the FAO. The template provides the final corresponding thresholds for the food security categories based on the respondent's raw score (sum of affirmative responses to the items in the scale) as well as the prevalence rates for the three food insecurity categories.

Table A1: The Food Insecurity Experience Scale (FIES) survey module

FIES items	Uganda	Tanzania	Sierra Leone	Mozambique	Total
1.WORRIED	0.49	0.38	0.85	0.66	0.60
2.HEALTHY	0.41	0.44	0.75	0.57	0.54
3.FEWFOOD	0.65	0.48	0.79	0.72	0.66
4.SKIPPED	0.28	0.30	0.81	0.58	0.50
5.ATELESS	0.44	0.34	0.82	0.64	0.56
6.RUNOUT	0.19	0.18	0.61	0.46	0.36
7.HUNGRY	0.27	0.27	0.68	0.46	0.42
8.WHLDAY	0.08	0.10	0.38	0.17	0.18
Observation	5,960	5,897	6,170	5,897	23,924

Note: The question was asked for the period of 4 weeks prior to the survey. The survey question was framed as: was there a time when - because of lack of money or other resources - you/others in your household —-? The values represent the proportion of respondents that answered "Yes".

Table A2: Number of days per week food groups are consumed in the household

Food groups	Uganda	Tanzania	Sierra Leone	Mozambique	Total
Cereals	6.39	5.97	6.04	6.49	6.22
	(1.3)	(1.3)	(1.5)	(1.4)	(1.4)
Pulses or nuts	4.12	2.50	2.90	1.12	2.66
	(2.2)	(2.1)	(2.0)	(1.7)	(2.3)
Vegetables	5.10	5.47	3.82	5.57	4.98
	(2.2)	(1.6)	(2.4)	(2.4)	(2.3)
Fruits	2.92	3.51	1.99	3.12	2.88
	(2.2)	(2.1)	(1.8)	(2.8)	(2.3)
Meat/fish/poultry/eggs	1.22	2.73	5.22	2.98	3.05
	(1.2)	(2.0)	(1.9)	(2.5)	(2.4)
Milk and dairy products	1.46	2.06	1.62	1.58	1.68
	(2.2)	(2.2)	(2.1)	(2.7)	(2.3)
Sugar/sweets	4.37	4.85	2.05	4.72	3.98
	(2.6)	(2.3)	(2.3)	(2.9)	(2.8)
Oils and fats	2.41	5.32	4.37	5.21	4.33
	(2.1)	(2.0)	(2.3)	(2.6)	(2.5)
Observations	6,033	6,021	6,216	6,000	24,270

Note: standard deviations are in parentheses

Table A3: External support by food insecurity status

	Food secure	Food insecure	Total
Assistance from government	0.06	0.13	0.10
Assistance from charitable org.	0.06	0.10	0.08
Assistance from unknown sources	0.04	0.06	0.05
Any assistance	0.11	0.19	0.15
Remittance from within country	0.15	0.23	0.19
Remittance from abroad	0.06	0.05	0.05
Any remittance	0.17	0.24	0.21

Note: The values represent the proportion of respondents that reported to have received support.

Table A4: External support by country and food insecurity status

	Uganda		Tanzania		Sierra Leone		Mozambique	
	Food secure	Food insecure	Food secure	Food insecure	Food secure	Food insecure	Food secure	Food insecure
Assistance from government	0.07	0.11	0.01	0.01	0.27	0.21	0.05	0.07
Assistance from charitable org.	0.02	0.03	0.06	0.05	0.27	0.19	0.02	0.03
Assistance from unknow sources	0.02	0.02	0.01	0.00	0.21	0.12	0.02	0.03
Any assistance	0.10	0.15	0.07	0.06	0.40	0.32	0.07	0.10
Remittance from within country	0.24	0.32	0.07	0.04	0.50	0.37	0.03	0.03
Remittance from abroad	0.02	0.02	0.01	0.01	0.41	0.10	0.02	0.01
Any remittance	0.25	0.32	0.07	0.04	0.58	0.40	0.04	0.04
Any help	0.31	0.41	0.13	0.09	0.65	0.50	0.11	0.12
Observation	3,341	2,627	4,494	1,458	1,197	4,973	2,530	3,421

Note: The values represent the proportion of respondents that reported to have received support, categorized by food security status.

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Competing interests

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