OXFORD UNIVERSITY PRESS | The World Bank Economic Review

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Journal:	*The World Bank Economic Review*
Manuscript ID	WBER-2023-107
Manuscript Type:	Article
Date Submitted by the Author:	04-Apr-2023
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Keywords:	Lockdowns, Labor Market, Covid, Food security, Coping mechanisms

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Impact of Twin Lockdowns on Hunger, Labor Market Outcomes, and Household Coping Mechanisms: Evidence from Uganda

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Abstract

We examine the short- and medium-run impacts of two of the strictest Covid-19 lockdowns in the developing world, employing longitudinal data from Uganda. Household fixed-effects estimations show significant, immediate increases in food insecurity after the first lockdown and a continued negative impact three months after its lifting. The second lockdown's medium-term impact was even worse, likely because of a compounding effect of a concurrent drought. The rising food insecurity was partly the result of the lockdown-related reductions in the availability of paid work. Agricultural households were more likely to continue working and consequently saw smaller increases in food insecurity. Furthermore, the likelihood of engaging in agricultural work increased after the first lockdown, suggesting a switch to agriculture as a coping mechanism. The other coping mechanisms that households typically rely on for idiosyncratic shocks failed in the face of a worldwide shock, contributing to the sizeable increase in food insecurity.

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1. Introduction

Uganda had some of the strictest Covid-19 lockdowns in Sub-Saharan Africa, one in 2020 and another in 2021 (BBC, 2020; Birner et al., 2021; Mahmud & Riley, 2021). Using longitudinal data and household fixed effects, we examine the impact of the twin lockdowns in Uganda on food insecurity, labor market outcomes, and how households attempted to cope with the lockdowns.

Early assessments of the impact of the pandemic in developing countries generally find a negative effect of lockdowns on food insecurity, income, employment, and agricultural production.[1] However, these studies have limitations, such as using only cross-sectional type data or having a narrow geographical focus covering only one or two villages or states in a country. These studies also suggest that households try to cope with the lockdowns through behavior changes, such as reducing non-food expenditure, drawing down savings, leaving savings and loan groups, increasing borrowing, and selling assets (Ceballos et al., 2021; Headey et al., 2020; Kansiime et al., 2021; Mahmud & Riley, 2023; Rönkkö et al., 2022; Ruszczyk et al., 2021). In addition, there is evidence that remittances declined, and there was insufficient government support to help households cope with the shock (Ceballos et al., 2021; Curi-Quinto et al., 2021).

Only four studies we could identify used household fixed-effects models to control for household-specific time-invariant factors when examining food insecurity.[2] Contrary to the cross-

[1] One set of studies examines the impact of Covid-19 lockdowns on food insecurity (Agamile, 2022; Ceballos et al., 2020, 2021; Dasgupta & Robinson, 2021; Egger et al., 2022; Gaitán-Rossi et al., 2021; Giacoman et al., 2021; Hamadani et al., 2020; Harris et al., 2020; Headey et al., 2020; Jaacks et al., 2021; Kansiime et al., 2021; Kesar et al., 2021; Kundu et al., 2021; Lee, Kenneth et al., 2022; Nguyen et al., 2021). Another part of the literature examine the impact on income, employment, or agricultural production (Balde et al., 2020; Deshpande, 2020; Egger et al., 2022; Harris et al., 2020; Headey et al., 2020; Jaacks et al., 2021; Kang et al., 2021; Kesar et al., 2021; Komin et al., 2021; Rönkkö et al., 2022; Ruszczyk et al., 2021; Wild et al., 2021).

[2] Two studies examine the impact on income and employment using panel data. Results for Ghana show that lockdowns significantly decreased employment and earnings (Schotte et al., 2021). In rural Uganda, household income declined sharply during the initial lockdown. However, a year later, those without a business mostly recovered, while business-owning households still had significantly lower incomes (Mahmud & Riley, 2023).

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sectional studies, three of these studies found no effect of lockdowns on food consumption across Liberia, Malawi, Kenya, and Ethiopia (Aggarwal et al., 2022; Hirvonen et al., 2021; Janssens et al., 2021). Only the Nigerian lockdown appeared to increase food insecurity (Amare et al., 2021).

These studies do, however, also have limitations. The Liberia survey had completion rates as low as 49% and evidence of a non-random attrition (Aggarwal et al., 2022). The Kenya study focused only on households with pregnant women or mothers with children below age four in one county (Janssens et al., 2021). Ethiopia never went into a complete lockdown, and the study covers only Addis Ababa (Hirvonen et al., 2021). Finally, the Nigeria study only examined the immediate effect of the lockdown on a limited set of food insecurity questions (Amare et al., 2021).

Our study contributes to two strands of the literature. First, we contribute to the literature on understanding the impacts of the lockdowns. Given the mixed findings and the limitations in data and estimation methods in the prior literature, our study contributes to the literature on the effects of lockdowns in three ways. First, we use country-wide panel data with household fixed-effects models—which allows us to control for unobservable household characteristics—to compare household food insecurity across almost one-and-a-half years of varying Covid-19 restriction levels. Second, we estimate short- and medium-run effects of lockdowns to understand the persistence of the impact of lockdowns in the months following their lifting. Moreover, the second lockdown coincided with a prolonged dry spell, which allows us to investigate whether a weather shock compounds the effect of the lockdown (Atamanov et al., 2022). Finally, rather than relying solely on reported lockdowns like in prior studies, we use additional data on the stringency of lockdowns and Google mobility data to conduct robustness checks of our analysis.

Second, we contribute to the small but growing body of research on the effects of aggregate shocks and how households cope with these shocks. There is a long-standing literature on how

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households in developing countries smooth consumption in response to idiosyncratic shocks through self-insurance approaches (Case, 1995). However, we know less about how these coping mechanisms fare when households are exposed to aggregate shocks. Most of the research on aggregate shocks has focused on financial shocks and natural disasters and has found varying degrees of ability to smooth consumption, although wealthier households are generally better able to deal with the shock (Del Ninno et al., 2003; Fallon & Lucas, 2002; Glewwe & Hall, 1998; Hallegatte et al., 2020; McKenzie, 2003; Skoufias, 2003; Thomas & Frankenberg, 2007).

We contribute to the literature on coping with aggregate shocks in two ways. First, we examine a repeated systemic shock, which was almost entirely unanticipated, especially the first instance. Second, we use panel data to directly analyze four broad categories of coping mechanisms that households may use to mitigate the effects of these shocks. The categories are changes in labor market participation, diversification of income sources, transfers and remittances, and changes in household structure through migration (Foster & Rosenzweig, 2002; Jayachandran, 2006; Kochar, 1999; McKenzie, 2003; Morduch, 1995; Townsend, 1994; Yang & Choi, 2007). Our paper complements recent work showing that rural households in Uganda, especially non-farm business owners, experienced significant asset decline and increased likelihood of net borrowing, presumably as a coping mechanism after the first lockdown (Mahmud & Riley, 2023).

Using the Food and Agriculture Organization's (FAO) eight-question food insecurity experience scale to measure food insecurity, we find that food insecurity significantly increased during the lockdowns. The point estimates are significant, with an increase of 25 percentage points for any food insecurity during the first lockdown compared to the period with no lockdowns. Even more concerningly, the two worst forms of food insecurity, skipping meals and going without eating the whole day, doubled and tripled in size relative to non-lockdown periods.

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We also find that lockdowns have a substantial medium-term impact, with food insecurity 12 percentage points higher two to three months after the first lockdown was lifted. The medium-term impact was even higher following the second lockdown, with a 22 percentage points increase in any form of food insecurity three months after the second lockdown had been lifted. The difference in the medium-run impact between the two lockdowns suggests that the drought compounded the negative effect of the lockdown.

To understand the mechanisms behind the significant impact on food insecurity, we examine the effect on labor market outcomes and find substantial decreases in paid work during the lockdowns and decreases across all income types, such as wage income, agricultural income, non-farm business income, and income from assets owned. However, households in the agricultural sector were significantly more likely to continue work during and after the first lockdown than non-agricultural households. Thus, their food security was less affected.

Furthermore, households attempted to cope with the lockdown by switching to agricultural work, as shown by a significant increase in the likelihood of working in agriculture after the first lockdown. However, that increase dissipated by the second lockdown, likely because the concurrent drought made agriculture less attractive as a coping mechanism.

Traditional sources of support, such as remittance from abroad or assistance from family members within the country, non-family individuals, and development organizations, decreased during the lockdowns. This suggests that the worldwide macroeconomic shock from Covid-19 affected everyone's ability to transfer resources to needy relatives or friends. This failure of the standard coping mechanisms likely is a significant factor in explaining lockdowns' substantial effect on food insecurity. Finally, we find evidence of a net increase in household members, suggesting that lockdowns forced individuals living elsewhere to join/rejoin the household.

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2. Lockdown Context

On March 18, 2020, the Ugandan government started imposing restrictions, including travel restrictions and cancellation of public gatherings, such as religious services, weddings, and music events (Uganda Bureau of Statistics, 2022). A total lockdown was imposed on March 30 with a nationwide curfew from 7 pm to 6:30 am, banning of public transportation, strict regulations on the movement of vehicles, and closure of all non-essential businesses, which extended till the end of May (Alfonsi et al., 2021; Margini et al., 2020).

Lockdowns were eased at the beginning of June 2020 with the resumption of public transportation and the opening of businesses (Guloba et al., 2021; Monitor, 2020; Schwartz et al., 2021; Wagner et al., 2022). Most small and medium businesses were back open by July-August 2020 (Alfonsi et al., 2021). International travel restrictions remained until the end of September, when land borders reopened, and international flights resumed (Guloba et al., 2021).

In response to the resurgence of Covid-19 infections in 2021, the government of Uganda imposed a second lockdown from June 2021 (Atamanov et al., 2022; Athumani, 2021). This second lockdown was partly eased by the end of July 2021 (Biryabarema, 2021).

3. Estimation Strategy and Data

To establish the causal effects of Covid-19 lockdowns, we use household fixed-effects models on a nationally representative longitudinal household data set, relying on the changes over time in government-imposed lockdowns to identify the effect.

Household data come from the *Uganda High-Frequency Phone Survey on Covid-19* (UHFS), conducted by the Uganda Bureau of Statistics in collaboration with the World Bank. The survey was conducted in seven waves, with four waves in 2020 (June, August, September, and October)

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and three in 2021 (February, March, and October). The goal was to understand the economic and social impacts of the Covid-19 pandemic by collecting high-frequency data on individuals and households (Uganda Bureau of Statistics, 2022). To this end, the survey asked detailed questions on food insecurity, employment, income, outside assistance, and agricultural practices.

The UHFS sample is a subset of the 3,098 households interviewed in the 8th wave of the Uganda National Panel Survey in 2019/20 (UNPS 2019/20). In UNPS 2019/20, respondents were asked to provide a phone number where they could be reached, either their own or that of a friend or neighbor. Originally, the goal was to ensure households could be reached in case they moved, but with the Covid lockdowns, the phone numbers became the basis for surveying households. Of the 2,386 households that provided a phone number, 2,225 were successfully interviewed for round 1 of the UHFS. The head of the household was typically the respondent. If the household head was not present, another member of the household over the age of 15 could respond to the survey.

A concern with phone surveys is that households with access to phones are fundamentally different from households without access to phones. It is, for example, possible that phone surveys have a higher likelihood of reaching wealthier households, who typically have better access to phones, than poorer households. This would bias our results. To avoid any biases to the extent possible, we use the UHFS-provided survey weights to ensure that the data is nationally representative (Uganda Bureau of Statistics, 2022).

Over the seven rounds, the cumulative attrition rate was 15.7 percent, with 1,875 households from the baseline interviewed in round 7 (October 2021). However, replacement households were added to the sample following the first round. This brings our total sample size to 2,302 households. The number of original households that remained in each round and the cumulative number of new households in the follow-up rounds are presented in Appendix Table A1.

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3.1 Empirical Specification

Our main specification regresses outcomes, *Y,* discussed below, on a set of variables using a linear fixed-effects model:[3]

$$Y_{i,t} = \beta_0 + \beta_1 L_1 + \beta_2 L_2 + \beta_3 L_7 + \beta_4 Cases_{i,t} + \beta_5 X_{1\,i,t-1} + \delta_i + \varepsilon_{i,t}, \quad (1)$$

where *i* denote household and *t* survey rounds. We use three indicator variables, L_1, L_2, and L_7, to represent lockdown-related periods, with 1 for a lockdown-related period and 0 otherwise. L_1 represents the first survey round in June 2020, which was towards the end of the first lockdown, and thus captures the immediate/short-run effect of that lockdown. L_2 represents the second survey round in August 2020 and captures the medium-run impact of the first lockdown. L_7 represents the seventh round in October 2021, which was two to three months after the lifting of the second lockdown end-July 2021. Thus, L_7 captures the medium-term impact of the second lockdown. In our estimations, we compare the periods during or soon-after lockdowns to the other periods with no lockdowns in rounds 3, 4, 5, and 6.

In addition to government-imposed lockdowns, individuals may be ill, decide to self-isolate, or take other steps to avoid contact with others if they perceive a high risk of contracting Covid-19, which may increase food insecurity. To capture the severity of the Covid situation, the *Cases* variable measures the number of new Covid-19 cases per 100,000 persons in the 30 days before the household's survey date. The number of Covid cases comes from "Our World in Data."[4]

[3] A linear model has two advantages over non-linear models, such as conditional logit, and has often been used in recent studies (Alam & Bose, 2020; Alam & Pörtner, 2018; Charles & DeCicca, 2008). First, coefficients are easier to interpret. Second, a linear model allows a more straightforward comparison of coefficients across regressions where some dependent variables are binary and some non-binary. Robustness checks, presented in Appendix Tables A1 show that conditional logit models lead to similar results.

[4] The advantage of using "Our World in Data" is that it collects available Covid-19 data from many sources. The data are available at https://covid.ourworldindata.org/data/owid-covid-data.csv, and a complete listing of underlying sources is at https://github.com/owid/covid-19-data/tree/master/public/data/owid-covid-codebook.csv.

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The household fixed-effects, δ_i, control for unobserved household-level time-invariant factors that may bias the results. This approach allows us to control for time-invariant characteristics associated with the individual/household, such as gender, race and religion, constant preferences, household characteristics, area characteristics, and other time-invariant factors.[5] For some estimations, we use individual-level dependent variables, like employment. In these cases, the models are individual fixed-effects models, as the same individual from the household is followed over the rounds.

3.2 Robustness Checks

Using indicator variables to capture the impact of lockdowns has the advantage of straightforward interpretation. Still, the binary approach of comparing periods with lockdowns to periods with no lockdowns might miss potentially important nuances in government and individual behavior over time. As consistency checks on our use of indicator variables to capture the impact of lockdowns, we, therefore, also employ two alternative measures of lockdowns: stringency of the lockdowns and changes in mobility over time.

To capture the stringency of the lockdowns, we employ a modified version of the lockdown stringency index developed at the Blavatnik School of Government, University of Oxford (Hale et al., 2021). The original index is a daily composite measure of how strict the lockdowns were based on nine indicators, including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100, where 100 is the strictest response. As some of the restrictions in the original index, such as school closure and international entry restrictions, are likely to have minimal immediate impacts on food insecurity, we recalculate the index using workplace closings, limits

[5] This means that any variable that does not change over time that are likely to influence our outcome variables would be controlled by the household fixed and would consequently drop out of the estimations.

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on public transport, stay-at-home requirements, and any restrictions on internal movement. We use the variation in the average of this revised index over the 30 days before the households were surveyed to capture the impact of the lockdowns.

Neither the lockdown indicator variables nor the stringency index captures the extent to which the lockdown policies were enforced or adhered to. We, therefore, also use Google Mobility data on the percent change in time spent at residential locations relative to the pre-Covid behavior (Google, 2022).[6] Our measure is the average of this percent change over the 30 days before each household's survey date.

A final concern is that seasonal agricultural patterns may bias our results. Uganda has two lean seasons, one in April and May and another in November and December (FAO, 2022). Hence, with the first survey round fielded in June 2020, it is possible that part of what we capture with the round 1 indicator variable is the effect of the April/May lean season on food security. To examine the role of seasonal variation, we compare the changes in food insecurity measures with the closest comparable from previous rounds of UNPS and estimate our main model on alternative samples to show that seasonal variation is unlikely to explain our results.

3.3 Main Outcomes: Food Insecurity

The survey measures food insecurity based on the Food Insecurity Experience Scale (FIES) developed by the FAO (FAO, 2016). FIES uses eight questions with dichotomous (yes/no) responses to understand the different challenges related to food insecurity. This measure has been empirically validated for cross-cultural use (Ballard et al., 2013; Kansiime et al., 2021). FIES asks

[6] Each day of the week is scaled relative to a "baseline day," which is the median value from the five weeks, January 3 – February 6, 2020. Other mobility information, such as the number of visitors to groceries and pharmacies per day, are available but tend to be noisier and give similar results to our time at home measure.

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whether, during the last 30 days, there was any time when any adult in the household experienced the following because of lack of money or other resources: (i) were worried about not having enough food to eat; (ii) were unable to eat healthy and nutritious/preferred foods; (iii) ate only a few kinds of foods; (iv) skipped a meal; (v) ate less than you thought you should; (vi) ran out of food; (vii) went hungry, but did not eat; and (viii) went without eating for a whole day. We create an indicator variable for each question where 1 represents "yes," and 0 represents "no." Additionally, we create another variable to capture whether a household experienced any food insecurity, with 1 for answering "Yes" to at least one of the eight FIES questions and 0 otherwise.

3.4 Mechanisms that Affect Food Insecurity

To understand how the government lockdowns affected food insecurity and how households responded to the lockdowns, we examine three broad categories: labor market outcomes, changes in income across sources, and whether households received assistance from outside sources.

Labor Market Outcomes

Lockdowns may affect the availability of employment, both because workplaces close and because of the overall reduction in economic activity likely to follow lockdowns. Respondents were asked whether they did "any work for pay, any kind of business, farming or other activity to generate income" in the last week. If yes, they were asked whether this was the same job as the previous round and the broad industry in which they worked in the current survey round. For round 1, respondents were also asked whether they did the same work as before the pandemic started and if it was a different job, which industry it was in. We create two indicator variables to capture the likelihood of working: doing any market work and working in the same job as the prior round.

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The UHFS also asked whether any household member had operated a non-farm family business since the preceding round, so we also created an indicator variable where 1 represents operating a business and 0 otherwise. However, round 1 only asks whether the family has operated a business since the beginning of 2020 and does not ask about operations since the start of the lockdown. This means we are unable to use round 1 information to examine the impact of the lockdown on operating a family business.

The closing of workplaces to enforce social distancing was one of the primary channels through which market work was affected. However, people may have been able to continue some types of work more easily than others. For example, in agriculture, workers can more easily socially distance themselves while working, and, in many cases, the workers are from the same household removing the need to socially distance. Furthermore, lockdowns are more challenging to enforce on farms in rural areas.

Thus, there are two implications of this differential lockdown effect on workplace closings. First, the impacts of lockdowns likely differ between households whose main sector is in agriculture, which we will refer to as agricultural households, and non-agricultural households. Agricultural households include any household that reported that their main activity was related to agriculture. This includes both farmers, casual farm labor, and those employed in any type of processing, sale, or transport of agricultural goods. These households can be either urban or rural.

Second, it is essential to understand how lockdowns affected the movement between unemployment, agricultural work, and non-agricultural work. We create a categorical variable where 0 represents non-agricultural work, 1 represents agricultural work, and 2 represents unemployment. As we know the industry before the first lockdown, we can utilize that data as a pre-lockdown round (i.e., round 0), so we have eight rounds of data for this estimation.

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With three potential outcomes, we use a conditional fixed-effects multinomial logit model to estimate the movements between unemployment, agricultural work, and non-agricultural work. There are two potential issues with this method. First, as with any multinomial model, the coefficient sign does not necessarily indicate the direction of the relationship between the explanatory variable and the outcome. Second, standard marginal analyses are not meaningful because the fixed-effects estimator cannot make predictions that account for the panel-level fixed effects, which are not estimated explicitly. We, therefore, present two relative risk ratios, one the likelihood of working in the agricultural sector against working in the non-agricultural sector, and the other the likelihood of not working against working in the non-agricultural sector.

Finally, the survey asked agricultural households whether they changed planting activities because of Covid-19. If yes, they are asked how they changed their activities. This allows us to examine whether households changed their agricultural strategy in response to the lockdowns.

Income

Households were asked questions related to income in rounds 1 through 6. Instead of the monetary value of their income, households were asked whether their income from different sources increased, remained the same, decreased, or was completely lost since the prior round (for round 1, the questions were asked relative to the start date of the lockdown). The income questions covered five sources: (i) family farming, livestock, or fishing, (ii) non-farm family business, (iii) wage employment, (iv) income from assets (properties, investments, or savings), and (v) pension. As the income question was ordinal, we created variables for each income source where 1 represents an increase in income, 0 represents income remaining unchanged, and -1 represents a decrease in income or a complete loss.

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Given that we use ordinal variables to represent changes in household income, we use a conditional fixed-effects ordered logistic model. The typical conditional logit model works by applying a fixed-effects logit model for households that see a change in the dependent variable over time. For the conditional *ordered* logit model, the actual values of the dependent variable are irrelevant. Instead, greater values correspond to higher-value outcomes (Baetschmann et al., 2015). Hence, for our regressions, a positive coefficient for lockdowns represents an increase in household income, a negative coefficient represents a decrease, and a coefficient near 0 indicates that income remained stable.

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Outside Assistance

In rounds 1 through 6, the UHFS asked households whether they received assistance from the following sources: (i) remittance from abroad, (ii) assistance from family members within the country, (iii) assistance from other non-family individuals, (iv) assistance from NGOs, and (v) assistance from the government.[7] The questions were asked the same way as the income questions, where households can either report income increase, remaining the same, decrease, or complete loss relative to the prior round. Therefore, like the income estimations, we create ordinal variables where 1,0 and -1 represent an increase, same, and decrease/complete loss, respectively, and estimate the effect of lockdowns using the same conditional fixed-effects ordered logistic model.

Using the household rosters from UHFS and the UNPS 2019/20, we have data on the number of household members, adults, and children. To understand the impact on household structure, we calculate the change in the number of household members by subtracting the number in the prior round from the current round's number.

[7] Households were also asked whether they received unemployment benefits, but there was only one observation representing a change, so we do not have any variation to conduct a conditional ordered logit estimation.

3.5 Summary Statistics

Figure 1 shows the daily stringency index, the daily Google Mobility measure of time spent at residential locations, the 7-day average number of new Covid-19 cases and deaths per 100,000 persons, and the data collection window for each of the UHFS rounds in shaded grey. The strictest restrictions are just before round 1, where there is an almost complete lockdown. Although, according to the stringency measure, the second lockdown was nearly as strict as the first. Furthermore, the four months after each lockdown show similar stringency levels, with stringency only dropping in September 2020.

That the lockdown policies were enforced is shown by the substantial increases in the amount of time spent at residential locations during the April through June 2020 and the June through August 2021 periods. Despite some remaining restrictions during the second and third rounds, the time spent at residential locations had returned to almost the baseline by the end of the second round's data collection in mid-August 2020, which is why we did not include the third round as a lockdown round. Through the non-lockdown periods, the time spent at home remained relatively stable except for the Christmas and New Year's celebrations.

The number of confirmed infections and deaths from Covid remained low in Uganda until halfway through 2021. For context, even with the spike in cases in 2021, Uganda's cumulative number of cases per 100,000 at the end of 2021 was only 306.9 compared with 16,294.5 in the US. Furthermore, as in many other developing countries, the number of Covid deaths was low. Even with the increase in cases and deaths by the end of 2021, Uganda had only 7.2 deaths per 100,000 persons, while, for comparison, the US had 245.1 deaths per 100,000 persons.

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We present the summary statistics of key variables in Table 1. Column 1 shows the overall sample mean, and columns 2, 3, and 4 show the respective sample means in round 1 (short-run effect of the first lockdown), round 2 (medium-run effect of the first lockdown), and round 7 (medium run effect of the second lockdown). Column 5 presents the mean for the non-lockdown-related rounds. Overall, the average food insecurity across all rounds is relatively high, with 55.4% reporting at least one type of food insecurity. However, the differences between the lockdown and non-lockdown periods are large. For example, 71.8 percent of households reported any food insecurity during the first lockdown (round 1) as opposed to 47.2 percent for the non-lockdown period, a difference of 24.6 percent.

4. Results

4.1 Food Insecurity

Table 2 shows the impact of the Covid-19 lockdowns in Uganda on the likelihood of food insecurity using a linear model with household fixed effects.[8] Overall, lockdowns caused a substantial increase in all types of food insecurity in both the short and medium run.

As shown in column 1, the first lockdown led to a substantial and statistically significant short-run increase in the likelihood of having any food insecurity by 25.2 percentage points. Furthermore, the lockdowns led to a significant increase in all eight food insecurity measures, where most of the point estimates are sizeable, with magnitudes of over 20 percentage points. Even more concerning, the worst forms of food insecurity ("had to skip a meal" and "went hungry but did not eat") more than doubled, and "went without eating for a whole day" almost tripled.

[8] As our point estimates are relative to non-lockdown periods, we present the mean of outcome variables in non-lockdown periods at the bottom of each column.

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The effects of the first lockdown persisted in the medium run, with significant increases in food insecurity about three months after the lockdowns were lifted. Any food insecurity was still 11.9 percentage points higher than in non-lockdown periods, and five of the nine measures had a point estimate of at least nine percentage points.

Moreover, the medium-run impact of the second lockdown is similar to the short-run effect of the first lockdown. The point estimates of the second lockdown are over 20 percentage points for six of the nine food insecurity measures. This suggests that the second lockdown, combined with a drought, had a worse impact on food insecurity than the first lockdown, at least in the medium run.

4.2 Impact on Work

One way lockdowns can affect food insecurity is by lowering people's ability to work. Table 3, column 1, shows that the likelihood of any market work decreased by a significant 18.6 percentage points during the first lockdown. These employment effects were driven mainly by lockdowns rather than being ill from Covid-19. As shown in Figure 1, there were almost no cases during the first lockdown. Furthermore, UHSF asked individuals the reason for not working, and the top three reasons reported are that the place of work is closed (62%), being ill from any illness or quarantined (10%), and being laid off from the job (8%).

In the medium run, the likelihood of market work is 2.5 percentage points lower than in non-lockdown periods. This suggests that the labor market was approaching but not yet fully recovered. The medium-run impact of the second lockdown combined with the drought is large, with the likelihood of market work decreasing by 13 percentage points. This large impact on market work may explain the large impact on food insecurity in the medium run following the second lockdown.

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While we do not have data for round 1 and cannot estimate the short-run effect, the likelihood of operating a non-farm family business in the medium run decreased by seven percentage points after the first lockdown (column 2). However, the second lockdown did not impact family business in the medium run, even though this coincided with the drought.

Given the overall decrease in market work, it is useful to understand whether individuals, who were able to continue work during the lockdowns, did so in the same jobs. The first lockdown significantly decreased the likelihood of working at the same job as the prior round by about 8.6 percentage points (column 3). Thus, we find both a decrease in market work and an increased likelihood of moving jobs. The impact in the medium run is small, indicating that people remained in their new jobs after the end of the lockdown. We do not have direct information on wages, but these new jobs likely paid less than the pre-lockdown job, suggesting continued labor market difficulties in the medium run, which would also affect food insecurity. There is a small effect in the medium run following the second lockdown. However, we cannot establish whether this is because the second lockdown follows the same pattern as the first or because there is less movement compared to the first lockdown.

With workplace closures during lockdowns, we expect significant movement between sectors, and from employment to unemployment. Layoffs are likely in both the agricultural and non-agricultural sectors. To complicate the picture, some may resort to agricultural production, even if there is a lower return than their original job. Table 3, columns 4 and 5 show the relative risk of being in the agricultural sector and being unemployed, respectively, versus working in the non-agricultural sector. Not surprisingly, the short-run effect of the first lockdown is to significantly increase unemployment relative to being employed in the non-agricultural sector, with the relative risk of unemployment increasing by 11.6 relative to working in the non-

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agricultural sector. However, there was also a significant shift to agriculture after the first lockdown: the relative risk of working in agriculture is 3.9 times higher compared to working in the non-agricultural sector. The results suggest that while more people were becoming unemployed, there is also a significant switch to agricultural work to cope with the effects of the first lockdown.[9] While the magnitude of the relative risk for unemployment declined to 2.8 times, the strong effect on working in agriculture persisted in the medium run, suggesting that people did not immediately shift back to non-agricultural work after the end of the first lockdown.

However, we do not find a higher likelihood of agricultural work in the medium run following the second lockdown compared to the non-lockdown periods, likely because the concurrent drought negatively affected the agricultural labor market. The lack of opportunities in the agricultural sector may also explain why individuals were likely to remain at the same job after the second lockdown (results from column 3). Overall, these results suggest that while some joined the agricultural sector to cope with the effects of the first lockdown, the negative impact of the drought on agriculture meant that this was a less attractive coping mechanism during the second lockdown.

4.3 Impact on Income

As shown in Panel B of Table 3, the first lockdown significantly decreased farm income, non-farm family business income, wage income, and income from assets, and the effects persisted in the medium run. These income effects are likely a major reason for the significant increase in food insecurity from the lockdowns. As a placebo, since pensions are typically not dependent on

[9] While not focusing on lockdowns, one prior study, Gupta et al. (2021), finds evidence that the pandemic itself led to a switch in occupations, particularly among salaried and business persons, with agriculture seeing the biggest inflow of labor compared to other industries.

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the state of the economy and remain steady over time, we also examine the impact on pension income. Not surprisingly, we do not find any changes in pension income during the lockdowns.[10]

4.4 Coping Mechanisms

Given the reductions in household income with the lockdowns, we examine potential coping mechanisms in Table 4 (Morduch, 1995; Townsend, 1994). Two possibilities are assistance from family members outside the household or from institutions. There were significant reductions in assistance from the family within the country, assistance from non-family individuals, and assistance from NGOs after the first lockdown. Remittances also decreased but not statistically significantly. The only increase came in government assistance, although the effect is statistically insignificant. These results suggest that households' standard coping mechanisms were unavailable during the lockdowns. This is in line with the substantial decline in remittances across the world in the second quarter of 2020, as lockdowns worldwide led to the closure of workplaces and limited people's movements (Cardozo Silva et al., 2022; Guha et al., 2021; Kpodar et al., 2021; Shimizutani & Yamada, 2021; Zhang et al., 2021). The failure of these coping mechanisms in the face of reductions in income likely contributed substantially to the large effects of lockdowns on food insecurity.

As households faced greater food insecurity during lockdowns, it is possible that, on the one hand, some household members left to look for better opportunities. On the other hand, as lockdowns led to reduced income and lower availability of work, migrants might return to their families. Panel B of Table 4 shows the impact of lockdowns on the change in the number of household members. We find an increase in household members during the first lockdown (column

[10] We do not have income data for round 7 and thus cannot examine the medium-term impact of the second lockdown.

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1). Furthermore, this effect holds for adults (column 2) and children (column 3). The positive effect continued in the medium run for total members, although statistically insignificant, and the number of children, but there was a slight reduction in the number of adults. In contrast to the effects from the first lockdown, there were larger effects in the medium run following the second lockdown.

The increase in the number of household members raises the question of whether the lockdowns caused an urban-to-rural migration. However, we find no such evidence of lockdown-induced migration in column 4, which shows the likelihood of living in an urban area.

Lastly, given the shift to agricultural work, we examine whether agricultural households change their agricultural strategy to cope with the lockdowns. We find suggestive evidence that agricultural households changed their farming strategy during the lockdowns, such as changing the farming area and changes in the variety of crops produced. The details of these results are in Appendix Section A1.

Overall, our results from the coping mechanisms suggest that the households, on average, could not take advantage of outside help, whether it was assistance from family members living outside of the household or assistance from institutions. We find evidence of net migration into the households and a switch to agricultural work, suggesting that some household members return to the family for farm work.

4.5 Agricultural vs. Non-agricultural households

Given the increase in agricultural work with the first lockdown, Table 5 examines whether agricultural households fared better than non-agricultural households. Note, as we previously treated households' work in agriculture as a choice variable, these estimations are exploratory rather than causal. As lockdowns affected the likelihood of working in agriculture, we interact

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lockdown variables with whether the household was engaged in agricultural production in the prior round.[11] As shown in column 1 of Table 5, agricultural households were 31 percentage points more likely to work during the first lockdown than non-agricultural households. However, this difference disappears in the medium run suggesting an improvement in employment conditions.

Agricultural households appeared to be more food secure than non-agricultural households during the first lockdown. Their likelihood of suffering "any food insecurity" during lockdowns was about 20 percentage points lower than non-agricultural households. Furthermore, all individual food security questions show that agricultural households do better than non-agricultural households. However, for "Had to skip a meal" and "Went hungry but did not eat," the effects are not statistically significant. Like the employment results, the difference disappears in the medium run. Overall, these results suggest that agricultural households were better able to keep working and did better in terms of food security. There is no difference in employment or food insecurity for the second lockdown between the two types of households. This is likely because of the concurrent drought during and after the second lockdown in Uganda that affected the agricultural households' employment and food production.

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5. Robustness Checks

As a consistency check on our use of indicator variables to capture lockdowns, we use the average of the revised daily lockdown stringency measure for the 30 days before the interview in our main specifications. The results are presented in Table 6. More stringent restrictions lead to significant increases in all food insecurity variables. During the first round, the average measure of the stringency index is 77, while the index in the non-lockdown rounds (rounds 3 through 6) is

[11] For round 1, the survey asks about the employment industry before the lockdown, which allows us to identify whether individuals were employed in agriculture before the round 1 lockdown.

47. Therefore, the point estimates imply that "any food insecurity" increased by 15 percentage points when comparing the first lockdown to the periods with no lockdown.

One downside of the stringency measure is that it does not capture the extent to which the policies were enforced. Therefore, we also use Google mobility data on the amount of time individuals spent at their residences. The results are presented in Table 7. The mobility measure also shows significant increases in food insecurity due to the lockdowns. For example, the difference between the non-lockdown and the first lockdown in time spent at residences implies a 30 percentage points increase in any food insecurity due to the first lockdown.[12]

To examine whether seasonality in food security might be behind our results, we first compare pre-Covid information on food insecurity with a subset of our measures. The UNPS 2015/16 and the UNPS 2019/20 both asked if the households had been faced with a situation when they did not have enough food to feed the household in the last 12 months. If yes, they were asked to list all months when this occurred. Although this question does not directly correspond to any of the food insecurity questions asked in the UHFS and the recall period is one year rather than the 30 days for the UHFS, it is close to three of our questions: ran out of food because of lack of money, went hungry but did not eat, and went without eating for a whole day.

For the UNPS question, we combined all observations by month and calculate the percentage who reported not having enough food to feed the household. For the UHFS questions, we calculate the percentages food insecure by interview month. Figure 2 shows the food insecurity percentages with the UNPS question shown in black for comparison. Despite FAO listing April/May and November/December as the lean periods, the UNPS data show that April, May, and June were the

[12] The average non-lockdown mobility measure is around 10 percent over baseline and the first lockdown mobility measure is about 30.

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three months with the highest proportion of food insecurity, while November and December were the months with the lowest proportion.[13]

All three UHFS questions follow the same general pattern as the UNPS question outside the lockdown periods, September 2020 through April 2021. For the initial lockdown, both the short- and medium-run effects show clearly in the UHFS questions. Although it is possible that these high values were the result of seasonal variation, we consider it unlikely for two reasons. First, there is no evidence of the same elevation for April 2021, which is also in the lean season but nine months after the lockdown. Second, the medium-term effects of the second lockdown show even worse medium-term food insecurity outcomes despite being in a non-lean period.

Our second approach is to re-estimate our main models on three subsets of the data. First, we make use of the fact that round 6 took place during the April/May lean season but was the round least affected by lockdowns and estimate our main model using only information from rounds 1, 2, and 6. The results are shown in Appendix Table A4. Compared to the main model, the short-run effects are slightly smaller and the medium effect larger. Second, the only two rounds collected during almost the same calendar month were rounds 4 and 7, and Appendix Table A5 shows the results when we restrict to those two rounds. The medium-run effect of the second lockdown for this sample is smaller but still statistically significant in most cases. Complicating this comparison is that the number of new Covid cases was close to constant within each round and smaller during round 7 than round 4, resulting in potential multicollinearity and statistically significant *negative* effects of new cases on food insecurity for some outcomes. Finally, we expect urban households to be less affected by seasonality, and Appendix Table A6, therefore, shows the results using only

[13] This pattern holds for both UNPS 2015/16 and UNPS 2019/20. The results for the individual surveys are available upon request. UNPS 2018/19 shows the same questions in the questionnaire, but the responses are not available in the data.

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urban households across all rounds. The short- and medium-run effects of the lockdowns are either the same or larger when we restrict the sample to urban households. Hence, our results are qualitatively the same, no matter how we account for seasonality.

6. Conclusion

Using country-wide panel data with a household fixed-effects model, we examine the impact of two Covid-19 lockdowns in Uganda on food insecurity. Food insecurity increased substantially during the first lockdown, with the relative effects largest for the worst types of food insecurity. The first lockdown also had a significant medium-run impact on food insecurity. The medium-run impact was even higher following the second lockdown, as a drought compounded the negative effect of the lockdown.

There were significant decreases in paid work and earned income. However, agricultural households were better able to continue working during the first lockdown than non-agricultural households. Consequently, their food security outcomes were better as well.

We find evidence that households attempted to cope with the first lockdown by temporarily switching to agricultural work. However, traditional sources of coping mechanisms, such as remittance from abroad, assistance from family members within the country, assistance from non-family individuals, and assistance from development organizations, all decreased during the lockdowns. The lack of assistance may explain lockdowns' substantial effect on food insecurity. Lastly, to make matters more challenging for households, there was a net increase in the number of household members, suggesting that lockdowns forced individuals living elsewhere to join/rejoin the household.

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Three broader conclusions emerge from our results. First, on average, agriculture is likely less productive than non-farm work but better than unemployment. With a slow rate of switching back from agriculture, the lockdowns can potentially have severe long-term adverse effects on Uganda's development. Second, the results show the limit of self-insurance and mutual insurance when faced with a systemic shock. Most of the literature has focused on the smaller and more frequent risk of idiosyncratic shocks and how households respond to these. However, a better understanding of systemic shocks and how households respond is still lacking. Finally, the case of Uganda illustrates well the issues with the wholesale lockdown of economies in response to Covid-19 in situations with low state capacity. Uganda has been hailed as a leading example of curbing Covid-19 (Adams et al., 2021). However, the mitigation efforts failed to reach those most affected by the lockdown. With the low mortality rate in Sub-Saharan Africa, including Uganda, the potential long-term cost of the lockdowns potentially significantly outweighs the benefits. Quantifying these costs and identifying possible avenues of mitigation are critical future areas of research.

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Funding

This work was supported, in part, by a Eunice Kennedy Shriver National Institute of Child Health and Human Development research infrastructure grant, P2C HD042828, to the Center for Studies in Demography & Ecology at the University of Washington.

Acknowledgements

We would like to thank seminar participants at Howard University, Alex Henke, and two anonymous referees for their helpful comments and suggestions on an earlier version of this paper. We would also like to thank Pascal Ntaganda for his research assistance.

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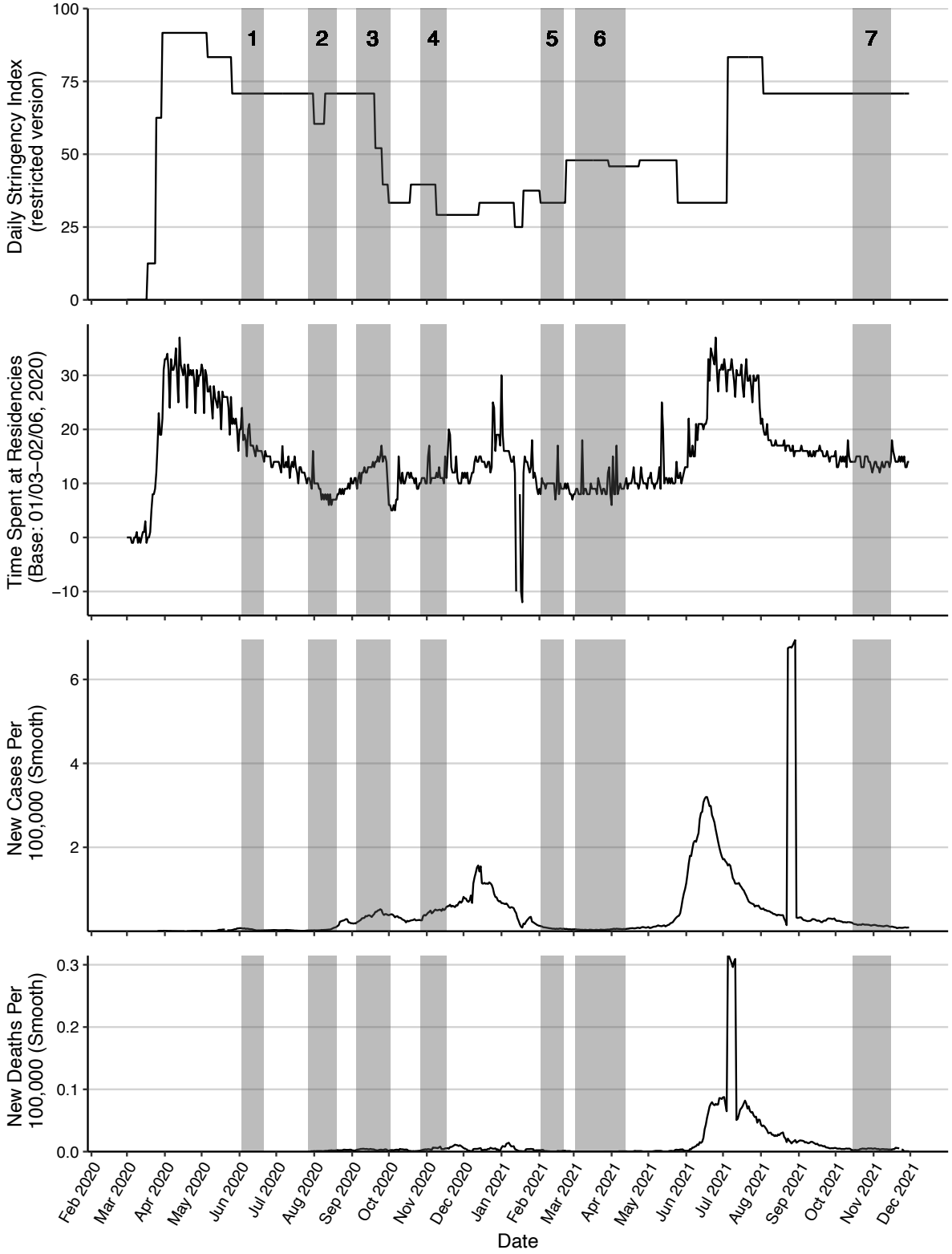

Figure 1: Revised Stringency Index, Time Spent at Residential Locations, Daily New Covid Cases per 100,000 persons and New Deaths per 100,000, and Data Collection Window for Each UHFS Survey Round.

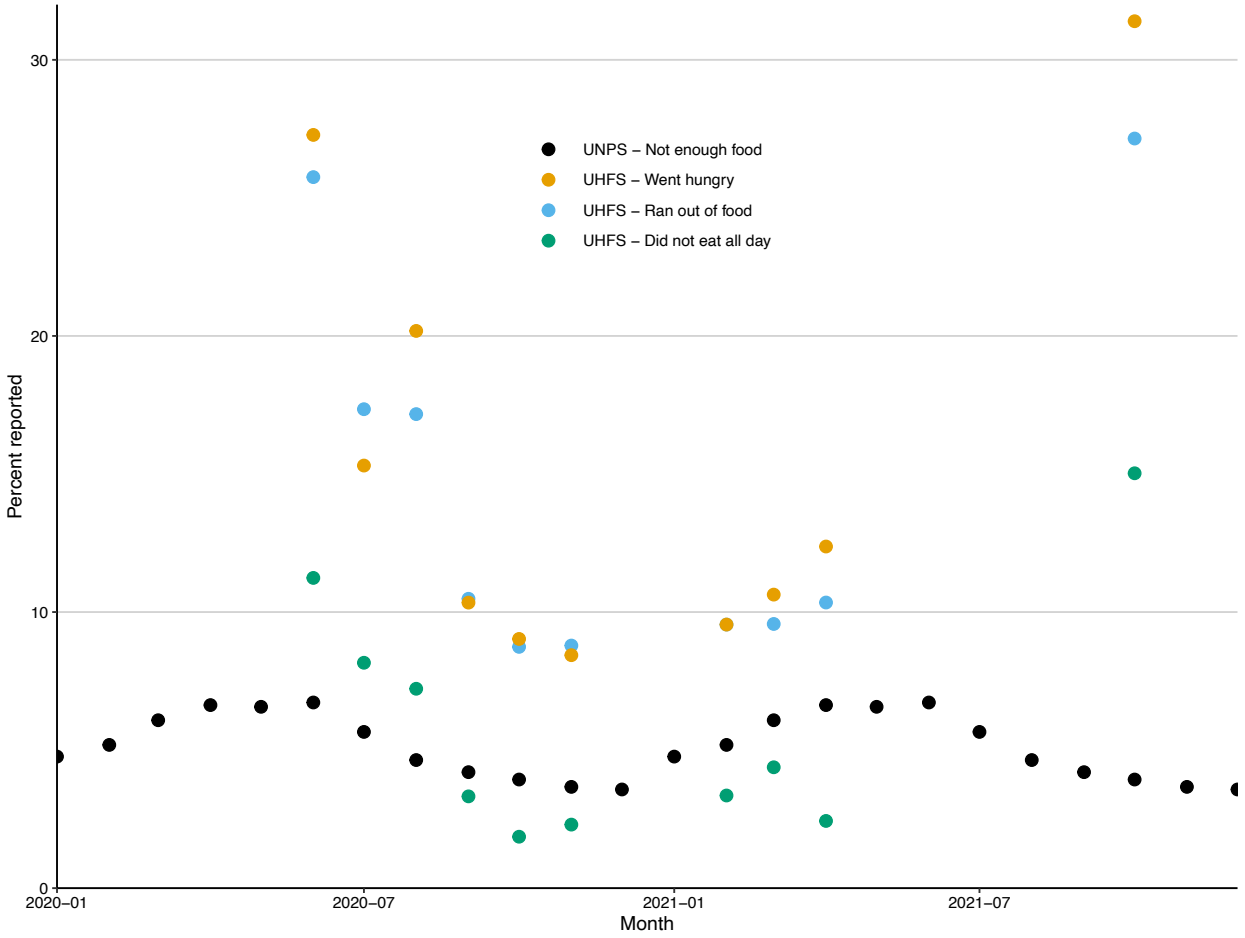

Figure 2: Projected Seasonality in Food Insecurity from UNPS and Observed Food Insecurity for Three UHFS Outcomes

Table 1: Summary statistics of key variables

	(1)	(2)	(3)	(4)	(5)
	Overall sample mean	Mean at round 1 (first lockdown)	Mean at round 2 (medium run of first lockdown)	Mean at round 7 (medium run of second lockdown)	Mean in non-lockdown rounds (Rounds 3, 4, 5, and 6)
Food Insecurity:					
Any food insecurity	55.6%	71.8%	58.7%	69.2%	47.5%
Worry about not having enough food to eat	37.8%	58.0%	42.0%	53.5%	27.8%
Unable to eat healthy and nutritious food	45.0%	58.6%	48.6%	59.8%	37.2%
Had to eat only a few kinds of food	44.2%	58.0%	44.3%	58.8%	37.4%
Had to skip a meal	21.0%	34.2%	25.4%	34.4%	13.4%
Ate less than they thought they should	28.4%	42.3%	31.3%	46.6%	19.9%
Ran out of food	14.4%	23.9%	16.5%	23.2%	9.3%
Went hungry but did not eat	15.3%	24.8%	18.1%	27.8%	9.2%
Went without eating for a whole day	6.0%	9.7%	6.4%	14.3%	3.1%
Employment and household variables:					
Likelihood of market work	83.2%	69.9%	86.3%	74.5%	87.8%
Likelihood of op. a non-farm family business	39.7%		35.5%	39.6%	40.7%
Likelihood of working in same job as before	95.2%	87.6%	95.7%	95.1%	96.9%
Agricultural household	57.9%	61.4%	60.5%	54.3%	57.2%
Total household members	5.02	5.0	5.0	5.2	5.0
Total number of adults in household	2.36	2.4	2.3	2.4	2.3
Total number of children in household	2.66	2.6	2.7	2.8	2.6
Likelihood of living in urban area	32.1%	32.8%	31.7%	31.9%	32.1%
Fraction of households reporting changes in income and assistance ('+' indicates increase, '-' indicates decrease, 0 indicates no change):					
Farm income	-13.2%	-38.0%	-16.8%		-5.8%
Nonfarm income	-12.3%	-36.6%	-17.8%		-4.5%
Wage income	-8.7%	-20.9%	-13.2%		-4.3%
Income from assets	-0.9%	-2.4%	-1.5%		-0.3%
Pension	0.0%	0.0%	0.0%		0.0%
Remittance	-0.6%	-1.0%	-0.8%		-0.5%
Assistance from family within country	-8.5%	-11.8%	-10.3%		-7.1%
Assistance from non-family individuals	-1.0%	-2.2%	-1.7%		-0.5%
Assistance from NGOs	-0.1%	-0.5%	-0.1%		0.0%
Assistance from government	0.0%	0.1%	0.0%		-0.1%
Number of observations	14,818	2,225	2,189	1,930	8,474

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Table 2: Impact of lockdowns on food insecurity

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
First lockdown: short run	0.252***	0.314***	0.221***	0.204***	0.194***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.014)
First lockdown: medium run	0.123***	0.155***	0.121***	0.070***	0.103***
	(0.015)	(0.017)	(0.017)	(0.016)	(0.013)
Second lockdown: medium run	0.215***	0.251***	0.224***	0.214***	0.204***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.016)
Covid-19 cases/100,000	0.002	0.003	0.001	0.000	-0.003**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
No of observations	14,818	14,818	14,818	14,817	14,818
Number of households	2,302	2,302	2,302	2,302	2,302
Mean of outcome at non-lockdown period	47.5%	27.8%	37.2%	37.4%	13.4%

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
First lockdown: short run	0.212***	0.145***	0.154***	0.063***
	(0.016)	(0.013)	(0.013)	(0.009)
First lockdown: medium run	0.101***	0.067***	0.085***	0.027***
	(0.016)	(0.011)	(0.012)	(0.008)
Second lockdown: medium run	0.264***	0.133***	0.180***	0.103***
	(0.018)	(0.015)	(0.015)	(0.011)
Covid-19 cases/100,000	-0.002	-0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
No of observations	14,818	14,818	14,818	14,818
Number of households	2,302	2,302	2,302	2,302
Mean of outcome at non-lockdown period	19.9%	9.3%	9.2%	3.1%

Note: Linear Model with household fixed effects. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%. All dependent variables are dummy variables. As point estimates are relative to non-lockdown periods, we present the mean of outcome variables in non-lockdown periods.

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Table 3: Impact of lockdowns on labor market outcomes

Panel A: Impact on work and employment outcomes

	Linear model			Multinomial logit	
	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Likelihood of market work	Likelihood of operating a non-farm family business	Working in same job as before	Comparing agriculture (1) vs non-agriculture (0)	Comparing unemployed (2) vs non-agriculture (0)
First lockdown: short run	-0.186***		-0.083***	3.78***	11.24***
	(0.016)		(0.014)	(0.607)	(1.753)
First lockdown: medium run	-0.022*	-0.066***	-0.009	3.66***	2.61***
	(0.012)	(0.015)	(0.012)	(0.541)	(0.436)
Second lockdown: medium run	-0.132***	-0.007	-0.016*	0.994	3.48***
	(0.015)	(0.015)	(0.010)	(0.191)	(0.632)
Covid-19 cases/100,000	-0.001	-0.003**	0.002	1.13***	1.08***
	(0.001)	(0.001)	(0.001)	(0.021)	(0.019)
No of observations	14,811	12,593	10,521	10,676	10,676
Number of households	2,300	2,282	2,174	1,407	1,407
Mean of outcome at non-lockdown period	87.8%	40.7%	96.9%	Agri.: 57.2%, Unemployed:12.2%	

Panel B: Impact on different types of income

	(6)	(7)	(8)	(9)	(10)
Outcome variables:	Farm income	Nonfarm income	Wage income	Income from assets	Pension
First lockdown: short run	-1.109***	-1.957***	-1.577***	-2.026***	-1.544
	(0.105)	(0.126)	(0.138)	(0.363)	(1.438)
First lockdown: medium run	-0.217**	-0.863***	-1.015***	-1.473***	-1.711
	(0.109)	(0.129)	(0.153)	(0.393)	(1.605)
Covid-19 cases/100,000	0.040***	-0.031**	-0.051***	-0.059	-0.312
	(0.010)	(0.013)	(0.016)	(0.043)	(0.385)
No of observations	10398	7238	5195	738	18
Number of households	1809	1258	911	128	3
Mean of outcome at non-lockdown period	-0.06	-0.05	-0.04	-0.003	0

Note: Columns 1 to 3 of Panel A represent coefficients from linear model with household fixed effects. Dependent variables in columns 1 to 3 are dummy variables. Columns 4 and 5 represent relative risk ratios from fixed effects multinomial logit model, where 0 represents non-agricultural work, 1 represents agricultural work, and 2 represents unemployment. Panel B represents coefficients from fixed effects ordered logit model, so for dependent variables in columns 6 to 10, 0 represents no change, 1 represents an increase, and -1 represents a decrease. For all columns, standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table 4: Impact of lockdowns on different kinds of coping mechanisms

Panel A: Impact on outside assistance

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Remittance	Assistance from family within country	Assistance from non-family individuals	Assistance from NGOs	Assistance from government
First lockdown: short run	-0.814	-0.406***	-1.541***	-2.604***	1.123
	(0.563)	(0.157)	(0.378)	(0.932)	(0.901)
First lockdown: medium run	-0.438	-0.217	-1.316***	-0.481	0.235
	(0.678)	(0.155)	(0.353)	(0.718)	(0.645)
Covid-19 cases/100,000	-0.027	0.026	-0.029	0.005	-0.030
	(0.049)	(0.020)	(0.035)	(0.149)	(0.071)
No of observations	363	4155	732	87	156
Number of households	63	724	129	15	26

Panel B: Impact on changes in number of household members and movement to urban area

	(6)	(7)	(8)	(9)
	Change in no. of household members	Change in no. of adult members	Change in no. of children members	Likelihood of living in urban area
First lockdown: short run	0.126***	0.043***	0.083***	-0.002
	(0.028)	(0.015)	(0.025)	(0.002)
First lockdown: medium run	0.021	-0.023**	0.044**	-0.001
	(0.021)	(0.010)	(0.018)	(0.002)
Second lockdown: medium run	0.244***	0.103***	0.140***	-0.008**
	(0.039)	(0.021)	(0.027)	(0.004)
Covid-19 cases/100,000	0.006***	0.003**	0.003**	-0.000
	(0.002)	(0.001)	(0.001)	(0.000)
No of observations	14,463	14,463	14,463	14,818
Number of households	2,282	2,282	2,282	2,302

Note: Panel A represents coefficients from fixed effects ordered logit model, so for the dependent variables, 0 represents no change, 1 represents an increase, and -1 represents a decrease. Panel B represent coefficients from linear model with household fixed effects where dependent variables are continuous variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table 5: Comparing the differences in effects of lockdowns between agricultural and non-agricultural households on market work and food insecurity

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Market work	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food
First lockdown: short run	-0.311***	0.339***	0.391***	0.282***	0.260***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
First lockdown: medium run	-0.023	0.146***	0.160***	0.135***	0.106***
	(0.017)	(0.021)	(0.022)	(0.022)	(0.021)
Second lockdown: medium run	-0.115***	0.231***	0.237***	0.237***	0.218***
	(0.022)	(0.025)	(0.025)	(0.025)	(0.025)
Ag household	0.063***	0.030	-0.034	0.041*	0.023
	(0.018)	(0.021)	(0.022)	(0.021)	(0.022)
Ag household x First lockdown: short run	0.308***	-0.204***	-0.187***	-0.140***	-0.130***
	(0.026)	(0.030)	(0.032)	(0.031)	(0.031)
Ag household x First lockdown: medium run	0.010	-0.054*	-0.017	-0.029	-0.084***
	(0.019)	(0.028)	(0.028)	(0.029)	(0.028)
Ag household x Second lockdown: medium run	-0.034	-0.030	0.027	-0.026	-0.007
	(0.030)	(0.035)	(0.035)	(0.035)	(0.037)
No of observations	14,811	14,818	14,818	14,818	14,817
Number of households	2,300	2,302	2,302	2,302	2,302

	(6)	(7)	(8)	(9)	(10)
Outcome variables:	Had to skip a meal	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
First lockdown: short run	0.203***	0.242***	0.176***	0.169***	0.077***
	(0.018)	(0.020)	(0.017)	(0.018)	(0.012)
First lockdown: medium run	0.100***	0.107***	0.070***	0.077***	0.019*
	(0.017)	(0.020)	(0.015)	(0.015)	(0.010)
Second lockdown: medium run	0.198***	0.255***	0.132***	0.196***	0.109***
	(0.022)	(0.026)	(0.021)	(0.022)	(0.016)
Ag household	-0.008	0.001	-0.002	-0.010	-0.012
	(0.018)	(0.020)	(0.017)	(0.016)	(0.012)
Ag household x First lockdown: short run	-0.022	-0.071**	-0.074***	-0.037	-0.036**
	(0.027)	(0.029)	(0.023)	(0.025)	(0.017)
Ag household x First lockdown: medium run	0.007	-0.015	-0.008	0.017	0.016
	(0.025)	(0.027)	(0.020)	(0.022)	(0.016)
Ag household x Second lockdown: medium run	0.012	0.019	0.003	-0.034	-0.014
	(0.032)	(0.036)	(0.029)	(0.030)	(0.022)
No of observations	14,818	14,818	14,818	14,818	14,818
Number of households	2,302	2,302	2,302	2,302	2,302

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table 6: Impact of stringency index on food insecurity

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
Stringency index	0.006***	0.007***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid-19 cases/100,000	-0.004***	-0.006***	-0.004***	-0.002	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of observations	14,818	14,818	14,818	14,817	14,818
Number of households	2,302	2,302	2,302	2,302	2,302

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
Stringency index	0.006***	0.003***	0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Covid-19 cases/100,000	-0.004***	-0.003***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
No of observations	14,818	14,818	14,818	14,818
Number of households	2,302	2,302	2,302	2,302

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table 7: Impact of time spent in residence on food insecurity

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
Time spent in residence	0.020***	0.024***	0.018***	0.017***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covid-19 cases/100,000	-0.002	-0.003**	-0.002	-0.000	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of observations	14,818	14,818	14,818	14,817	14,818
Number of households	2,302	2,302	2,302	2,302	2,302

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
Time spent in residence	0.018***	0.011***	0.012***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Covid-19 cases/100,000	-0.003**	-0.002**	-0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
No of observations	14,818	14,818	14,818	14,818
Number of households	2,302	2,302	2,302	2,302

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Appendix

Table A1: Number of original and new households following round 1 for each survey round

	Rounds						
	1	2	3	4	5	6	7
Number of original households from Round 1	2,225	2,145	2,091	2,085	2,070	2,040	1,875
Cumulative new households added after round 1		44	46	44	46	52	55
Total sample size for a particular round	2,225	2,189	2,137	2,129	2,116	2,092	1,930

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Table A2: Impact of lockdowns on food insecurity using conditional logit model

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
First lockdown: short run	1.852***	1.998***	1.454***	1.456***	1.757***
	(0.087)	(0.082)	(0.080)	(0.080)	(0.091)
First lockdown: medium run	0.861***	1.052***	0.742***	0.494***	0.974***
	(0.087)	(0.084)	(0.082)	(0.082)	(0.097)
Second lockdown: medium run	1.632***	1.867***	1.545***	1.539***	1.965***
	(0.075)	(0.068)	(0.069)	(0.069)	(0.075)
Covid-19 cases/100,000	0.015	0.004	0.004	-0.002	-0.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)
No of observations	9,821	11,169	10,785	10,835	8,715
Number of households	1,484	1,688	1,634	1,639	1,319

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
First lockdown: short run	1.723***	1.674***	1.694***	1.420***
	(0.085)	(0.104)	(0.103)	(0.142)
First lockdown: medium run	0.860***	0.878***	1.001***	0.710***
	(0.090)	(0.113)	(0.110)	(0.157)
Second lockdown: medium run	2.093***	1.793***	2.147***	2.145***
	(0.072)	(0.082)	(0.083)	(0.110)
Covid-19 cases/100,000	-0.025**	-0.014	-0.041***	-0.068***
	(0.010)	(0.014)	(0.014)	(0.020)
No of observations	9,962	7,036	7,112	4,016
Number of households	1,509	1,063	1,076	603

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Section A1:

In this section, we examine whether agricultural households change their agricultural strategy to better cope with the effects of the lockdowns. The survey asked in rounds 1, 4, and 7 to households engaged in planting activities whether they changed their "planting activities in the current agricultural season because of changes in the country or community due to coronavirus?". 22.6 percent of agricultural households during the first lockdown and 19.1 percent during the second lockdown reported changing their planting activities because of the pandemic. This is as opposed to 5 percent for the non-lockdown period of round 4. We create an indicator variable where 1 represents a change in planting activities, and 0 represents no change. We present the estimates of the impact of lockdowns on changes in planting activities in Panel A of Table A3. The estimates show that the first lockdown led to a 52 percentage point increase in the likelihood of changing crop planting activities and the second lockdown led to a 26 percentage points increase compared to round 4.

For households with a change in activities, the survey also asked them how they changed their activities. This allows us to shed more light on how agricultural households attempted to change their farming strategy to cope with the effect of the shock. Panel B shows that the biggest change was a change in the use of farm areas, where 8.6 percent reported a reduction and 8.7 percent reported an increase in the use of farm areas after the first lockdown. It is followed by changes in the number of varieties of crops produced, where both an increase (4%) and a decrease (2.4%) in variety are mentioned after the first lockdown. Only a small fraction of farmers delayed planting (1.2%) or abandoned crop farming (1.5%) altogether for that season after the first lockdown.

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Table A3: Impact of lockdowns on agricultural strategies

Panel A: Impact of lockdowns on crop planting activities

Outcome variables:	Changed crop planting activities because of Covid
First lockdown: short run	0.581***
	(0.139)
Second lockdown: medium run	0.275***
	(0.048)
Covid-19 cases/100,000	0.051***
	(0.017)
No of observations	5,230
Number of households	2,071

Panel B: Means of changes in agricultural strategy because of Covid-19 (in percentages)

	First Lockdown	Second Lockdown	No lockdown (round 4)
Changed planting acitivities because of COVID-19	22.6%	18.8%	5.1%
Strategies:			
Reduced farm area	8.6%	10.2%	2.1%
Increased farm area	8.6%	3.8%	0.0%
Planted less variety/number of crops	4.0%	6.4%	1.5%
Planted more variety/number of crops	2.4%	1.6%	1.1%
Delayed planting	1.2%	2.9%	0.3%
Planted crops that mature quickly	1.0%	1.6%	0.0%
Abandoned crop farming	1.5%	0.5%	0.0%

Note: Questions on crop planting activities are only asked in rounds 1, 4, and 7. Panel A represents linear model with household fixed effects where the dependent variable is a dummy variable. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table A4: Impact of lockdowns on food insecurity only using the rounds in lean seasons - rounds 1, 2, and 6

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
First lockdown: short run	0.258***	0.305***	0.220***	0.195***	0.186***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.016)
First lockdown: medium run	0.109**	0.230***	0.159***	0.140**	0.179***
	(0.051)	(0.055)	(0.054)	(0.054)	(0.043)
Covid-19 cases/100,000	-0.030	0.153	0.075	0.144	0.148*
	(0.099)	(0.105)	(0.104)	(0.107)	(0.084)
No of observations	6,506	6,506	6,506	6,506	6,506
Number of households	2,286	2,286	2,286	2,286	2,286

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
First lockdown: short run	0.195***	0.147***	0.149***	0.055***
	(0.017)	(0.014)	(0.015)	(0.010)
First lockdown: medium run	0.209***	0.105***	0.148***	0.107***
	(0.048)	(0.037)	(0.038)	(0.026)
Covid-19 cases/100,000	0.223**	0.066	0.122*	0.154***
	(0.090)	(0.069)	(0.073)	(0.049)
No of observations	6,506	6,506	6,506	6,506
Number of households	2,286	2,286	2,286	2,286

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table A5: Comparing the effect of lockdown during round 7 to round 4, both of which occurred during the same calendar month

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
Second lockdown: medium run	0.139*	0.176**	0.171**	0.066	0.129**
	(0.073)	(0.069)	(0.074)	(0.078)	(0.064)
Covid-19 cases/100,000	-0.031	-0.031	-0.021	-0.057*	-0.034
	(0.028)	(0.026)	(0.029)	(0.030)	(0.024)
No of observations	4,059	4,059	4,059	4,059	4,059
Number of households	2,220	2,220	2,220	2,220	2,220

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
Second lockdown: medium run	0.166**	0.021	0.156**	-0.024
	(0.071)	(0.062)	(0.065)	(0.054)
Covid-19 cases/100,000	-0.040	-0.046**	-0.009	-0.051**
	(0.026)	(0.023)	(0.024)	(0.021)
No of observations	4,059	4,059	4,059	4,059
Number of households	2,220	2,220	2,220	2,220

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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Table A6: Impact of lockdowns on food insecurity in urban areas

	(1)	(2)	(3)	(4)	(5)
Outcome variables:	Any food insecurity	Worry about not having enough food to eat	Unable to eat healthy and nutritious food	Had to eat only a few kinds of food	Had to skip a meal
First lockdown: short run	0.390***	0.407***	0.308***	0.295***	0.245***
	(0.032)	(0.032)	(0.033)	(0.032)	(0.027)
First lockdown: medium run	0.194***	0.206***	0.155***	0.131***	0.136***
	(0.028)	(0.028)	(0.029)	(0.027)	(0.023)
Second lockdown: medium run	0.257***	0.241***	0.246***	0.227***	0.208***
	(0.034)	(0.034)	(0.033)	(0.035)	(0.029)
Covid-19 cases/100,000	0.003	0.007***	0.004	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
No of observations	3,804	3,804	3,804	3,804	3,804
Number of households	619	619	619	619	619

	(6)	(7)	(8)	(9)
Outcome variables:	Ate less than they thought they should	Ran out of food	Went hungry but did not eat	Went without eating for a whole day
First lockdown: short run	0.271***	0.199***	0.194***	0.076***
	(0.028)	(0.024)	(0.023)	(0.015)
First lockdown: medium run	0.130***	0.073***	0.085***	0.029**
	(0.027)	(0.018)	(0.017)	(0.011)
Second lockdown: medium run	0.240***	0.149***	0.181***	0.120***
	(0.035)	(0.025)	(0.028)	(0.020)
Covid-19 cases/100,000	-0.001	0.003	0.003**	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
No of observations	3,804	3,804	3,804	3,804
Number of households	619	619	619	619

Note: Linear Model with household fixed effects. All dependent variables are dummy variables. Standard errors are in parentheses. *** indicates significance at 1% level; ** at 5%; * at 10%.

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