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The COVID-19 pandemic and food security: Micro-level evidence from Uganda, Tanzania, Sierra Leone and Mozambique

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Abstract
The COVID-19 pandemic caused extensive food insecurity in low-income countries. However, most studies rely on aggregate-level exposure measures, overlooking individual-level heterogeneity and introducing measurement errors that limit causal inference. To overcome these gaps, we examine the impact of COVID-19 exposure on food security in four African countries — Uganda, Tanzania, Sierra Leone, and Mozambique - using large-scale phone survey data collected throughout 2021. We introduce a novel micro-level measure of "COVID-19 exposure" and employ a heteroskedasticity-based IV method to mitigate potential endogeneity concerns. We find that one in two households faced moderate-to-severe food insecurity during this period, with particularly pronounced impacts among households characterized by large family sizes, limited access to public services, fewer assets, and with female, younger, and less educated household heads. Our analysis identifies significant declines in household income in COVID-19 exposed areas as primary drivers of worsened food insecurity. Moreover, vulnerable households often lacked financial support from governments, leading them to adopt harmful coping strategies. Our analysis offers nuanced insights into the mechanisms linking individual pandemic exposure to food insecurity and provides valuable implications for designing targeted policy interventions to protect vulnerable households in low- and middle-income countries.

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1. Introduction

The onset of the COVID-19 pandemic significantly exacerbated risks of poverty and food insecurity in low and middle-income countries (LMICs). The fear of contracting the virus and the countermeasures 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. These challenges put additional stress on already fragile food security conditions in LMICs (Bundervoet et al., 2022; Devereux et al., 2020; Laborde et al., 2021).

In this paper, we study the causal impact of "COVID-19 exposure" on food security outcomes in LMICs in Africa, utilizing micro-level survey data from the *Life with Corona – Africa* research project. The survey collected continuous phone-based household data throughout 2021 in Uganda, Tanzania, Sierra Leone, and Mozambique, resulting in an overall sample of 24,000 responses. To enhance comparability with national populations, each monthly sample was drawn using a stratified random sampling approach, targeting representativeness by gender, age group, and urban-rural location based on national population distributions. We spatially and temporally matched the survey data with external data on government-imposed countermeasures and agroecological variables.

We introduce a novel micro-level measure of "COVID-19 exposure" to examine its causal impact on food security. We use Food Insecurity Experience Scale (FIES) and Food Consumption Score (FCS) to measure food insecurity (Cafiero et al., 2018; WFP, 2024). Our empirical strategy employs a heteroskedasticity-based IV method to address potential endogeneity concerns related to COVID-19 exposure. Furthermore, we identify and evaluate the mechanisms through which individual exposure to the pandemic influences food insecurity, providing a nuanced understanding of its underlying dynamics.

Our findings reveal that food insecurity is highly prevalent in the survey countries. When measured by FIES, approximately 50% of households were classified as moderately or severely food insecure, with prevalence rates ranging from 24% in Tanzania to 77% in Sierra Leone. In terms of FCS, the share of households with inadequate diet is 36% overall, with a rate ranging from 27% in Sierra Leone to 47% in Mozambique. In general, food insecure households tend to be larger in size, have limited access to services, possess fewer assets, and are more likely to be headed by female, younger, and less educated individuals. Both food insecurity indicators are strongly correlated and exhibit significant causal links with household-level exposure to COVID-19, defined as direct infection or proximity to infected individuals. A major mechanism driving worsening food insecurity during the pandemic was reductions in household income.

Our research contributes to understanding how the COVID-19 pandemic affects food insecurity in LMICs. A large body of evidence documents worsened food insecurity globally due to the pandemic, particularly in low-income countries (Agamile, 2022; Bundervoet et al., 2022; Dasgupta & Robinson, 2022; Devereux et al., 2020; Laborde et al., 2021; Tabe-Ojong et al., 2023). However, the evidence is mixed in some aspects, such as in terms of the resilience of agrifood systems to provide food supply (Headey et al., 2022), but also in terms of the resilience of households to shift diets to overcome food shortages and rising food prices (Mkupete et al., 2023). Variations in evidence arise from differences in data collection modes, measurement methods, timing of data collection, and respondent heterogeneity (Gourlay et al., 2021; Swinnen & Vos, 2021). Most studies on the pandemic and food insecurity rely on aggregate-level exposure measures, such as policy stringency, and/or focus primarily on temporal changes (e.g., before and after the pandemic) (e.g. Abay et al., 2023; Ahmed et al., 2023). However, these approaches overlook individual-level heterogeneity, limit causal inference, and introduce measurement errors due to variations in compliance.

This paper offers several contributions to the existing literature. First, it introduces a novel measure of individual-level exposure to COVID-19, capturing micro-level variation often overlooked in macro-level indicators. Second, it employs the full set of FIES items, enabling the statistical validation of food insecurity categories through a standardized methodology. Third, by combining the FIES with FCS, the analysis provides a more comprehensive understanding of food insecurity. Fourth, using a heteroskedasticity-based IV method, we tease out the causal link between COVID-19 exposure and food security. Finally, the study presents a unique dataset based on harmonized, phone-based survey data collected across four African countries throughout 2021 – a period during which the pandemic had progressed beyond its initial shock – allowing for meaningful cross-country comparisons and insights into the protracted effects of COVID-19.

The rest of the paper is structured as follows: Section 2 presents a summary of the literature on the link between the COVID-19 pandemic and food security. Section 3 describes the data, measurement of the key variables and the econometric approach. Section 4 presents the main results and the underlying mechanisms. We discuss the results in Section 5 before we conclude the paper.

2. Background to food insecurity and countries of study

2.1 Evidence on COVID-19 and food security

The outlook of worsening global food insecurity was abundant as soon as the implications of the pandemic-bound mobility restrictions became clearer (Laborde et al., 2020). Over the subsequent months and years, a detrimental impact of the pandemic on food insecurity has realized itself to a substantial degree, not only in LMICs but also in developed countries (Bundervoet et al., 2022; Ismail et al., 2023; Laborde et al., 2021; Milovanska-Farrington, 2023; Swinnen & Vos, 2021). Vulnerable and poor households in LMICs, who already were at substantial risk of food insecurity before the start of the pandemic, were hit the hardest since the start of the crisis (Akalu & Wang, 2023; Swinnen & McDermott, 2020). COVID-19 undermined food insecurity on the supply-side by disrupting food systems and trade, followed after some time by increasing food prices, and on the demand-side, through the impacts of the countermeasures on incomes shocks and job losses (Devereux et al., 2020).

The reduced physical access to food due to closed roads and markets is one of the key channels through which the pandemic affects food insecurity. The closure of small markets worsened the availability of fresh food, turned the consumers to buy more expensive food from supermarkets, and eventually worsened the quality of household nutrition (Devereux et al., 2020). The evidence points to a much more strenuous situation for urban poor households who tended to be residing in informal, densely populated areas, and who obtained most of their daily food from small markets (Chirisa et al., 2022; Montoya et al., 2021). Many households substituted fish and meat with poultry, eggs, and dried fish during the pandemic (Mandal et al., 2021). For example, in Dhaka, Bangladesh, the percentage of residents purchasing fish from wet markets dropped from 80% before the pandemic to 45%. Such closures of markets also affected the input markets, such as seeds and fertilizers, further affecting the food value chain. Additionally, mobility restrictions limited people's ability to provide inter-household support, a critical form of assistance commonly relied upon during times of crisis (Balana et al., 2023; Palma & Araos, 2021).

The rise in food insecurity was consistently driven by a loss of income and jobs, which in turn resulted mainly from the countermeasures imposed by governments (Balana et al., 2023; Egger et al., 2021; Josephson et al., 2021). For example, Bundervoet et al. (2022) found that food insecurity was closely related to job and income losses at the peak of the first waves of the pandemic, using household data from 31 low- and middle-income countries. They show that pandemic-induced job and income losses resulted in about 15% of the household sample experiencing severe food insecurity. In country-specific studies in developing countries, a larger share of female, young, less educated, and urban workers were found to have stopped working, which led to a large real income shock and jeopardized household food insecurity (Agamile, 2022; Arndt et al., 2020; Kugler et al., 2021; Mandal et al., 2021).

In the early phases of the pandemic, food prices remained relatively stable despite short-term trade disruptions (Engemann et al., 2022). In some cases, prices even dropped due to the decline in demand from the hospitality industry and low oil prices, which reduced transportation costs (Beckman et al., 2021). However, around the end of 2020, global food prices started rising, and the adverse price effects on food security became noticeable in import-dependent and integrated markets (Dietrich et al., 2022). With the persistent restrictions and the rising food prices, the adverse effects of the pandemic on food insecurity became more apparent. Some country studies show that pandemic-related government cash transfers exacerbated food stockpiling practices, contributing 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 support to households and tax reliefs on top of the existing public transfers which proved extremely effective in easing food insecurity pressures for beneficiary households (Abay et al., 2023; Ahmed et al., 2023; Stojetz et al., 2024). In addition, the governments in sub-Saharan African countries minimized restrictions related to agrifood systems (Devereux et al., 2020; Ismail et al., 2023). As a result, the agrifood value chains remained resilient to the shock associated with the pandemic (Engemann et al., 2022; Hirvonen et al., 2021).

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., 2023). 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 & Floro, 2020; Smith & Wesselbaum, 2020; Beck et al., 2024).

Despite a large body of research on the effects of COVID-19 on food insecurity, several methodological gaps remain. First, we underscore the importance of capturing micro-level exposure to COVID-19, rather than relying solely on aggregate indicators such as the Oxford Stringency Index (Hale et al., 2021; Regassa et al., 2025). While most existing studies draw on phone survey data and some incorporate national-level stringency measures, few include respondent-level perceptions of exposure, an important omission given the heterogeneous impacts of the pandemic. Although individual-based measures may be affected by limited testing, awareness, or stigma, well-designed questions capturing various forms of subjective exposure can provide valuable insights into household-level conditions (e.g. Mueller et al., 2021). Second, food insecurity in phone surveys is often assessed using items from FIES. However, many studies rely on a subset of FIES items rather than employing the full scale, thereby limiting interpretability and weakening the accuracy of food insecurity classification (e.g. Bundervoet et al., 2022; Dasgupta & Robinson, 2022; Headey et al., 2022). Full use of the FIES, supported by statistical validation, is essential for precise measurement (Cafiero et al., 2018). Moreover, integrating FIES with complementary indicators, such as FCS, enables a more multidimensional understanding of food insecurity, especially within the constraints of phone-based data collection. Finally, much of the literature to date focuses on correlations between food insecurity and COVID-19-related shocks, such as income or employment loss, with limited attention to causal identification (e.g. Agamile, 2022; Bundervoet et al., 2022). This study seeks to address these gaps by offering a more comprehensive and methodologically rigorous analysis of food insecurity during the COVID-19 pandemic.

2.2 Study countries

The selection of countries included in this study – Uganda, Tanzania, Sierra Leone, and Mozambique – was motivated by variations not only in income levels and geographic representation of East and West Africa but also in political contexts and pandemic policies. In 2020, among the four low- and lower-middle-income countries analyzed, Tanzania had the highest per capita GDP at approximately 1076 USD, while Mozambique had the lowest at 449 USD (Table 1). The rural population is predominant in all four countries, with Uganda having the highest level, at approximately three-quarters of the total population. However, the contribution of agriculture to GDP is only in line with the rural population ratio in Sierra Leone, while in the other three countries, the contribution of agriculture is much lower – approximately a quarter to GDP. Prior to the pandemic, these countries experienced solid economic growth; however, all of them, with the exception of Tanzania, reported negative real GDP growth in 2020.

Table 1: Key demographic, economic, and COVID-19 related indicators, 2020

Country	Uganda	Tanzania	Sierra Leone	Mozambique
Population, million	45.7	59.7	8.0	31.3
Rural population, % of total	75	65	57	63
Real GDP growth in 2017-19, %	6.7	6.9	4.2	3.1
Real GDP growth, %	-1.4	4.8	-2.0	-1.2
GDP per capita, USD	822	1,076	509	449
Agriculture, % to GDP	*24*	*27*	*59*	*26*
Stringency index, average 2020-21	62	18	39	52
COVID fiscal measures, % to GDP	2.2	…	7.6	4.9

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

As is the case with most countries around the globe, all four countries introduced economic and mobility restrictions at the outset of the pandemic. The restrictions included limitations on domestic and international travel, the closure of schools, shops, and restaurants, and bans on large gatherings. These restrictions were initially implemented between March and May 2020 and subsequently eased or re-imposed in accordance with the evolving situation regarding the prevalence of cases of the novel coronavirus. Tanzania experienced the shortest period of such restrictions, with the country opening up within four months; other countries maintained varying degrees of restrictions throughout 2021. The Stringency Index, developed by Oxford University (Hale et al., 2021), provides a useful summary of the levels and duration of these restrictions. Except for Tanzania, the other three countries implemented relatively high levels of restrictions, with average scores ranging from 39 to 62 out of a maximum of 100 (Figure A1).

The governments of the four countries played an important role in supporting their populations during the pandemic, but the extent of this support was less pronounced than in higher-middle and higher-income countries (Stojetz et al., 2022). The additional spending or liquidity provided by governments in the four countries in response to COVID-19 since the beginning of 2020 were not large, averaging about 5% of GDP (excluding Tanzania)[1], while the global average was at around 10% of GDP (IMF, 2021).

Prior to the advent of the global pandemic, these four countries exhibited a considerable prevalence of food insecurity. The Food and Agriculture Organization (FAO) estimated that the prevalence of undernourishment in these countries ranged from 26% of the population in Sierra Leone to 41% in Uganda in 2017, with Mozambique and Tanzania falling in between at 28% and 31%, respectively – all well above the African average of 20% (FAO et al., 2020). The food security of these countries before the pandemic was adversely affected by a number of factors, including fluctuations in the price of staple foods, adverse weather conditions and regional conflicts (FAO et al., 2019; Gebre & Rahut, 2021; Rudolf, 2019). The advent of the pandemic

[1] Data on Tanzania were not available from the IMF.

had exacerbated these existing challenges, placing additional pressure on food security, particularly in the context of the surge in global food prices observed since the end of 2020.

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: Uganda, Tanzania, Sierra Leone, and Mozambique, between January and December 2021. Using repeated cross-sections, the survey collected data from 500 new, randomly selected respondents per month per country. In total, the dataset contains information from 24,000 households collected continuously throughout 2021 across these four countries. For ease of reference, we occasionally refer to each month of data collection as a "round" – for example, Round 1 refers to January, Round 2 to February, and so on – though data were collected monthly.

In all countries, the sampling frames used were large databases generated over the past decade through random digit dialing and/or face-to-face interviews. In Mozambique, the data were collected by the survey company Intercampus, which drew the sample from a large database of around 600,000 mobile phone contacts. In Sierra Leone, Tanzania, and Uganda data were collected by BRAC International[3]. 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 include respondents from all regions, they are not nationally representative. Therefore, in each round, we followed a stratified random sampling procedure to generate a sample whose distribution reflected the national population by gender, age group, and location. However, we could not fully reach this goal due to two limitations.

First, mobile phone subscriptions are not universal in any of these countries. In Sierra Leone and Tanzania, there are about 80 subscriptions per 100 people. The subscription rate is much lower in Uganda and Mozambique (61 and 49 subscriptions per 100 people, respectively)[4]. Second, given the large sample size of the study, the databases did not contain enough respondents to maintain sample balance at the national level (e.g., many of the BRAC projects focus on women). Although the results cannot be generalized to the country level, the large sample size and the consistency of survey timing and structure across the four countries provide novel insights into how the response to COVID-19 has affected food security in African countries and beyond.

The LwC-A survey questionnaire includes information on basic socio-demographic characteristics, housing and asset ownership, and household economic well-being such as food security and food consumption. It also 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 survey modules were kept short to suit phone

[2] For details of the LwC-A project, see https://lifewithcorona.org/africa.
[3] The website of BRAC International is https://bracinternational.org/.
[4] World Bank: https://databank.worldbank.org/Mobile-penetration-Rates-vs-pop/id/ea19059d#

interviews which averaged 17 minutes and most of the questions and response options were simplified (e.g., using Yes/No format).

3.2 Main variables

We measure food insecurity using FIES and FCS. FIES is an experience-based measure of food insecurity developed by the FAO. It 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 key indicators used to monitor Sustainable Development Goal (SDG) indicator 2.1 (Ballard et al., 2013; Cafiero et al., 2018).

The FIES module in the LwC-A survey includes eight questions related to household access to food in the last four weeks (see Appendix A1). These questions are designed to capture the range of severity of food insecurity (Nord, 2014) and ask respondents about their worry of not having enough food, compromising on food variety, quantity, or quality, insufficient food intake, and experiencing hunger due to lack of money or other resources (Cafiero et al., 2018). Typically, an aggregate food insecurity score is used in empirical analysis rather than the individual items (as presented in Table A1). The first step in constructing such a score is to statistically validate and standardize the data using the Rasch model (Nord, 2014). Statistical validation was conducted jointly for the four countries using FAO's online application (FAO, 2024). The initial eight-variable model exceeded suggested range values for *infit* and *outfit* statistics, indicating poor model fit[5]. By eliminating the ATELESS variable, we adopted a seven-variable model that met the fit statistical requirements and achieved a high reliability score. The calculated model classified food insecurity into three levels: mild (scores 1-3), moderate (scores 4-5), and severe (score 7), with scores of 4 or higher indicating food insecurity. Appendix A presents technical details of these steps.

Figure 1 shows the proportion of households experiencing food insecurity in the four countries. Overall, about half of the households were moderately or severely food insecure. However, considerable variation exists between countries. The proportion of (moderately and severely) food insecure households was lower in Uganda (35%) and Tanzania (24%). In contrast, Sierra Leone faced the most severe situation, where more than 75% of households were food insecure. Mozambique falls in between, with 56% of households experiencing food insecurity.

[5] Infit statistics assess the assumption of equal relation to food security, while outfit statistics are used to flag outliers and unexpected response patterns.

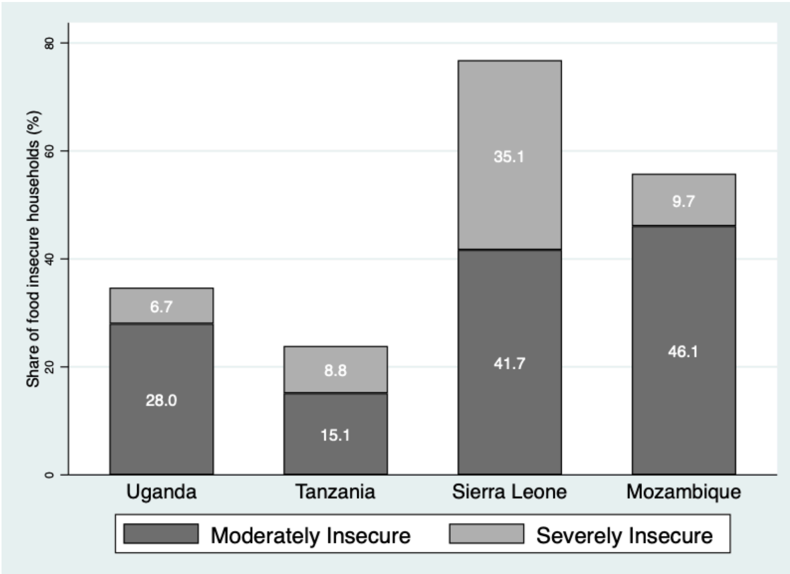

Figure 1. Prevalence of food insecurity by country based on FIES
Source: Life with Corona – Africa survey 2021.
Note: Food insecurity indicators are generated based on the Food Insecurity Experience Scale (FIES).

The second outcome variable is based on the Food Consumption Score (FCS). Compared to the widely used Household Dietary Diversity Score, FCS not only accounts for 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 FCS data are based on questions about the type and frequency of food intake over the seven days prior to the survey. The FCS is calculated as a weighted sum of the number of days per week that different food groups are consumed, with weights representing the relative caloric contribution of the food groups consumed (Wiesmann et al., 2009)[6]. For each household, the score ranges from 0 to 112, with higher scores indicating better diet quality/adequacy. Based on this score, households are then grouped into three categories: poor consumption (FCS from 0 to 28 points), borderline consumption (28-42), and acceptable consumption (42-112)[7]. Figure 2 shows that 36% of households have less than adequate (borderline or poor) dietary intake in the four countries surveyed. However, there is considerable variation between and within countries. Among the four countries, Mozambique has the highest proportion of households with inadequate diet (47%), while the other three countries have comparable proportions (27-38%).

Overall, food insecurity measured using FIES and FCS is consistent, except in Sierra Leone, where the FCS shows a slightly less severe food insecurity condition compared to FIES. This discrepancy in the indicators for Sierra Leone arises due to its population's higher consumption of meat, fish, eggs, and milk – the categories with higher weight in the FCS. Despite this variation, the two food security indicators together offer valuable insights into food security

[6] 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).
[7] Different cut-offs at 21 and 35 are commonly used. However, a large share of the households in our data consume sugar and oil which justified the use of higher cut-offs (WFP, 2024).

conditions in the surveyed countries. FIES measures how individuals perceive and experience food insecurity over the last four weeks, capturing a range of situations that increase by severity, while FCS captures dietary diversity and energy adequacy over the past week. Together, these indicators provide a comprehensive assessment, addressing both access limitations and dietary quality, and offer a nuanced understanding of food security during the pandemic.

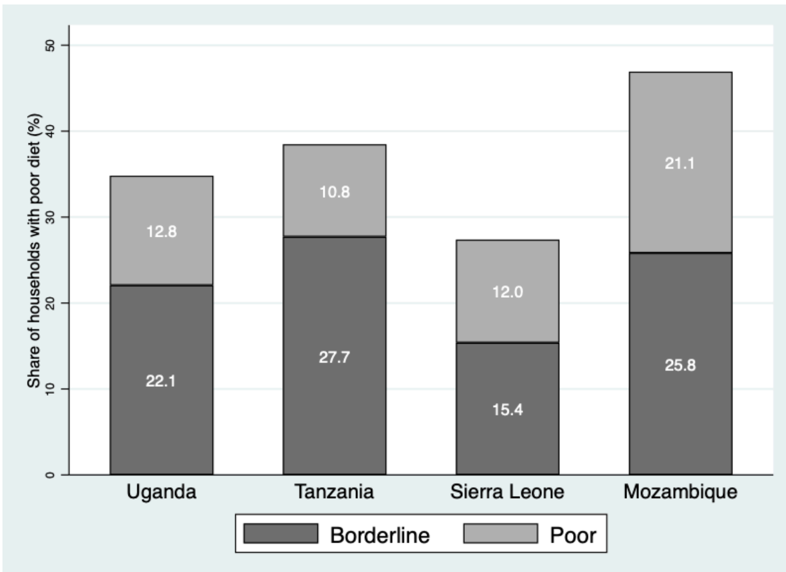

Figure 2. Prevalence of food insecurity by country based on FCS
Source: Life with Corona – Africa survey 2021.
Note: Diet intake indicators (borderline & poor) are derived from the Food Consumption Score (FCS).

Our main explanatory variable is the *COVID-19 exposure* indicator. We generated this indicator from four questions included in the survey with trichotomous (yes/no/don't know) responses. The questions were: 1) "Have you ever had the coronavirus, or do you think you have ever had the coronavirus?"; 2) "In the past 14 days, have you met (seen) someone 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 constructed as a binary variable, taking a value of one if the respondent answered affirmatively to at least one of these four questions, and zero – otherwise (see Table A2). 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 produces a continuous indicator that differentiates the intensity of exposure, the results produced by the two approaches remained qualitatively similar. Therefore, for ease of interpretation, we report the basic results using the binary COVID-19 exposure indicator. The results using the COVID-19 exposure index (PCA) are presented and discussed in Section 4.3.

In addition to the LwC-A survey data, we use the stringency index, a measure of policy stringency related to COVID-19 countermeasures. This index, derived from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021), reflects the intensity of government-imposed measures to curb the pandemic. OxCGRT collected data during 2020-2023 on various policy actions and constructed the stringency index based on nine key indicators: school closures, workplace closures, cancellation of public events, restrictions on public gatherings, public transport closures, stay-at-home requirements, public information campaigns, and restrictions on both nationwide and international movements. Each indicator is scored from 0 to 100, with 100 representing the strictest restrictions. See Figure A1 for the dynamics of the stringency index on a monthly basis for the four countries in 2021. The overall stringency index is calculated as the mean score of these nine indicators (Figure A2). It was updated daily from early 2020 till May 2023 and reported at the country level, providing a dynamic measure of policy stringency throughout the pandemic.

3.3. Descriptive statistics for control variables

We continue describing our data by comparing the demographic, economic, and location characteristics of food-secure and food-insecure households, classified using the FIES indicator (Table 2). The last column shows the mean difference tests. Panel A provides information on the mean value of the food consumption score and the proportion of households with poor dietary quality (per FCS). The first row shows that the average FCS of the whole sample is 51.4 (out of a possible 112) and that 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% of food secure households have poor consumption, which is significantly lower than the share of food insecure households with poor consumption (23%). Two points emerge from these statistics. First, our two indicators of food insecurity – FIES and FCS – are strongly correlated. Second, the prevalence of poor consumption among food secure households and the prevalence of adequate consumption among food insecure households suggest that FCS and FIES are complementary indicators of food insecurity.

The final row of Panel A indicates that 88% of households across the surveyed countries resorted to negative coping strategies, including depleting savings, accumulating debt, selling productive assets, and reducing essential non-food expenditures, such as healthcare and education. Among food insecure households, the adoption of these harmful strategies was even more prevalent, with 95% of such households reporting their use. This finding aligns with the study by Baliki et al. (2025), which demonstrates that the adoption of these strategies is more common among poorer households and is causally linked to government-imposed movement restrictions in response to COVID-19.

Panel B of Table 2 presents information on covariates related to individual and household characteristics. The means comparison tests show that the distributions of most of these covariates differ significantly by 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 female, younger, and less educated heads/respondents. The distribution of the asset index – an index of durable assets generated by PCA from individual assets owned by households – indicates that food insecurity is more prevalent among households with fewer assets.

Table 2. Descriptive statistics by food security status

Variable	[1] Total	[2] Food Secure	[3] Food Insecure	[4] Mean diff.
Panel A: Alternative welfare indicators				
Food consumption score	51.4	57.3	45.1	12.2***
Poor dietary quality	0.14	0.06	0.23	-0.17***
Negative coping strategy used	0.88	0.82	0.95	-0.14***
Panel B: Individual & household characteristics				
Respondent is female	0.55	0.51	0.59	-0.07***
Age of respondent in years	36.61	37.78	35.35	2.43***
Education of respondent in years	9.54	10.13	8.90	1.23***
Number of HH members under 18	2.70	2.55	2.87	-0.31***
Number of HH members over 60	0.33	0.27	0.40	-0.12***
Number of HH members, 18-60	3.09	2.91	3.30	-0.37***
Access to drinking water	0.22	0.30	0.13	0.16***
Access to electricity	0.74	0.81	0.65	0.14***
Household owns radio	0.72	0.79	0.65	0.20***
Household owns TV	0.59	0.69	0.49	0.97***
Asset index (PCA)	0.00	0.46	-0.50	0.04***
Panel C: COVID-19 related indicators				
COVID-19 exposure	0.19	0.21	0.17	0.04***
Stringency index	42.6	40.3	45.1	-4.81***
Official assistance received	0.16	0.12	0.19	-0.08***
Inter-household remittances received	0.21	0.20	0.22	-0.02***
Any support received	0.28	0.26	0.31	-0.05***
Panel D: Location characteristics				
Rural household	0.34	0.33	0.34	-0.01
Capital city household	0.16	0.18	0.14	0.05***
Peri-urban household	0.21	0.20	0.22	-0.02***
Other urban household	0.30	0.29	0.30	-0.02***
Rainfall quantity (z-score)	-0.14	-0.15	-0.14	-0.02
Soil terrain (z-score)	0.00	0.02	-0.03	0.05***
Log (road density)	5.41	5.11	5.72	-0.61***
Log (distance to market in km)	3.02	3.00	3.04	-0.05**
Uganda	0.25	0.31	0.18	0.13***
Tanzania	0.25	0.36	0.12	0.24***
Sierra Leone	0.26	0.12	0.41	-0.28***
Mozambique	0.25	0.21	0.29	-0.08***
Observations	23,924	12,421	11,503	23,924

Source: Life with Corona – Africa survey 2021.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel C examines COVID-19 related indicators. Interestingly, food insecure households reported lower COVID-19 exposure (17%) compared to food secure households, potentially due to reduced mobility, lower testing rates, or different geographical distributions. Despite lower reported exposure, food insecure households experienced more stringent COVID-19 containment measures, suggesting disproportionate impacts from lockdowns and restrictions. Pandemic assistance appears pro-poor: approximately 20% of food insecure households received official aid from government and charitable organizations, compared to 12% of food-secure households. Inter-household transfers, including overseas remittances, were more significant, with 21% of all households receiving such support, primarily from within countries. The higher levels of both formal assistance and inter-household remittances for food insecure households may indicate either targeted aid or greater vulnerability during the pandemic.

Panel D presents information on location characteristics. Column 1 shows the share of households from each location in the total sample. Of the total sample, the shares of households from rural areas, the capital, small urban centers, and peri-urban areas are 34%, 16%, 30%, and 21%, respectively. Similarly, columns 2 and 3 show the shares of households from the different locations in the two food security categories. For example, column 2 shows that households from the capital city account for 18% of the food secure households – disproportionately more than their contribution to the total sample pool. Overall, we find that there is systematic spatial variation, with households in small towns and peri-urban areas being significantly more likely to be food insecure than households from the capital. Similarly, the distribution across countries shows that the proportion of food insecure households is much higher in Sierra Leone and Mozambique than in Uganda and Tanzania.

These differences in household and location characteristics point to the need to control for a number of household and community-level variables in the analysis to mitigate potential sources of selection bias. That is, while the mean difference test results of the outcome variables presented in this subsection are informative, they cannot be used to draw causal inferences regarding the effect of COVID-19 exposure on food insecurity, as they do not account for potential confounding factors. We employ a heteroscedasticity-based identification strategy to address potential endogeneity concerns.

3.4. Econometric approach

We model the outcome variables (F_{icm}) – food insecurity – reported by household i in a country c during month m as a function of COVID-19 exposure (C_{icm}), and specify the basic econometric model as:

$$F_{icm} = \alpha + \beta C_{icm} + \gamma' X_{icm} + FE_c + FE_m + \varepsilon_{icm} \tag{1}$$

where X_{icm} 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 include urbanization level of the place of residence, road density, proximity to the nearest market, and agro-ecological variables such as precipitation and soil terrain z-scores. Furthermore, we include country (FE_c) and time (FE_m) fixed effects to control for observable and unobservable heterogeneity across space and time. While the country fixed effects control for observable and unobservable economic, demographic, agroecological, and other characteristics associated with the countries, the time fixed effects may capture aggregate shifts in the outcome variables or correlated shifts in the right-hand side variables. The last term in the equation, ε_{icm}, is the random error term. Standard errors are clustered at the district level[8].

In equation 1, β captures the main relationship of interest: the effect of COVID-19 exposure on food insecurity. Our central hypothesis is that COVID-19 exposure worsens food insecurity as fear of the virus and mobility restrictions due to the countermeasures contribute to incomes decline, and/or job losses, leading to lower food consumption. Hence, we expect β to be 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, $corr(C_{icm}, \varepsilon_{icm}) \neq 0$ and β 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 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_{icm} represents the vector of exogenous variables and C_{icm}, representing COVID-19 exposure, is endogenous. In the first stage, the endogenous variable, C_{icm}, is regressed on the exogenous variables, Z_{icm}, and the vector of residuals is retrieved. Next, the instruments are obtained as $(Z_{icm} - E(Z_{icm}))$, where $E(Z_{icm})$ is the expected value of Z_{icm}. The basic requirement of the model is that there is heteroscedasticity in the residual, $\underline{\in}$ (i.e., $cov(\underline{\epsilon}^2, z_{icm}) \neq 0$). 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 (e.g., 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_{icm}) and then retrieve the residuals ($\underline{\in}$). The included exogenous variables include location-level characteristics (urban/rural indicator, road density, distance to the nearest market, and various agro-ecological variables including precipitation z-score, soil terrain, and stringency score). The Breusch-Pagan test rejects the null hypothesis of homoscedasticity at the 1% level for COVID-19 exposure (Table A3).

Following the literature, we selected the exogenous variables based on their relevance to either the endogenous regressor (COVID-19 exposure) or the outcome variable (food insecurity) and

[8] This choice to cluster at district level is informed by the administrative structures across the four countries, where the district is the primary unit of local governance and service delivery. Additionally, the number of districts (in contrast to country or regions) is sufficiently large to support reliable statistical inference.

the resulting residual is heteroscedastic. Furthermore, IV diagnostic 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 minimum 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.

Our empirical strategy is designed to address the key challenges of causal identification, measurement error, and individual-level heterogeneity. By employing a heteroskedasticity-based identification strategy, we account for potential endogeneity in COVID-19 exposure. Our use of a micro-level exposure indicator improves measurement precision relative to aggregate proxies, reducing bias from variation in policy compliance. Finally, the use of detailed household-level data and complementary food insecurity measures allows us to capture meaningful heterogeneity in both exposure and outcomes.

4. Results

4.1. COVID-19 exposure and food insecurity

To set the stage, we first estimate the association between COVID-19 exposure and the food security indicators using a Linear Probability Model (LPM)[9]. Results presented in columns 1 and 3 of Table 3 indicate that COVID-19 exposure is positively associated with food insecurity.

As previously discussed, however, COVID-19 exposure is endogenous in the models explaining food insecurity. To address this issue, we utilize a heteroscedasticity-based identification strategy (IV-2SLS), employing relatively exogenous variables to instrument COVID-19 exposure (Lewbel, 2012). The regression results for food insecurity based on IV-2SLS estimates are presented in columns 2 and 4 of Table 3 for FIES and FCS, respectively. The results demonstrate that exposure to COVID-19 has caused an increase in the likelihood of household food insecurity. On average, households exposed to COVID-19 are about 7 percentage points more likely to be food insecure than non-exposed households.

The results of the ordinary least squares (OLS) regressions and the IV (2SLS) estimations are largely consistent. However, the coefficients of the COVID-19 exposure are generally higher for the IV estimates than their corresponding values from the OLS regressions. These differences are consistent with the presence of measurement error, which is to be expected in retrospective data from household surveys. While measurement errors can lead to an attenuation bias towards zero in OLS and LPM coefficients (Theil, 1971), IV approaches often mitigate such a problem (Gujarati, 2002). Overall, we argue that COVID-19 exposure increases the likelihood of food

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

insecurity across the surveyed countries. The fear of contracting the virus and/or the physical restrictions imposed to contain the virus has led to a notable decline in food security. These findings align with previous studies conducted in African countries, which have shown that individuals with close exposure to infected persons experienced higher incidences of food insecurity and income shocks (Kansiime et al., 2021; Mueller et al., 2022).

Table 3. COVID-19 exposure and food insecurity

	[1]	[2]	[3]	[4]
	Food insecurity (FIES)		Food insecurity (FCS)	
	OLS	**IV (2SLS)**	**OLS**	**IV (2SLS)**
COVID-19 exposure	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
	(0.000)	(0.000)	(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***	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Number of household members, over 60	0.027***	0.027***	0.030***	0.030***
	(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***	-0.030***	-0.029***
	(0.013)	(0.013)	(0.009)	(0.009)
Stringency index 30-day average	0.035	0.035	-0.063	-0.062
	(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	0.010	0.021
	(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	0.398***	0.402***	0.234***	0.238***
	(0.033)	(0.032)	(0.018)	(0.018)
Regional FE	yes	yes	yes	yes
Survey FE	yes	yes	yes	yes
Constant	0.267**	0.241**	0.365*	0.355*
	(0.106)	(0.105)	(0.187)	(0.186)
Observations	23,898	23,898	23,898	23,898
R2	0.270	0.269	0.122	0.119
Adjusted R2	0.268	0.267	0.120	0.118
IV DIAGNOSTICS:				
Kleibergen-Paap LM statistic		16.21		16.21
Kleibergen-Paap p-value		0.01		0.01
Cragg-Donald test		536.1		536.1
Hansen-J test		0.924		6,027
Hansen-J p-value		0.968		0.304

Source: Life with Corona – Africa survey 2021.

*Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Food insecurity (FIES) is a binary variable generated from the Food Insecurity Experience Scale (FIES). The variable takes a value of 1 if a household is moderately or severely food insecure, zero otherwise; Food insecurity (FCS) is a binary variable derived from the Food Consumption Score (FCS). Estimates of regional and survey fixed effects are not reported for brevity.*

The results presented in Table 3 also demonstrate that food insecurity is significantly correlated with numerous other covariates. Younger and less educated respondents are more likely to experience food insecurity compared to their respective counterparts. As anticipated, food insecurity is 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 a more energy-dense diet than households from the reference country, Uganda.

4.2. Transmission mechanisms

The main result shows that exposure to COVID-19 increases the likelihood of food insecurity. In this section, we highlight a major mechanism that is likely to underlie this basic finding – a decline in income. In our survey, we asked respondents whether their income had declined since the onset of COVID-19. Figure 3 shows that, from the onset of COVID-19 to the time of the interview, the income of more than three-quarters of households had declined. 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 were less affected. Similar effects of the pandemic on household income in the survey countries were reported in other studies (e.g. in Kansiime et al., 2021; Mueller et al., 2022).

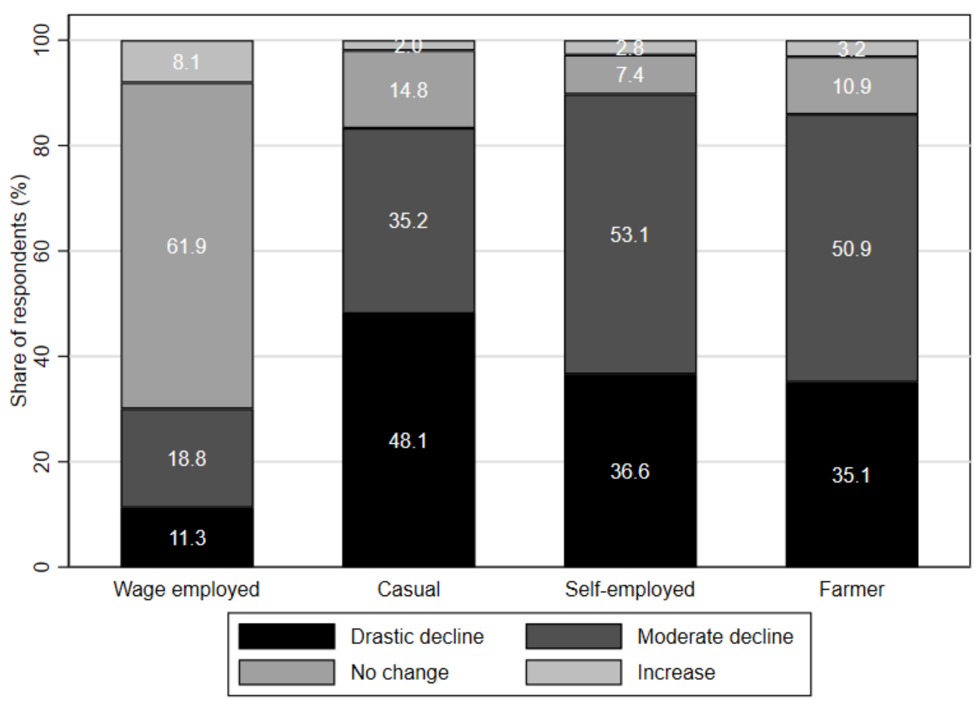

Figure 3. Change in income since the start of the pandemic by type of employment
Source: Life with Corona – Africa survey 2021.

To further examine the link between our measures of COVID-19 exposure, the outcome variables, and the underlying mechanism (negative income shock), we conducted a simple statistical mediation analysis. This method involves quantifying the indirect effect of an independent variable (COVID-19 exposure) on the dependent variable (food insecurity) through a third variable called the mediator (decline in income). This analysis would reveal to us whether the adverse impact of the pandemic on food insecurity could indeed be (partly) due to the indirect influence of income shock. We perform a mediation analysis using the structural equation modeling (SEM) framework (Mehmetoglu, 2018). Income shock 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 result of the mediation analysis presented in Table 4 shows that negative income shock and the independent variable (COVID-19 exposure), are associated positively with food insecurity. It also shows that COVID-19 exposure is positively correlated with income shock. The ratio of indirect to total effect (RIT, %) indicates that 11-17% of the effect of COVID-19 exposure on food insecurity is mediated by the income shock. 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 4. Results from mediation analysis

	[1] Food insecurity (FIES)	[2] Food insecurity (FCS)
Income shock on food insecurity	0.145***	0.077***
	(0.006)	(0.005)
COVID-19 exposure on food insecurity	0.027***	0.024***
	(0.008)	(0.006)
COVID-19 exposure on income shock	0.038***	0.038***
	(0.008)	(0.008)
RIT - Income shock	17.3%	11.1%
Controls	yes	yes
Observation	23,366	23,366

Source: Life with Corona – Africa survey 2021.
*Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; RIT: Indirect effect / Total effect.*

4.3. Sensitivity Analysis

We assess the robustness of the main 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 PCA[10]. The results presented in Panel A of Table 5 using IV-2SLS indicate that the COVID-19 exposure index increases the propensity of food insecurity – consistent with the result in Table 3.

Second, the binary outcome variables used for the main result are each generated from non-binary indicators. In this part, we test the sensitivity of the main result using the continuous (non-binary) versions of the outcome variables. For FIES, we use a raw parameter score, which is generated as a part of the data validation (see Appendix A1 for detailed description). For FCS, we use the raw FCS score which ranges from 0 to 112 depending on the type and frequency of food groups consumed. Panel B of Table 5 shows that exposure to COVID-19 increases the probability of experiencing food insecurity, measured using FIES raw score parameter. For FCS, the COVID-19 exposure index appears with negative and statistically significant coefficients indicating that exposure to COVID-19 reduces the FCS score of households, which is consistent with our main results.

Table 5. Alternative measurements of COVID-19 exposure and food security indicators

	Panel A		**Panel B**	
	[1]	**[2]**	**[3]**	**[4]**
	Food insecurity (FIES)	**Food insecurity (FCS)**	**Food insecurity (FIES)**	**Food insecurity (FCS)**
Covid-19 exposure	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	23,898
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	0.000	0.000	0.010	0.000
Cragg-Donald test	1133.39	1133.39	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

Source: Life with Corona – Africa survey 2021.
*Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;* In Panel A, the food insecurity indicators are binary variables. *Food insecurity (FIES) takes a value of 1 if a household is moderately or severely food insecure, zero otherwise; Food insecurity (FCS) takes a value of 1 if a household's diet is poor. In Panel A, the COVID-19 exposure indicator is generated by combining the four individual COVID-19 exposure variables using principal component analysis (PCA). In Panel B, the outcome variables are continuous - FIES raw score parameter and FCS scores, respectively. The COVID-19 exposure indicator is a binary variable that takes a value of 1 if any of the four individual exposure variables are answered in affirmative, zero otherwise. Estimates of regional and survey fixed effects are not reported for brevity.*

Third, although the two outcome variables are binary, the initial analysis employed an ordinary least squares (OLS) model, a linear approach which treats these outcomes as continuous. 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 & Pischke, 2009; Caudill,

[10] The reduced sample size in Panel A is due to missing observations in the PCA calculation of COVID-19 exposure. To address concerns about potential bias from missing data, we re-estimated the model in Panel B using only the sub-sample of respondents with non-missing values across all four questions. The results are qualitatively consistent with the main findings (see revised Table A4).

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 6 from using standard logit model regression indicate that the basic results remain robust and do not seem to be driven by the non-linear nature of the outcome variables.

Panel B of Table 6 reports the results from the categorical versions of the outcome variables. For FIES, 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 quality; cat.2 = borderline diet quality; and cat.3 = poor diet quality. Due to the ordered nature of both variables (larger numbers represent worse food security), the reported results are based on an 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 by 0.2 and 0.1 respectively for FIES and FCS, given all the other variables in the model are held constant at mean values. The marginal effects corresponding to these estimates are presented in Table A5 in the Appendix.

Table 6. Results from using limited dependent variables model

	Panel A		Panel B		Panel C	
	[1] Food insecurity (FIES)	[2] Food insecurity (FCS)	[3] Food insecurity (FIES)	[4] Food insecurity (FCS)	[5] Food insecurity (FIES)	[6] Food insecurity (FCS)
COVID-19 exposure	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 controls	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)	(1.730)			(0.330)	(0.424)
Observations	23,898	23,898	23,898	23,898	23,898	23,898
Adjusted R2	0.220	0.149	0.176	0.106		

Source: Life with Corona – Africa survey 2021.

*Note: * p < 0.10, ** p < 0.05, *** p < 0.01. In Panels A and C,* the food insecurity indicators are binary variables. *Food insecurity (FIES) takes a value of 1 if a household is moderately or severely food insecure, zero otherwise; Food insecurity (FCS) takes a value of 1 if a household's diet is poor. Panel A estimates are based on a logit model; Panel C estimates are based on a multilevel random intercept logit model. In Panel B,* the food insecurity indicators are categorical variables estimated using an *ordered logit model. Estimates of regional and survey fixed effects are not reported for brevity.*

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-19 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 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 results presented in Panel C of Table 6 show that the effect of COVID-19 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-19 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 variable bias could remain a concern, given the observational nature of the data. For example, it is plausible that food secure households have stronger immunity to the virus and hence they are less exposed to the pandemic. We assess the degree of omitted variable bias using the sensitivity analysis proposed by Imbens (2003). The test helps to examine whether our results are detectably 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 causal results in Table 3) and consider the correlation between COVID-19 exposure and unobserved covariates that are also correlated with both food insecurity outcome variables. 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-19 exposure on our full set of controls. Panel A and Panel B of Figure 4 present this analysis separately for food insecurity (FIES) and food insecurity (FCS), respectively.

Panel A: outcome variable – Food insecurity (FIES)	*Panel B: outcome variable – Food insecurity (FCS)*

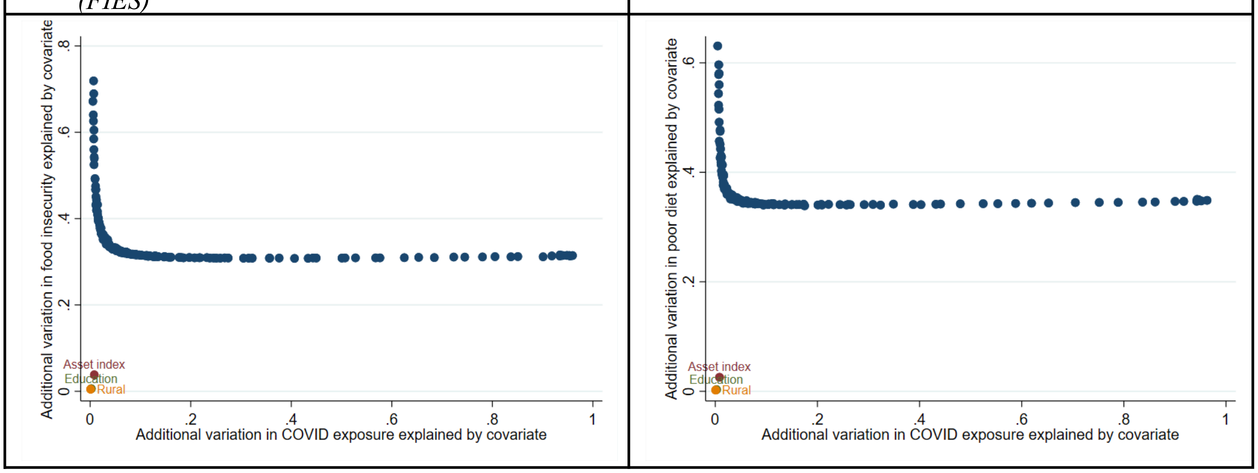

Figure 4. Sensitivity of estimated effect to omitted variable bias
Source: Life with Corona – Africa survey 2021.

From the figure, we can see that a correlation between COVID-19 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-19 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 COVID-19 exposure 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-19 exposure leads to or worsens food insecurity and is unlikely to have been driven by omitted variable bias.

5. Discussion and conclusion

This study contributes to the existing literature on the effects of the COVID-19 pandemic on food insecurity by analyzing data from four low- and middle-income African countries, namely, Uganda, Tanzania, Sierra Leone, and Mozambique. Using a phone-based survey with a sample of 24,000 responses collected throughout 2021, the study examines the extent to which the pandemic has exacerbated food insecurity and the underlying mechanisms driving this impact. We used FIES and FCS as complementary food insecurity indicators, along with a micro-level measure of COVID-19 exposure derived from four underlying survey questions.

Our findings reveal a significant level of food insecurity in all four countries, as measured by the FIES, which measures access to food as a key indicator. Specifically, we found that half of all households experience some degree of moderate to severe food insecurity. However, there was notable variation between countries, with rates ranging from 24% in Tanzania to 75% in Sierra Leone. Additionally, approximately 36% of the sample reported inadequate diet levels measured by FCS, with levels varying from 27% in Sierra Leone to 47% in Mozambique.

Our analysis further shows that exposure to COVID-19 – either through personal infection or proximity to infected individuals – has had a significant impact on the likelihood of experiencing food insecurity. The decline in household incomes largely due to job losses, reduced earnings, and mobility restrictions are the key mechanisms through which the pandemic has worsened food insecurity in these four African countries. The interconnected nature of both health and economic adverse impacts meant that even households without direct exposure to COVID-19 experienced significant economic strain, highlighting the pandemic's systemic disruption of economic livelihoods.

The role of government support appears relatively limited, with financial and social assistance to affected households being modest, though our data suggest that assistance was targeted at those most in need. A more important source of economic assistance has been inter-household transfers including overseas remittances at about one fifth of all households received inter-household remittances, primarily from within countries (Table 2). It is plausible that this channel, particularly in the context of food transfers between households, was also influenced by government-imposed mobility restrictions, a finding documented in other studies (Palma & Araos, 2021). Moreover, our data shows that food insecure households are more likely to adopt harmful coping strategies, such as depleting savings, accumulating debt, selling productive assets, and cutting back on essential non-food expenditures (e.g. health and education). This is causally linked to income shortfalls caused by the COVID-19 related movement restrictions imposed by governments (Baliki et al., 2025). This finding aligns with the widespread, covariate nature of the pandemic, which has disrupted both formal and informal capital and insurance systems – an issue highlighted in studies conducted in similar settings (Janssens et al., 2021; Mahmud & Riley, 2021; Schotte et al., 2021).

We acknowledge four limitations of this study: (1) challenges related to the measurement of food insecurity, (2) cross-country differences and the limited representativeness of the selected countries for the broader region, (3) inherent limitations of phone-based survey methodologies, and (4) potential shortcomings of the individual-level COVID-19 exposure indicator. First, the measures of food insecurity used in this study, FIES and FCS, are not without limitations. FIES, an experience-based measure, captures subjective experiences of food insecurity but does not quantify actual food consumption or dietary intake. To gain a more holistic understanding, we combined FIES with FCS. However, FCS itself has limitations, as it emphasizes diversity and frequency of food consumption rather than actual quantities. Additionally, both FIES and FCS overlook disparities in food distribution within households, which can obscure vulnerabilities faced by specific groups, such as women and children.

Secondly, the countries included in this study – Uganda, Tanzania, Sierra Leone, and Mozambique – vary in income levels, political contexts, and pandemic policies, though these nations share some commonalities as African countries facing development challenges. Economically, Uganda and Tanzania are relatively higher-income compared to Sierra Leone and Mozambique, which represent the lower-income spectrum within Sub-Saharan Africa. This diversity in economic status offers a broader view of pandemic impacts across richer and poorer contexts in the region. On pandemic policies, Uganda implemented strict lockdown measures, whereas Tanzania's initial public health response was minimal (Figure A1). While these differences present certain challenges, the consistency of data collection across these countries and the study's focus on pandemic-related impacts lend credibility to our findings.

Thirdly, phone-based surveys provided clear advantages during the COVID-19 pandemic, including enhanced personal safety and the ability to collect immediate responses. However, these surveys come with notable limitations – particularly in terms of response rates, coverage bias, and data quality (Gourlay et al., 2021). A significant risk of coverage bias exists, as phone surveys often result in unrepresentative samples, potentially excluding disadvantaged socioeconomic and demographic groups without reliable phone access (Brück & Regassa, 2023). This limitation may lead to gaps in capturing the experiences of more vulnerable populations, impacting the comprehensiveness of the findings. For example, although change in food prices might be one of the driving factors of food insecurity, our survey did not cover food prices.

Finally, the individual-level COVID-19 exposure indicator may be subject to both underreporting and ambiguity in reference to the respondent's area of residence. Self-reported illness may be underreported due to stigma or limited testing access, particularly among low-income groups. To address this, our COVID-19 exposure indicator extends beyond self-reported infection, incorporating three other dimensions: contact with a potentially infected person, knowing someone who died from the virus, and perceived local prevalence (Table A2). These additional components capture indirect and community-level exposure, reducing reliance on individual health awareness or willingness to disclose symptoms. While stigma may still affect reporting, evidence suggests varying levels across the four countries studied, most documented in Uganda, with less research for Mozambique, Sierra Leone, and Tanzania (Nakireka et al., 2023; Roelen et al., 2020). As LwC-A data were collected in 2021, when public awareness and understanding of the virus were high, stigma-related underreporting was likely reduced. In addition, the COVID-19 exposure indicator relies on a subjective interpretation of the term "area", which was intended to refer to a village in rural settings and a neighborhood in urban settings. However, it is possible that respondents interpreted this term differently, so we cannot assume a universally consistent understanding in terms of geographical reference.

Our findings have three main implications for research and policy. First, because households typically reduce food consumption only after other coping mechanisms – such as social transfers, inter-household remittances, and similar supports – are exhausted (Janssens et al., 2021), the impact of COVID-19 on food security reported here likely represents a lower bound of the pandemic's overall welfare implications. Secondly, the higher tendency of poor and food-insecure households to adopt negative coping strategies suggests that the adverse effects of the pandemic may persist at least in the medium term. The pandemic-induced sale of productive assets, reduced spending on education and health, and depletion of savings are likely to trap these households in poverty over the long term (Dercon & Christiaensen, 2011). This suggests that the negative impacts on food security may continue well beyond the pandemic, a topic that warrants further research. Lastly, the disproportionately severe effects of the pandemic on vulnerable groups also imply that COVID-19 has reinforced pre-existing socioeconomic inequalities within and across countries. The countries in our study already faced episodes of food insecurity prior to the pandemic, and COVID-19's impact on welfare has been significant. Existing social transfer programs proved effective in protecting poor households, suggesting that making these programs more crisis-responsive and flexible in times of emergency – such as during the COVID-19 pandemic – could be an effective and viable policy option.

Declaration

Authorship contribution statement

Mekdim D. Regassa: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft
Damir Esenaliev: Conceptualization, Methodology, Data curation, Writing – original draft, Funding acquisition
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Ghassan Baliki: Writing – review & editing, Funding acquisition
Monika Schreiner: Writing – review & editing, Funding acquisition
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Tilman Brück: Conceptualization, Supervision, Writing – review & editing, Funding acquisition

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Appendix A: Methodological Notes and Tables

Methodological note on FIES-based food insecurity estimates

The 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 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 used for monitoring the SDG's 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 household access to food. 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)?

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, quality and quantity of food intake, and experience of hunger due to lack of money or other resources (Cafiero & FAO, 2016). The FIES questions in the Life with Corona - Africa survey were asked for periods over four weeks prior to the interview day.

The construction of the FIES-based food insecurity indicator using the LwC-A data involved statistical validation of the data, performed with the online application for FIES data analysis provided by the FAO (FAO, 2020). Before the data diagnostics, we removed records with response patterns that did not meet model expectations, specifically eliminating the responses where respondents consistently answered affirmatively on the right side of the response scale, as the question sequence typically is expected to show declining frequency across the eight FIES questions. The first iteration of the diagnostics with all eight questions showed that the data did not meet the fit statistics. The infit statistic, which should be in the range of 0.7 to 1.3, was higher for the HEALTHY variable. The outfit statistics, which are considered high if they exceed 2, were elevated for the HEALTHY and FEWFOOD variables. To bring the model within the fit statistics expected ranges, we opted to remove the variable ATELESS. This resulted in the *infit* and *outfit* statistics falling within the expected ranges for the other seven variables. The Rasch reliability value was 0.72, which met the minimum requirement of 0.6, and the residual correlations between the variables did not exceed 0.3, staying within the acceptable limit of up to 0.4. In this model with seven variables the severe food insecurity corresponds to a raw score of 7, moderate food insecurity to scores from 4 to 5, and mild food insecurity to scores from 1 to 3. We classify respondents with moderate and severe food insecurity as food insecure. Additionally, we also use the raw score parameter in the sensitive analysis (e.g. in Table 5), that is calculated in the validation process. Compared to the category-based raw score, the raw score parameter is of an interval nature and the distances between values make sense quantitatively.

Table A1. FIES items fit and reliability statistics

FIES Items	Positive responses	Default model Infit	Default model Outfit	Selected model Infit	Selected model Outfit
WORRIED	10,672	0.90	0.97	0.90	0.90
HEALTHY	9,383	**1.38**	**2.11**	1.27	1.84
FEWFOOD	12,188	1.17	**2.21**	1.09	1.90
SKIPPED	9,773	0.86	0.94	0.83	0.87
ATELESS	8,221	0.80	0.65		
RUNOUT	5,045	0.89	0.76	0.87	0.76
HUNGRY	6,496	0.93	0.84	0.95	0.94
WHLDAY	718	1.00	0.91	1.00	1.20
Rash reliability		*0.75*		*0.72*	
Max absolute residual correlation		*0.35*		*0.29*	

Source: Life with Corona – Africa survey 2021.

Table A2. COVID-19 exposure indicators

The respondent….	Total	Uganda	Tanzania	Sierra Leone	Mozambique
...ever had, or believes has ever had, the coronavirus, yes=1	0.037	0.068	0.019	0.01	0.055
...thinks has met (seen) anyone who may have the virus, yes=1	0.056	0.088	0.035	0.017	0.09
... thinks area has a high incidence of COVID, yes=1	0.097	0.252	0.033	0.019	0.096
... knows someone who has died from the COVID, yes=1	0.133	0.218	0.093	0.012	0.213
COVID-19 exposure indicator, yes=1	0.189	0.282	0.117	0.042	0.322
COVID-19 exposure index, PCA	-0.002	0.612	-0.262	-0.453	0.222

Source: Life with Corona – Africa survey 2021.

Table A3. Test for heteroskedasticity

	Coef	**SE**
Rural household	-0.028***	0.006
Stringency index 30-day average	0.106***	0.004
Rainfall quantity (z-score)	-0.008***	0.003
Soil terrain (z-score)	0.004*	0.003
Log (road density)	-0.029***	0.002
Log (distance to market in km)	-0.003	0.002
Constant	-0.017	0.017
Number of observations	23,907	
R2	0.038	
Adjusted R2	0.038	
Breusch–Pagan test for heteroskedasticity		
Chi2(1) = 1195.09		
Prob > chi2 = 0.0000		

Note: Dependent variable: COVID exposure; * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A4. COVID-19 exposure and food insecurity

	[3]	[4]
	FIES	**FCS**
COVID-19 exposure	0.314***	-0.119***
	(0.106)	(0.044)
Household controls	yes	yes
Regional FE	yes	yes
Survey FE	yes	yes
Constant	0.072	3.201***
	(0.456)	(0.301)
Observations	20,434	20,434
R2	0.318	0.166
Adjusted R2	0.316	0.165
IV DIAGNOSTICS:		
Kleibergen-Paap LM statistic	14.61	15.63
Kleibergen-Paap p-value	0.02	0.02
Cragg-Donald test	438.4	466.1
Hansen-J test	3.986	12.058
Hansen-J p-value	0.551	0.034

Source: Life with Corona – Africa survey 2021.

*Note: * p < 0.10, ** p < 0.05, *** p < 0.01; COVID-19 exposure indicator is a binary variable that takes a value of 1 if the respondent answers any of the four individual exposure variables in the affirmative, zero otherwise. The food insecurity measures use continuous outcome variables generated from FIES and FCS scores, respectively. Estimates of regional and survey fixed effects are not reported for brevity. The number of observations is restricted to a sub-sample of respondents with non-missing values across all four exposure questions.*

Table A5. Results from using limited dependent variables model, marginal effects

	Panel A		Panel B		Panel C	
	[1] FIES	[2] FCS	[3] FIES	[4] FCS	[5] FIES	[6] FCS
COVID-19 exposure	0.033***	0.027***	0.017***	0.013*	0.013***	0.031***
	(0.009)	(0.008)	(0.004)	(0.007)	(0.007)	(0.006)
Household controls	yes	yes	yes	yes	yes	yes
Regional FE	yes	yes	yes	yes	yes	yes
Survey FE	yes	yes	yes	yes	yes	yes
Observations	23,898	23,898	23,898	23,898	23,898	23,898

Source: Life with Corona – Africa survey 2021.

*Note: * p < 0.10, ** p < 0.05, *** p < 0.01. In Panels A and C, the food insecurity indicators are binary variables. Food insecurity (FIES) takes a value of 1 if a household is moderately or severely food insecure, zero otherwise; Food insecurity (FCS) takes a value of 1 if a household's diet is poor. Panel A estimates are based on a logit model; Panel C estimates are based on a multilevel random intercept logit model. In Panel B, the food insecurity indicators are categorical variables estimated using an ordered logit model. All the estimates are marginal effects. For Panel B, the reported marginal effects are, respectively, for the severe food insecurity and the poor diet categories. Estimates of regional and survey fixed effects are not reported for brevity.*

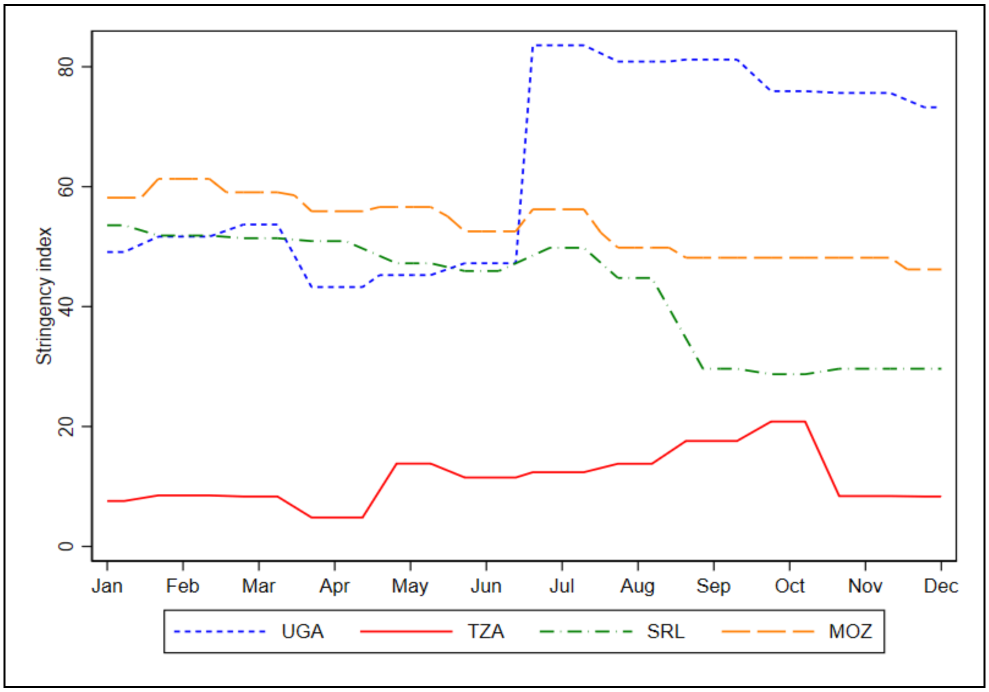

Figure A1. Stringency levels by country and month in 2021

Source: Hale et al. (2021).

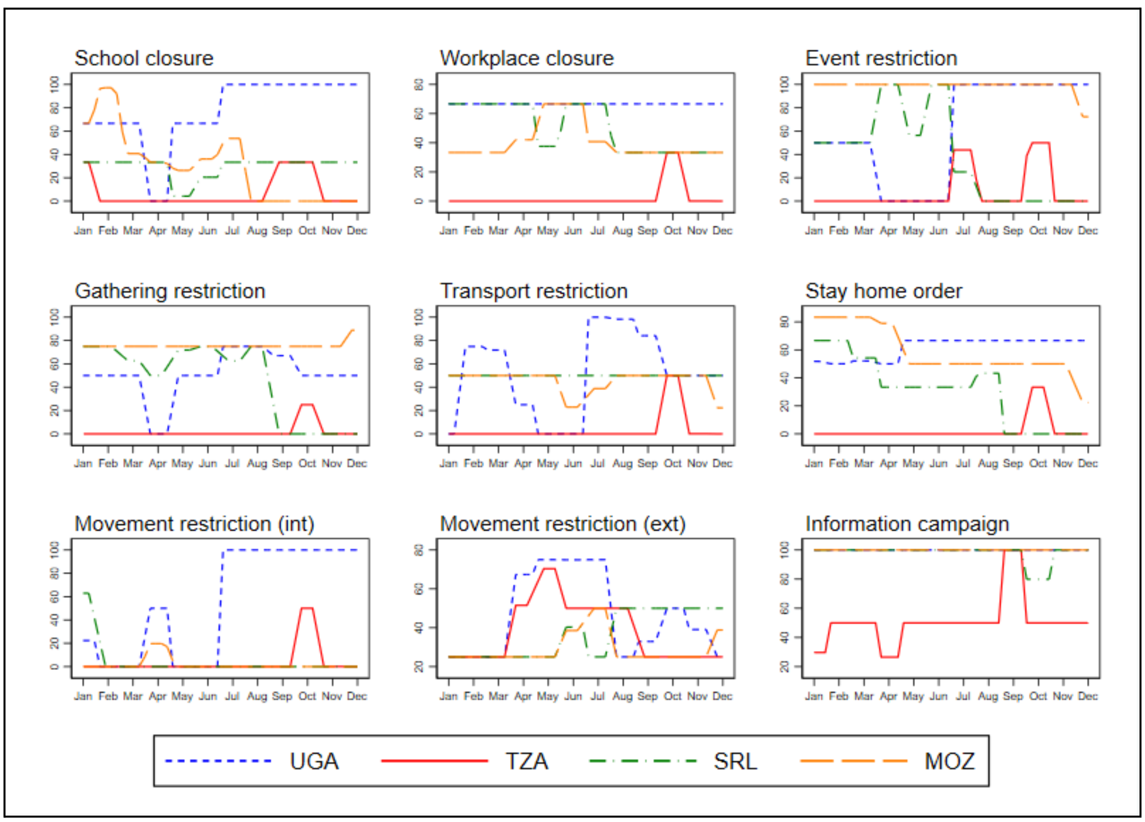

Figure A2. The pattern in the specific measures by country

Source: Hale et al. (2021).

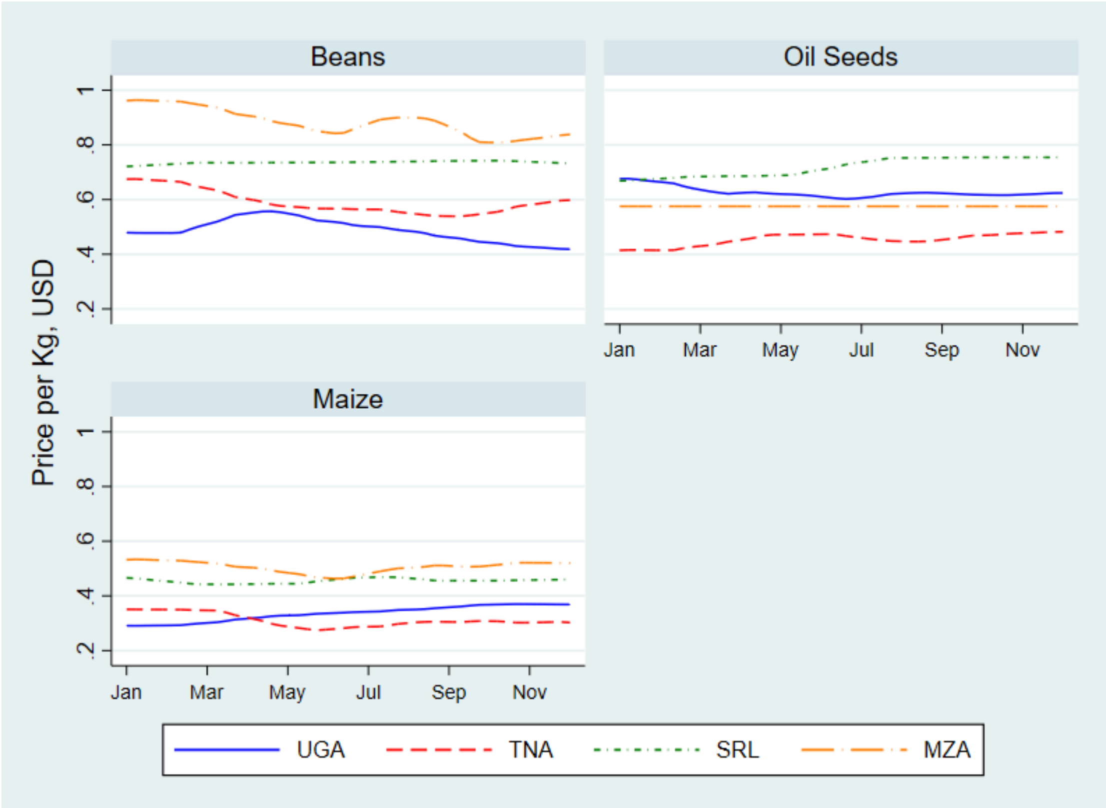

Figure A3. Average price trends of selected food items during the survey period, by country
Source: World Food Program (WFP)