World Development 175 (2024) 106479

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Regular Research Article

Short- and long-term food insecurity and policy responses in pandemics: Panel data evidence from COVID-19 in low- and middle-income countries ☆

Peter Hangoma [a,b,c,*], Kusum Hachhethu [d], Silvia Passeri [d], Ole Frithjof Norheim [b], Johnathan Rivers [d], Ottar Mæstad [a]

[a] Chr. Michelson Institute (CMI), Bergen, Norway
[b] University of Bergen, Bergen, Norway
[c] University of Zambia, Lusaka, Zambia
[d] World Food Programme, Italy

ARTICLE INFO

Keywords:
Food insecurity
Cash transfers
COVID-19
Low- and middle-income countries
Long-term effects

ABSTRACT

We leverage unique panel household phone survey data collected by the World Food Programme (WFP) several months before and 3 years into the COVID-19 pandemic in nine low-and middle-income countries to examine whether the COVID-19 period was associated with increases in food insecurity. We also combine this data with data from the Oxford COVID-19 response tracker to examine how lockdown policies and economic support policies to households have affected food consumption.

Our household level panel models show that the COVID-19 period was associated with increases in the proportion of people with insufficient food consumption in seven countries (Niger, Mali, Burkina Faso, Mozambique, Guatemala, Syria, and Yemen) but not in the other two (Cameroon and El-Salvador). Three years into the pandemic, most of the countries have not recovered from the initial negative impacts that were observed within the first year. The use of coping strategies, such as relying on less preferred food or borrowing to buy food, increased in countries where there was an increase in the proportion of people with insufficient food. Country fixed effect models show that strictness of lockdowns was associated with reductions in food consumption while economic support for COVID-19 to households was associated with improvements in food consumption. We conclude that food security has not recovered 3 years after the onset of COVID-19 and that lockdown policies and other associated generalized effects of the pandemic may be key drivers of food insecurity during pandemics. Household own coping strategies may not be sufficient to protect households from deterioration in food insecurity, but economic support interventions, such as cash transfers, may minimize these deteriorations.

1. Introduction

In 2019, an estimated two billion people in the world were food insecure, lacking regular access to safe, nutritious, and sufficient food (FAO, IFAD, UNICEF, WFP & WHO, 2020). Major drivers of food insecurity include economic conditions such as chronic poverty (Smith, El Obeid, & Jensen, 2000) and changes in food prices (Jolliffe, Seff, & De La Fuente, 2018), as well as non-economic factors such as rainfall instability (Ngoma et al., 2019), conflict (Brück & d'Errico, 2019), and disease (Hangoma, Aakvik, & Robberstad, 2018; Smith, Machalaba, Seifman, Feferholtz, & Karesh, 2019). The emergence of the coronavirus pandemic (COVID-19) as a potentially unprecedented global health and economic threat renewed concerns about further deterioration in global food insecurity (The Lancet Global Health, 2020). Understanding food insecurity is not only important for overall economic well-being but also health as food insecurity and malnutrition account for more disease burden than any other cause (Alaimo, Chilton, & Jones, 2020).

As COVID-19 spread rapidly in early 2020 infecting and killing many people, governments across the world imposed massive lockdowns. In the short term, lockdown policies significantly disrupted livelihoods (Chakravorty et al., 2023; Nordhagen et al., 2021), lowered household incomes and overall projected Gross National Product (Zeufack et al., 2020). There has been mixed evidence on whether these

☆ Acknowledgments: The authors are thankful to the World Food Programme for providing data used in this study. The views expressed in this study does not represent those of the World Food Programme. We are also thankful to two anonymous reviewers for their valuable comments.

* Correspondence to: Chr. Michelsen Institute, P.O. Box 6033, N-5892 Bergen, Norway.
E-mail addresses: peter.hangoma@cmi.no (P. Hangoma), kusum.hachhethu@wfp.org (K. Hachhethu), silvia.passeri@wfp.org (S. Passeri), ole.norheim@uib.no (O.F. Norheim), jonathan.rivers@wfp.org (J. Rivers), ottar.maestad@cmi.no (O. Mæstad).

https://doi.org/10.1016/j.worlddev.2023.106479
Accepted 22 November 2023
Available online 12 December 2023

disruptions increased food insecurity in different countries in the short term. Apart from documenting changes in food insecurity in the short term, a complementary question that is yet to be addressed relates to medium to longer term effects, or whether three years after the onset of the COVID-19 pandemic, countries have recovered from the effects observed in the short term.

The question of recovery is relevant in assessing whether the poverty effects that COVID-19 may have occasioned in the short term are transitory or chronic and whether measures taken to reverse these effects have been sufficient. Possible long term effects have been suggested from economic models (Decerf, Ferreira, Mahler, & Sterck, 2021; von Wachter, 2021). For example, Decerf et al. (2021) shows that within the first few months of COVID-19 onset, the pandemic had generated 68 million additional poverty years. But there is limited or no evidence, beyond these modeling studies, on the medium- to long-term impact of COVID-19 on the food insecurity dimension of poverty. Examining the evolution of food insecurity in the long term is crucial because short term effects may not review the full impact of the pandemic on households. In the short term, households have a tendency to smooth consumption using coping strategies such as eating less preferred food and borrowing money when hit by income shocks (Islam & Maitra, 2012; Liu, 2016). But in the medium- to long-term, as the income shock is prolonged, households may no longer be able to smooth consumption. This is especially true if the shock is severe—as to push households into chronic poverty, which is typical for job loses or business loss in pandemics.

In this paper, we have two main objectives. First, we examine the generalized effects of COVID-19 on food insecurity one year, two years, and three years into the pandemic. We do this by looking at whether the COVID-19 period was associated with a deterioration in standard indices of food insecurity. The indices capture both quantity and quality of food consumption as well as food consumption related coping behaviors. Second, we narrow down to examine the effects of specific COVID-19 policy measures–lockdown policies and household economic support policies–on food insecurity.

The generalized effects of COVID-19, consistent with our first objective, reflects both the micro- and macro-channel of impact. The micro-channel relates to how food insecurity of specific households may be impacted as a result of household members getting sick and not being able to work, especially in instances of highly prevalent long COVID (Woodrow et al., 2023). The extended sickness from long COVID may affect productivity of those affected, subsequently reducing their ability to provide for their families (Hangoma et al., 2018). In the macro-channel, which is typical for pandemics, there may be restrictions, lockdown policies and other behavioral barriers such as generalized fear that may make it difficult for people to continue their businesses while others lose jobs. Some people who lose jobs or businesses due to COVID-19 may not get them back even after a long period of time (Chakravorty et al., 2023; von Wachter, 2021). While our first objective looks at both micro- and macro-channels, our second objective only focuses on the macro-channel by exploring how policy responses, such as lockdown policies and economic support for households, may have been associated with food consumption in different countries that we study.

Our study relates to a broad and mature literature on the impact of COVID-19 on food insecurity, mostly focusing on short term effects. However, the evidence is mixed, and effects appear to vary by country. While increases in the number of food insecure people have been documented in Bangladesh (Hamadani et al., 2020), Burkina-Faso (Ouoba & Sawadogo, 2022), Nigeria (Amare, Abay, Tiberti, & Chamberlin, 2021), and Guatemala (Ceballos, Hernandez, & Paz, 2021), other studies have found no changes in food insecurity in Malawi and Liberia (Aggarwal et al., 2020), and improvements in dietary diversity in Myanmar (Ragasa, Lambrecht, Mahrt, Aung, & Wang, 2021). Even within countries, evidence can be mixed depending on the aspect of food insecurity being analyzed, the type of data and the estimation method being used. For example, Kansiime et al. (2021) uses cross-sectional data to report increases in food insecurity in Kenya. On the other hand, Janssens et al. (2021) uses household financial data collected before and after COVID-19 to show that reduction in income did not lead to reduction in household expenditure and spending on food.

Egger et al. (2021) compiles multiple datasets during the COVID-19 period to assess changes in living standards three months into the pandemic in nine countries. They document declines in employment, income, and food security. A multi-country analysis of Ethiopia, Malawi, Nigeria, and Uganda, with pre-COVID-19 data for Nigeria only, equally documents increases in food insecurity (Josephson, Kilic, & Michler, 2021). Amare et al. (2021) uses the same pre-COVID-19 data and also finds increases in food insecurity. The pre-COVID-19 data used consist of household survey data from the Living Standards Monitoring Survey (LSMS) supported by the World Bank. This data is very well suited for most household economic analyses although it is limited in the analysis of food insecurity because data covers a short period, limiting the ability to account for seasonality. Bundervoet, Dávalos, and Garcia (2022) uses similar high frequency phone survey data collected during the COVID-19 period by the World Bank and documents short term increases in food insecurity accompanied with job loses.

This paper contributes to the literature examining the impact of COVID-19 on food insecurity in at least five ways. First, we use unique household level panel data on indices of food insecurity from nine LMICs across Africa, Asia, and South-America collected continuously for a number of months before and up to three years after the onset of COVID-19 to provide an original assessment of medium- to long-term generalized effects of COVID-19 on food insecurity. The long span of our household panel data which tracks the same households before and during the COVID-19 period allows us to control for unobservable confounders by using fixed effects, and thus look at within household, rather than cross-section variation in food insecurity. The data also allow us to account for seasonality (Gilbert, Christiaensen, & Kaminski, 2017; Sibhatu, 2017), which few or no studies have been able to credibly account for. Seasonality is an important aspect to consider given that many households in low- and middle-income countries have access to less food in lean seasons than in harvest seasons. Mahmud and Riley (2021) highlights that seasonality is the biggest challenge in their effort to identify and separate the impact of COVID-19 on food insecurity in Uganda. To account for seasonality, one requires comparable data collected for a number of calendar months before and during the COVID-19 period.

Apart from seasonality, it is also important to account for general trends in food insecurity as food consumption may change due to households becoming better off, or worse off, over time. The long span of our data enables us to account for both seasonality and time trends. In addition to being able to account for seasonality and trends, the data collected before and during COVID-19 should be comparable or collected using the same mode to overcome some of the biases related to mode effects. Most of the studies examining the effect of COVID-19 on food insecurity have challenges with data comparability as data collected before the COVID-19 period is mainly from in-person household surveys while that collected during the COVID-19 period uses phone surveys. Our study uses data collected using the same mode before and during COVID-19.

Second, we contribute to the current literature by being the first to isolate medium- to long-term effects of COVID-19 on food insecurity up to 3 years after the onset of the COVID-19 pandemic. Previous studies have focused on short term effects of up to a year into the pandemic (Bundervoet et al., 2022; Egger et al., 2021; Josephson et al., 2021). As highlighted earlier, an analysis looking at the longer term effects may shade light on whether the food insecurity dimension of poverty occasioned by COVID-19 was mostly chronic or transient, highlighting whether effects observed in the short term are sustained.

Third, while previous studies have mostly focused on one or a few countries, our study contributes to the literature by being the first to use household level panel data for nine low- and middle-income countries (LMICs) across 3 regions collected the same way before and 3 years into the COVID-19 period. The countries we assess are Burkina Faso, Cameroon, Mali, Mozambique, Niger, El-Salvadore, Guatemala, Syria, and Yemen. This enables us to analyze whether the effects of COVID-19 on indicators of food insecurity have differed across countries. A few studies have looked at multiple countries but not in the same way as we do, with all of them documenting short term effects. For example, Bundervoet et al. (2022) and Egger et al. (2021) did not have access to pre-COVID data for most countries and their data could not permit them to accounting for seasonality. Josephson et al. (2021) looked at 4 countries, but they were only able to look at changes in food insecurity in one country. Rudin-Rush, Michler, Josephson, and Bloem (2022) also look at four countries in Africa to document changes in food insecurity between rural and urban areas as well as male- and female-headed households using pre-COVID data from a single in-person survey in each country and phone surveys data during the COVID-19 period. This does not allow them to account for seasonality.

Fourth, and extending the work of previous studies, we look at multiple indicators of food insecurity–both food consumption scores and consumption-related behaviors households employ to cope with lack of food or money–allowing for triangulation of results and a better understanding of how households are potentially affected by COVID-19. Fifth, we are able to examine the effects of policy responses such as lockdowns and economic support measures on food insecurity by combining daily data on food security from the World Food Program (WFP) with daily country level data on COVID-19 cases, levels of lockdown stringency, and levels of economic support from the Oxford COVID-19 tracker. In this sense, we contribute to the literature looking at the role of policy responses such as cash transfers in averting the effects of COVID-19 (Abay, Berhane, Hoddinott, & Tafere, 2021).

The rest of this paper proceeds as follows; in Section 2.1, we describe the data, how it was collected and how it was processed to ensure completeness. Section 3 presents the empirical model. Results are presented in Section 4, and the discussion in Section 5. We give conclusions and policy implications of this study in Section 6.

2. Methods

2.1. Data

Our main data comes from the Mobile Vulnerability Assessment and Monitoring program (mVAM) surveys, which are nationally representative household phone surveys conducted by the WFP using a near-real time continuous monitoring system in several countries to monitor food security. As one of the measures to sidestep some of the concerns on sample representativeness common in phone surveys, WFP attempts to make sure that the data represents all regions of each country by interviewing specified samples at lower administrative regions. The data is collected using computer assisted telephone interviewing (CATI) and is available upon request from the WFP. Our second data source is the publicly available Oxford Covid-19 Government Response Tracker which contains daily information on COVID-19 cases, levels of stringency in lockdown measures, levels of economic support, and related information for several countries. We first describe the WFP data and then the Oxford tracker data.

The WFP implemented its first continuous monitoring system in early 2018 and scaled-up rapidly to over 35 countries during the COVID-19 outbreak. For purposes of this paper, we focus on nine LMICs which had pre-COVID data and use the earliest available data for each country, covering the period June 2019 to March 2023. In each of the countries, the surveys are representative at the national and the first administrative level. The sampling frame consists of phone numbers generated through screened Random-Digit Dialing (RDD). Although the sampling unit in the RDD is the individual, typically head of household, the survey asks questions about the household, including questions on household food security and demographics. The WFP ensures that the RDD sampling frame in each country gives all telephone numbers the same chance to be selected as all major mobile network operators active in the country are included in the sampling frame. The surveys are designed to be nationally representative every day, but not the same households are interviewed each day. In each of the countries, a rolling panel approach is used in which 80% of participants are called back (repeat respondents) in the coming months and 20% of respondents are newly added every round. Unlike in one-shot household surveys where households are followed up at fixed discrete regular intervals, say once after each year, high frequency rolling panel surveys do not have fixed intervals at which households are followed up. In the WFP rolling panel data, the follow-up time for each household varies between 3 to 7 months. In our sample, as we discuss shortly, each household is surveyed about 6 times on average over the period 2019–2023

An important concern is that phone-based surveys are prone to sampling bias as households who do not have access to phones may be underrepresented. These households also tend to be from low-income groups with different socioeconomic characteristics. Although phone penetration rates are high in Africa (sim connections 77% and unique subscribers 46% (GSMA, 2021)) and South America (sim connections 100% and unique subscribers 68% (GSMA, 2021)), it is likely that not as many low socioeconomic status households are represented. This is further complicated by low response rates in phone surveys (Himelein et al., 2020). In order to correct for some of the biases and ensure a more representative sample, we apply post-stratification weights. These are used to compensate for over- or under-sampling of specific administrative areas and to mitigate selection bias (Please see Appendix C for details on how post-stratification weights are applied). Table 1 presents a summary of the data available in each country.

For each country, we disaggregate the data by the number of households in the panel sample and those in the whole sample. While our main analysis (objective 1—generalized impact of COVID-19 on food insecurity) uses the household panel sample, the country panel data to examine policy responses (objective 2) collapses all the data to create country panel observations. Our descriptive plots in the main analysis also uses all the data.

In the panel sample, the number of households surveyed each day averages 54, varying from 4 in El-Salvador to 130 in Yemen and the frequency of observing each household is as high as eight in Cameroon and Yemen, seven or six in Burkina Faso, Niger, Mozambique, and Syria to as low as two in Guatemala and El-Salvador (Table 1). The numbers surveyed each day in the overall sample on the other hand varied from 41 in El-Salvador (compared to 4 in the panel). The numbers in the overall sample allow us to collapse the data into daily averages in the policy response analysis.

With the pre-COVID period defined as the time before the first COVID-19 lockdown measures in each country (around mid-march 2020 for most countries), the pre-COVID-19 period varied in each country so that the extent to which seasonality can be accounted for in the first year of the pandemic is limited. However, in year 2 and 3, seasonality is fully captured. Nonetheless, as will be discussed later, we will also run the analysis keeping only those daily observations with corresponding pre-COVID calender months as robustness. For the household panel, countries with longer pre-COVID data series are Burkina-Faso and Cameroon, where there is daily data for the period June 2019–March 2023 translating to a pre-COVID sample of 10397 in Cameroon and the period July 2019–March 2023 in Burkina-Faso translating to a pre-COVID sample of 10228.

In all countries, the panel sample during COVID was at least 27,279 except in El-Salvador where it was 316 observations. In other countries, pre-COVID daily data stretches from September 2019 in Niger, October 2019 in Mali and Mozambique, and January 2020 in Syria, Yemen, Guatemala, and El-salvador. Noteworthy however is the fact

Table 1
Sample sizes, survey period, and frequency of observing each household.

	Daily sample (mean)	pre-COVID sample	Sample during COVID	Period	Frequency of surveying each household (mean)
Burkina-Faso:					
Panel	52	10 228	58 429	7/19 to 3/23	7
All	55	10,799	61,657	7/19 to 3/23	
Cameroon:					
Panel	46	10 397	53 223	6/19 to 3/23	8
All	49	10 463	57 037	6/19 to 3/23	
Niger:					
Panel	50	9252	53 905	9/19 to 3/23	6
All	53	9336	57 826	9/19 to 3/23	
Mali:					
Panel	27	1776	31 535	8/19 to 3/23	5
All	33	4167	36 635	8/19 to 3/23	
Mozambique:					
Panel	42	2756	45 646	10/19 to 3/23	6
All	47	3429	51 307	10/19 to 3/23	
Syria:					
Panel	46	3105	40 542	1/20 to 3/23	6
All	54	3479	48 033	1/20 to 3/23	
Yemen:					
Panel	130	5979	144 673	1/20 to 3/23	8
All	140	6708	155 722	1/20 to 3/23	
Guatemala:					
Panel	26	492	27 279	1/20 to 3/23	4
All	50	2180	53 438	1/20 to 3/23	
El-Salvador:					
Panel	4	144	316	1/20 to 1/21	2
All	41	1568	42 026	1/20 to 3/23	

that observations for December 2019 and January 2020 are missing for Mozambique while El-Salvador has no data for January and February 2020.

We use data from the Oxford Covid-19 Government Response Tracker (OxCGRT) for the second objective of assessing the impact of policy responses on food consumption. The data contains information on policy responses to control COVID-19 and its consequences which was tracked from 1st January 2020 covering over 180 countries and 23 indicators, including school closures, travel restrictions, economic support, among others (Hale et al., 2021). Different policies are then combined into indices to show the extent of government action. For purposes of this paper, we focus on daily data on the stringency index, the economic support index, and the number of COVID-19 cases from January 2020 stretching one year into the pandemic (up to May 2021). We could not extend the analysis to a longer time span because some indicators and countries in our sample were no longer being tracked.

2.2. Variables

Our data for the main analysis (WFP data) has variables on household demographics, household food consumption, coping strategies (food-based and livelihood-based), access to food and other country-specific livelihood-related questions. We focus on two main indicators of acute food insecurity at the household level computed as indices from a combination of questions: the Food Consumption Score (FCS) and the reduced Coping Strategy Index (rCSI).[1] FCS measures the diversity of household diets, and how frequently food is consumed. It is calculated based on the question asking respondents on the frequency of consumption of eight food groups during the seven days before the survey and uses standardized weights for each of the food groups reflecting its nutrient density. Multiplying the weights and the number of days for each food group and summing across the eight groups means that the FCS ranges from 0 to 120. However, most households have scores that are much lower (in our data, average is 48, with 90% of households having a score of 66 or less). FCS classifies households as having 'poor', 'borderline' or 'acceptable' food consumption, using a universal set of thresholds that takes into consideration the consumption of oil and sugar in the country. Our main outcome is the prevalence of food insufficiency which is the proportion of households with poor or borderline food consumption.

The rCSI measures the frequency and severity of behaviors households engage in when faced with food shortages, assessing whether there has been a change in the consumption patterns of a given household. The rCSI is calculated from the question that asks whether a household used a set of five standard food-based coping strategies and how many days during the past seven days, the coping strategy was used. The five negative coping strategies are relying on less preferred food, borrowing food or relying on help from friends or relatives, reducing the number of meals eaten per day, reducing portion size, and reducing the quantities consumed by adults. Based on the frequency of use and standard weighting, the rCSI ranges from 0 to 27. A higher score indicates that households are employing more frequent and/or extreme negative coping strategies. Using a conventional cut-off of 19 (rCSI$\geq$19), we convert the rCSI raw score into prevalence of using crisis or above crisis-level food-based coping strategies. We also examine how each of the components of rCSI was affected. We will also separately estimate the impact on each of five negative coping strategies, namely number of days in last seven days households relied on (1.) less preferred or less expensive food, (2.) borrowing food or relying on help from friends or relatives, (3.) reducing the number of meals eaten per day, (4.) reducing portion size, and (5.) reducing the quantities consumed by adults. Details on the FCS and rCSI are described elsewhere (Vhurumuku, 2014), and we provide a brief description in Appendix A.

Different indicators of food security classify food-insecure households differently (Maxwell, Coates, & Vaitla, 2013). Although we expect a positive correlation between the proportion of people with insufficient food consumption (based on FCS) and the proportion of people with crisis coping scores that is above threshold (based on rCSI), we also expect that these two measures could in some instances be not correlated at all or negatively correlated in other instances. To see this, note that the two indicators measure different aspects of food insecurity. While the FCS measures dietary quality by looking at the

[1] See Appendix A for more details.

frequency of eating specific food groups in the past seven days, it does not capture the quantity consumed of those foods, whether they were preferred, or whether they were financed from borrowing. The rCSI on the other hand qualitatively asks about whether households reduced quantity of food, borrowed to eat, or ate less preferred food, all important dimension of food security that may not automatically be captured in the FCS. In one instance therefore, we would see zero correlation between the two measures if, for example, a household maintained the frequency of eating everything they were eating–keeping FCS intact–but uses one of the coping strategies such as reducing portion sizes, or increase borrowing—and hence experiencing an increase in rCSI. There are at least two ways we also expect the two measures to exhibit a negative correlation. First, this could happen if households experience a reduction in borrowing or assistance from friends (one of the components of the rCSI)–leading to reduction in people with coping scores above crisis level–and yet the proportion of people with insufficient food may increase as they cut down on the frequency of eating specific food types. Second, when many households are hit by a major shock such as a pandemic, the proportion of people with crisis level coping, based on rCSI, may first increase in the short term, but eventually, it may start reducing with the increase in the proportion of people with insufficient food (based on FCS) as people run out of coping options. Thus, depending on the stage of a major shock or crisis, these two indicators may show opposite signs.

In the analysis where we look at policy responses, we use three main variables. First is daily reported COVID-19 cases per 1000 population. Second is the stringency index which is a daily composite measure calculated from eight policy response measure: (1) stay at home requirements; (2) workplace closing; (3) canceling of public events; (4) restrictions on gathering; (5) schools closing; (6) restrictions on internal movement; (7) restrictions on international travel; and (8) closing public transport. It is re-scaled to a value from 0 to 100 (100 = strictest). Our third measure of policy response, the economic support index, is a composite measure of the level of economic support: (1) income support to households; (2) debt/contract relief to households; (3) announced economic stimulus spending; and (4) giving COVID related financial aid to other countries, which was zero for all 9 countries in our data. The measures driving the economic support index in the 9 countries are income support where government provides direct cash to households who cannot work or have lost their jobs and debt relief to households where government stops or freezes financial obligations for households such as payment of utility bills and loans. Details of the COVID tracker are documented elsewhere (Hale et al., 2020).

We also obtained monthly consumer price index data which is freely available from the IMF data portal (IMF, 2023). The consumer price index data is fit for the analysis of food insecurity because all prices, including fuel and agricultural inputs prices, are ultimately reflected in consumer prices. The CPI allows us to account for changes in components of food insecurity which may be unrelated to COVID-19, but other drivers of food availability and cost. Nonetheless, we expect that COVID-19 itself may have affected food availability and prices. Therefore, by accounting for prices, our estimates are conservative. However, there was no data for Syria and Yemen, and we could not collect it from anywhere else. Therefore, the analysis for these two countries did not account for CPI.

3. Empirical specification

3.1. Impact of the COVID-19 pandemic on food insecurity

In our estimation, we exploit the fact that each households is followed up over time and use a fixed effects (within) estimator to control for time invariant confounders. These confounders may include initial wealth, levels of risk aversion, having insurance or not, levels of social capital, etc. This means time invariant variables are differenced out. Our fixed effects estimator applies a recursive regression estimation with a window of one year (Mahadi, Ballal, Moinuddin, & Al-Saggaf, 2022; Pesaran & Timmermann, 1995). This means we first estimate the model using all the data going one year into the pandemic (until may 2021), then increment the model by one year, by estimating the second model with all the data until two years into the pandemic, and finally until three years into the pandemic (data ending March 2023). This allows us to assess effects one year, two years and three years into the pandemic and assess parameter stability. We prefer recursive estimation to split sample models or models with three dummy variables to avoid losing substantial panel dimensions of our data. This is because our data consists of a rolling panel with no predefined follow-up time when a household is surveyed next.[2] Thus, suppose D_{y0} represents data for the period before the first covid-19 lockdown measures, then D_{y0+1} represents data one year into the pandemic, D_{y0+2} two years, and D_{y0+3} three year into the pandemic. Using each of the three datasets, (D_{y0+1}, D_{y0+2}, and D_{y0+3}) separately, we are interested in estimating the parameter θ_1 in a fixed effects model of the form:

$$y_{itc} = \theta_i + \theta_1 \text{post}_{ic} + \theta_2 \text{Trend} + \boldsymbol{\beta}' X_{it} + \boldsymbol{\gamma}_1 \sum_{r=1}^{11} \text{Month}_r + \epsilon_{itc} \quad (1)$$

where y_{itc} is the observed outcome for household i in country c on day t. θ_i captures household fixed effects that may be unobserved such as initial wealth, preferences etc. The variable of interest is post_{ic} which is equal to 1 if the outcome for household i was observed after the first lockdown measures and zero otherwise. Thus, θ_1 shows the difference in outcomes (e.g., prevalence of food insufficiency, above crisis-level coping, or days using a particular coping strategy) before and after the first lockdown measures.

Differences in food consumption over time may simply be due to general trends as households become wealthier or poorer or due to wider changes in the country over time. To control for this, we include the variable Trend which controls for time trends. The variable is equal to one in the first month when data collection begun in country c. For example in Burkina Faso it runs from 1 to 45, where it is 1 in July 2019, then 2 in August 2019, 3 in September 2019, and so on until 45 in March 2023. Apart from trends, food consumption in LMICs varies by season, were there is better consumption in months of harvest than in lean seasons. We control for such seasonality by including month fixed effects Month_r for each calendar month. Since there are 12 calendar months, we include 11 month dummies . X_{it} captures time varying observable characteristics such as consumer price index to control for some of the changes in prices that may not be captured by the linear trend, household size, household head characteristics including sex, and type of water source the household uses, which can proxy changes in type of housing or wealth over time. Type of water source is not collected for countries outside Africa while consumer price data is not available for Syria and Yemen. We also add country specific structural dummies for specific or new events that a country may have experienced. These include floods or a new conflict that may affect food insecurity. For example, Mozambique experienced floods from December to around February/March 2020. Thus, we add dummies for February and March 2020 (there was no data collection for December and January partly due to the disaster.[3])

Despite all these controls, our results cannot be taken as causal but suggestive of likely effects. We also present descriptive plots, showing average levels of each variable each month. This is achieved by computing average levels of each variable for each month before the lockdown

[2] This means we are looking for cumulative effects in year two and three unlike in a three dummy variable framework which is equivalent to fitting three separate regressions where each regression only uses the data for that relevant year and pre-COVID 19 data, and the rest of the data omitted. The recursive regression models are estimated using the Stata "rolling" command.

[3] To save space and time, we only report parameters of interest, full results are available from the authors upon request.

measures and after. In all estimations, we use post-stratification weights and cluster standard errors at the first administrative level in each country to sidestep the problem of false positives. Also, using the indices, rather than individual indicators, of food security sidesteps the problem of multiple hypothesis.

3.2. Policy response

It is important to explain mechanisms or what policy responses may be driving changes or lack of changes in food consumption that we could observe based on model (1). For example, why would changes in food insecurity across countries be different? This is not an easy question to answer simply by looking at cross country differences in policy responses as there are many other country specific unobservables that may be driving such results. It is critical hence to focus only on within-country, rather than cross-country, variation by relying on country level fixed effects models.

We consider two policy responses, namely lockdown measures and economic support measures. Lockdowns are policy responses meant to control the COVID-19 pandemic. We directly assess the possible unintended consequences on food consumption that the lockdowns could have generated. Second, we examine whether the policy response, defined in terms of economic support to households in the COVID period, was associated with improvements in food consumption. To address these questions, we combine WFP data used in the main analysis and data from the Oxford COVID-19 tracker. As previously indicated, the data from the Oxford tracker consists of country level daily indicators which form a country-level panel dataset. Since these policy responses vary at the national level, we collapse the WFP data to daily national level estimates. We focus on the food consumption score from the WFP data and stringency index, economic support index, and COVID-19 cases from the Oxford data.

Our goal is to look at how effects varied by country. Thus, our fixed effects models are specified as least squares dummy variable models, accounting for first order serial correlation. The two questions here are: (1) Given the level of COVID-19 cases and economic support in a country, was lockdown stringency associated with reductions in the food consumption index, and (2) Given the level of COVID-19 cases, and stringency in a country, was providing economic support to households associated with improvements in the food consumption score? To address these questions, we obtain marginal effects from the following country-level fixed effects model (dummy variable model) of the form:

$$\begin{aligned}\text{Food}_{ct} = {} & \theta_0 + \theta_1 \text{economic support}_{ct} + \theta_2 \text{Stringency}_{ct} \\ & + \sum_{c=1}^{8} \theta_{3c} \text{Stringency}_{ct} * \text{Country}_c \\ & + \sum_{c=1}^{8} \theta_{4c} \text{Country}_c + \theta_5 \text{Covid}_c + \theta_6 \text{Time} \\ & + \sum_{m=1}^{11} \theta_{7m} \text{Month}_m + \theta_8 \text{cpi}_{cmy} + \epsilon_{tc}\end{aligned} \tag{2}$$

Where Food_{ct} is the average food consumption index for country c on day t, economic support_c is the economic support index, Stringency_c, is the stringency index for country c at time t, cpi_{cmy} is the consumer price index of country c in month m of year y. Time is a trend indicator starting at 1 on day one and increases one step until the last day of the data. Other variables are as previously defined. To obtain effects of stringency, we first run Eq. (2) and then obtain marginal effects for the overall effect and effects for each country. However, since not all countries implemented economics support policies for households, and this varied very little over time even for countries that implemented them, we are not able to reliably interact economic support with country dummies to obtain reliable country specific estimates as we do for lockdown stringency. Thus, we only focus on the overall effect.

It should be noted that since stringency and economic support data is only available during the COVID-19 period (after February 2020), the post dummy does not appear in Eq. (2) as it did in Eq. (1). Our interest in this case is not how food consumption changed between the pre- and post-lockdown period but on how changes in economic support and lockdowns are associated with food consumption. As mentioned earlier, this model is estimated up to May 2021. One other point to note is the possibility of simultaneity bias. While the likely direction of causality is for lockdowns to affect food consumption, there is a theoretical possibility that the stringency of lockdown may be responsive to food consumption.

Robustness

We conduct robustness checks to see if alternative specifications substantially change our results or conclusions. As earlier alluded, the pre-COVID data does not cover all the calendar days and months before COVID-19 outbreak. This means that for models looking at effects within the first year, seasonality may not be fully accounted for. We therefore run the analysis for a restricted sample keeping days and months in the COVID period with corresponding days and months in the pre-COVID period.

4. Results

4.1. Descriptive statistics

We present descriptive statistics for our outcomes of interest for both the WFP and Oxford COVID-19 data. Table 2 shows descriptive statistics for the WFP household panel data sample for the period 2019–2023. Overall food insecurity has been very high in most countries. The highest levels of food insecurity has been in the Sahel region where the share of households reporting food insufficiency is 65% in Burkina Faso, 60% in Niger, 57% in Mali, and 46% in Cameroon. Outside of the Sahel, reported food insufficiency is also high in Mozambique (50%), Yemen (48%), and Syria (49%). The share of households reporting food insufficiency is lowest in El-Salvador (7%) and Guatemala (11%).

The proportion of households reporting crisis-level coping strategies is highest in Yemen (50%) and Syria (48%). It is lowest in Burkina Faso (15%) and El-Salvador (19%). The food-based coping strategy that is reported most often in all countries is relying on less preferred food, with households reporting that in the last seven days, they relied on less preferred food for an average of up to 4 days in Guatemala and around 2–3 days in other countries. Reducing meal size is the next most dominant coping strategy. Borrowing to meet food needs is more typical in countries such as Syria and Yemen (2 days on average).

We now use the overall sample to graphically present average levels of each of the outcome variables (Appendix B). It is important to appreciate that these are purely descriptive because fixed effects, period effects, seasonality, changes in prices, demographics or other confounders are not accounted for. Additionally, these data use both panel and non-panel households. Overall, the figures show that the prevalence of food insufficiency was higher in the COVID-19 period in Niger, Mali, Burkina-Faso, Mozambique, Syria, and Yemen (Fig. B.5—Panel A and B). In most of these cases, the proportion of households with insufficient food was higher in the same months during the COVID-19 period compared to the same months before COVID-19. We see counter-intuitive results in Cameroon were there was an improvement in indicators of food insecurity during the COVID-19 period. Food insufficiency appears broadly unchanged in El-Salvador but with some jumps around March–May 2021 and August–October 2022. Note that there is no data for El-Salvador in February and March 2020. In addition, as earlier noted in Table 1, although there are more than 43,594 observations for El-Salvador over the period 2020–2023, only a small number are in the panel sample (144 pre-COVID and 416 during COVID). Guatemala also appears to have had an increase in food insufficiency immediately following the first lockdown measures.

Table 2
Levels of food insufficiency, above crisis-level coping, and days relying on specific coping strategies: 2019–2021.

	(1) Burkina-Faso	(2) Cameroon	(3) El-Salvador	(4) Guatemala	(5) Mali	(6) Mozambique	(7) Niger	(8) Syria	(9) Yemen
Percentage of households with:									
Insufficient food	65.25	46.42	7.20	11.37	57.23	50.16	60.44	49.10	48.11
	(47.62)	(49.87)	(25.8)	(31.74)	(49.48)	(50.00)	(48.90)	(49.99)	(49.96)
Above crisis-level coping	15.39	32.91	19.13	26.82	30.25	28.05	23.38	47.98	50.86
	(36.08)	(46.99)	(39.38)	(44.30)	(45.93)	(44.93)	(42.32)	(49.96)	(49.99)
Number of days in the past 7 days households relied on:									
Less preferred food	1.51	2.75	3.31	4.32	2.75	2.76	2.31	3.08	2.79
	(2.39)	(2.47)	(2.54)	(2.61)	(2.96)	(2.43)	(2.13)	(2.58)	(2.54)
Borrowing for food	0.32	0.91	0.71	1.00	0.78	0.96	1.24	2.23	2.11
	(0.89)	(1.55)	(1.37)	(1.56)	(1.61)	(1.56)	(1.51)	(2.58)	(2.24)
Reducing meals size	1.23	2.41	1.69	2.66	1.78	2.18	1.33	2.34	3.01
	(2.25)	(2.55)	(2.26)	(2.64)	(2.71)	(2.60)	(1.82)	(2.70)	(2.57)
Reducing number of meals	1.18	2.49	0.97	1.41	1.18	2.92	1.17	3.01	2.50
	(2.32)	(2.68)	(1.78)	(2.12)	(2.28)	(2.89)	(1.75)	(3.03)	(2.53)
Reducing meals for adults	1.06	1.43	0.61	0.956	1.89	1.21	1.15	2.44	2.56
	(2.05)	(2.00)	(1.50)	(1.79)	(2.69)	(1.92)	(1.79)	(2.88)	(2.54)
Observations (N)	68 657	63 620	460	27 771	33 311	48 402	63 157	43 642	150 652

Standard deviations in parentheses.

In Fig. B.6, we also present figures showing prevalence of use of crisis coping strategies (Appendix C—Panel A and B) and days relying on specific coping strategies before and during COVID-19 period (Figs. B.7 to B.25).

Two aspect are worth pointing out. First, as earlier highlighted, Mozambique had a sharp increase in food insufficiency just before the first lockdown measures. This coincides with severe flooding from December 2019 to February/March 2020 which displaced a lot of people. In the model, we add dummies for February and March 2020 to account for this structural break (there was no data collection for December and January partly due to the disaster). Second, in some countries, there were some food price shocks unrelated to COVID-19 and these could have caused spikes in food insufficiency. We will control for consumer price indices to capture these.

Coming to COVID-19 cases and lockdown measures, Table 3 presents summary statistics from the Oxford COVID-19 response tracker data on COVID-19 cases per 1000 population, lockdown stringency, and economic support for households as well as the food consumption score from WFP data. Reported COVID-19 cases were by far highest in Guatemala (54.5 cases per 1000 population) and El-Salvador (46.1 cases per 1000 population) and lowest in Yemen (0.6 cases per 1000 population) and Niger (0.6 cases per 1000 population).[4]

The level of lockdown stringency was also highest in countries with the highest COVID-19 cases and lowest in countries with the fewest cases, for example El-Salvador had a stringency index almost three times (60.5) that of Niger (21.1).

The economic support index was also many times higher in Guatemala and El Salvador, the countries with the highest COVID-19 cases and strictest lockdowns. Although lockdowns stringency was also high in Syria, Yemen, and Mozambique, there were no recorded household economic support for COVID-19. In the other countries, such as Burkina Faso, Cameroon, and Mali, the economic support index was very low.

The food consumption score is 50% or less of its maximum possible value (120) in all countries except El-Salvador. It is lowest in Burkina-Faso, Niger, Mozambique, and Mali, ranging from a score of 39 to 47. The highest scores are in El-Salvador with a score of 75 and Guatemala (64). Syria, Yemen, and Cameroon are next with scores of slightly above or below 50.

Fig. 1 shows the evolution of daily COVID-19 cases per 1000 population over time while Fig. 2 shows how countries responded in terms of lockdown policy stringency. As can be seen, Yemen, Syria, and the countries in Africa responded almost at the same time by imposing strict lockdowns in mid-March 2020 and the number of cases did not appear to rise until later in 2020. At this time, most of these countries had relaxed the lockdowns. Some countries increased the stringency of lockdowns again, but far below the initial levels.

On the other hand, in Guatemala and El-Salvador, stringency was substantially increased around June 2020 corresponding to the time the cases started increasing. Although the cases continued increasing, the stringency was progressively reduced.

Fig. 3 shows the economic support index for the countries considered. Clearly, there seems to be lack of sustained economic support in all countries except in El Salvador and Guatemala. These two countries maintained the economic support index score of more than 60 (out of 100) throughout the period May 2020–May 2021.

Looking at the type of economic support policies in these countries, our data shows that in 2020, Cameroon, El-Salvador, Guatemala, and Mali had implemented varying types of economic support and debt relief programs. Gentilini, Almenfi, Orton, and Dale (2020) provides more detail on some of the measures introduced. In Cameroon, government increased the family allowance and implemented a 3-month cash transfer program targeted at poor households. The size of pension payment was also increased by 20%. Mali substantially scaled up its cash transfer program during COVID targeting both rural and urban households. In Guatemala, the new emergency transfer program (Bono Familia) targeted 2 million people and wage subsidies were issued

[4] It is worth mentioning that there are possible differences in reporting accuracy across countries. But this may not affect our findings since our fixed effects estimator uses within country variation and as long as reporting accuracy does not vary much within country, our findings will be consistent. However, although our interest is in the stringency and economic support variables, measurement error in any of the variables, including reporting accuracy and accuracy is capturing stringency and economic support measures will attenuate our estimates, suggesting a downward bias. In this case, our estimated effects will be lower bound.

Table 3
Period average daily COVID-19 cases, Levels of lockdown stringency, and economic support.

	(1) Burkina-Faso	(2) Cameroon	(3) ElSalvador	(4) Guatemala	(5) Mali	(6) Mozambique	(7) Niger	(8) Syria	(9) Yemen
COVID-19 and Policy response:									
COVID daily cases per 1000 population	1.40	5.10	46.11	54.51	1.65	5.40	0.63	3.78	0.56
	(2.11)	(6.52)	(35.09)	(42.57)	(1.88)	(7.59)	(0.73)	(4.07)	(0.52)
Lockdown stringency index (0–100)	24.06	27.99	60.45	60.90	35.34	52.72	21.15	50.62	30.32
	(25.11)	(25.91)	(28.28)	(27.77)	(24.21)	(24.07)	(17.84)	(22.06)	(19.88)
Economic support index (0–100)	6.33	7.49	68.2	58.68	18.16	0	19.69	0	0
	(19.87)	(13.26)	(20.20)	(21.55)	(24.01)	(0)	(21.90)	(0)	(0)
Food consumption score (0–120)	39.20	49.30	74.80	64.00	47.00	47.00	43.10	52.10	50.20
	(5.60)	(6.80)	(7.40)	(5.80)	(7.90)	(7.10)	(4.50)	(6.10)	(3.60)

Standard deviations in parentheses.

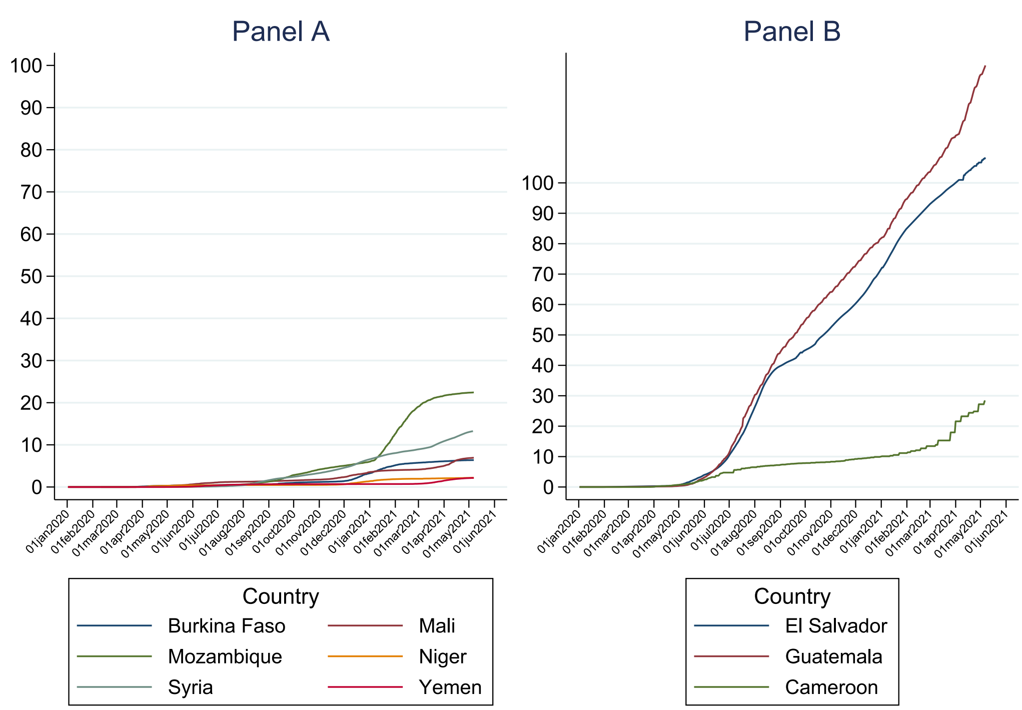

Fig. 1. Trends in COVID-19 cases per 1000 population in countries with low case counts (Panel A) and high case counts (Panel B).

for formal private sector workers. In addition, the National Electricity Institute (INDE) provided subsidized electricity to targeted households. The program in El-Salvador was even bigger reaching almost 80% of the population just by supporting informal sector workers and was classified as being among the top 10 cash transfer programs by coverage (Gentilini et al., 2020). Niger had only implemented a debt relief program but no economic support. Burkina Faso only implemented economic support and debt relief in 2021, at which time some countries such as Mali, Cameroon, and Niger had stopped the economic support policies. No economic support for COVID-19 was recorded in Syria, Yemen, and Mozambique.

However, it should be noted that the economic support index from OxCGRT data has important limitations on comprehensiveness, which may result in omission of economic support that may be substantial. This is because some economic support efforts, including income support, are not captured if they are limited to some areas and do not provide relief at national scale (Hale et al., 2020). For example, Gentilini et al. (2020) documents that Mozambique established a Post Emergency Direct Cash Transfers Program (PASD-PE Covid) targeting 1,102,825 new households, representing 35 percent of the poor population living in urban areas. However, this is not reflected in the OxCGRT data. Thus, we treat the indicators captured by the OxCGRT as being measured with error and with the consequence that any estimate derived from this data is attenuated and therefore a lower bound.

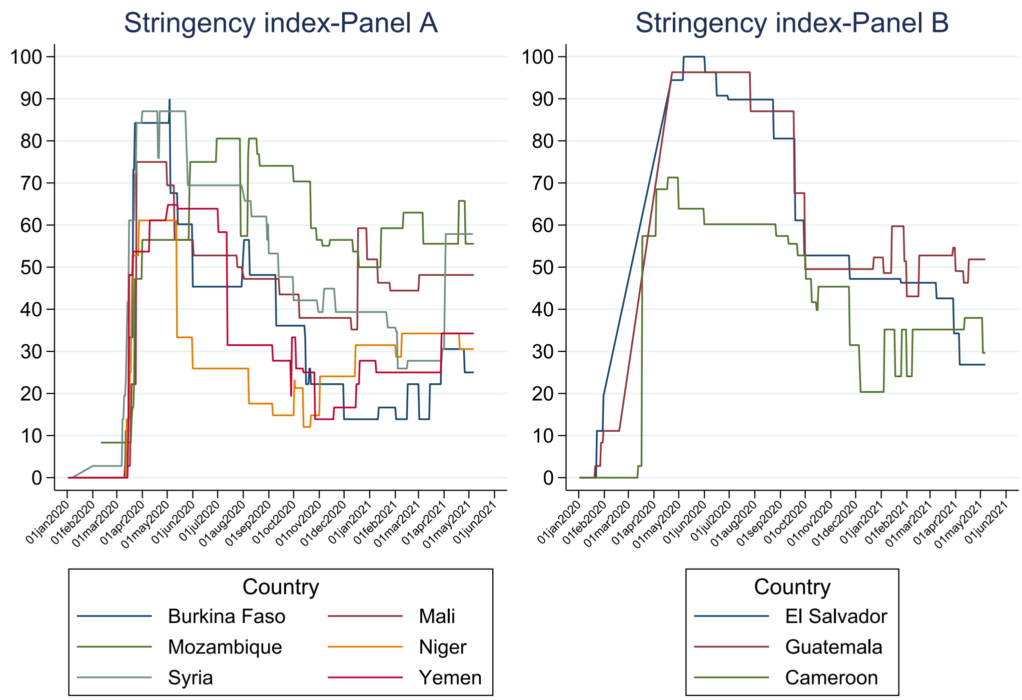

Fig. 2. Trends in levels of lockdown stringency index in Panel A countries (those with low COVID-19 case counts) and Panel B countries (with generally high case counts).

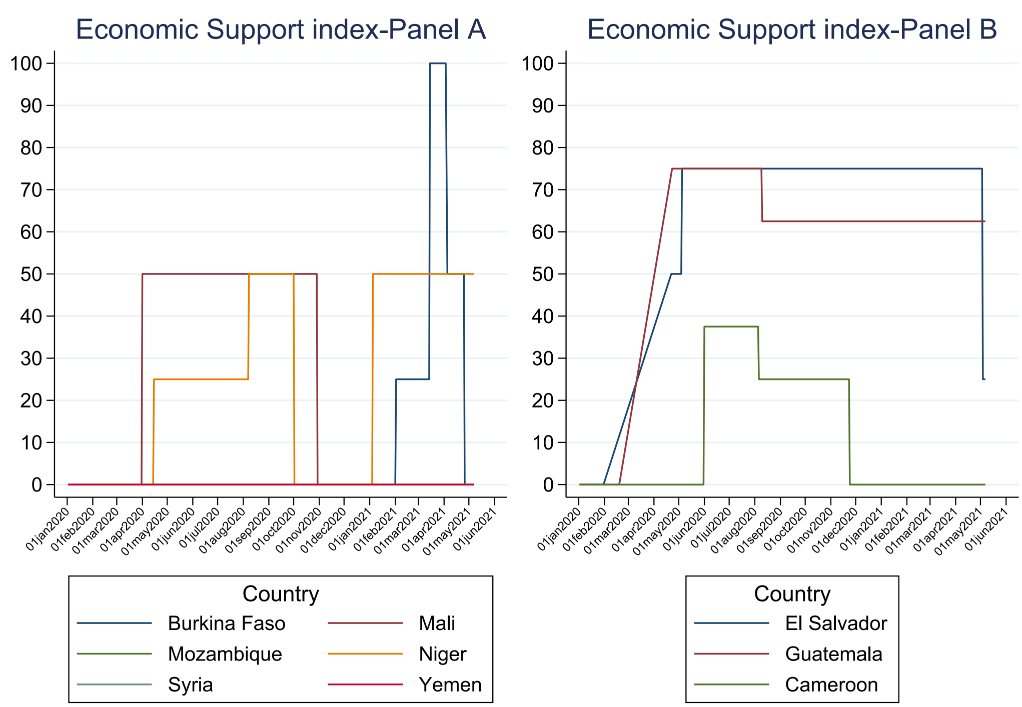

Fig. 3. Trends in levels of household economic support index stringency in Panel A countries (those with low COVID-19 case counts) and Panel B countries (with generally high case counts).

4.2. *Overall impact of the COVID-19 pandemic on food insecurity*

Table 4 shows estimates from household fixed effects models on how the covid-19 period was associated with changes in the prevalence of insufficient food and use of crisis level coping strategies 1 year—(Year 1), 2 years—(Year 1–2), and 3 years (Year 1–3)—into the pandemic. The results show that the COVID-19 period was associated with increases in the proportion of people reporting insufficient food consumption in seven of the nine countries (Niger, Mali, Burkina Faso, Mozambique, Yemen, Syria, and Guatemala) while there was no statistically significant change in one country (El-Salvador) and in another country, there was an improvement (Cameroon). And while these effects were dying out over time in some countries, they stayed the same or changed very little over time in other countries.

Specifically, within one year of the pandemic, the proportion of people with insufficient food consumption significantly increased by 30.7 percentage points (pp) in Niger, 13.9pp in Mali, 15.5pp in Burkina Faso, 10.6pp in Mozambique, 2.9pp in Yemen, and 3.0 pp in Syria.

Table 4
Changes in levels of food insufficiency, above crisis-level coping, and days relying on specific coping strategies: 2019–2021.

	(1) Niger	(2) Mali	(3) Burkina	(4) Mozambique	(5) Cameroon	(6) Yemen	(7) Syria	(8) ElSalvador	(9) Guatemala
Δ in Insufficient food prevalence									
Year 1	30.66***	13.86**	15.48***	10.65***	−17.62***	2.87***	3.03*	11.53	17.13
	(1.67)	(5.43)	(1.12)	(2.10)	(1.70)	(0.95)	(1.78)	(8.37)	(25.68)
Year 1–2	16.66***	15.23***	13.93***	7.25***	−18.65***	−0.08	7.98***	–	12.07***
	(1.14)	(2.32)	(0.88)	(1.97)	(1.21)	(0.80)	(1.34)	–	(3.02)
Year 1–3	1.88*	13.16***	12.45***	7.03***	−18.74***	−1.04	10.19***	–	16.47***
	(0.97)	(2.23)	(0.82)	(1.84)	(1.21)	(0.76)	(1.25)	–	(2.69)
Pre-lockdown levels	48.34	46.28	65.76	48.24	51.02	35.91	38.84	5.73	18.76
	(49.97)	(49.86)	(47.45)	(49.97)	(49.99)	(47.98)	(48.74)	(23.26)	(34.95)
Δ in above crisis-level coping prevalence									
Year 1	1.71	15.86***	−6.29***	−0.99	−2.12	0.45	4.44***	7.17	25.82
	(1.45)	(4.69)	(0.98)	(1.94)	(1.74)	(0.99)	(1.69)	(14.76)	(30.46)
Year 1–2	−3.31***	12.01***	−0.91	3.20*	0.82	−1.05	6.58***	–	24.15***
	(1.00)	(2.05)	(0.83)	(1.86)	(1.19)	(0.83)	(1.29)	–	(3.45)
Year 1–3	−7.56***	11.94***	0.25	1.67	−0.76	−3.91***	7.60***	–	25.90***
	(0.88)	(1.97)	(0.76)	(1.74)	(1.18)	(0.79)	(1.20)	–	(3.00)
Pre-lockdown levels	34.14	21.45	12.74	39.95	25.51	39.81	52.41	21.30	21.63
	(47.420)	(41.05)	(33.35)	(48.98)	(43.60)	(48.95)	(49.94)	(40.95)	(41.18)
Observations									
Year 1	30 896	11 575	30 440	21 359	28 578	63 450	20 238	460	3657
Year 1–2	49 251	23 594	51 726	37 286	48 217	111 730	32 629	–	16 865
Year 1–3	61 792	29 566	68 657	41 301	59 169	150 652	43 642	–	27 771
Unique households	13 958	9066	13 978	11 227	11 253	29 168	11 269	230	9227

Fixed effects estimates of θ_1 from Eq. (1). Standard errors in parentheses clustered at the first sub-national level for each country.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These changes were statistically significant below the 1% or 5% level (10% level for Syria in Year 1). However, the effects in Niger reduced by almost half two years into the pandemic and where almost gone in three years. In Mali, Burkina-Faso, and Mozambique, the effects remained broadly the same, implying no recovery. Yemen recovered to pre-locked levels two years into the pandemic while for Syria, levels of food insufficiency remained high throughout the period.

On the other hand, the proportion of people with insufficient food consumption reduced by 17.6pp in Cameroon, with changes being statistically significant below 1% level (Table 4). The improvements in Cameroon were maintained two and three years into the pandemic. In El Salvador, results show that there was no statistically significant increase in food insufficiency, yet the coefficient is large (11.53pp). The likely reason for the insignificance could be the very low pre-COVID prevalence of food insufficiency and relatively small number of households surveyed in the panel sample (only 230 households). The same can be said about Guatemala for year one. However, the estimates for Guatemala were significant as the sample expanded in year 2 and 3. As noted earlier, the panel sample for El Salvador only went up to January 2021, this means that we were only able to estimate effects for year 1.

The results observed in food insufficiency were generally reflected in the use of crisis coping levels (Table 4). The proportion of people using crisis level food-based coping strategies progressively reduced over time in Niger. This is consistent with results showing that the proportion of people with food insufficiency was almost back to pre-lockdown levels three years into the pandemic. Similarly for Mali, consistent with the food insufficiency results, the increase in the use of coping strategies observed in the first year remained generally unchanged three years into the pandemic. The increases in crisis coping in Syria and Guatemala mirror the increases in food insufficiency. In Mozambique, prevalence of using crisis coping strategies was only significant two years into the pandemic.

There were no significant changes in crisis coping in Cameroon and El-Salvador. An interesting exception is Burkina-Faso where, despite the increase in the proportion of people with insufficient food consumption, the proportion of people with crisis coping strategies significantly reduced by 6.3pp one year into the pandemic, although these effects fizzled out within the first year.

4.3. Changes in days households relied on particular food based coping strategies

The average number of days households relied on all five food coping strategies significantly increased in most countries (Table 5, Panel A, B, and C). The most notable changes were an increase in the number of days reducing meal size (Table 5, Panel A), relying on less preferred food (Table 5, Panel A), and reducing number of meals (Table 5, Panel C). These increased in all countries, except in Niger in year 1–2 and Year 1–3. In Niger and Syria, the COVID-19 period was associated with an increase in number of days relying on borrowing for food which is not broadly the case in other countries as it reduced (Table 5, Panel B).

The results also highlight that the reduction in the proportion of households with crisis level coping in Burkina Faso seen in Table 4 were driven by the fact that there was a reduction in the number of days adults reduced their meal size in order to provide for children. This is despite other coping strategies such as reducing number of meals, reducing meal sizes, and relying on less preferred food worsening. This coping strategy has the highest weight in computing the crisis level coping index.

4.4. Robustness

As mentioned earlier, having access to data spanning at least 4–5 years (2019, 2020, 2021, 2022, and 2023) enables us to fully account for seasonality in the results for year 1–2 and year 1–3, but not in year 1. Pre-COVID data was not available for all calendar months but we can estimate the same model for a sub-sample were we only keep those days and months in the COVID-19 period which have corresponding days and months before COVID-19. Households in this sub-sample must be observed both before and during the COVID-19 period.

Table 5
Change in days relied on specific coping strategies: 2019–2023.

Panel A

	(1) Niger	(2) Mali	(3) Burkina	(4) Mozambique	(5) Cameroon	(6) Yemen	(7) Syria	(8) ElSalvador	(9) Guatemala
Δ number of days reduced meal size									
Year 1	0.40***	0.99***	0.15**	0.40***	0.08	0.14***	0.16*	2.59***	1.60
	(0.04)	(0.30)	(0.06)	(0.10)	(0.10)	(0.05)	(0.09)	(0.95)	(2.03)
Year 1–2	−0.03	0.40***	0.20***	0.43***	0.44***	0.09**	0.20***	–	2.73***
	(0.03)	(0.13)	(0.05)	(0.08)	(0.06)	(0.04)	(0.07)	–	(0.20)
Year 1–3	−0.11***	0.36***	0.15***	0.31***	0.30***	0.02	0.27***	–	2.80***
	(0.03)	(0.12)	(0.04)	(0.09)	(0.06)	(0.03)	(0.06)	–	(0.17)
Pre-lockdown levels	1.59	1.33	1.12	1.76	3.22	2.80	1.77	1.62	1.71
	[1.600]	[2.49]	[1.95]	[1.85]	[2.86]	[2.40]	[2.43]	[2.47]	[2.22]
Δ number of days relied on Less preferred food									
Year 1	0.05	0.90***	1.30***	0.32***	0.18**	0.09*	0.19**	0.30	0.03
	(0.05)	(0.33)	(0.07)	(0.09)	(0.09)	(0.05)	(0.09)	(0.94)	(1.55)
Year 1–2	−0.17***	0.61***	1.28***	0.13	0.41***	0.01	0.27***	–	1.97***
	(0.04)	(0.15)	(0.06)	(0.09)	(0.06)	(0.04)	(0.07)	–	(0.20)
Year 1–3	−0.14***	0.68***	0.90***	−0.07	0.35***	−0.07*	0.39***	–	2.27***
	(0.03)	(0.14)	(0.05)	(0.08)	(0.06)	(0.04)	(0.06)	–	(0.17)
Pre-lockdown levels	2.70	3.20	2.81	2.65	3.70	2.83	2.58	3.66	3.76
	[1.72]	[3.05]	[2.68]	[2.07]	[2.62]	[2.45]	[2.43]	[3.02]	[2.70]
Observations									
Year 1	30 896	11 575	30 440	21 359	28 578	63 450	20 238	460	3657
Year 1–2	49 251	23 594	51 726	37 286	48 217	111 730	32 629	–	16 865
Year 1–3	61 792	29 566	68 657	41 301	59 169	150 652	43 642	–	27 771
Unique households	13 958	9066	13 978	11 227	11 253	29 168	11 269	230	9227

Panel B

	(1) Niger	(2) Mali	(3) Burkina	(4) Mozambique	(5) Cameroon	(6) Yemen	(7) Syria	(8) ElSalvador	(9) Guatemala
Δ number of days relied on borrowing for food									
Year 1	0.56***	−0.15	−0.011	−0.15**	−0.37***	−0.04	0.22**	0.43	−0.65
	(0.04)	(0.20)	(0.02)	(0.06)	(0.04)	(0.04)	(0.09)	(0.58)	(0.97)
Year 1–2	0.35***	−0.24***	−0.01	0.02	−0.40***	−0.05	0.39***	–	−0.05
	(0.03)	(0.08)	(0.02)	(0.06)	(0.03)	(0.03)	(0.07)	–	(0.11)
Year 1–3	0.09***	−0.24***	−0.01	−0.06	−0.41***	−0.14***	0.29***	–	−0.03
	(0.02)	(0.08)	(0.02)	(0.06)	(0.03)	(0.03)	(0.06)	–	(0.09)
Pre-lockdown levels	1.80	0.85	0.40	1.19	0.97	2.17	2.16	0.92	0.86
	[1.467]	[1.67]	[0.93]	[1.49]	[1.53]	[2.21]	[2.54]	[1.70]	[1.41]
Δ number of days relied on reducing meals for adults									
Year 1	−0.14***	1.19***	−0.53***	−0.16*	−0.12**	0.16***	0.12	−0.28	2.65**
	(0.05)	(0.29)	(0.05)	(0.08)	(0.05)	(0.05)	(0.09)	(0.65)	(1.19)
Year 1–2	−0.43***	0.96***	−0.40***	−0.01	0.04	0.09**	0.23***	–	−0.002
	(0.03)	(0.12)	(0.04)	(0.08)	(0.04)	(0.04)	(0.07)	–	(0.14)
Year 1–3	−0.52***	0.96***	−0.25***	−0.02	0.00	−0.09**	0.30***	–	0.05
	(0.03)	(0.12)	(0.04)	(0.07)	(0.04)	(0.03)	(0.06)	–	(0.11)
Pre-lockdown levels	1.38	1.20	0.93	1.45	0.94	2.61	2.08	0.85	0.89
	[1.737]	[2.36]	[1.86]	[1.89]	[1.46]	[2.44]	[2.73]	[1.76]	[1.68]
Observations									
Year 1	30 896	11 575	30 440	21 359	28 578	63 450	20 238	460	3657
Year 1–2	49 251	23 594	51 726	37 286	48 217	111 730	32 629	–	16 865
Year 1–3	61 792	29 566	68 657	41 301	59 169	150 652	43 642	–	27 771
Unique households	13 958	9066	13 978	11 227	11 253	29 168	11 269	230	9227

(*continued on next page*)

Table 5 (*continued*).

Panel C

	(1) Niger	(2) Mali	(3) Burkina	(4) Mozambique	(5) Cameroon	(6) Yemen	(7) Syria	(8) ElSalvador	(9) Guatemala
Δ number of days reduced number of meals									
Year 1	0.14***	0.07	0.12*	0.46***	0.46***	0.19***	0.38***	2.69***	−3.21
	(0.04)	(0.28)	(0.06)	(0.11)	(0.09)	(0.05)	(0.11)	(0.87)	(1.97)
Year 1–2	−0.01	0.07	0.23***	0.60***	0.66***	0.06	0.61***	–	1.69***
	(0.03)	(0.12)	(0.05)	(0.11)	(0.06)	(0.04)	(0.08)	–	(0.18)
Year 1–3	−0.09***	0.09	0.22***	0.34***	0.61***	−0.09**	0.67***	–	1.93***
	(0.03)	(0.11)	(0.04)	(0.10)	(0.06)	(0.04)	(0.08)	–	(0.16)
Pre-lockdown levels	1.49	0.96	0.86	1.84	3.37	2.49	2.30	1.15	1.55
	[1.57]	[2.20]	[1.77]	[1.95]	[2.93]	[2.42]	[2.82]	[2.13]	[1.96]
Observations									
Year 1	30 896	11 575	30 440	21 359	28 578	63 450	20 238	460	3657
Year 1–2	49 251	23 594	51 726	37 286	48 217	111 730	32 629	–	16 865
Year 1–3	61 792	29 566	68 657	41 301	59 169	150 652	43 642	–	27 771
Unique households	13 958	9066	13 978	11 227	11 253	29 168	11 269	230	9227

Fixed effects estimates of θ_1 from Eq. (1). Clustered standard errors in round brackets and standard deviations in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
Robustness: Changes in food insufficiency, above crisis-level coping: restricted-/sub-sample.

	(1) Niger	(2) Mali	(3) Burkina	(4) Cameroon	(5) Yemen	(6) Syria
Δ in Insufficient food prevalence						
Year 1	28.10***	4.64	5.28**	−34.30***	−8.15	19.80*
	(4.82)	(4.96)	(2.08)	(11.0)	(3.75)	(11.9)
Year 1–2	19.0***	26.80***	11.60***	−25.50	−1.64	12.30**
	(1.85)	(5.19)	(2.19)	(14.50)	(2.37)	(4.20)
Year 1–3	−1.10	29.60***	11.20***	−26.20*	2.13	10.10***
	(1.27)	(4.90)	(2.12)	(13.8)	(1.56)	(3.06)
Pre-lockdown levels	48.34	46.28	65.76	51.02	35.91	38.84
	(49.97)	(49.86)	(47.45)	(49.99)	(47.98)	(48.74)
Δ in above crisis-level coping prevalence						
Year 1	−35.50***	−0.41	13.40***	−19.50*	−2.45	8.99***
Year 1–2	−14.90***	6.25	5.49	−0.29	−2.20	13.90***
	(1.61)	(4.49)	(5.33)	(9.05)	(2.50)	(4.38)
Year 1–3	−15.20***	5.65	6.10	−2.42	−0.77	12.30***
	(1.17)	(4.23)	(4.04)	(8.63)	(2.32)	(3.37)
Pre-lockdown levels	34.14	21.45	12.74	25.51	39.81	52.41
	(47.420)	(41.05)	(33.35)	(43.60)	(48.95)	(49.94)
Observations						
Year 1	18 083	7833	22 842	22 704	13 588	5269
Year 1–2	27 548	13 436	34 532	38 089	22 027	7672
Year 1–3	37 452	15 741	48 538	50 166	30 509	10 636

Sub-sample fixed effects estimates of θ_1 from Eq. (1). Clustered standard errors in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We are only able to do this for countries that have at least 3 months of pre-COVID data and sufficient pre-COVID panel households. As such, we have not included countries like Guatemala, El-Salvador, and Mozambique which had insufficient panel households for us to carry out the estimation after deleting non-corresponding observations. It is important to mention however that we do not expect the magnitude of estimates to be the same in the full sample and the sub-sample because dropping several months of observations means the composition of observations may not be the same. But we expect the results to be qualitatively similar.

Table 6 shows that the pattern of results for changes in prevalence of insufficient food consumption in this sub-sample is consistent with those of the larger sample presented in Table 4 for all countries across years. The magnitudes are different, and as we said this is expected because the composition of households may be different for sub-group estimates. For crisis coping, results are consistent in direction and significance for Niger, Cameroon, and Syria. Yemen also has insignificant results for crisis coping as in the larger sample. The only results that seem to be inconsistent with the larger sample are those of Burkina Faso for crisis coping which become positive (from negative in the full sample) while for Mali, they are positive as in the larger sample, but insignificant. For Burkina Faso, the estimates showing that crisis coping increased in this sub-sample may not be surprising. This is because most of the components used to create the crisis coping index were found to be worsening in the main (larger) sample and we had expected the change in crisis coping to be positive, but it was negative because the indicator "number of days households had to reduce meals for adults to provide for children" improved and this standard index places the highest weight on this indicator of coping. In the sub-sample, an increase in crisis coping implies that households in this sample experienced more of aspects captured in the indicators that worsened than the one influential indicator that improved".

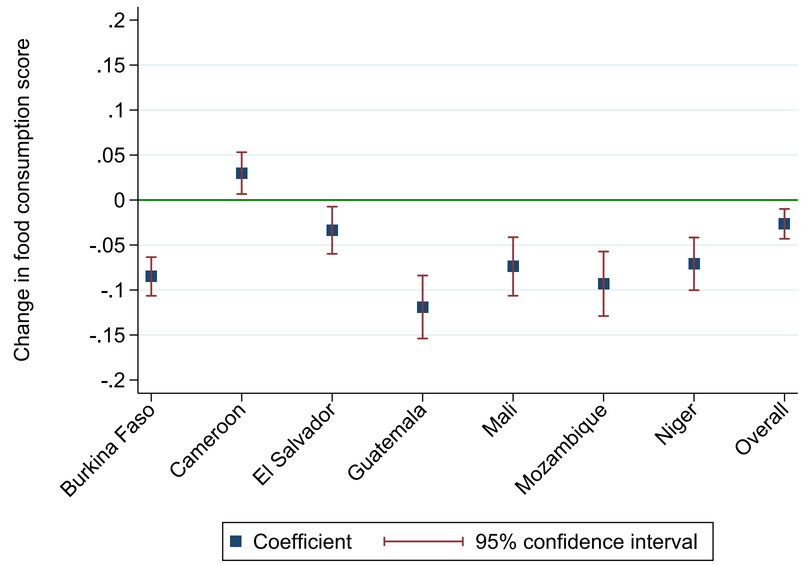

Fig. 4. Lockdown stringency and changes in food consumption.

Table 7
Policy responses and changes in food consumption score.

	Stringency index	Economic support index
Overall:		
	−0.02***	0.03***
	(0.00)	(0.00)
Burkina-Faso:		
	−0.10***	
	(0.01)	
Cameroon:		
	0.02**	
	(0.01)	
El-Salvador:		
	−0.04***	
	(0.01)	
Guatemala:		
	−0.12***	
	(0.02)	
Mali:		
	−0.08***	
	(0.01)	
Mozambique:		
	−0.09***	
	(0.02)	
Niger:		
	−0.08***	
	(0.01)	
Observations:		
	3782	3782

Country fixed effects marginal effects from Eq. (2). Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Policy responses

We now turn to see whether COVID-19 policy responses–lockdowns and economic support–were associated with changes in food consumption. Recall that the food consumption score is a summary measure of the quantity and quality of food consumed by the household in the past seven days based on eight important food groups. The higher the score the better the food consumption. Results on how lockdown stringency and economic support are associated with food consumption, based on Eq. (2), are shown in Table 7 above.[5] Because the economic support index is zero in some countries and varies little over time in other countries, we only compute the overall estimate for all countries. For stringency, results are further broken down by country and also plotted in Fig. 4.

While lockdown stringency is associated with a lower food consumption score, economic support is associated with higher food consumption scores (Table 7). Looking at country heterogeneities, stringency is associated with lower food consumption in Burkina Faso, El Salvador, Guatemala, Mali, Mozambique, and Niger but not in Cameroon. Since there were possible mismeasurement of the stringency and economic support indices, so that our estimates are attenuated, and thus lower bound, we focus mostly on the signs and significance of the estimates and not their sizes.

5. Discussion

Devising policies to eliminate hunger and malnutrition calls for evidence on how global pandemics, like COVID-19, and associated policy responses impact the evolution of food insecurity at household level. While short term effects are important to examine, it is crucial to examine medium- to long-term effects to assess the extent of recovery. However, rigorous evidence is limited, partly due to absence of sufficiently long comparable data collected before and during the COVID-19 period. Using household daily phone panel survey data collected by the World Food Programme (WFP) several months before and 3 years into the COVID-19 pandemic in nine LMICs, we examine the medium- to long term-impact of COVID-19 on household food consumption and consumption-related coping behaviors. We also use data from the Oxford COVID-19 policy response tracker and run country fixed effects models to examine how policy responses such as level of lockdown stringency and economic support to households could have been associated with food insecurity.

Overall, results show that the levels of food insecurity are high in most countries and that the COVID-19 period was associated with increases in food insufficiency and food-based coping in seven of the nine countries we examined. Our results not only confirm findings of previous literature in three countries–(Guatemala Ceballos et al., 2021, Burkina Faso Ouoba & Sawadogo, 2022; Rudin-Rush et al., 2022,

[5] Yemen and Syria are not included because we had no access to consumer price data which is used in the model.

and Mali Adjognon, Bloem, & Sanoh, 2021)–on short term impacts but also document medium- and longer-term effects. Importantly, we document additional impacts in six countries (Cameroon, El-Salvador, Niger, Syria, and Yemen) that have few or no comparable studies on how COVID-19, as well as lockdown and household economic support measures, may have been associated with food insecurity.

An important finding is that the initial negative impacts of COVID-19 on food security in some countries were sustained three years into the pandemic. Only in Niger and Yemen do we see food insecurity returning to pre-covid levels over time, although the recovery was not full even in year 3 in Niger. Rudin-Rush et al. (2022) looked at impacts within the first year (up to June 2021) in four countries, including Burkina Faso and found persistent effects and that severe food insecurity remained fairly stable throughout the period. Our findings for Burkina Faso show that the effect observe in 2021 was sustained in 2023, suggesting that there has been no recovery in countries like Burkina Faso, Mali, Mozambique, Syria, and Guatemala. The explanation for sustained effects into year 3 even when lockdowns have been removed could be that the COVID-19 period may have increased chronic, rather than transient poverty. This would be the case if people lose jobs or businesses which they fail to get back in the same way. For example, von Wachter (2021) estimated that 15–37 percent of the reduction in employment-to-population (EPOP) ratio observed in the US by December 2020 was permanent.

Perhaps surprising are results for Cameroon where food insufficiency reduced both in the panel sample–our main estimation–and the sample that also has cross-section observations (plots in Appendix B). This does not necessarily imply that food insecurity was not impacted in Cameroon. While we account for trends, it is possible that there are other things that were happening in Cameroon that were driving improvements in food consumption and had it not been for COVID-19, food insecurity could have improved much more than we observe. Another important consideration is that different regions could have been impacted differently yet the average effect shows overall improvements.

We also find that the level of lockdown policy strictness may have been a key driver of increases in food insecurity. Encouragingly, our findings show that economic support policies such as cash transfer or economic support to households are associated with improvements in food consumption during the COVID-19 period. For example, the size of the economic support program during COVID by El Salvador which, as mentioned earlier, covered more than 80% of the population, could have helped in moderating the COVID effects on food insecurity. Our findings on the effects of economic policies complement those of Abay et al. (2021) who show that in Ethiopia, social protection program for households potentially mitigated the negative effects of COVID-19 on food security.

While our fixed effects models and long-time span of the data account for important time varying observable confounders and unobservable time invariant confounders, it is important to highlight that our findings are not causal. There may be other things, such as emerging conflict and concurrent shocks, that could have impacted food insecurity. Pre-existing conflict and shocks do not affect the validity of our estimates. Additionally, changes in food prices and food availability not related to COVID-19 may also affect food security. Since all prices, including fuel and agricultural inputs are ultimately reflected in consumer prices for them to affect food security, we included a consumer price index to account for changes in food prices and food availability unrelated to COVID-19. Nonetheless, we expect that COVID-19 itself may have affected food availability and prices. Therefore, by accounting for prices, our estimates are conservative.

We also added structural dummies in our models to account for some known concurrent shocks and other things that may have been happening at the same time, for example, floods in Mozambique. Also, Yemen had a fuel crisis from June 2020 to October 2020 during the height of the first wave of the COVID-19 outbreak (Hashim et al., 2021; Looi, 2020). Although our descriptive plots show that food insecurity increased between March and June 2020, after the first lockdown measures but before the onset of the fuel crisis, we still added structural dummies for the period of fuel crisis. Similarly in Mali, there were floods that affected several regions in September 2020 and civil unrest earlier in July–August 2020. Our descriptive plots show that deterioration in food insecurity had happened much earlier in the COVID-19 period before these events. These results are supported by Adjognon et al. (2021) who used data pre- and post-pandemic, as well as before the July–August political crisis to show that moderate food insecurity increased by 8pp. Importantly, we would only expect our findings on food insecurity to be driven by conflict if new conflict arose, or old conflict escalated during the COVID-19 period and we did not account for it with appropriate structural dummies. However, Bloem and Salemi (2021) shows that conflict globally reduced as a result of COVID-19 (Bloem & Salemi, 2021), implying that the observed increases in food insecurity was due to factors other than conflict. New conflict of international economic significance worth mentioning is the Russia–Ukraine war. This may prevent recovery by affecting food access in ways not captured by rising food prices. It is possible for example that the war may have affected food availability for countries that rely heavily on Ukraine and Russia (Lin et al., 2023), especially Yemen. For other countries in our sample which are not reliant on Ukraine and Russia for grain and fertilizer imports, the effects may be mediated through increased prices of these commodities, which is accounted for in our model.

Overall, the consistent picture reviewed by our findings both for the analysis looking at overall effects of COVID-19 on food insecurity, regardless of whether this was from lockdowns or other more generalized COVID-19 effects and the analysis focusing on how lockdowns could have impacted food insecurity raises confidence in our findings. This is further augmented by the fact that our short term (Year 1) findings are consistent with findings from the broader literature, but our study extends the analysis to the medium term (year 2) and longer term (year 3) as well as adding more countries.

We also contribute to the literature by attempting to overcome challenges in identifying effects of COVID-19 on food insecurity and how different policies may have impacted food insecurity in a more unique way than previously done. As highlighted earlier, the challenge in the rich literature examining the impact of COVID-19 on food insecurity is that may not be easy to isolate the impact of COVID-19 alone from other factors because creating a counterfactual or comparison situation without COVID-19 is very challenging given the scale of the pandemic and limited time span of widely available data. The long span of our data, careful model that follow up same households over time before and during the COVID-10 pandemic, accounting for fixed effects, trends, other structural changes, consumer prices, and composition changes helps us to estimate, though not causally, how the overall effects on food insecurity in the short-, medium-, and long-term as well as how lockdown policies and economic support could have been associated with food insecurity

Yet an important limitation relates to reliance on phone survey data. Most studies looking at food insecurity and COVID-19 use phone survey data with phone numbers generated either during in-person nationally representative surveys conducted prior to the COVID period or from through random digit dialing (RDD). In RDD numbers are generated randomly based on the format of phone numbers in that country, or better yet, a list of active phone numbers is procured from an operator. Our data from WFP uses screened RDD with numbers from all major operators in each country. However, as Henderson and Rosenbaum (2020), Himelein et al. (2020) show, phone surveys may generate samples that are not representative when compared to nationally representative data on dimensions such as sex, age, education, and residence. As discussed in Section 2.1, our study applies several post stratification weights as recommended by Himelein et al. (2020). However, this may not fully correct the problems of non-representativeness of the sample.

Lastly, another important concern is the problem of attrition in panel data surveys were households surveyed in the initial periods are lost to followup. However, this problem is mitigated by a rolling panel approach that is used with the mVAM surveys by the WFP.

6. Conclusions and policy implications

In conclusion, our findings show that the impact of the COVID-19 pandemic on food insecurity observed in the first year were sustained in most of the countries three years into the pandemic. Our findings also indicate that lockdowns policies may have contributed to increasing food insecurity. A direct policy implication is that more support is needed in countries to help recovery. Also, differences in effects, as we have shown, for El-Salvador and Cameroon, could be related to differences in economic support measures but also the extent of household resilience, in terms of the coping capacity, within countries.

While lockdown policies may increase food insecurity, which accounts for a large share of malnutrition and deaths, their purpose is to prevent death and disease due to widespread infections. Given this trade-off, policy makers should carefully weigh whether the extent of infections is sufficient to justify lockdown measures. Our study suggest that lockdown policies may need to be implemented when complemented with economic support policies. Economic support programs should not only focus on short term relief but building household resilience so that households are better able to cope with future shocks (Tefera, Demeke, & Kayitakire, 2017).

Sustainable resilience is built when households have enough assets or precautionary savings that they can use to protect their food consumption in case of both idiosyncratic and covariate shocks. Our analysis shows that the use of crisis food based coping strategies was very high indicating that households do not have sufficient assets or precautionary savings they could liquidate to protect their consumption in light of COVID-19 and similar shocks. In conflict situations where people have to move many times, building resilience through assets such as livestock could be a challenge. In this case, more liquid forms of assets could be crucial and this may well link to expanding access to financial products that people could invest in and save for precautionary motives.

CRediT authorship contribution statement

Peter Hangoma: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Kusum Hachhethu:** Methodology, Investigation, Writing – review & editing, Data curation, Validation. **Silvia Passeri:** Methodology, Investigation, Data curation, Validation. **Ole Frithjof Norheim:** Writing – review & editing, Funding acquisition. **Johnathan Rivers:** Data curation, Validation. **Ottar Mæstad:** Writing – review & editing, Methodology, Funding acquisition.

Declaration of competing interest

The authors have no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgments

The authors are thankful to the World Food Programme for providing data used in this study. The views expressed in this study does not represent those of the World Food Programme. We are also thankful to two anonymous reviewers for their valuable comments.

Appendix A. Construction of food insecurity indicators

People with insufficient food consumption

People with insufficient food consumption refer to those with poor or borderline food consumption, according to the Food Consumption Score (FCS). The FCS is a proxy indicator for food security that measures the diversity of household diets, and how frequently food is consumed. The FCS is calculated using the frequency of consumption of eight food groups by a household during the 7 days. The eight food groups are (1) Cereals and tubers, (2) pulses, (3) milk and diary, (4) Meat, fish, and eggs, (5) Vegetables, (6) fruits (7) Oil and fats, and (8) Sugars.

In collecting data for computing the FCS, the caller first introduces themselves and says "Now I will ask you a series of questions about how often members of your household ate/drank food items, prepared and/or consumed at home ....". They Then, for each of the eight food groups, ask a question "Over the last 7 days, how many days did members of your household eat XXXX", where XXX is a list of locally relevant food in that food group. The FCS is a weighted sum of food groups. The score for each food group is calculated by multiplying the number of days the commodity was consumed and its relative weight. The weights for each of the food groups are displayed in Table A.1:

The following are the steps in calculating the FCS:

1. Multiply the value obtained for each food group by its weight and create new weighted food group scores.
2. Sum the weighed food group scores, thus, creating the food consumption score (FCS). The most diversified and best consumption with maximal FCS at 112 means that all food groups are eaten 7 days a week.
3. Using the appropriate thresholds, recode the variable food consumption score, from a continuous variable to a categorical variable, to calculate the percentage of households of poor, borderline and acceptable food consumption.

Once the FCS is calculated, it can be classified into three categories: poor consumption ($1 \leq FCS \leq 28$); borderline ($28.1 \leq FCS \leq 42$); and acceptable consumption ($FCS \geq 42.0$). Our measure of prevalence of insufficient food is the proportion of people with poor or borderline food consumption as described in Table A.2:

Crisis or above crisis consumption-based coping

People with crisis or above crisis food-based coping refers to those scoring 19 or above in the reduced Coping Strategy Index (rCSI). rCSI measures the frequency and severity of the consumption-related behaviors households engage in when faced with shortages of food or financial resources to buy food. It assesses whether there has been a change in the consumption patterns of a given household. The rCSI is calculated using standard food consumption-based strategies and severity weighting. The rCSI is based on a list of 5 food-related coping strategies applied during the past 7 days prior to the interview, and severity weights assigned. A higher score indicates that households are employing more frequent and/or extreme negative coping strategies. The weight for computing the rCSI are given in Table A.3

Appendix B. Descriptive plots of outcome variables

Prevalence of food insufficiency 2019–2023

See Figs. B.5–B.7.

Prevalence of above crisis level coping strategies, 2019–2023

See Figs. B.8–B.10.

Number of days using different coping strategies, 2019–2023

See Figs. B.11–B.25.

Table A.1
Weights in computing the FCS.

No	Food group	Weight
1	Cereals (Bread, rice, maize, barley) and tubers (potatoes and sweet potatoes)	2
2	Pulses and nuts (beans, lentils, peas, peanuts, etc.)	3
3	Vegetables	1
4	Fruits	1
5	Meat and fish (all types)	4
6	Dairy products (milk, yoghurt, cheese, other milk's products)	4
7	Sugar, honey	0.5
8	Oil, butter, fat	0.5

Table A.2
Food consumption categories.

Food consumption group	Food consumption score	Description
Poor	1 ≤ FCS ≤ 28	An expected consumption of staple 7 days, vegetables 5–6 days, sugar 3–4 days, oil/fat 1 day a week, while animal proteins are totally absent
Borderline	28.1 ≤ FCS ≤ 42	An expected consumption of staple 7 days, vegetables 6–7 days, sugar 3–4 days, oil/fat 3 days, meat/fish/egg/pulses 1–2 days a week, while dairy products are totally absent
Acceptable	FCS ≥ 42.0	As defined for the borderline group with more number of days a week eating meat, fish, egg, oil, and complemented by other foods such as pulses, fruits, milk

Table A.3
Weights for the coping strategy index.

Coping strategies	Raw score	Universal severity weight	Weighted Score = Frequency × Weight
1. Rely on less preferred and less expensive foods	5	1	5
2. Borrow food or rely on help from friends or relatives	2	2	4
3. Limit portion size at mealtime	7	1	7
4. Restrict consumption by adults in order for small children to eat	2	3	6
5. Reduce number of meals eaten in a day	5	1	5
5. Total Reduced CSI			27

Appendix C. Application of post-stratification weights

In order to mitigate the potential selection bias in the phone-based real-time food security monitoring surveys, WFP utilizes a household weighting scheme that combines geographic weights and socioeconomic weights. To calculate sociodemographic weights, WFP compiles the most recent nationally representative survey such as the DHS and then analyzes all socio-demographic variables available. The sociodemographic variables are analyzed to compare the profile of households sampled by the reference survey with the real-time food security survey. This allows for a better understanding of which populations may be undersampled/ underrepresented or oversampled/overrepresented in the phone-based survey. Importantly, comparisons are conducted at strata level and not at the national level, meaning that comparisons of sociodemographic disparities is visible for each strata and weights are applied accordingly. The most common variables used for weighting include the highest level of education of household head, water sources, urban/ rural status, size of household, number of sim cards owned, among others. To calculate geographics weights, all households are assigned a weight based on population distribution within strata on any given day, based on the number of interviewed households vis-à-vis the quotas—over the previous analysis window. This means that the populations weights are dynamic and are generated daily according to the sample distribution over the analysis window. Finally, each day a new combined household weight is generated taking both the sociodemographic weight and the daily generated population weight. This mitigates to a significant extent the impact of the potential sampling bias on the overall results. Note that geographic weights may not be applied if mobile phone ownership is high and geographic quotas are not difficult to achieve. In these cases, geographic weights do not fundamentally alter the results in any meaningful way. For sociodemographic weights, these are only not applied in cases where various demographic patterns, across multiple variables, are the same between face-to-face surveys and the near real time monitoring systems.

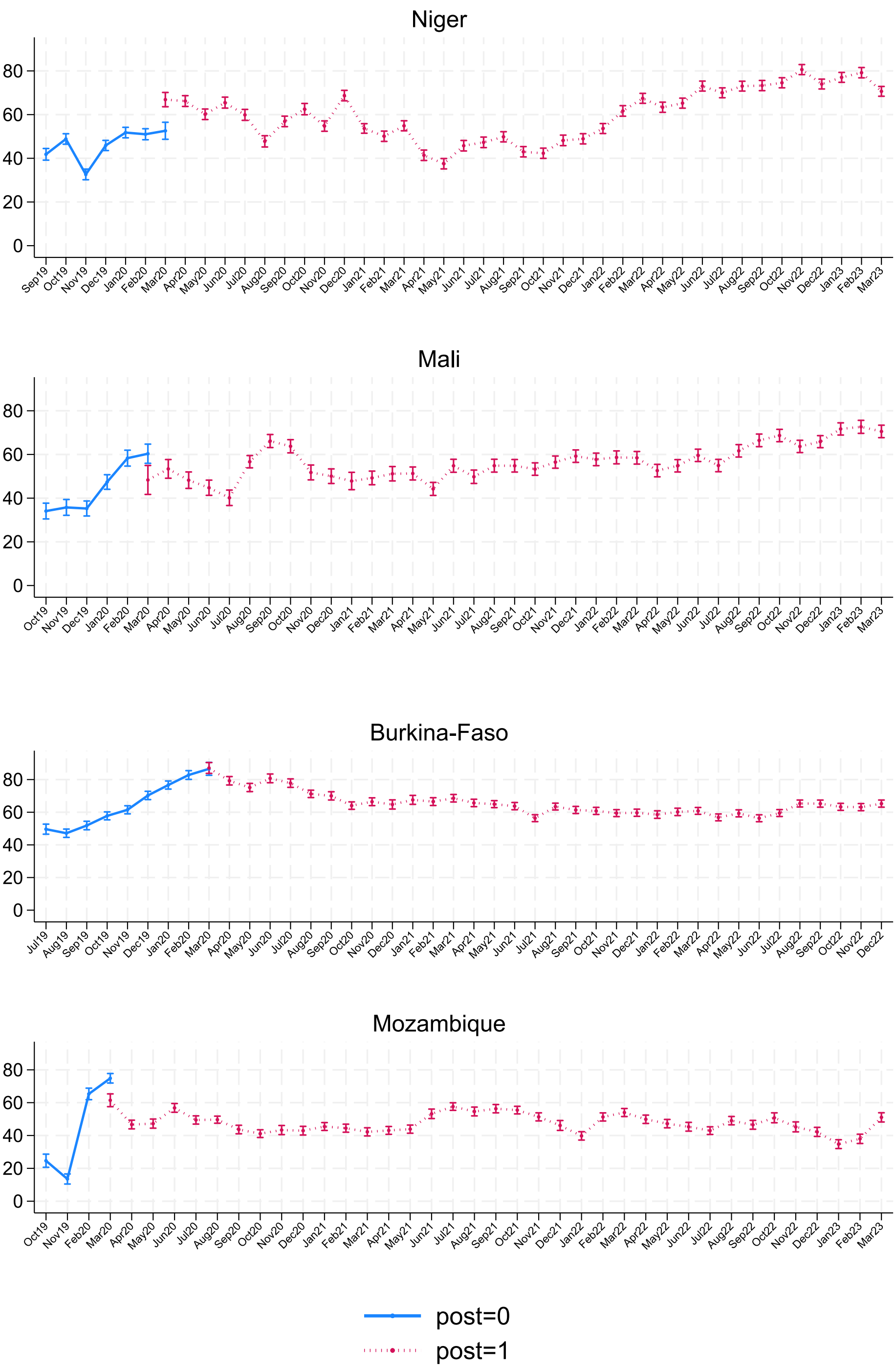

Fig. B.5. Panel A—Percentage of people with insufficient food consumption over time: Pre- and Post-first COVID-19 lockdown.

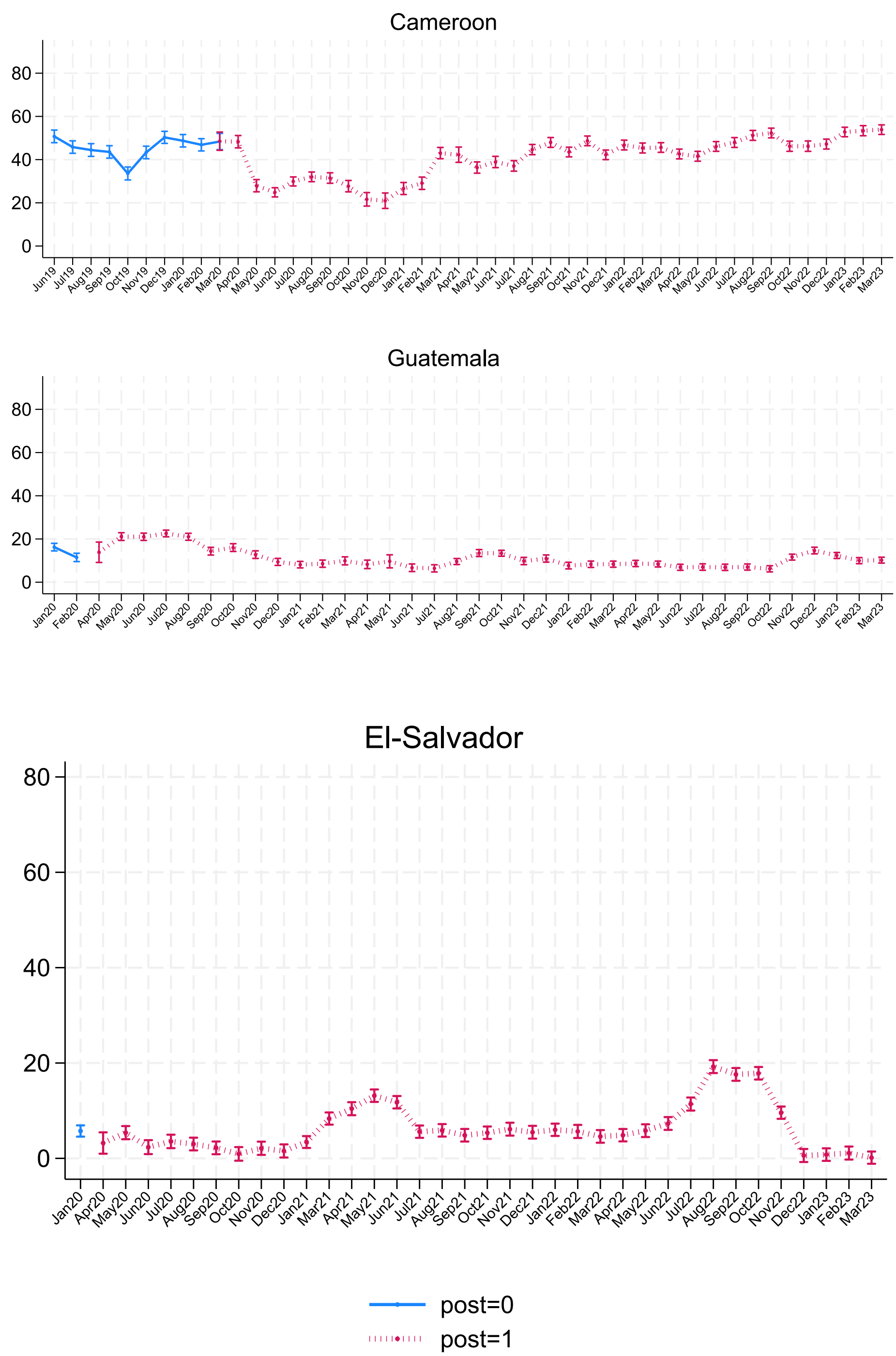

Fig. B.6. Panel B—Percentage of people with insufficient food consumption over time: Pre- and Post-first COVID-19 lockdown.

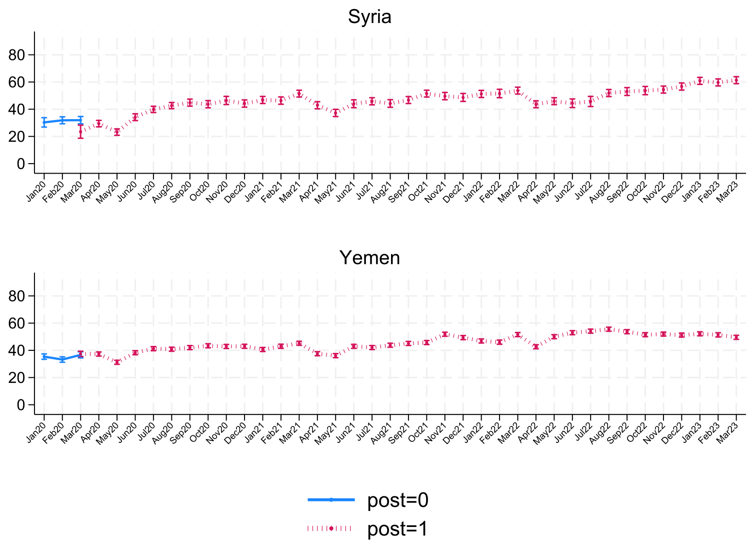

Fig. B.7. Panel C—Percentage of people with insufficient food consumption over time: Pre- and Post-first COVID-19 lockdown.

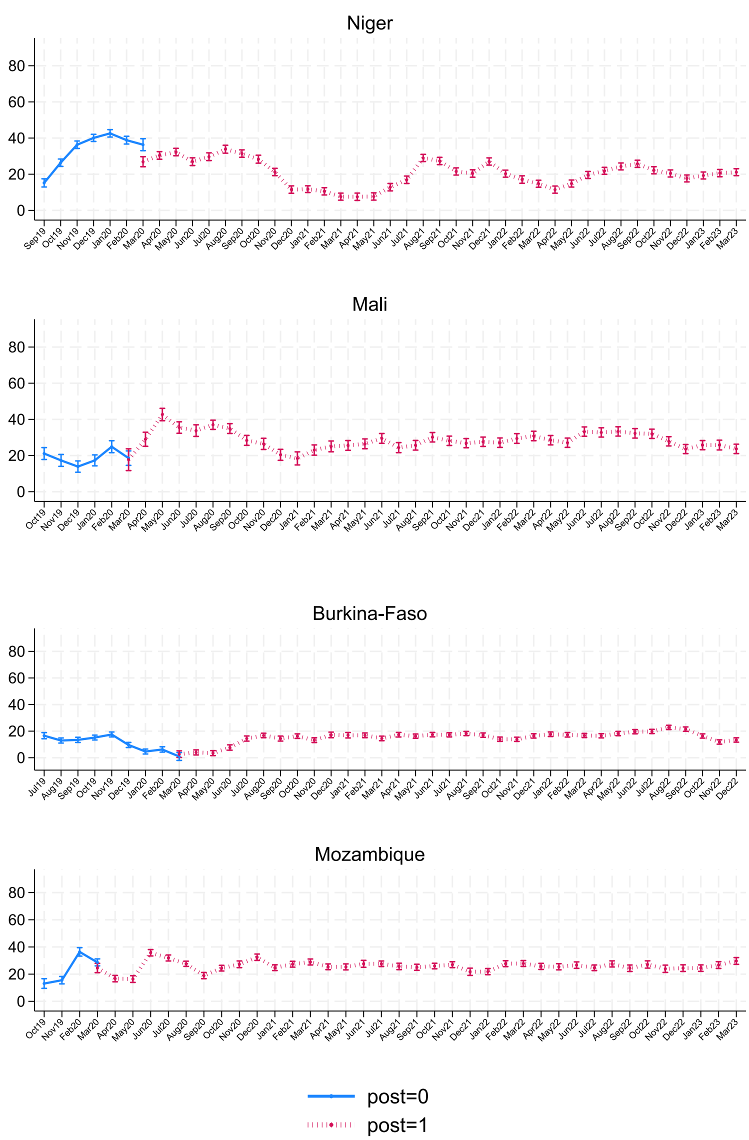

Fig. B.8. Percentage of people with above crisis-level food based coping: Pre- and Post-first COVID-19 lockdown.

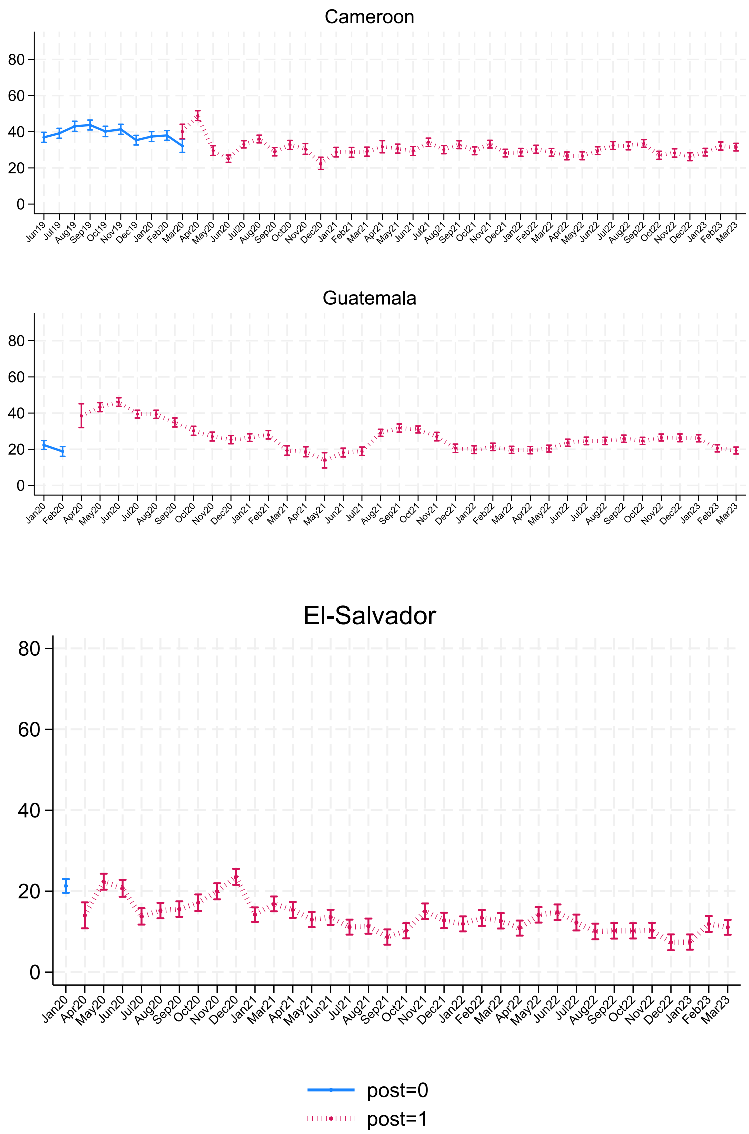

Fig. B.9. Percentage of people with above crisis-level food based coping: Pre- and Post-first COVID-19 lockdown.

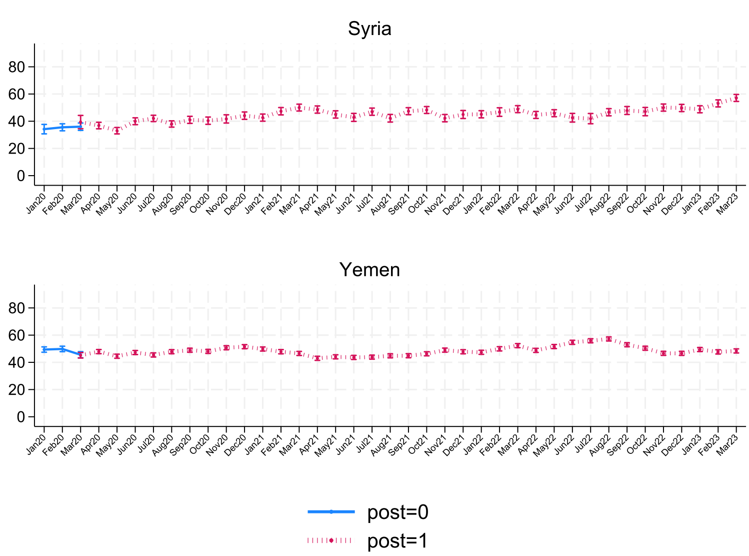

Fig. B.10. Panel C-Percentage of people with above crisis-level food based coping: Pre- and Post-first COVID-19 lockdown.

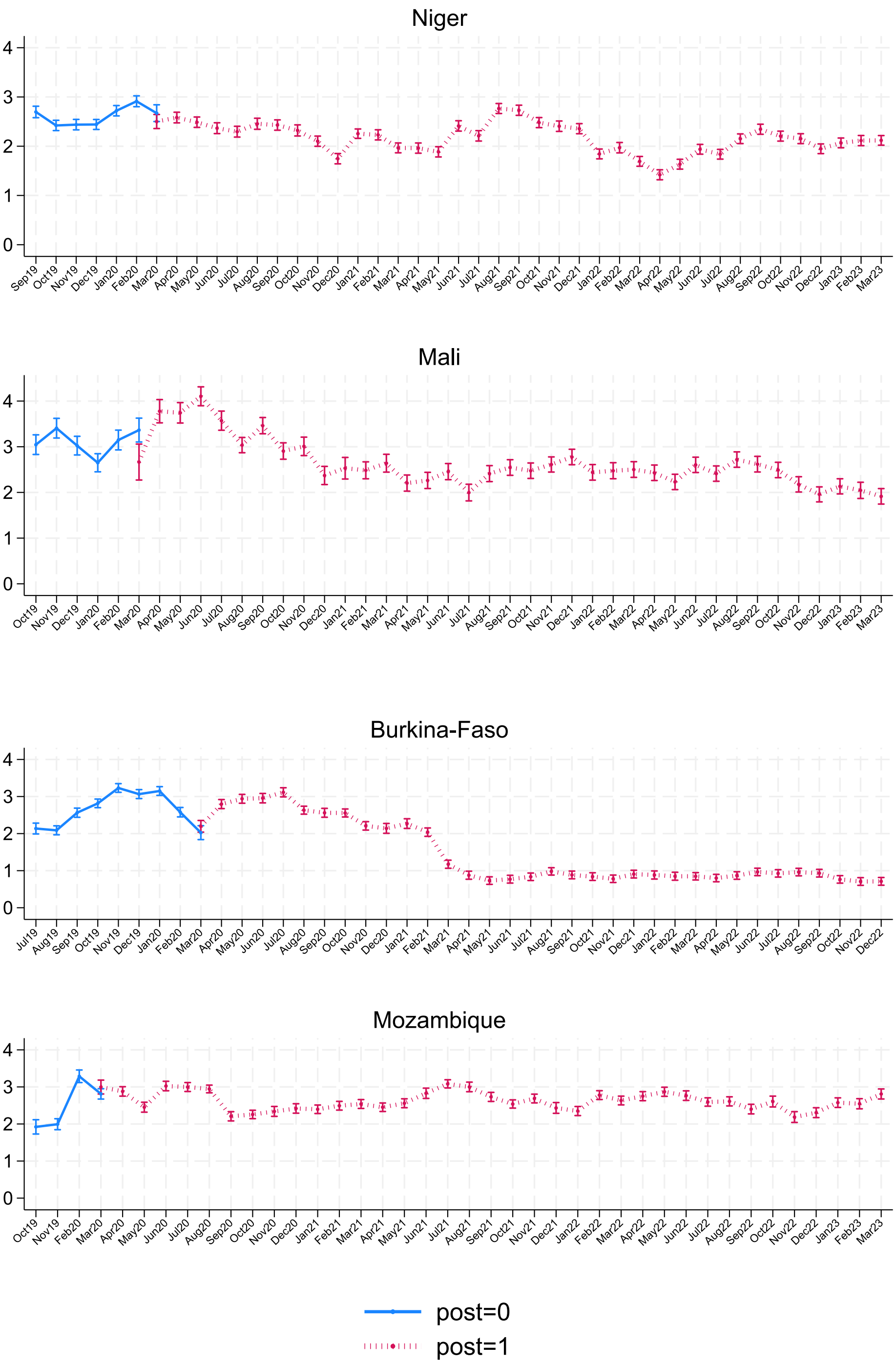

Fig. B.11. Panel A—Number of days in past seven relied on less preferred food; Pre- and Post-first COVID-19 lockdown.

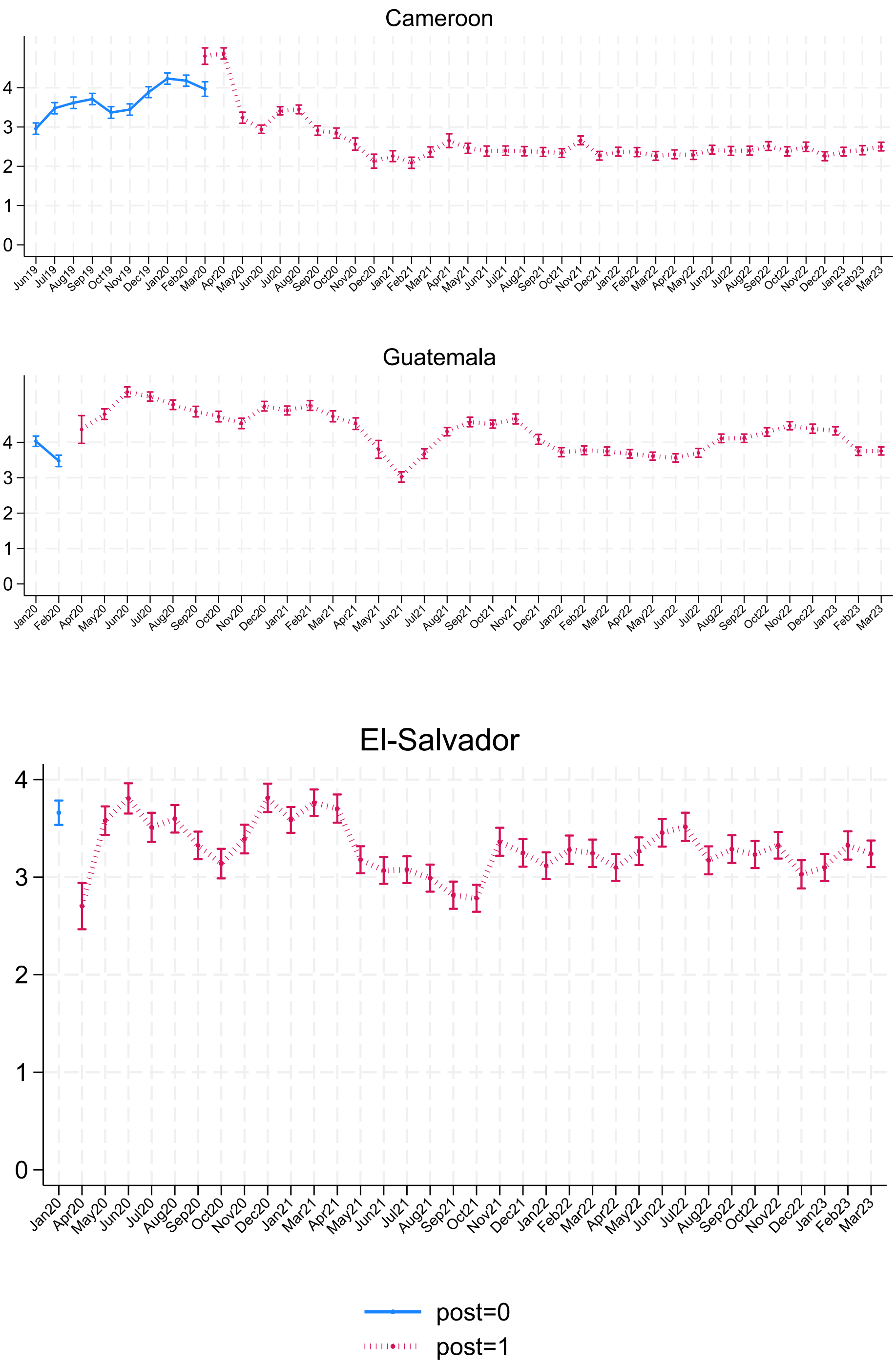

Fig. B.12. Panel B—Number of days in past seven relied on less preferred food; Pre- and Post-first COVID-19 lockdown.

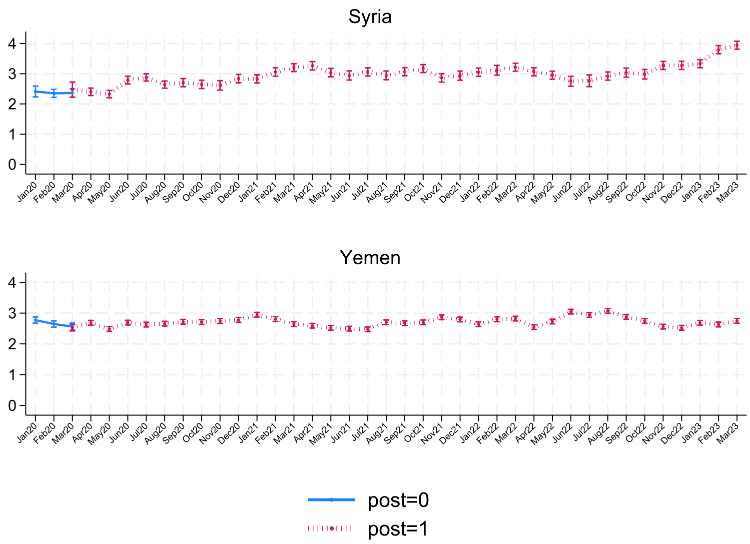

Fig. B.13. Panel C—Number of days in past seven relied on less preferred food; Pre- and Post-first COVID-19 lockdown.

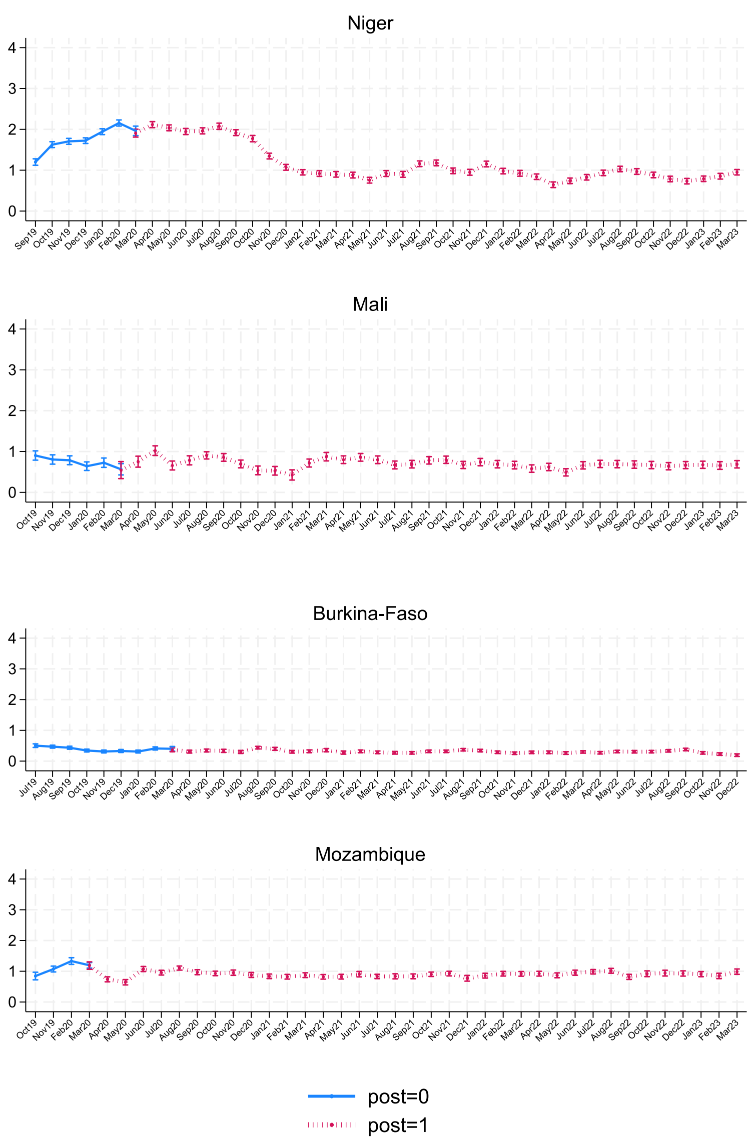

Fig. B.14. Panel A-Number of days in past seven relied on borrowing for food; Pre- and Post-first COVID-19 lockdown.

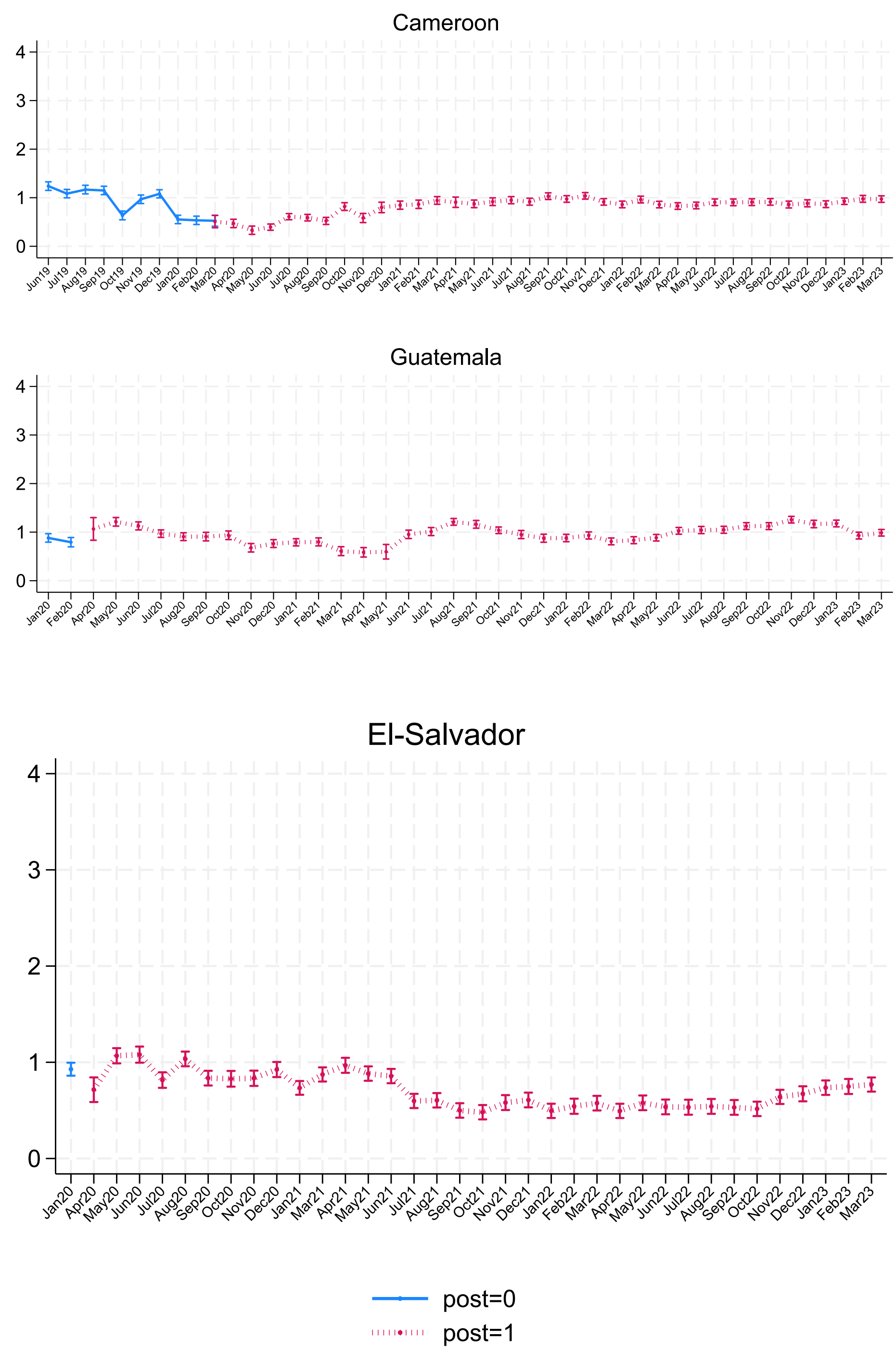

Fig. B.15. Panel B-Number of days in past seven relied on borrowing for food; Pre- and Post-first COVID-19 lockdown.

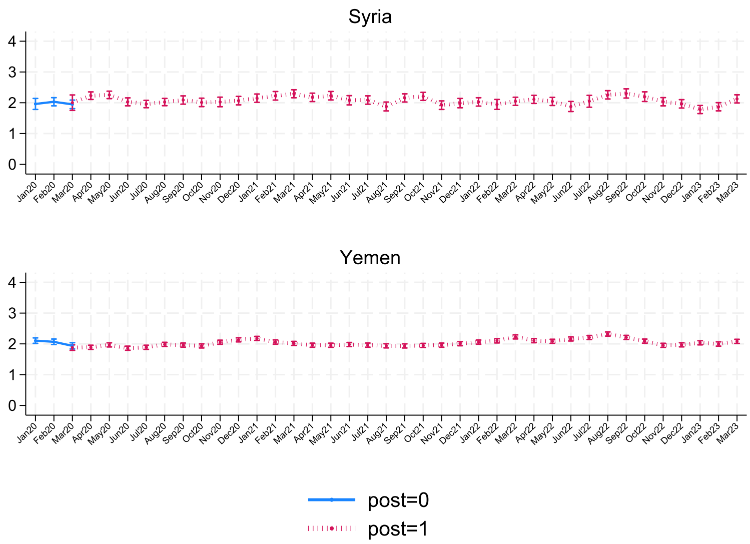

Fig. B.16. Panel C-Number of days in past seven relied on borrowing for food; Pre- and Post-first COVID-19 lockdown.

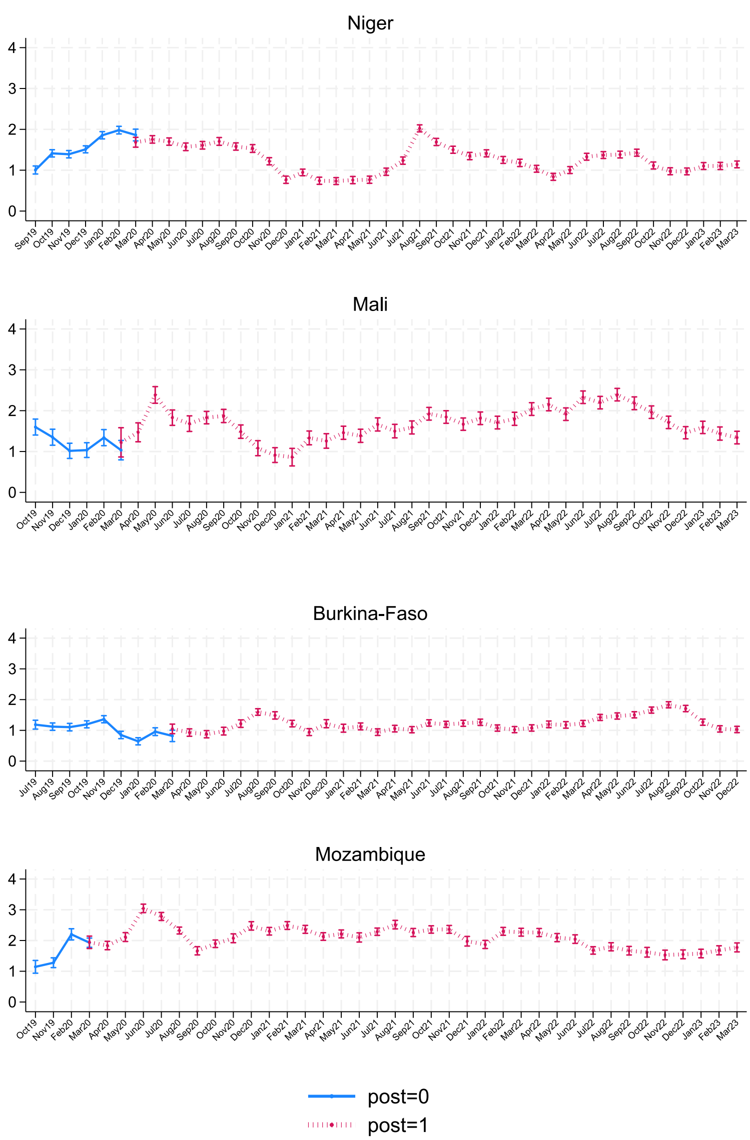

Fig. B.17. Panel A-Number of days in past seven relied on reducing meal size; Pre- and Post-first COVID-19 lockdown.

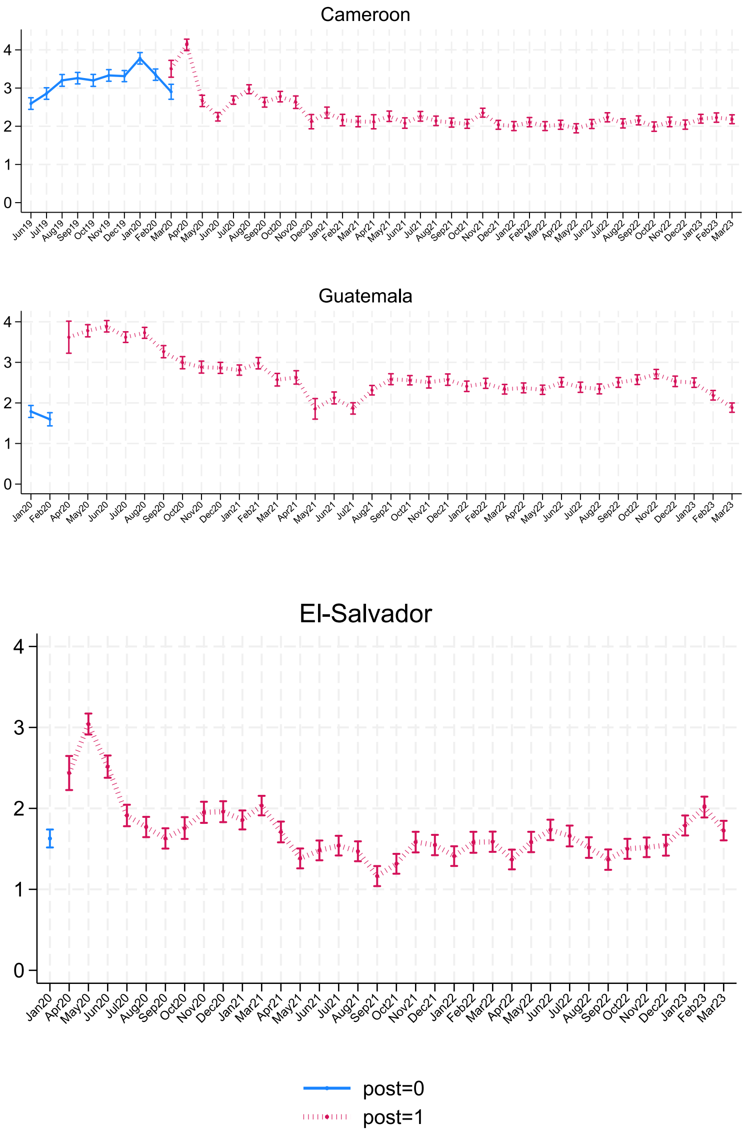

Fig. B.18. Panel B-Number of days in past seven relied on reducing meal size; Pre- and Post-first COVID-19 lockdown.

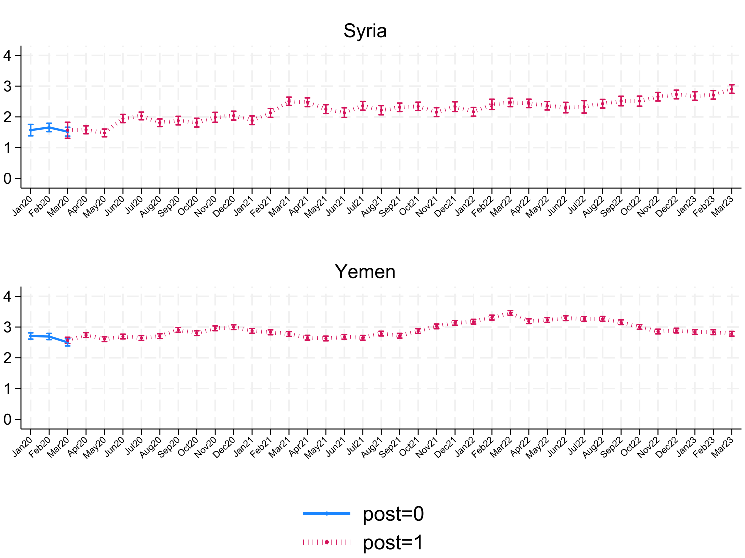

Fig. B.19. Panel C-Number of days in past seven relied on reducing meal size; Pre- and Post-first COVID-19 lockdown.

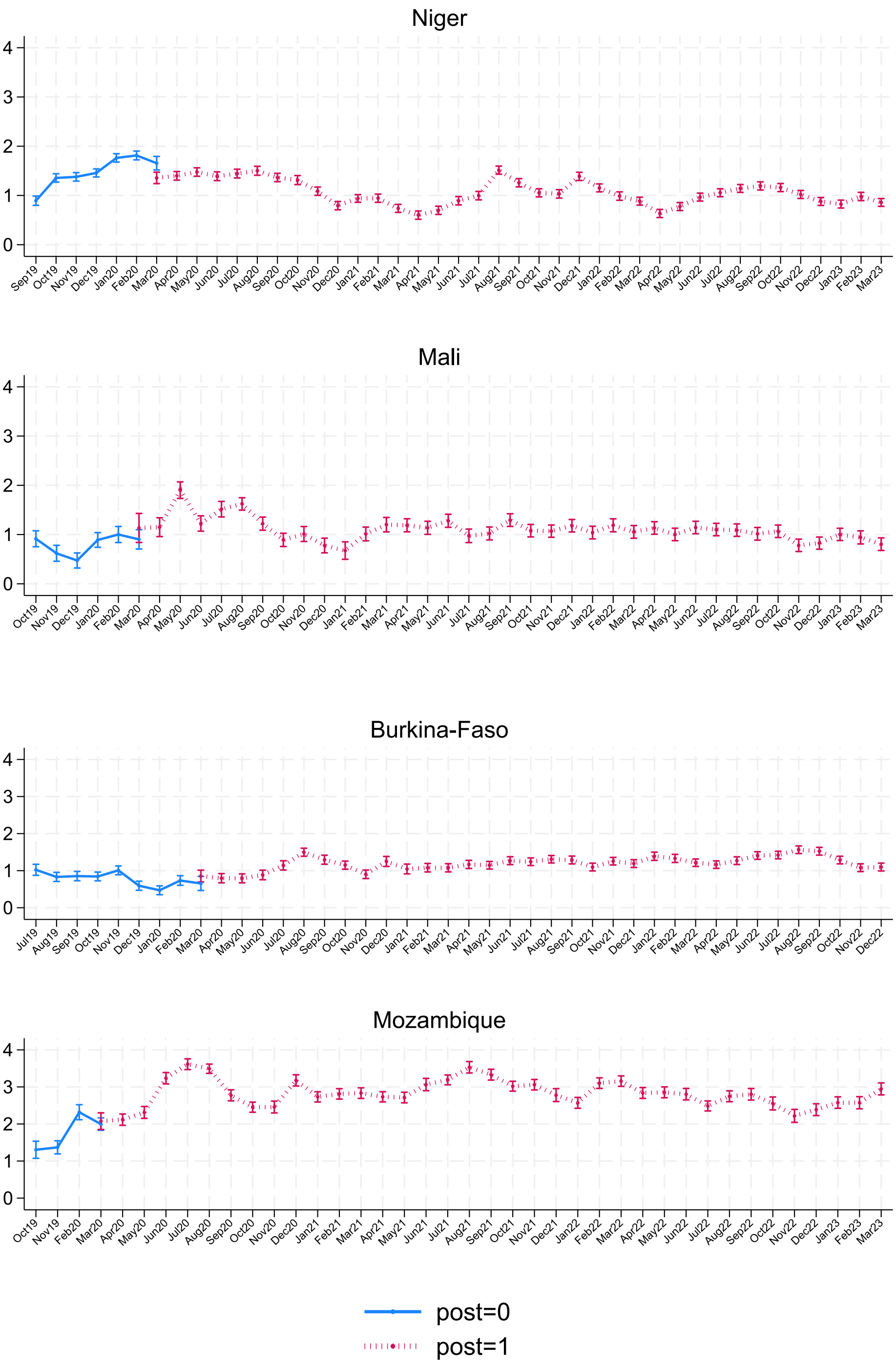

Fig. B.20. Panel A-Number of days in past seven relied on reducing number of meals; Pre- and Post-first COVID-19 lockdown.

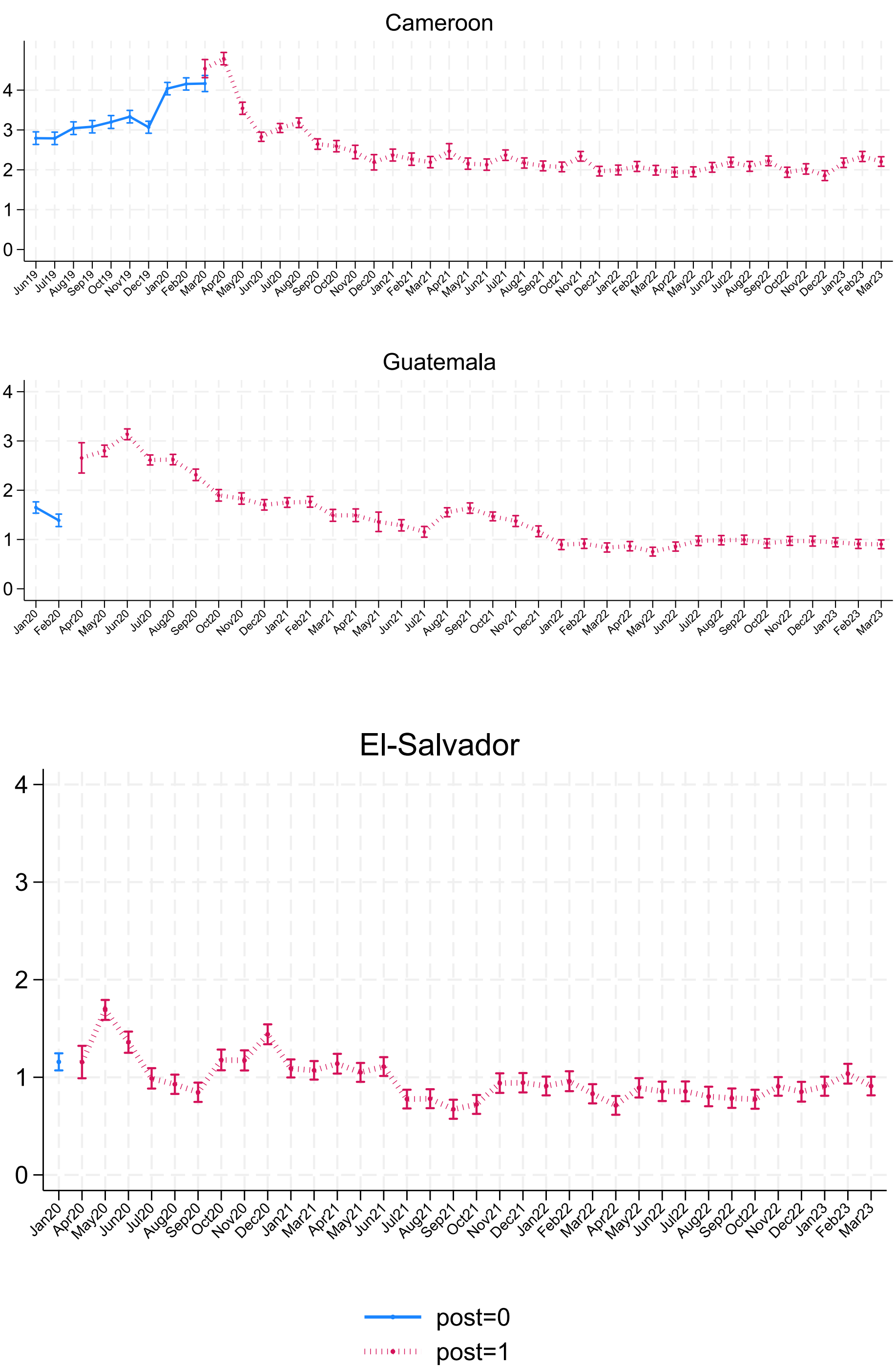

Fig. B.21. Panel B-Number of days in past seven relied on reducing number of meals; Pre- and Post-first COVID-19 lockdown.

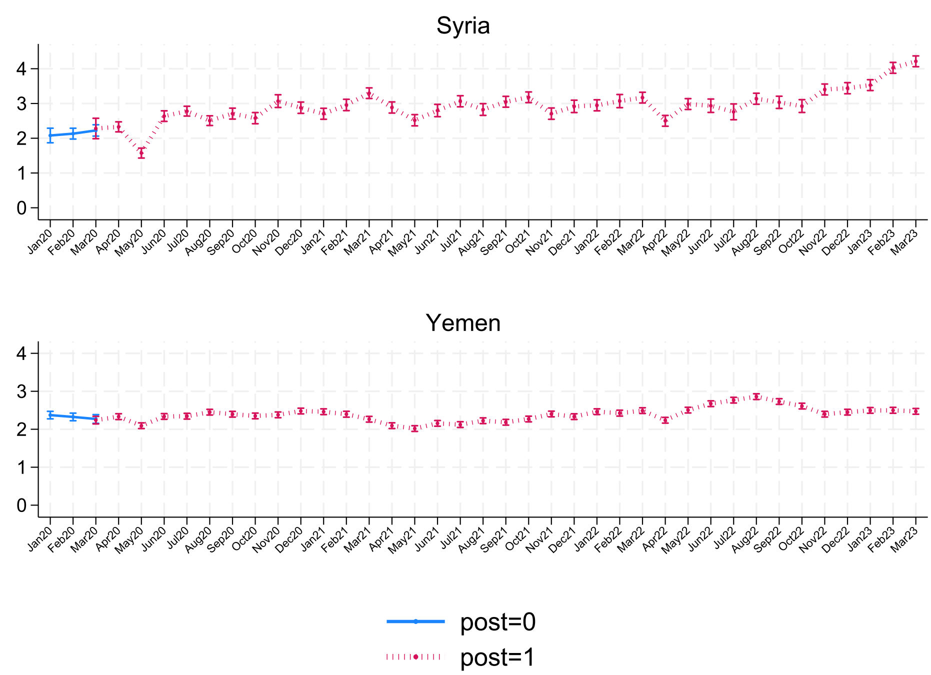

Fig. B.22. Panel C-Number of days in past seven relied on reducing number of meals; Pre- and Post-first COVID-19 lockdown.

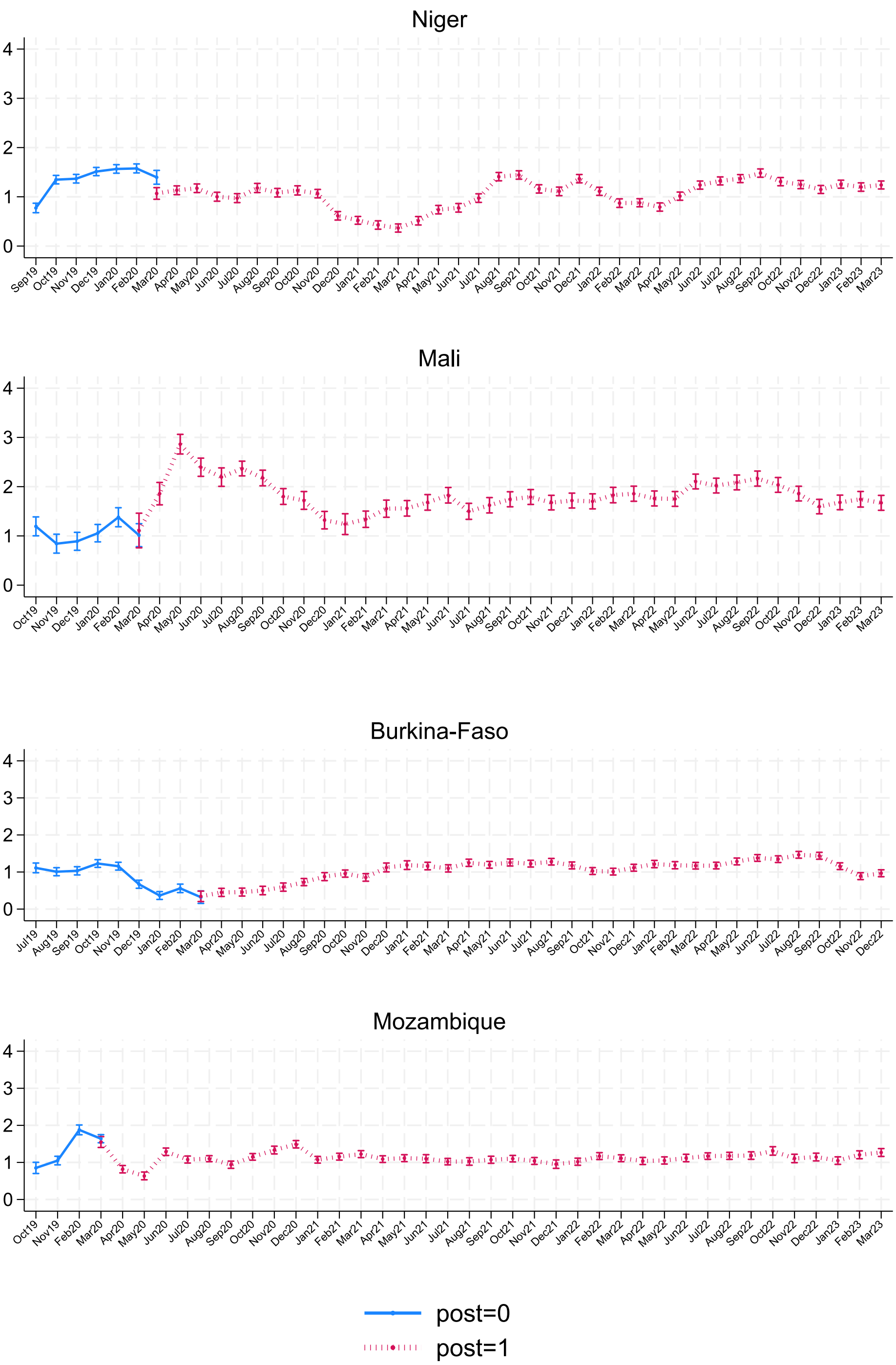

Fig. B.23. Panel A-Number of days in past seven relied on reducing meals for adults; Pre- and Post-first COVID-19 lockdown.

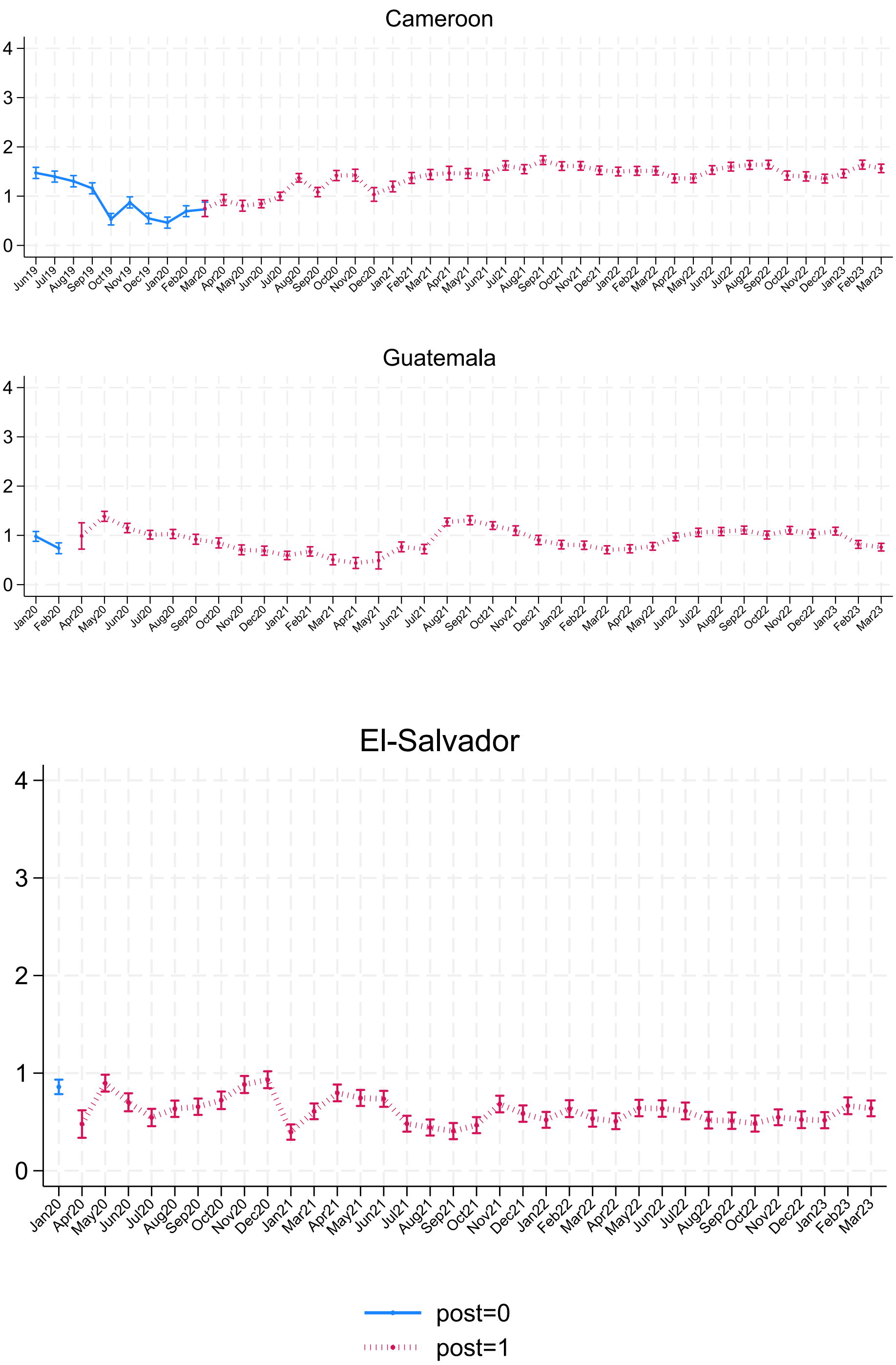

Fig. B.24. Panel B-Number of days in past seven relied on reducing meals for adults; Pre- and Post-first COVID-19 lockdown.

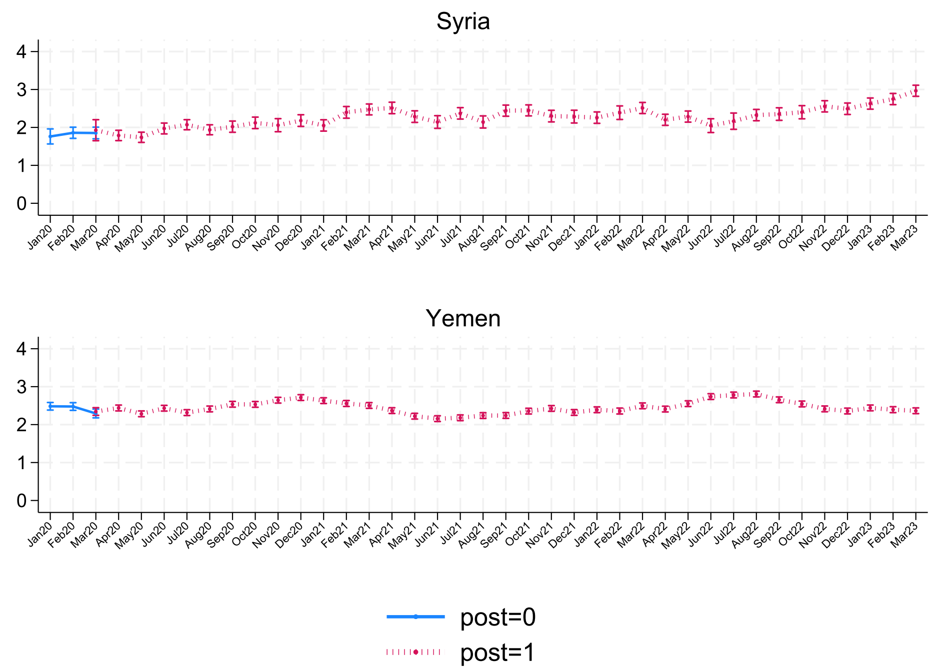

Fig. B.25. Panel C-Number of days in past seven relied on reducing meals for adults; Pre- and Post-first COVID-19 lockdown.

References

Abay, Kibrom, Berhane, Guush, Hoddinott, John, & Tafere, Kibrom (2021). COVID-19 and food security in ethiopia: Do social protection programs protect? *Economic Development and Cultural Change*, http://dx.doi.org/10.1086/715831.

Adjognon, Guigonan Serge, Bloem, Jeffrey R., & Sanoh, Aly (2021). The coronavirus pandemic and food security: Evidence from Mali. *Food Policy*, [ISSN: 0306-9192] *101*, Article 102050. http://dx.doi.org/10.1016/j.foodpol.2021.102050, URL https://www.sciencedirect.com/science/article/pii/S0306919221000282.

Aggarwal, Shilpa, Jeong, Dahyeon, Kumar, Naresh, Park, David Sungho, Robinson, Jonathan, & Spearot, Alan (2020). *Did COVID-19 market disruptions disrupt food security? Evidence from households in rural liberia and Malawi: Technical report*, National Bureau of Economic Research.

Alaimo, Katherine, Chilton, Mariana, & Jones, Sonya J. (2020). Chapter 17 - Food insecurity, hunger, and malnutrition. In Bernadette P. Marriott, Diane F. Birt, Virginia A. Stallings, & Allison A. Yates (Eds.), *Present knowledge in nutrition* (eleventh ed.). (pp. 311–326). Academic Press, ISBN: 978-0-12-818460-8, http://dx.doi.org/10.1016/B978-0-12-818460-8.00017-4, URL https://www.sciencedirect.com/science/article/pii/B9780128184608000174.

Amare, Mulubrhan, Abay, Kibrom A., Tiberti, Luca, & Chamberlin, Jordan (2021). COVID-19 and food security: Panel data evidence from Nigeria. *Food Policy*, [ISSN: 0306-9192] *101*, Article 102099. http://dx.doi.org/10.1016/j.foodpol.2021.102099, URL https://www.sciencedirect.com/science/article/pii/S0306919221000786.

Bloem, Jeffrey R., & Salemi, Colette (2021). COVID-19 and conflict. *World Development*, [ISSN: 0305-750X] *140*, Article 105294. http://dx.doi.org/10.1016/j.worlddev.2020.105294, URL https://www.sciencedirect.com/science/article/pii/S0305750X20304216.

Brück, Tilman, & d'Errico, Marco (2019). Food security and violent conflict: Introduction to the special issue. *World Development*, [ISSN: 0305-750X] *117*, 167–171. http://dx.doi.org/10.1016/j.worlddev.2019.01.007, URL http://www.sciencedirect.com/science/article/pii/S0305750X19300130.

Bundervoet, Tom, Dávalos, Maria E., & Garcia, Natalia (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*, [ISSN: 0305-750X] *153*, Article 105844. http://dx.doi.org/10.1016/j.worlddev.2022.105844, URL https://www.sciencedirect.com/science/article/pii/S0305750X22000341.

Ceballos, Francisco, Hernandez, Manuel A., & Paz, Cynthia (2021). Short-term impacts of COVID-19 on food security and nutrition in rural Guatemala: Phone-based farm household survey evidence. *Agricultural Economics*, *52*(3), 477–494. http://dx.doi.org/10.1111/agec.12629, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/agec.12629, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/agec.12629.

Chakravorty, Bhaskar, Bhatiya, Apurav Yash, Imbert, Clément, Lohnert, Maximilian, Panda, Poonam, & Rathelot, Roland (2023). Impact of the COVID-19 crisis on India's rural youth: Evidence from a panel survey and an experiment. *World Development*, [ISSN: 0305-750X] *168*, Article 106242. http://dx.doi.org/10.1016/j.worlddev.2023.106242, URL https://www.sciencedirect.com/science/article/pii/S0305750X23000608.

Decerf, Benoit, Ferreira, Francisco H. G., Mahler, Daniel G., & Sterck, Olivier (2021). Lives and livelihoods: Estimates of the global mortality and poverty effects of the Covid-19 pandemic. *World Development*, [ISSN: 0305-750X] *146*, Article 105561. http://dx.doi.org/10.1016/j.worlddev.2021.105561, URL https://www.sciencedirect.com/science/article/pii/S0305750X21001765.

Egger, Dennis, Miguel, Edward, Warren, Shana S., Shenoy, Ashish, Collins, Elliott, Karlan, Dean, et al. (2021). Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries. *Science Advances*, *7*(6), eabe0997. http://dx.doi.org/10.1126/sciadv.abe0997, arXiv:https://www.science.org/doi/pdf/10.1126/sciadv.abe0997. URL https://www.science.org/doi/abs/10.1126/sciadv.abe0997.

FAO, IFAD, UNICEF, WFP, & WHO (2020). *The State of Food Security and Nutrition in the World 2020. Transforming food systems for affordable healthy diets: Technical report*, Rome, FAO: Food and Agriculture Organization (FAO), URL http://www.fao.org/3/ca9692en/CA9692EN.pdf.

Gentilini, Ugo, Almenfi, Mohamed, Orton, Ian, & Dale, Pamela (2020). *Social protection and jobs responses to COVID-19: World Bank Working paper*, Washington, DC: World Bank.

Gilbert, Christopher L., Christiaensen, Luc, & Kaminski, Jonathan (2017). Food price seasonality in Africa: Measurement and extent. *Food Policy*, [ISSN: 0306-9192] *67*, 119–132. http://dx.doi.org/10.1016/j.foodpol.2016.09.016, URL https://www.sciencedirect.com/science/article/pii/S0306919216303840. Agriculture in Africa – Telling Myths from Facts.

GSMA, Intelligence (2021). *The mobile economy:Sub-Saharan Africa 2021*. GSMA, Association.

Hale, Thomas, Angrist, Noam, Goldszmidt, Rafael, Kira, Beatriz, Petherick, Anna, Phillips, Toby, et al. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538.

Hale, Thomas, Angrist, Noam, Kira, Beatriz, Petherick, Anna, Phillips, Toby, & Webster, Samuel (2020). *Variation in government responses to COVID-19: BSG Working Paper Series*, University of Oxford.

Hamadani, Jena Derakhshani, Hasan, Mohammed Imrul, Baldi, Andrew J, Hossain, Sheikh Jamal, Shiraji, Shamima, Bhuiyan, Mohammad Saiful Alam, et al. (2020). Immediate impact of stay-at-home orders to control COVID-19 transmission on socioeconomic conditions, food insecurity, mental health, and intimate partner violence in Bangladeshi women and their families: an interrupted time series. *The Lancet Global Health*, [ISSN: 2214-109X] *8*(11), e1380–e1389. http://dx.doi.org/10.1016/S2214-109X(20)30366-1, URL http://www.sciencedirect.com/science/article/pii/S2214109X20303661.

Hangoma, Peter, Aakvik, Arild, & Robberstad, Bjarne (2018). Health shocks and household welfare in zambia: An assessment of changing risk. *Journal of International Development*, *30*(5), 790–817. http://dx.doi.org/10.1002/jid.3337, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/jid.3337. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/jid.3337.

Hashim, Hashim Talib, Miranda, Adriana Viola, Babar, Maryam Salma, Essar, Mohammad Yasir, Hussain, Hasham, Ahmad, Shoaib, et al. (2021). Yemen's triple emergency: Food crisis amid a civil war and COVID-19 pandemic. *Public Health in Practice*, [ISSN: 2666-5352] *2*, Article 100082. http://dx.doi.org/10.1016/j.puhip.2021.100082, URL https://www.sciencedirect.com/science/article/pii/S2666535221000070.

Henderson, Savanna, & Rosenbaum, Michael (2020). Remote surveying in a pandemic: research synthesis. Innovation for Poverty Action.

Himelein, Kristen, Eckman, Stephanie, Kastelic, Jonathan G, Mcgee, Kevin Robert, et al. (2020). *High frequency mobile phone surveys of households to assess the impacts of COVID-19 (Vol. 2): Guidelines on sampling design*. World Bank Group.

IMF (2023). IMF data: Consumer price index. URL https://data.imf.org/?sk=4FFB52B2-3653-409A-B471-D47B46D904B5&sId=1485878855236.

Islam, Asadul, & Maitra, Pushkar (2012). Health shocks and consumption smoothing in rural households: Does microcredit have a role to play? *Journal of Development Economics*, [ISSN: 0304-3878] *97*(2), 232–243. http://dx.doi.org/10.1016/j.jdeveco.2011.05.003, URL https://www.sciencedirect.com/science/article/pii/S0304387811000484.

Janssens, Wendy, Pradhan, Menno, de Groot, Richard, Sidze, Estelle, Donfouet, Hermann Pythagore Pierre, & Abajobir, Amanuel (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*, [ISSN: 0305-750X] *138*, Article 105280. http://dx.doi.org/10.1016/j.worlddev.2020.105280, URL https://www.sciencedirect.com/science/article/pii/S0305750X20304071.

Jolliffe, Dean, Seff, Ilana Julie, & De La Fuente, Alejandro (2018). *Food Insecurity and Rising Food Prices: What do we learn from experiential measures? World Bank Policy Research Working Paper*, (8442).

Josephson, Anna, Kilic, Talip, & Michler, Jeffrey D. (2021). Socioeconomic impacts of COVID-19 in low-income countries. *Nature Human Behaviour*, *5*(5), 557–565.

Kansiime, Monica K., Tambo, Justice A., Mugambi, Idah, Bundi, Mary, Kara, Augustine, & Owuor, Charles (2021). COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment. *World Development*, [ISSN: 0305-750X] *137*, Article 105199. http://dx.doi.org/10.1016/j.worlddev.2020.105199, URL https://www.sciencedirect.com/science/article/pii/S0305750X20303260.

Lin, Faqin, Li, Xuecao, Jia, Ningyuan, Feng, Fan, Huang, Hai, Huang, Jianxi, et al. (2023). The impact of Russia-Ukraine conflict on global food security. *Global Food Security*, [ISSN: 2211-9124] *36*, Article 100661. http://dx.doi.org/10.1016/j.gfs.2022.100661, URL https://www.sciencedirect.com/science/article/pii/S2211912422000517.

Liu, Kai (2016). Insuring against health shocks: Health insurance and household choices. *Journal of Health Economics*, [ISSN: 0167-6296] *46*, 16–32. http://dx.doi.org/10.1016/j.jhealeco.2016.01.002, URL https://www.sciencedirect.com/science/article/pii/S0167629616000035.

Looi, Mun-Keat (2020). Covid-19: Deaths in yemen are five times global average as healthcare collapses. *BMJ*, *370*, http://dx.doi.org/10.1136/bmj.m2997, arXiv:https://www.bmj.com/content/370/bmj.m2997.full.pdf. URL https://www.bmj.com/content/370/bmj.m2997.

Mahadi, Maaz, Ballal, Tarig, Moinuddin, Muhammad, & Al-Saggaf, Ubaid M. (2022). A recursive least-squares with a time-varying regularization parameter. *Applied Sciences*, [ISSN: 2076-3417] *12*(4), http://dx.doi.org/10.3390/app12042077, URL https://www.mdpi.com/2076-3417/12/4/2077.

Mahmud, Mahreen, & Riley, Emma (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*, [ISSN: 0305-750X] *140*, Article 105318. http://dx.doi.org/10.1016/j.worlddev.2020.105318, URL https://www.sciencedirect.com/science/article/pii/S0305750X20304459.

Maxwell, Daniel, Coates, Jennifer, & Vaitla, Bapu (2013). *How do different indicators of household food security compare? Empirical evidence from Tigray* (pp. 1–19). Feinstein International Center.

Ngoma, Hambulo, Hamududu, Byman, Hangoma, Peter, Samboko, Paul, Hichaambwa, Munguzwe, & Kabaghe, Chance (2019). *Irrigation development for climate resilience in Zambia: the known knowns and known unknowns: Technical report*.

Nordhagen, Stella, Igbeka, Uduak, Rowlands, Hannah, Shine, Ritta Sabbas, Heneghan, Emily, & Tench, Jonathan (2021). COVID-19 and small enterprises in the food supply chain: Early impacts and implications for longer-term food system resilience in low- and middle-income countries. *World Development*, [ISSN: 0305-750X] *141*, Article 105405. http://dx.doi.org/10.1016/j.worlddev.2021.105405, URL https://www.sciencedirect.com/science/article/pii/S0305750X21000176.

Ouoba, Youmanli, & Sawadogo, Natéwindé (2022). Food security, poverty and household resilience to COVID-19 in Burkina Faso: Evidence from urban small traders' households. *World Development Perspectives*, [ISSN: 2452-2929] *25*, Article 100387. http://dx.doi.org/10.1016/j.wdp.2021.100387, URL https://www.sciencedirect.com/science/article/pii/S245229292100103X.

Pesaran, M. Hashem, & Timmermann, Allan (1995). Predictability of stock returns: Robustness and economic significance. *The Journal of Finance*, *50*(4), 1201–1228.

Ragasa, Catherine, Lambrecht, Isabel, Mahrt, Kristi, Aung, Zin Wai, & Wang, Michael (2021). Immediate impacts of COVID-19 on female and male farmers in central myanmar: Phone-based household survey evidence. *Agricultural Economics*, *52*(3), 505–523. http://dx.doi.org/10.1111/agec.12632, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/agec.12632. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/agec.12632.

Rudin-Rush, Lorin, Michler, Jeffrey D., Josephson, Anna, & Bloem, Jeffrey R. (2022). Food insecurity during the first year of the COVID-19 pandemic in four African countries. *Food Policy*, [ISSN: 0306-9192] *111*, Article 102306. http://dx.doi.org/10.1016/j.foodpol.2022.102306, URL https://www.sciencedirect.com/science/article/pii/S0306919222000823.

Sibhatu, Matin (2017). Rural food security, subsistence agriculture, and seasonality. *PLoS One*, *12*(10), 1–15. http://dx.doi.org/10.1371/journal.pone.0186406.

Smith, Lisa C., El Obeid, Amani E., & Jensen, Helen H. (2000). The geography and causes of food insecurity in developing countries. *Agricultural Economics*, *22*(2), 199–215. http://dx.doi.org/10.1111/j.1574-0862.2000.tb00018.x, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1574-0862.2000.tb00018.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1574-0862.2000.tb00018.x.

Smith, Kristine M., Machalaba, Catherine C., Seifman, Richard, Feferholtz, Yasha, & Karesh, William B. (2019). Infectious disease and economics: The case for considering multi-sectoral impacts. *One Health*, [ISSN: 2352-7714] *7*, Article 100080. http://dx.doi.org/10.1016/j.onehlt.2018.100080, URL http://www.sciencedirect.com/science/article/pii/S235277141830034X.

Tefera, Nigussie, Demeke, Mulat, & Kayitakire, Francois (2017). *Building sustainable resilience for food security and livelihood dynamics: The case of rural farming households in Ethiopia*. Ispra, Italy: European Commission.

The Lancet Global Health (2020). Food insecurity will be the sting in the tail of COVID-19. *The Lancet Global Health*, *8*(6), Article e737.

Vhurumuku, Elliot (2014). Food security indicators. In *Workshop on integrating nutrition and food security programming for emergency response*. Kenya, Nairobi: Food and Agriculture Organization (FAO).

von Wachter, Till (2021). Long-term employment effects from job losses during the COVID-19 crisis? A comparison to the great recession and its slow recovery. *AEA Papers and Proceedings*, *111*, 481–485. http://dx.doi.org/10.1257/pandp.20211091, URL https://www.aeaweb.org/articles?id=10.1257/pandp.20211091.

Woodrow, Mirembe, Carey, Charles, Ziauddeen, Nida, Thomas, Rebecca, Akrami, Athena, Lutje, Vittoria, et al. (2023). Systematic Review of the Prevalence of Long COVID. *Open Forum Infectious Diseases*, [ISSN: 2328-8957] *10*(7), ofad233. http://dx.doi.org/10.1093/ofid/ofad233, arXiv:https://academic.oup.com/ofid/article-pdf/10/7/ofad233/51009574/ofad233.pdf.

Zeufack, Albert G, Calderon, Cesar, Kambou, Gerard, Kubota, Megumi, Cantu Canales, Catalina, & Korman, Vijdan (2020). *Africa's pulse, No. 22, Fall 2020*. The World Bank.