Policy Research Working Paper 9466

Socioeconomic Impacts of COVID-19 in Four African Countries

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WORLD BANK GROUP
Development Economics
Development Data Group
November 2020

Abstract

The coronavirus disease 2019 (COVID-19) and the attempts to limit its spread have resulted in profound economic impacts, and a significant contraction in the global economy is expected. This paper provides some of the first evidence on the socioeconomic impacts of and responses to the pandemic among households and individuals in Sub-Saharan Africa. To do so, reduced-form econometric methods are applied to longitudinal household survey data from Ethiopia, Malawi, Nigeria, and Uganda—originating from the pre-COVID-19 face-to-face household surveys and from the novel phone surveys that are being implemented during the pandemic. The headline findings are fourfold. First, although false beliefs about COVID-19 remain prevalent, government action to limit the spread of the disease is associated with greater individual knowledge of the disease and increased uptake of precautionary measures. Second, 256 million individuals—77 percent of the population in the four countries—are estimated to live in households that have lost income due to the pandemic. Third, attempts to cope with this loss are exacerbated by the inability to access medicine and staple foods among 20 to 25 percent of the households in each country, and food insecurity is disproportionately borne by households that were already impoverished prior to the pandemic. Fourth, student-teacher contact has dropped from a pre-COVID-19 rate of 96 percent to just 17 percent among households with school-age children. These findings can help inform decisions by governments and international organizations on measures to mitigate the effects of the COVID-19 pandemic and reveal the need for continued monitoring.

This paper is a product of the Development Data Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at tkilic@worldbank.org.

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JEL Codes: C83, I15, I31, O12.
Keywords: SARS-CoV-2, COVID-19, behavioral change, income loss, household enterprises, access to basic needs, food insecurity, concerns, access to basic needs, access to education, Ethiopia, Malawi, Nigeria, Uganda, Sub-Saharan Africa.

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1. Introduction

SARS-CoV-2 is a major global threat to human health, with 36 million cases and 1 million deaths worldwide as of October 9, 2020.[1] Governments have sought to limit the spread of the virus and mitigate the negative health outcomes of the disease through various policy measures that have limited travel, imposed quarantines and lockdowns, and closed businesses and schools.[11] In addition to the economic burden of COVID-19 related morbidity and mortality, government attempts to limit the spread of SARS-CoV-2 are having profound economic impacts, with the global economy projected to shrink by 8%.[2] To date, the greatest health and economic burden has been borne by the Americas and Europe.[1] However, recent evidence indicates that low-income countries, with their limited health system capacities, are likely to suffer infection and mortality rates similar to or greater than those currently suffered by upper-income countries.[5] While research on the health impacts of COVID-19 in low-income countries is rapidly emerging,[3] there is limited evidence on the socioeconomic impacts of the pandemic.[4] The evidence that exists relies primarily on pre-COVID-19 macroeconomic data and simulation models to forecast potential future scenarios based on assumptions about the disease spread.[6] In contrast, we rely on direct measurements of socioeconomic indicators to present evidence on the effects of the pandemic on households, individuals, and children living in low-income countries, as well as the actions that households are taking to mitigate these impacts.

An acute challenge emerging from the global pandemic is how individuals and communities are to strike the balance between the health benefits and the economic costs of managing the spread of the virus.[11] Even in high-income countries, which tend to be data rich in terms of health and economic information, striking this balance frequently proves politically difficult. By contrast, low-income countries, which tend to be resource-constrained, are data poor in terms of reliable and timely information on the spread of SARS-CoV-2 and on the economic impacts of anti-contagion policies. Our objective is to directly, at the household, individual, and child levels, the socioeconomic impacts of the pandemic and the policies implemented to slow the spread of the virus. Our hope is to learn from how individuals in these four countries cope with the socioeconomic effects of the virus. This can inform decisions by governments and international aid organizations regarding how best to mitigate the persisting effects of the COVID-19 pandemic.

2. Data and Methods

Our findings are based on the longitudinal data from the high-frequency phone surveys conducted in Ethiopia, Malawi, Nigeria, and Uganda with support from the World Bank. Starting in May 2020, every month, the phone surveys aim to interview a national sample of households that had been interviewed face-to-face prior to the COVID-19 pandemic as part of the national longitudinal household surveys that have been supported under the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative.

The pre-COVID-19 LSMS-ISA-supported surveys that serve as sampling frames for the phone surveys were designed to be representative at the national, regional and urban/rural levels. These surveys include the Ethiopia Socio-economic Survey (ESS) 2018/19, Malawi Integrated Household Panel Survey (IHPS) 2019, Nigeria General Household Survey (GHS) - Panel 2018/19, and Uganda National Panel Survey (UNPS) 2019/20. In Ethiopia, Malawi, and Uganda, the phone survey attempted to call all LSMS-ISA households for whom at least one phone number was available either for a household member or for a reference individual. In Nigeria, a national sub-sample was drawn from the universe of LSMS-ISA households with phone numbers. The anonymized survey data and documentation are accessible through the World Bank Microdata Library[12-15] and are comparable across countries, based on the template questionnaire modules and the phone survey sampling guidelines that were made publicly available by the World Bank prior to the start of the phone survey activities (see Supplementary Materials – Methods).

We directly measure the effects of the pandemic on 8,603 households across the four countries, as well as how households attempt to cope with these effects. We use well-established sampling techniques[7-9] to correct for potential selection bias associated with not interviewing households that do not own mobile phones or that cannot be reached despite repeated call attempts (see Supplementary Materials – Methods for more details on the calculation of phone survey sampling weights). The correction for selection bias allows us to provide estimates of the total number of households, individuals, and children associated with any of the reported outcomes.

We then use reduced-form econometric techniques,[10] which are common to the field, in order to estimate heterogeneity in effects across 1) countries, 2) rural and urban sectors, 3) pre-COVID-19 wealth, 4) gender, and 5) time (see Supplementary Materials - Methods). Tracking how people's lives are differentially affected by the COVID-19 pandemic can enable governments and policy makers to better understand the circumstances faced by their citizenry and to make data-driven, informed policy decisions. The need to understand the contemporaneous impacts and coping strategies of households is and will continue to be important for low-income countries, as they are likely to lack access to a vaccine for longer than high-income countries.[16,17] The longitudinal data collected through the high-frequency phone surveys cultivate this understanding by documenting near-real-time trends.

3. Results

Government action is reflected in household knowledge of and behavior around COVID-19: With the global spread of the SARS-CoV-2 virus, numerous low-income countries followed worldwide trends by declaring states of emergency, issuing stay-at-home orders, closing schools, and imposing curfews.[18] Considering the countries in our data set, Ethiopia closed schools on March 16[19] and declared a state of emergency on April 8.[20] Nigeria and Uganda issued stay-at-home orders on March 29 and 30, respectively.[21, 22] Malawi attempted to issue stay-at-home orders on April 14,[23] but the country's High Court barred the government from implementing the lockdown.[24] As a result, Malawi, unlike the other countries in our study, instituted no stay-at-home orders, though schools did close. This heterogeneity in government responses is reflected in the data (Figure 1A), with individuals in Malawi significantly less likely to report that governments and local authorities have taken specific steps to curb the spread of the virus (see Table S1 in Supplementary Evidence).

This divergent path observed in Malawi also impacts individual knowledge of COVID-19 and the adoption of behaviors to limit the spread of SARS-CoV-2. In Ethiopia, Nigeria, and Uganda, knowledge about measures that can be adopted to reduce the risk of contracting the virus is extremely high (Figure 1B). In Uganda, we estimate that over 90% of individuals are familiar with all six mitigation measures asked about in the survey, while in Ethiopia and Nigeria at least 80% of individuals are familiar with five of the six measures. By comparison, in Malawi, handwashing with soap is the only mitigation strategy with which at least 80% of individuals are familiar. For the other five mitigation strategies, Malawians are significantly less knowledgeable than those in Ethiopia, Nigeria, or Uganda (Table S2).

The heterogeneity in knowledge between Malawi and the other three countries is reflected in changing behavior related to the virus (Figure 1C). In Ethiopia, Nigeria, and Uganda we estimate that adoption of handwashing is near universal, as is avoidance of physical contact within the week prior to the interview. Even in Malawi, we estimate that 91% of individuals wash their hands more frequently than before. While an estimated 80% to 90% of individuals in Ethiopia, Nigeria, and Uganda report adapting their behavior to help reduce the spread of the virus, significantly fewer do so in Malawi (Table S3). In Uganda and Malawi, where we have behavioral data over time, we show that the number of people continuing to wash hands and avoid crowds decreases significantly over the period of June to August 2020 (Tables S4 and S5).

The lack of knowledge and behavioral change in Malawi is further manifested in a greater prevalence of beliefs in unproven, disproven, or false claims about the virus and the disease (Figure 1D). These data exist only for Malawi and Uganda. Malawians are significantly more likely than Ugandans to believe that Africans are immune to the virus, that children are not affected by the virus, and that the disease is no different than the common flu. While Malawians are significantly more likely to hold several of these false beliefs (Table S6), the number of people in Uganda that lack accurate information of SARS-CoV-2 is greater than the number in Malawi, due to Uganda's larger population. In Malawi, we estimate that 3.1 million individuals believe that the virus is just the common flu, the most common false belief. In Uganda, the most common false belief is that the virus cannot survive warm weather, with an estimated 6.1 million individuals subscribing to this disproven claim (Table S7). An estimated 1.3 million to 3.3 million adults in each country believe the other false claims. These represent substantial shares of the population in each country and reveal the continued need for clear and accurate messaging about COVID-19.

Economic impacts and food security vary by country and gender of household head: As countries declared states of emergency and issued stay-at-home orders, hundreds of millions of individuals in low-income countries found themselves out of work, both in the formal and informal labor markets.[25] Correspondingly, households have lost income across a variety of sources (Figure 2A). We estimate that 256 million individuals - 77% of the population across the four countries - live in households that have lost income due to the pandemic (Table S8). To have lost income from a particular source, the household must have previously received income from that source; that is, our estimates of losses are conditional on having received income from a given source in the previous 12 months (Table S9). Considering country-level heterogeneity in income loss, Ethiopian households are significantly less likely to have lost income from every source, except business income, compared to the other three countries. The share of households that have lost income tends to be the same across Malawi, Nigeria, and Uganda (Table S10). In the majority of cases, we find no evidence of heterogeneity in income loss between rural and urban households (Table S11). This suggests that income losses have been borne equally across the rural and urban populations, both within and across countries. However, we do find evidence of heterogeneity in income loss by gender (see Figure S1A in Supplementary Evidence). Female-headed households are significantly more likely to lose income from remittances while male-headed households are significantly more likely to lose income from other sources, including from investments, savings, pensions, and government assistance (Table S12).

While households have lost income from a variety of sources, we focus on losses to non-farm enterprises, as they are the income sources likely to be most affected by shutdown and lockdown orders. An estimated 35% of households across all four countries operated a non-farm enterprise (NFE) prior to the pandemic. Of these, a majority report that revenue is down, compared with pre-COVID-19 levels (Figure 2B). As with income losses, reduced revenue from NFEs varies by country. We estimate that Ethiopians with NFEs are significantly less likely to experience revenue losses than their Nigerian, Malawian, and Ugandan counterparts. Conversely, Ugandans with NFEs are significantly more likely to experience revenue loss than those in the other countries. Modeling these dynamics over time shows that some NFEs are recovering revenue relative to previous rounds: across all countries, significantly more individuals are making the same or greater revenue than they were in the first round of interviews. However, in Ethiopia and Nigeria the estimated differences between the second and third rounds are not significantly different from one another (Table S13). This suggests the lack of a clear trajectory in recovery for household businesses over the coming months.

Estimating these income and revenue losses is important as they may have reverberating impacts on other elements of the household economy, in particular food security. We estimate the prevalence of food insecurity among the adult population, as measured by the Food Insecurity Experience Scale (FIES) (see Supplementary Materials - Methods). Based on our estimates, 61% of the adult population, representing more than 100 million adults across all four countries, suffer moderate or severe food insecurity. Severe food insecurity alone affects an estimated 38 million adults, or 23% of the adult population (Table S14). Using the pre-COVID-19 LSMS-ISA survey data, we can calculate household annual per capita income to generate consumption quintiles (see Supplementary Materials - Methods). Examining heterogeneity across consumption quintiles, poorer households (in lower quintiles) suffer significantly greater prevalence of food insecurity (Figure 2C). Further, there is significant heterogeneity in the prevalence of food insecurity, across countries (Table S15). Nigeria suffers from the greatest prevalence food insecurity where an estimated 76% of adults (63 million) are moderately or severely food insecure. This is followed by Malawi with 68% (6.2 million), Ethiopia with 47% (24 million) and Uganda with 33% (6.9 million). As with loss of income, there is a high degree of heterogeneity based on the gender of the household head (Figure S1B). Since the global pandemic began, female-headed households have significantly higher prevalence of moderate and/or severe food insecurity than male-headed households, though food insecurity is decreasing over time at an equal rate for adults in both types of households (Table S16).

Levels of concern are high across all four countries: an estimated 257 million individuals (78%) are concerned that someone will fall ill with COVID-19 and 292 million individuals (88%) are concerned about COVID-19-related financial threats (Table S17). Higher prevalence of food insecurity is associated with concerns about household health and financial status, especially in Malawi (Figure 2D). There is substantial heterogeneity in the degree of concern over health and finances based on food insecurity, initial wealth, and the gender of the household head. Those concerned about the financial threat of COVID-19 have a significantly higher prevalence of food insecurity than those unconcerned about financial threats (Table S18). At the same time concerns about household finances do not vary by the gender of the household head nor across pre-COVID-19 consumption quintiles (Tables S19 and S20; Figures S1C and S2). The opposite is true for those concerned about household health: differences are not significant based on food insecurity, though male-headed households and households from the lowest two consumption quintiles are significantly more likely to be concerned about someone falling ill with COVID-19 than the relevant comparison group. This sort of variation provides no clear pattern regarding who is concerned about finances versus health and why, though it is clear that COVID-19 related concerns weigh heavily on individuals in many contexts.

Households struggle to access medicine, staple foods, and education: Since the closure of schools and the issuance of emergency stay-at-home orders, households have suffered a variety of economic shocks, including job loss, closure of a business, or the lack of availability of farm inputs. In total, an estimated 25 million households have suffered a virus-related shock to their income, around 42% of all households. This ranges from 26% of households (5 million) in Ethiopia to 56% of households (15 million) in Nigeria (Table S21). Households have adopted a number of strategies to try and cope with these shocks (Figure 3A). To employ a coping strategy a household must have previously experienced an economic shock; that is, our estimates for the adoption of each coping strategy are conditional on exposure to a shock. The specific coping strategy that households adopt is context dependent, but the estimated number of households adopting some strategy is indicative of the scale of economic loss. In total, an estimated 33 million households, about 56% of the household population across the four countries, have adopted some coping strategy (Table S22). These strategies include living off of savings (12 million), selling assets (3.5 million), reducing food or non-food consumption (21 million and 6.5 million, respectively), receiving help from family (8.1 million), and receiving government assistance (4.3 million), though there is significant heterogeneity across countries (Table S23). This is also heterogeneity between rural and urban households: we estimate that rural households are significantly more likely to rely on the sale of assets, while urban households are significantly more likely to reduce food consumption or rely on friends and family (Table S24). In terms heterogeneity by gender of the household head, male-headed households are significantly more likely to rely on savings, sale of assets, and on reducing non-food consumption (Figure S1D, Table S25). Female-headed households are significantly more likely than male-headed ones to receive assistance from the government or an NGO.

The challenges of coping with lost income are exacerbated by the inability to purchase basic necessities (Figure 3B). Conditional on the households having sought to purchase medicine, an estimated 20% are unable to buy what they need. Access to staple foods is even more limited, with an estimated 24% of households unable to purchase the staple. Soap is relatively more available, with only an estimated 12% of households unable to purchase soap when they needed it (Table S26). This lack of access to basic necessities varies by consumption quintile. Households that were in the lowest consumption quintile before the global pandemic are significantly less likely to be able to access medicine than households that were in the highest consumption quintile (Table S27). Similarly, households in the lowest consumption quintile are less likely to have access to staple foods and soap than households in other quintiles. The disproportionate burden of the disease on the poorest has been noted previously,[26] and the distribution of the economic burden has been speculated on,[27] but we provide econometric evidence of this playing out in the past few months among the surveyed households.

Prior to the spread of SARS-CoV-2, the global community made substantial progress towards completing Millennium Development Goal 2: universal primary education. As of 2015, primary school enrollment rates in low-and middle-income countries had reached 91%.[28] Based on our data, an estimated 96% of households with school-aged children had their children attending school before the outbreak. Following the outbreak and school closures, the incidence of school-aged children engaging in any learning activity fell to an estimated 46% and we estimate the incidence of student-teacher contact at just 17%. These estimates amount to 68 million school-aged children across in the four countries without any education engagement (Table S28). As with access to basic necessities, there is a disproportionate lack of access to education among poorer households (Figure 3C). Children from households in the top 40 percent of the pre-COVID-19 consumption distribution were significantly more likely to be engaged in any learning activity after the outbreak than children from households in the lower quintiles (Table S29).

The loss of educational contact is widespread and likely to have long-term impacts, though we find evidence that households are using technologies, such as radios, televisions, and mobile learning apps, to mitigate educational losses (Figure 3D). While millions of children in these countries are participating in various types of educational contact, millions more are unable to do so. We estimate that the share of households with school-aged children using these technologies to be below 50%. This may have short-term consequences for adults trying to return to work, as well as long-term consequences on children's educational attainment. Further, linkages between economic outcomes and educational attainment already exist: the incidence of moderate or severe food insecurity is significantly higher in households whose school-aged children are not engaged in learning activities (Table S30; Figure S3). There is good news, though, in that our estimates show engagement with several of these technologies is increasing over time. In Ethiopia, Malawi, and Nigeria there has even been significant increases in student contact with teachers (Table S31).

4. Discussion

In order to formulate policies and target resources at mitigating the adverse health and economic impacts of the COVID-19 pandemic, governments, international organizations, NGOs, and other stakeholders need reliable and timely data and estimates of the circumstances faced by individuals and households.

The results presented here illustrate some of the first evidence of the socioeconomic impacts of the COVID-19 pandemic in low-income countries. Governments in these countries were already facing complex and mutually reinforcing development challenges prior to the pandemic, and the arrival of a COVID-19 vaccine in the region is not expected until 2022.[16,17] Our econometric analysis relies on sampling techniques to correct for bias and reduced-form methods and is focused on Ethiopia, Malawi, Nigeria, and Uganda. Our findings give insight on government policies and perceptions related to suppression of the virus, as well as consequences related to income loss, food security, education, and the ability to access and purchase basic necessities. Although false beliefs about COVID-19 are prevalent, government action to limit the spread of the disease is associated with greater knowledge about the disease and increased uptake of precautionary measures. We estimate that 256 million individuals, around 77% of the population across the four countries, live in households that have lost income due to the pandemic. Attempts to cope with this lost income are exacerbated by an inability to access medicine and staple foods for an estimated 20% to 25% of households who need these items. Income loss and lack of access to necessities have disproportionately been borne by households that were already impoverished prior to the pandemic, as well as female-headed households. Finally, the loss of educational access has been profound, as the rate of maintaining student-teacher contact dropped to an estimated 17% among households with school-aged children.

Presently, it is not possible to reliably predict the trajectory of SARS-CoV-2 and its impacts within any given country. The precise mortality and disease burden, and the economic benefits and drawbacks of different approaches to controlling the virus, remain unknown. We present some of the first results of the economic burden of the global pandemic in low-income countries, where data have proven particularly scarce. The need to understand the contemporaneous socioeconomic impacts of the pandemic and the related restrictions on households, individuals, and children will continue to be important for evidence-based policy making.

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Acknowledgments: We gratefully acknowledge the research assistance provided by Ann Furbush and Joshua Brubaker. We also owe a great debt to the individuals involved in the design, implementation and dissemination of high-frequency phone surveys on COVID-19, specifically the World Bank Living Standards Measurement Study (LSMS) team, and the phone survey managers and interviewers at the Malawi National Statistical Office, the Nigeria Bureau of Statistics, the Uganda Bureau of Statistics, and Laterite Ethiopia.

Author contributions: Authors are listed alphabetically. Anna Josephson: conceptualization, formal analysis, data curation, writing - original draft, visualization. Talip Kilic: conceptualization, investigation, writing - review & editing, visualization. Jeffrey D. Michler: conceptualization, formal analysis, data curation, writing - original draft, visualization. All authors contributed to the final draft.

Competing interests: Authors declare no competing interests.

Figure 1: Knowledge of COVID-19 restrictions, behaviors, and false beliefs

(A) Percentage of individuals with knowledge regarding government actions undertaken to curb the spread of COVID-19. **(B)** Percentage of individuals with knowledge of actions that an individual can take to reduce exposure to COVID-19. **(C)** Percentage of individuals reporting a change in behavior in the previous 7 days. **(D)** Percentage of individuals in Malawi and Uganda with beliefs about common misconceptions regarding coronavirus.

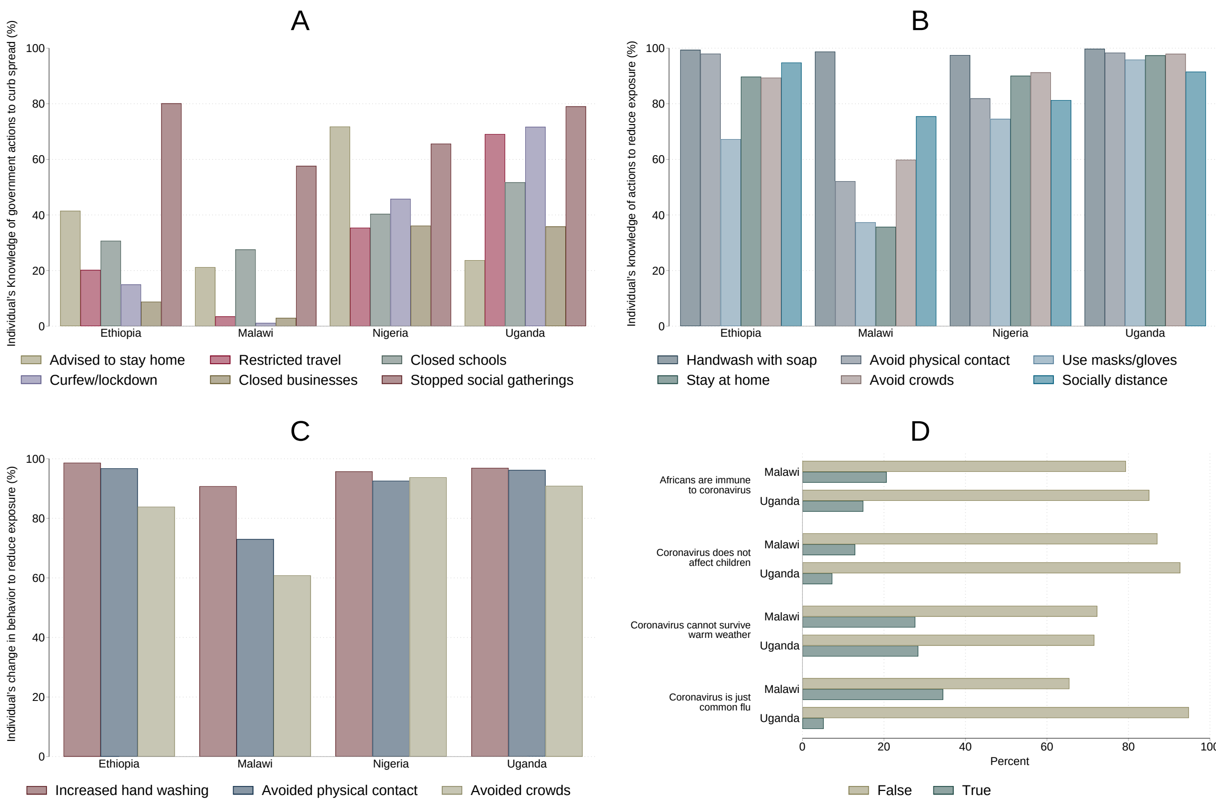


Figure 2: Household income, food insecurity, and concerns about COVID-19

(A) Percentage of households reporting loss of income sources, by country and rural/urban residence. **(B)** Percentage of households reporting change in business revenue, by country and round. **(C)** Prevalence of moderate and/or severe food insecurity among adult individuals, by country and pre-COVID-19 household annual per capita consumption quintile. **(D)** Prevalence of food insecurity among adult individuals, by country and COVID-19-related concerns linked to health and finance.

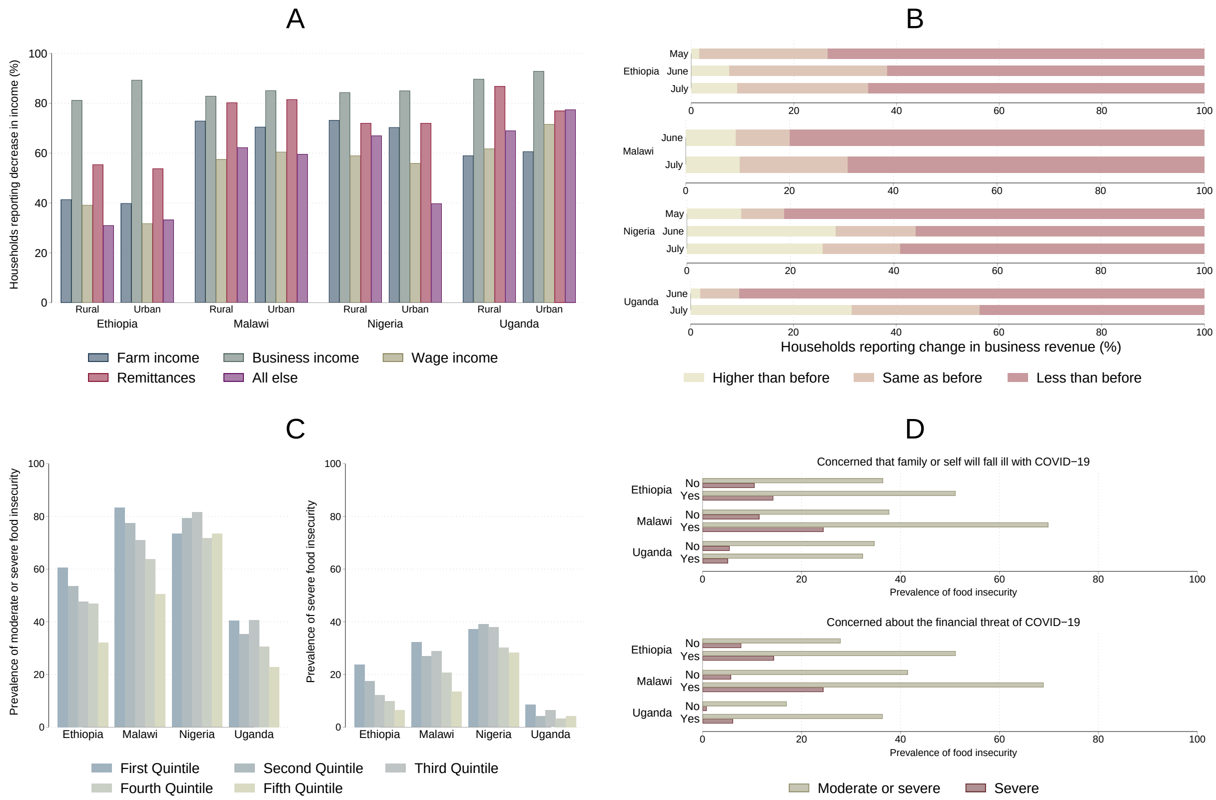
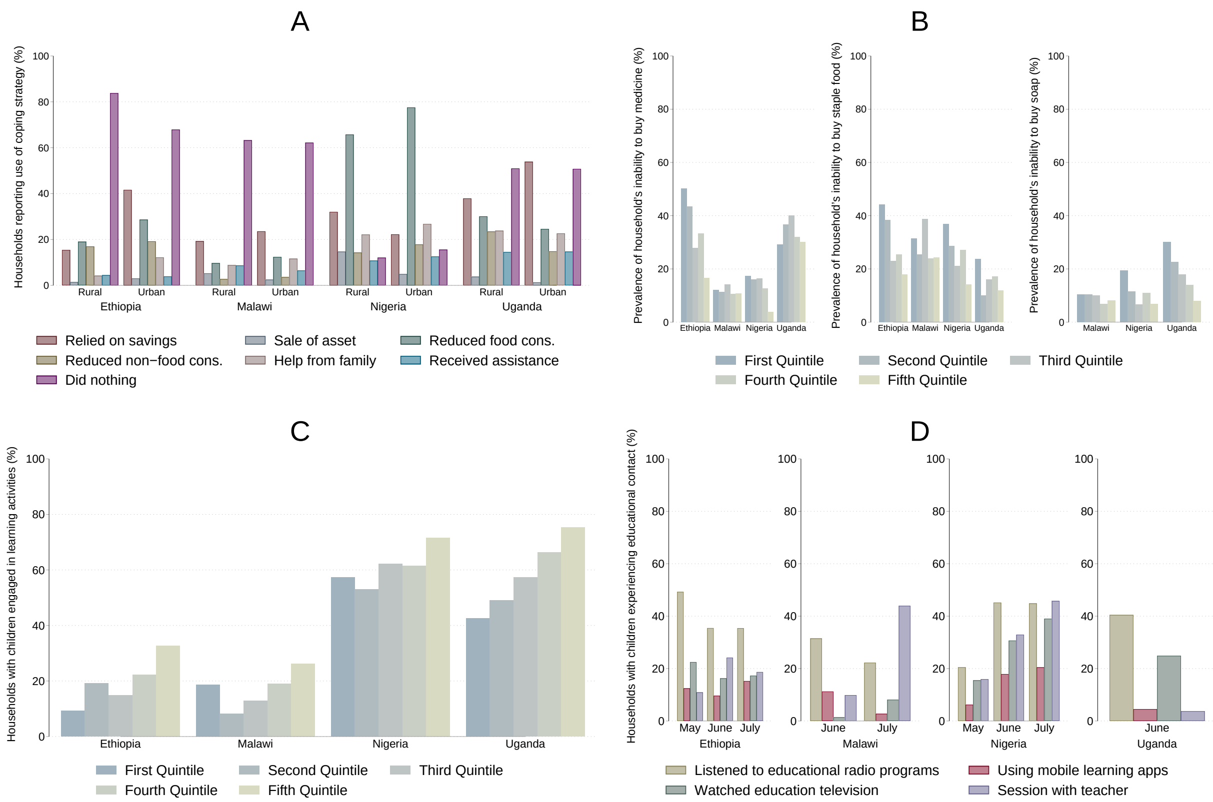


Figure 3: Household coping strategies and access to basics necessities

(A) Percentage of households reporting use of coping strategy, by country and rural/urban residence. **(B)** Share of households reporting a lack of access to medicine, staple food, and soap, by country and pre-COVID-19 household annual per capita consumption quintile. **(C)** Percentage of households with school-aged children experiencing educational contact, by country and survey round. **(D)** Percentage of households with children engaged in learning activities, by country and pre-COVID-19 household annual per capita consumption quintile.



Supplementary Materials

Methods

Data Collection: This paper leverages high-frequency phone surveys on COVID-19 that were implemented in Ethiopia, Malawi, Nigeria, and Uganda during the period of May-July 2020, with support from the World Bank Living Standards Measurement Study (LSMS) and the Poverty and Equity Global Practice. In each country, the phone survey aims to conduct monthly phone interviews, for a period of 12 months. The sample for these surveys is a national sample of households that had been interviewed during the latest round of the national longitudinal household survey implemented by the respective national statistical office, with financial and technical assistance from the World Bank LSMS-ISA initiative. Please see below for more information on the calculation of phone survey sampling weights.

The implementing agency for the phone survey in Ethiopia, Malawi, Nigeria, and Uganda, is, respectively, Laterite Ethiopia, Malawi National Statistical Office, Nigeria Bureau of Statistics, and Uganda Bureau of Statistics. The anonymized, unit-record phone survey data associated with each monthly survey round are made publicly available, within approximately four weeks of completion of phone interviews, through the World Bank Microdata Library, under the High-Frequency Phone Survey collection: http://bit.ly/microdata-hfps.

The publicly-available data for each survey round is coupled with a basic information document, interview manual, and questionnaire for that round, which can be accessed through the following:

- Ethiopia: http://bit.ly/ethiopia-phonesurvey
- Malawi: http://bit.ly/malawi-phonesurvey
- Nigeria: http://bit.ly/nigeria-phonesurvey
- Uganda: http://bit.ly/uganda-phonesurvey

The approach to the phone survey questionnaire design and sampling is comparable across countries. It is informed by the template questionnaire and the phone survey sampling guidelines that have been made publicly available by the World Bank. These can be accessed through the following:

- Template Questionnaire: http://bit.ly/templateqx
- Manual: http://bit.ly/interviewermanual
- Sampling Guidelines: http://bit.ly/samplingguidelines.

All regressions and results presented in the paper are based on the publicly available data from the World Bank Microdata Library. Data is downloaded from the website and processed using Stata

16.1. All cleaning, processing, and analysis was conducted by the research team and the code is available[29].

Food Insecurity Experience Scale: The estimates of prevalence of (i) moderate or severe and (ii) severe food insecurity among adult individuals are based on the eight-question Food Insecurity Experience Scale (FIES), which was included as a module in the high-frequency phone survey. The FIES is an experience-based metric of food insecurity severity, which relies on people's direct responses to questions about their experiences with access to adequate food. This metric makes it possible to compare prevalence rates of food security across national and sub-national populations[30]. Widely used around the world, FIES is an appropriate measure for assessing food security as it is a direct measure of food insecurity which produces comparable estimates of food insecurity experienced by people in different contexts.

In the high-frequency phone surveys that inform our analyses, the FIES questions had a reference period of the last 30 days. Following the FIES standard survey model, eight questions were asked, aimed to capture whether the respondent or other adult households members: (i) were worried they would not have enough to eat, (ii) were unable to eat healthy and nutritious food, (iii) ate only a few kinds of foods, (iv) had to skip a meal, (v) ate less than they thought they should, (vi) ran out of food, (vii) were hungry but did not eat, and (viii) went without eating for a whole day.

The approach to process and analyze FIES data comes from Item Response Theory[31], also known as the Rasch model[32], which accounts for the measurement of unobservable traits through the analysis of responses to survey. Analysis of FIES data involves parameter estimation, statistical validation, and calculation of individual and population prevalence estimates, as appropriate, for food insecurity. In this analysis, a respondent's raw score (an integer number between zero and eight) is determined. Based on this raw score, an interval measure of the severity of food security, based on global standards, is determined, by equating (calibrating the score on a common metric)[33]. Equating is completed for each household, which allows us to estimate the probability of (i) moderate or severe and (ii) severe food insecurity among adult household members. Following procedures detailed by the Food and Agriculture Organization of the United Nations and the associated program, Voices of the Hungry, we calculate FIES for households in our data as follows:

1. Beginning with Stata constructed data files, we construct binary variables for each of the eight FIES components that take a value of 1 for "Yes", and 0 for "No" answers (and leave untouched any missing answers). We reorder the variables and recode the variable names to ensure the following order and naming convention: Worried, Healthy, FewFood, Skipped, AteLess, RunOut, Hungry, and WhlDay.
2. We construct adult population weights (w_a), by multiplying household sampling weights ($w_{i,final}$) with the count of adult members in each household. This household sampling

weight is retained. The resulting file is exported to .csv format. We upload the .csv file to the FIES Shiny App: https://fies.shinyapps.io/ExtendedApp/, which was developed by the Food and Agriculture Organization of the United Nations (FAO), the custodian agency for FIES[34].

3. In the App, under the "Item and Raw Score Stat" tab, we check the Infit statistic for each component. If it is not within the bounds 0.7 and 1.3, it is dropped from the analysis. At least six questions should be retained in this step.
4. We equate the included items to the global standard. It is sometimes the case that some items may diverge from the global standard to be included in the calibration of the country scale to the global standard. The rule then is to exclude items that differ by > 0.35. This is accomplished in the "Equating" tab. If there were multiple items differing by > 0.35 in our sample, we iterate on which set of items to exclude. At least five items must be retained for a robust estimation. The items that are excluded from the equating procedure are not dropped entirely from the construction of the FIES indicators but are simply ignored when equating the country scores to the global standard.
5. Under the "Additional Information" tab, we next "download respondent-level model-based variables". This provides a dataset with as many rows as the .csv file that was uploaded into the Shiny App in step #2. This downloaded dataset includes the estimates of prevalence of (i) moderate or severe and (ii) severe food insecurity among adult individuals in accordance with the "raw score" for each household (that is, the count of "yes" answers across the eight questions).
6. We import the data downloaded in step #5 into Stata and using "raw score" as the linking variable, merge it with other Stata formatted data files that are defined at the household-level.

Consumption quintiles: To define pre-COVID-19 household per capita consumption quintiles, we rely on the pre-public-dissemination versions of the consumption aggregates. These are provided by the Living Standards Measurement Study (LSMS) team on an exceptional basis, with clearance from the respective NSOs, for the pre-COVID-19 LSMS-ISA-supported surveys that serve as a sampling frame for the high-frequency phone surveys on COVID-19. In the case of Ethiopia, Nigeria and Malawi, the consumption aggregates are computed by the respective NSO, with technical assistance from the LSMS. In the case of Uganda, the consumption aggregate is computed by and has been obtained from the Uganda Bureau of Statistics. In the specific case of Malawi, the consumption aggregate is for the IHPS 2016, as this information is unavailable for the IHPS 2019.

Econometric Analysis

Phone Survey Weights: Since we rely on phone interviews with a sample of households that had been interviewed face-to-face prior to the COVID-19 pandemic as part of the LSMS-ISA-supported national longitudinal household survey, there are two potential sources of bias in the resulting data: (i) selection bias associated with not being able to call LSMS-ISA households that do not own mobile phones and (ii) non-response bias associated with not being able to interview households that are targeted for phone interviews. Without correcting for these two sources of bias, results of our analysis are likely to underestimate the negative impacts of COVID-19, since poorer households are less likely than wealthier households to have phones, and less likely to respond even if they do have phones.

In our analysis, we use the phone survey weights that are provided in public use datasets and that are computed in an attempt to address the aforementioned potential sources of bias using well-established sampling techniques.[7,9]. The phone survey weights in each country build on the sampling weights for the associated LSMS-ISA-supported survey. They are calibrated to address the selection bias introduced from LSMS-ISA households not owning a mobile phone and non-response bias from not answering the phone. This latter issue is overwhelmingly due to non-working phone numbers or prospective respondents not answering calls (as opposed to refusals). To calculate survey weights for the phone survey, we implement the following steps in Ethiopia, Malawi, and Uganda[8].

1. We begin with the existing sampling weight for each household, as computed for the associated LSMS-ISA-supported survey ($w_{i,pre}$), which are available in those datasets.
2. We calculate the probability of selection into the phone survey for each household (p_i), as the total number of LSMS-ISA households for which contact was attempted in that household's region (m_r) divided by the total number of LSMS-ISA households in that region (M_r).

$$p_i = \frac{m_r}{M_r}$$

3. We multiply the existing LSMS-ISA sampling weight with the reciprocal of the probability of selection in the phone survey, as calculated in step #2.

$$w_{i,phone} = w_{i,pre} \frac{1}{p_i}$$

4. Using the entire LSMS-ISA sample, we run a multivariate logistic regression in which the dependent variable is a binary variable that is equal to 1 for LSMS-ISA households that were successfully interviewed for the phone survey and equal to 0 otherwise. The independent variables included represent a range of household, dwelling, and head of household attributes that predict the likelihood of a completed phone survey interview.

$$\Pr\,(\text{phone} = 1) = F\left(\beta_0 + \sum_{k=1}^{K} \beta_k X_k\right)$$

The independent variables included vary by country and round, since the sampling frame and survey instrument vary by country and round. The basic information document for each phone survey provides specifics of what variables are included.

5. We predict the probability of response (i.e. propensity score) and create ten equal groups (deciles) for this variable. Within each decile d, we compute the mean value and take the reciprocal as the phone survey attrition correction factor for observations in each decile ($ac_{D=d}$):

$$ac_{D=d} = 1 \Big/ \frac{\sum_{i=1}^{N} \widehat{\text{phone}_\imath}}{N}$$

where $\widehat{\text{phone}_\imath}$ is the predicted value (i.e. propensity score) for each observation i. N is the total number of individuals in each decile. We then apply the attrition correction factor to the adjusted household sampling weight as derived in step #3.

$$w_{i,ac} = ac_{D=d} * w_{i,phone}$$

6. We winsorize the resulting weight ($w_{i,ac}$) by replacing the top two percent of observations, with the value at the 98th percentile cut-off point.
7. Finally, we post-stratify weights to reduce standard errors and to match the projected population totals at the highest spatial resolution possible, ranging from region to district, based on the data availability in each country. Population projections come from national statistic bureaus, often as part of census data. The post-stratification weights (w_{ps}) are calculated as the weighted total number of observations from the data divided by the census projections:

$$w_{ps} = \frac{\sum_{i=1}^{M_r} w_{i,ac}}{population}$$

where M_r is the total population in the region, or whatever is the highest spatial resolution available, and $population$ is the national statistic bureau's projected population for that region. The final weight is then calculated as:

$$w_{i,final} = w_{ps} * w_{i,ac}$$

In our case, post-stratification is not a major adjustment to the weights but a fine tuning of their values.

In the case of Nigeria, to obtain a nationally representative sample for the phone survey, a sample size of approximately 1,800 successfully interviewed households was targeted. Based on the experience with prior phone surveys in Nigeria, a response rate of 60% was assumed, implying that the required number of households to contact in order to reach the interview target was 3,000. These households were selected from the frame of 4,934 GHS-Panel households with at least one phone number for a household member or a reference individual. Given the large amount of auxiliary information available in the GHS-Panel for these households, a balanced sampling approach (using the cube method) was adopted[35]. This balanced sampling approach enables selection of a random sample that still retains the properties of the pre-COVID sampling frame across selected covariates. Balancing on these variables results in a reduction of the variance of the resulting estimates, assuming that the chosen covariates are correlated with the target variable. Calibration to the balancing variables after the data collection further reduces this variance[9]. The sample was balanced across several important dimensions: state, sector (urban/rural), household size, per capita consumption expenditure, household head sex and education, and household ownership of a mobile phone.

Reduced form estimation: The reduced form econometric methods applied here describe behavior of the various outcomes of interest in the data (e.g. food security, education, income loss). This setup allows us to make inference and conduct more complex statistical tests with multiple controls for differences across populations than simple univariate tests for differences in means[10]. For a given outcome, y, define the conditional expectation function (CEF)[36] as:

$$\mathrm{E}[y_i|X_i = x] = \int t f_y(t|X_i = x)dt$$

Here the CEF is the expectation, or sample mean, of individual outcomes y_i, given a $k \times 1$ vector of covariates X_i, which is held fixed. The conditional density function of y_i is $f_y(t|X_i = x)$. In our case, the expectation is the mean in the population-weighted sample surveyed by the high-frequency phone surveys on COVID-19. Given that the calculated weights correct for selection bias and non-response bias, the CEF allows us to make unbiased inference about the impact of a specific x_k (a single covariate element in X) on the outcome for the national population. Stated another way, we can use the weighted sample CEF to learn about the population CEF.
Using the law of iterated expectations, we can rewrite the CEF as:

$$y_i = \mathrm{E}[y_i|X_i] + \epsilon_i$$

where ϵ_i is mean independent of X_i. For an arbitrary function $\beta(X_i)$, the CEF solves:

$$\mathrm{E}[y_i|X_i] = \underset{\beta(X_i)}{\operatorname{argmin}} \mathrm{E}\left[\left(y_i - \beta(X_i)\right)^2\right]$$

which is simply the minimum mean squared error prediction problem. Using the first order condition, the solution is $\beta = \mathrm{E}[X_i X_i']^{-1}\mathrm{E}[X_i y_i]$, which is the well-known least squares estimator[10]. To ensure correct inference of statistical tests, we calculate Huber-White robust standard errors, which correct for heteroskedasticity.

Our reduced form approach to estimating the weighted CEF allows us to produce unbiased estimates of impacts of covariates on the population as a whole without explicitly describing the underlying mechanisms. However, this approach can only plausibly identify causal effects and requires the maintained assumption that $\mathrm{E}[\epsilon_i|X_i] = 0$. In some cases, this assumption is easily maintained, such as testing for the effect of living in one country versus another on COVID-19 related loss in income. That a particular household j lives in Ethiopia as opposed to Nigeria is unlikely to be correlated with any relevant (non-ignorable) omitted variables. Obviously, our reduced form approach allows us to say nothing about why households in Ethiopia have lost less income due to COVID-19 than households in Nigeria. The approach simply allows us to produce an unbiased estimate of the likelihood that a household in Ethiopia has lost income and compare it to the likelihood for households in Nigeria. This allows us to conclude that the simple fact of living in Ethiopia means that COVID-19 has had a different impact on household j's income relative to the impact the disease would have had had the household lived in Nigeria.

However, in some cases, such as the gender of the household head or the location of a household in a rural region, the assumption of exogeneity may be more difficult to maintain. As an example, it is possible for the likelihood that household j is female-headed to be correlated with an omitted variable, such as disease susceptibility of male household members, and also correlated with concern for COVID-19 related health impacts. If male members of household j are more likely to die young due to disease, then that household is more likely to be female-headed and may also be more likely to be concerned about additional disease burdens. In this case, estimates of the effect of living in a female-headed household on COVID-19 related health concerns may be biased. Because of this, we encourage the reader to be cautious in interpreting some regression results as causal effects. This concern does not apply to estimates of population weighted means or totals, bias in which are fully corrected for by our calculation of sampling weights.

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Supplementary Evidence

Supplementary figures: Figure S1 provides graphical evidence of heterogeneous effects based on the gender of the household head. Panel A shows differences in loss of income. Panel B shows differences in the prevalence of food insecurity. Panel C shows differences in concern about COVID-19 related health and financial hardships. Panel D shows differences in coping strategies. Figures S2 and S3 primarily provide evidence of "null" results referenced in the paper. Figure S2 present results regarding expected heterogeneity in food insecurity by consumption quintile, though as the figures demonstrate, there is in fact no heterogeneity in these measures. Figure S3 presents results regarding expected heterogeneity in food insecurity by child engagement in learning activities. The lack of heterogeneity in food insecurity along both of these variables is interesting, though we caution overinterpreting the "null" that no heterogeneity exists.

Supplementary tables: Tables S1 – S31 present either (1) biased corrected estimates of population means and population totals or (2) reduced form regressions of heterogenous effects. Tables S4, S7 - S9, S14, S17, S21 – S22, S26, and S28 are type (1). These tables present estimates of the mean number of households, individuals, adults, or school-aged children using corrected for selection bias using survey weights as described above. We use the sample means and total to make inference about the means and totals in the national-level population of interest (households, individuals, adults, or school-aged children). Standard errors for these estimates are presented in parentheses.

Tables S1 - S3, S5 - S6, S10 - S13, S15 - S16, S18 - S20, S23 – S25, S27, S29, and S30 – S31 are type (2). These tables present results from reduced form regressions to test for heterogenous effects across 1) countries, 2) rural and urban sectors, 3) pre-COVID-19 wealth, 4) gender, and 5) time. Every regression uses weights to correct for selection bias. Huber-White robust standard errors are reported in parentheses for all of these tables. With the exception of Table S13, all estimates use the least squares estimator derived above. Table S13 reports results from an ordered logit regression. Tables testing heterogeneity across country use Malawi as the base case. To test differences between the other countries (not Malawi) we conduct Wald tests for equality in the estimated coefficients for each country pair.

Data and Code Availability

The data used in this study can be freely downloaded from the World Bank Microdata Library. The code used to generate these analyses is available at Zenodo[29]. The code is licensed under the MIT license.

Model Code

The code used to generate these analyses is available at: http://doi.org/10.5281/zenodo.4060416

Data

All data used in this study can be downloaded from the cited sources. Each specific country dataset can be found at the following:

Data S1. World Bank, Ethiopia - High-Frequency Phone Survey on COVID-19 2020. (World Bank, Washington, D.C., 2020); https://microdata.worldbank.org/index.php/catalog/3716.
Data S2. World Bank, Malawi - High-Frequency Phone Survey on COVID-19 2020. (World Bank, Washington, D.C., 2020); https://microdata.worldbank.org/index.php/catalog/3766.
Data S3. World Bank, Nigeria - High-Frequency Phone Survey on COVID-19 2020. (World Bank, Washington, D.C., 2020); https://microdata.worldbank.org/index.php/catalog/3712.
Data S4. World Bank, Uganda - High-Frequency Phone Survey on COVID-19 2020. (World Bank, Washington, D.C., 2020); https://microdata.worldbank.org/index.php/catalog/3765.

Figure S1: Heterogeneity in outcomes by gender

(A) Percentage of households reporting loss of income sources, by country and gender of the head of household. **(B)** Prevalence of moderate and/or severe food insecurity among adult individuals, by country and gender of the head of household. **(C)** Percentage of households concerned about COVID-19-related issues linked to health and finance, by country and gender of the head of household. **(D)** Percentage of households reporting use of coping strategy, by country and gender of the head of household.

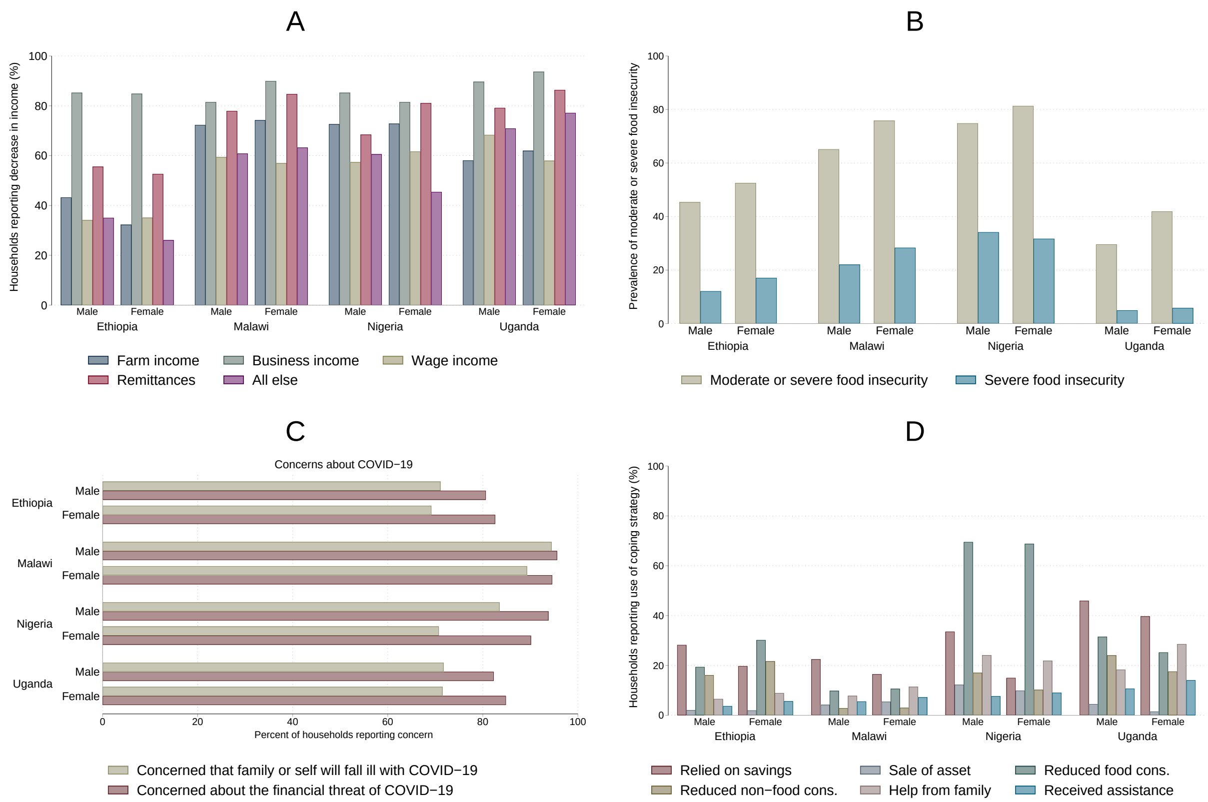
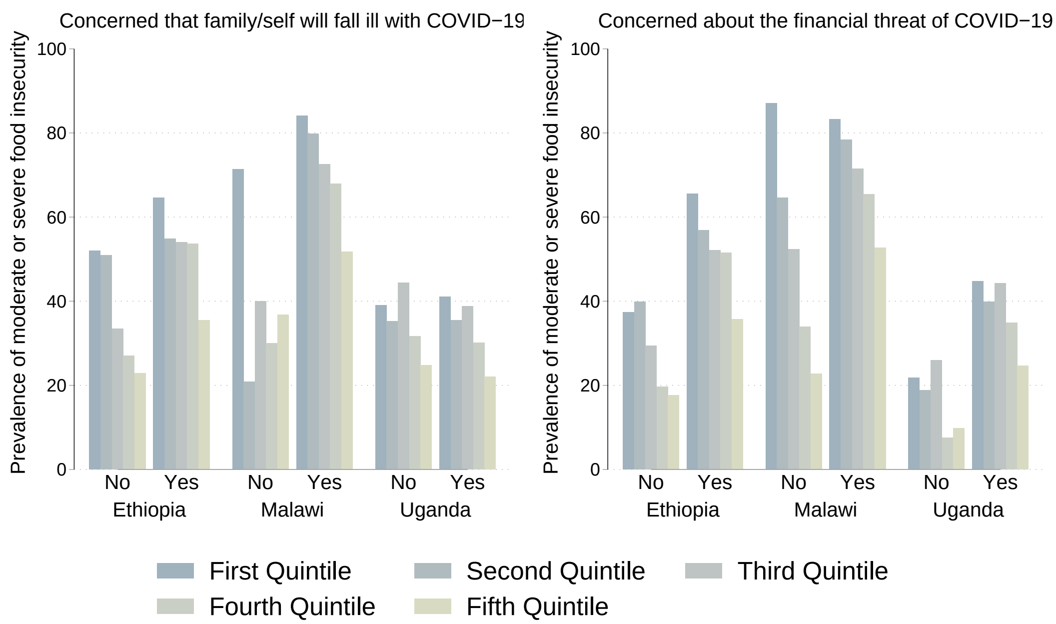


Figure S2: Prevalence of moderate and/or severe food insecurity food insecurity among adults, by health/financial concerns and consumption quintiles

(A) Prevalence of moderate or severe food insecurity in adults is calculated using the FIES and is presented by (i) whether respondent reports being concerned that a family member or the respondent will fall ill with COVID-19 (left panel) or that the household will suffer financially from the pandemic (right panel), and (ii) household annual per capita consumption quintile using pre-COVID-19 data. **(B)** Prevalence of severe food insecurity in adults is calculated using the FIES and is presented (i) by whether respondent reports being concerned that a family member or the respondent will fall ill with COVID-19 (left panel) or that the household will suffer financially from the pandemic (right panel), and (ii) by household annual per capita consumption quintile using pre-COVID-19 data.

A



B

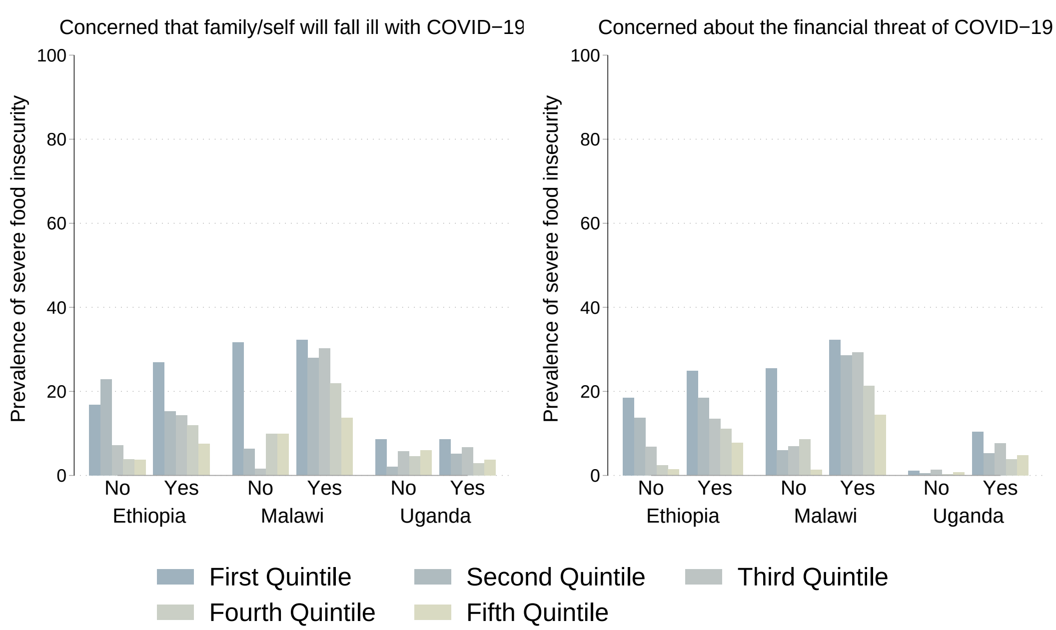


Figure S3: Prevalence of moderate and/or severe food insecurity among adults, by whether household children are engaged in learning activities

Prevalence of food insecurity among adults is calculated using the FIES and is presented by whether the household has school-age children that are engaged in any learning activities following the school closures.

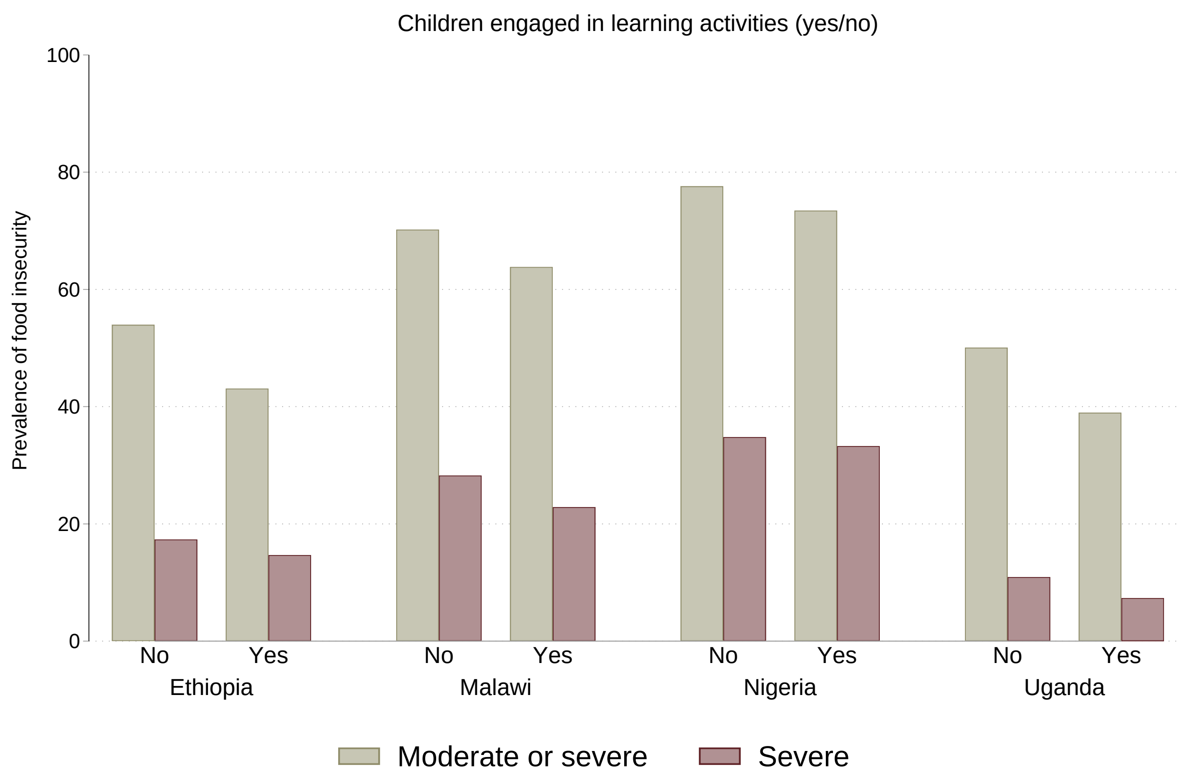


Table S1. Knowledge of government actions undertaken to curb the spread of COVID-19

	Stay at home	Restricted travel	Close schools	Lockdown	Close businesses	Limit social gatherings
Ethiopia	0.203***	0.167***	0.031	0.139***	0.059***	0.225***
	(0.024)	(0.016)	(0.024)	(0.013)	(0.009)	(0.025)
Nigeria	0.506***	0.319***	0.128***	0.446***	0.332***	0.080***
	(0.024)	(0.020)	(0.026)	(0.019)	(0.020)	(0.027)
Uganda	0.025	0.656***	0.242***	0.705***	0.329***	0.214***
	(0.022)	(0.017)	(0.024)	(0.015)	(0.017)	(0.025)
Ethiopia-Nigeria	0.000	0.000	0.000	0.000	0.000	0.000
Ethiopia-Uganda	0.000	0.000	0.000	0.000	0.000	0.591
Nigeria-Uganda	0.000	0.000	0.000	0.000	0.898	0.000
Observations	9,113	9,113	9,113	9,113	9,113	9,113
R-squared	0.157	0.123	0.021	0.178	0.096	0.029

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent was familiar with the government action and 0 otherwise. The binary variable is then regressed on indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S2. Knowledge of actions that can reduce exposure to COVID-19

	Soap reduces risk	Avoid physical greetings	Use masks or gloves	Stay at home	Avoid crowds	Maintain distance of one meter
Ethiopia	0.006	0.459***	0.299***	0.540***	0.295***	0.193***
	(0.005)	(0.022)	(0.027)	(0.022)	(0.024)	(0.021)
Nigeria	-0.013*	0.298***	0.372***	0.544***	0.314***	0.058**
	(0.007)	(0.026)	(0.026)	(0.023)	(0.024)	(0.025)
Uganda	0.010**	0.462***	0.585***	0.617***	0.381***	0.161***
	(0.004)	(0.021)	(0.021)	(0.020)	(0.022)	(0.021)
Ethiopia-Nigeria	0.007	0.000	0.003	0.838	0.218	0.000
Ethiopia-Uganda	0.340	0.585	0.000	0.000	0.000	0.006
Nigeria-Uganda	0.000	0.000	0.000	0.000	0.000	0.000
Observations	9,127	9,127	9,128	9,127	9,127	9,128
R-squared	0.006	0.122	0.078	0.160	0.067	0.038

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent was familiar with the action and 0 otherwise. The binary variable is then regressed on indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.10$).

Table S3. Change in behavior since COVID-19 outbreak

	Handwashed with soap more often	Avoided physical greetings	Avoided crowds
Ethiopia	0.079***	0.238***	0.231***
	(0.014)	(0.019)	(0.024)
Nigeria	0.050***	0.196***	0.329***
	(0.016)	(0.022)	(0.023)
Uganda	0.061***	0.232***	0.301***
	(0.014)	(0.019)	(0.023)
Ethiopia-Nigeria	0.001	0.001	0.000
Ethiopia-Uganda	0.005	0.485	0.000
Nigeria-Uganda	0.235	0.004	0.037
Observations	9,138	9,138	9,131
R-squared	0.011	0.045	0.064

Note: Each column reports results from a single regression of a binary variable equal to 1if the respondent changed their behavior and 0 otherwise. The binary variable is then regressed on indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S4. Average incidence of engaging in safe practices, by survey round

	Malawi			Uganda		
	Hand washed	Avoided physical greetings	Avoided crowds	Hand washed	Avoided physical greetings	Avoided crowds
Round 1	0.908	0.730	0.609	0.969	0.962	0.909
	(0.013)	(0.019)	(0.020)	(0.005)	(0.006)	(0.010)
Round 2	0.817	0.740	0.346	0.805	0.855	0.768
	(0.017)	(0.019)	(0.021)	(0.013)	(0.011)	(0.013)
Observations	3375	3375	3375	4376	4376	4376

Note: Each column reports the estimated population-weighted mean number of people living in households that report changing their behavior. Standard errors are in parenthesis.

Table S5. Behavioral change over time in Malawi and Uganda

	Malawi			Uganda		
	Hand washed	Avoided physical greetings	Avoided crowds	Hand washed	Avoided physical greetings	Avoided crowds
Round 2	-0.090***	0.010	-0.263***	-0.164***	-0.107***	-0.141***
	(0.022)	(0.027)	(0.029)	(0.014)	(0.013)	(0.017)
Observations	3,375	3,375	3,375	4,376	4,376	4,376
R-squared	0.017	0.000	0.069	0.068	0.035	0.037

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent changed their behavior and 0 otherwise. The binary variable is then regressed on an indicator for phone survey round number, with the first round as the base case. Regressions are run for each country (Malawi and Uganda) separately. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S6. Prevalence of false beliefs about COVID-19 in Uganda versus Malawi

	Africans immune	Not affect children	Survive warm weather	Common flu
Uganda	-0.057***	-0.056***	0.007	-0.293***
	(0.022)	(0.017)	(0.027)	(0.024)
Observations	3,662	3,651	3,152	3,621
R-squared	0.005	0.008	0.000	0.150

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent stated that they thought a false belief was in fact true and 0 if they knew it was false. The binary variable is then regressed on an indicator for Uganda, with Malawi as the base case. The questions about false beliefs were only asked in the first phone survey round in Uganda and only asked in the second round in Malawi. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S7. Estimated population counts in accordance with response to false beliefs about COVID-19

Panel A: Malawi

Response	Africans immune	Not affect children	Survive warm weather	Common flu
Yes	2,372,739	1,333,154	2,550,250	3,140,407
	(264,328)	(211,726)	(267,776)	(296,737)
No	5,711,152	5,620,943	4,798,198	4,550,404
	(281,989)	(244,100)	(279,246)	(293,239)
Don't Know	871,254	738,656	1,291,835	1,007,683
	(173,078)	(163,452)	(179,043)	(184,135)
Observations	731	679	764	723

Panel B: Uganda

Response	Africans immune	Not affect children	Survive warm weather	Common flu
Yes	3,271,887	1,661,419	6,115,156	1,307,071
	(346,188)	(242,429)	(451,666)	(237,573)
No	14,205,739	14,780,783	11,799,655	15,115,205
	(383,993)	(278,064)	(493,215)	(311,635)
Don't Know	1,109,367	831,381	3,629,792	1,137,212
	(205,851)	(147,278)	(357,983)	(220,189)
Observations	947	880	1,080	881

Note: Each column reports the estimated total number of people living in households that respond "yes," "no," or "don't know" to whether a series of statements were true. The questions about false beliefs were only asked in the first phone survey round in Uganda and only asked in the second round in Malawi. Standard errors are in parentheses.

Table S8. Estimated total number of households that report income loss due to COVID-19 pandemic and average household-level incidence of income loss, by source

	Any type of income loss	Farm income reduced	Business income reduced	Wage income reduced	Remittances reduced	Other income sources reduced
Total	748,720,384	223,353,008	174,818,736	67,815,688	44,469,788	38,765,196
	(4,869,609)	(4,087,100)	(2,156,618)	(2,204,293)	(1,403,495)	(1,964,309)
Mean	0.773	0.637	0.856	0.527	0.707	0.522
	(0.009)	(0.012)	(0.011)	(0.020)	(0.026)	(0.027)
Observations	9,153	5,624	3,849	3,447	1,687	1,574

Note: Each column reports the estimated total number of households that report loss of income and the average household-level incidence of reporting a loss of income. The estimates are based on the pooled data from 4 countries. Reporting loss of income from a given source is conditional on receiving income from that source prior to the COVID-19 pandemic. Data are only from the first phone survey round in each country. Standard errors on the estimates are in parenthesis.

Table S9. Estimated total number of households that report pre-COVID-19 income and average household-level incidence of income receipt, by source

Panel A: All Countries

	Farm income	Business income	Wage income	Remittances	Other income sources
Total	62,095,944	35,097,532	25,267,792	103,765,224	18,852,056
	(607,921)	(656,727)	(575,150)	(946,421)	(619,989)
Mean	0.730	0.447	0.284	0.652	0.253
	(0.008)	(0.010)	(0.008)	(0.009)	(0.009)
Observations	9,155	9,155	9,155	9,155	9,155

Panel B: Ethiopia

	Farm income	Business income	Wage income	Remittances	Other income sources
Total	12,545,457	4,207,898	4,740,819	0	3,865,377
	(283,973)	(249,049)	(243,303)	(0)	(254,336)
Mean	0.634	0.213	0.240	0.000	0.195
	(0.014)	(0.013)	(0.012)	(0.000)	(0.013)
Observations	3,249	3,249	3,249	3,249	3,249

Panel C: Malawi

	Farm income	Business income	Wage income	Remittances	Other income sources
Total	3,243,256	1,584,694	1,210,010	3,600,947	1,054,078
	(32,910)	(68,720)	(64,491)	(8,046)	(63,054)
Mean	0.893	0.436	0.333	0.991	0.290
	(0.009)	(0.019)	(0.018)	(0.002)	(0.017)
Observations	1,729	1,729	1,729	1,729	1,729

Panel D: Nigeria

	Farm income	Business income	Wage income	Remittances	Other income sources
Total	21,167,000	16,985,522	8,020,662	26,334,226	9,433,393
	(380,014)	(444,969)	(403,349)	(127,001)	(427,423)
Mean	0.785	0.630	0.298	0.977	0.350
	(0.014)	(0.017)	(0.015)	(0.005)	(0.016)
Observations	1,950	1,950	1,950	1,950	1,950

Panel E: Uganda

	Farm income	Business income	Wage income	Remittances	Other income sources
Total	6,025,480	3,533,057	2,773,255	8,462,181	547,760
	(124,336)	(128,328)	(125,664)	(10,362)	(64,285)
Mean	0.709	0.416	0.326	0.995	0.064
	(0.015)	(0.015)	(0.015)	(0.001)	(0.008)
Observations	2,227	2,227	2,227	2,227	2,227

Note: Each column reports the estimated total number of households that reported pre-COVID-19 income from each source and the average household-level incidence of pre-COVID-19 income receipt from each source. Data are only from the first phone survey round in each country. Standard errors on the estimates are in parenthesis.

Table S10. Income loss due to the COVID-19 pandemic, by source

	Farm income reduced	Business income reduced	Wage income reduced	Remittances reduced	Other income sources reduced
Ethiopia	-0.314***	0.016	-0.240***	-0.260***	-0.299***
	(0.028)	(0.033)	(0.041)	(0.053)	(0.054)
Nigeria	-0.001	0.011	-0.005	-0.086*	-0.029
	(0.024)	(0.025)	(0.042)	(0.044)	(0.055)
Uganda	-0.133***	0.075***	0.074*	0.028	0.116
	(0.025)	(0.025)	(0.041)	(0.040)	(0.072)
Ethiopia-Nigeria	0.000	0.853	0.000	0.001	0.000
Ethiopia-Uganda	0.000	0.048	0.000	0.000	0.000
Nigeria-Uganda	0.000	0.002	0.044	0.007	0.034
Observations	5,624	3,849	3,447	1,687	1,574
R-Squared	0.080	0.004	0.056	0.037	0.075

Note: Each column reports results from a single regression of a binary variable equal to 1 if the household lost income from that source and 0 otherwise. Reporting loss of income from a given source is conditional on receiving income from that source prior to the COVID-19 pandemic. The binary variable is then regressed on indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S11. Income loss due to the COVID-19 pandemic, by income source and urban/rural residence

	Farm income reduced	Business income reduced	Wage income reduced	Remittances reduced	Other income sources reduced
Urban	-0.019	0.024	-0.016	-0.016	-0.137***
	(0.025)	(0.022)	(0.035)	(0.045)	(0.046)
Ethiopia	0.001	0.009	-0.004	-0.083*	-0.017
	(0.024)	(0.025)	(0.042)	(0.045)	(0.054)
Nigeria	-0.132***	0.072***	0.076*	0.029	0.157**
	(0.025)	(0.025)	(0.041)	(0.040)	(0.074)
Uganda	-0.314***	0.011	-0.234***	-0.256***	-0.281***
	(0.028)	(0.034)	(0.045)	(0.056)	(0.055)
Observations	5,624	3,849	3,447	1,687	1,574
R-Squared	0.081	0.005	0.056	0.038	0.091

Note: Each column reports results from a single regression of a binary variable equal to 1 if the household lost income from that source and 0 otherwise. Reporting loss of income from a given source is conditional on receiving income from that source prior to the COVID-19 pandemic. The binary variable is then regressed on indicators for each country, with Malawi as the base case, along with an indicator equal to 1 if the household was located in an urban area, as opposed to a rural area. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S12. Income loss due to the COVID-19 pandemic, by income source and gender of household head

	Farm income reduced	Business income reduced	Wage income reduced	Remittances reduced	Other income sources reduced
Female Head	-0.021	-0.008	-0.003	0.082*	-0.100*
	(0.025)	(0.030)	(0.037)	(0.044)	(0.057)
Ethiopia	-0.004	0.012	-0.009	-0.079*	-0.046
	(0.024)	(0.026)	(0.042)	(0.044)	(0.056)
Nigeria	-0.136***	0.076***	0.068	0.011	0.128*
	(0.025)	(0.026)	(0.041)	(0.042)	(0.073)
Uganda	-0.318***	0.018	-0.245***	-0.258***	-0.290***
	(0.028)	(0.033)	(0.041)	(0.054)	(0.054)
Observations	5,556	3,816	3,420	1,666	1,567
R-Squared	0.082	0.004	0.056	0.044	0.080

Note: Each column reports results from a single regression of a binary variable equal to 1 if the household lost income from that source and 0 otherwise. Reporting loss of income from a given source is conditional on receiving income from that source prior to the COVID-19 pandemic. The binary variable is then regressed on indicators for each country, with Malawi as the base case, along with an indicator equal to 1 if the household head is female, as opposed to male. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S13. Change in business revenue loss over time

	Business Revenue Loss
Round 2	-1.010***
	(0.112)
Round 3	-1.026***
	(0.134)
Ethiopia	0.032
	(0.115)
Nigeria	-0.145
	(0.108)
Uganda	-0.569***
	(0.090)
Ethiopia-Nigeria	0.084
Ethiopia-Uganda	0.000
Nigeria-Uganda	0.000
Round 2-Round 3	0.907
Observations	7,242
Pseudo R-Squared	0.030

Note: The table reports the result from a single ordered logit regression in which the dependent variable equals 1 if revenue is higher than the previous period, equal to 2 if revenue is the same as in the previous period, equal to 3 if revenue is less than the previous period, and 4 if they received no revenue. The ordinal variable is then regressed on indicators for each country, with Malawi as the base case, and indicators for each phone survey round, with round 1 as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country or wave indicator equals the coefficient on an indicator for a different country or round. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S14. Estimated total number of adults that are (i) moderately or severely food insecure and (ii) severely food insecure and average incidence of (i) moderate or severe food insecurity and (ii) severe food insecurity among the adult population

Panel A: Total

	All Countries	Ethiopia	Malawi	Nigeria	Uganda
Moderate or	100,014,992	24,130,336	6,232,031	62,767,288	6,885,341
Severe	1,577,726	846,790	150,580	1,191,869	285,413
Severe	38,032,228	6,787,466	2,167,532	27,992,446	1,084,782
	1,376,278	600,851	123,643	1,144,950	110,423
Observations	8,713	3,051	1,646	1,820	2,196

Panel B: Mean

	All Countries	Ethiopia	Malawi	Nigeria	Uganda
Moderate or	0.609	0.469	0.676	0.757	0.330
Severe	(0.010)	(0.016)	(0.016)	(0.014)	(0.014)
Severe	0.231	0.132	0.235	0.338	0.052
	(0.008)	(0.012)	(0.013)	(0.014)	(0.005)
Observations	8,713	3,051	1,646	1,820	2,196

Note: Each column in Panel A reports the estimated total number of adults who are moderately or severely food insecure, or just severely food insecure. Each column in Panel B reports the average incidence of (i) moderate or severe food insecurity and (ii) severe food insecurity among the adult population. In both panels, food insecurity is measured using the FIES. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia, round 2 in Malawi, Nigeria, and Uganda. Standard errors on the estimates are in parenthesis.

Table S15. Prevalence of food insecurity

	Moderate or Severe Food Insecurity	Severe Food Insecurity
Ethiopia	-0.207***	-0.103***
	(0.023)	(0.018)
Nigeria	0.081***	0.102***
	(0.022)	(0.019)
Uganda	-0.346***	-0.183***
	(0.021)	(0.014)
Ethiopia-Nigeria	0.000	0.000
Ethiopia-Uganda	0.000	0.000
Nigeria-Uganda	0.000	0.000
Observations	8,713	8,713
R-squared	0.147	0.119

Note: Each column reports results from a single regression of the prevalence of either moderate or severe food insecurity or just severe food insecurity. Food insecurity is measured using the FIES. The FIES variable is regressed on indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia, round 2 in Malawi, Nigeria, and Uganda. Robust standard errors are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.10$).

Table S16. Prevalence of food insecurity by gender of household head

	Moderate or Severe Food Insecurity	Severe Food Insecurity
Female Head	0.111***	0.039***
	(0.023)	(0.015)
Round 2	-0.075***	-0.042***
	(0.017)	(0.011)
Round 3	-0.087***	-0.070***
	(0.029)	(0.019)
Female × Round 2	-0.027	-0.028
	(0.029)	(0.023)
Female × Round 3	-0.040	0.011
	(0.045)	(0.036)
Ethiopia	-0.172***	-0.098***
	(0.021)	(0.016)
Nigeria	0.108***	0.089***
	(0.020)	(0.017)
Uganda	-0.323***	-0.205***
	(0.015)	(0.011)
Observations	15,687	15,687
R-squared	0.130	0.114

Note: Each column reports results from a single regression of the prevalence of either moderate or severe food insecurity or just severe food insecurity. Food insecurity is measured using the FIES. The FIES variable is regressed on indicators for each country, with Malawi as the base case, and round, along with an indicator equal to 1 if the household head is female, as opposed to male. Data come from all rounds of phone survey data in which FIES questions exist. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S17. Estimated population concerned about health and finances

Panel A: Concerned about household health

	All Countries	Ethiopia	Malawi	Nigeria	Uganda
Total	257,414,816	71,449,632	17,517,492	137,937,232	30,510,464
	(3,083,491)	(1,858,111)	(189,537)	(2,295,302)	(623,196)
Mean	0.779	0.707	0.933	0.821	0.716
	(0.009)	(0.018)	(0.010)	(0.014)	(0.015)
Observations	8,849	3,058	1,646	1,948	2,197

Panel B: Concerned about household finances

	All Countries	Ethiopia	Malawi	Nigeria	Uganda
Total	292,328,256	81,848,456	17,919,304	157,232,592	35,327,904
	(2,431,731)	(1,526,779)	(164,040)	(1,785,593)	(510,836)
Mean	0.884	0.810	0.954	0.935	0.829
	(0.007)	(0.015)	(0.009)	(0.011)	(0.012)
Observations	8,850	3,058	1,646	1,949	2,197

Note: Each column reports the estimated total number of households using a coping strategy in response to COVID-19-relaated income loss and average household-level incidence of using a coping strategy. Adoption of a strategy is condition on experiencing a COVID-19 related loss of income per Table S8. Data come from the most round of phone survey data available. This is round 3 in Ethiopia and Nigeria, round 2 in Malawi, and round 1 in Uganda.

Table S18. Prevalence of food insecurity as it relates to health and financial concerns

	Moderate or Severe Food Insecurity	Severe Food Insecurity
Concerned about household health	0.042	0.010
	(0.030)	(0.021)
Concerned about household finances	0.206***	0.062***
	(0.031)	(0.019)
Ethiopia	-0.170***	-0.093***
	(0.023)	(0.018)
Uganda	-0.311***	-0.173***
	(0.022)	(0.015)
Ethiopia-Uganda	0.000	0.000
Observations	6,893	6,893
R-squared	0.089	0.051

Note: Each column reports results from a single regression of the prevalence of either moderate or severe food insecurity or just severe food insecurity. Food insecurity is measured using FIES. The FIES variable is regressed on indicators whether or not the respondent is concerned about the health impacts of COVID-19 and the financial impacts of COVID-19. Also included are indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia, round 2 in Malawi and in Uganda. Nigeria is not included because questions about concerns were not asked in the same rounds as questions about food insecurity. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S19. Concerns about health and finance by gender of household head

	Concerned about household health	Concerned about household finances
Female Head	-0.059***	-0.003
	(0.022)	(0.016)
Ethiopia	-0.228***	-0.144***
	(0.021)	(0.017)
Nigeria	-0.119***	-0.020
	(0.017)	(0.014)
Uganda	-0.213***	-0.124***
	(0.018)	(0.015)
Observations	8,814	8,815
R-squared	0.028	0.035

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent answered "yes" to the question of whether they were concerned that a household member may fall ill with COVID-19 or that the household would experience financial distress due to COVID-19. The binary variable is regressed on indicators for each country, with Malawi as the base case, along with an indicator equal to 1 if the household head is female, as opposed to male. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia, round 2 in Malawi and Uganda, and round 1 in Nigeria. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S20. Concerns about health and finance across consumption quintile

	Concerned about household health	Concerned about household finances
Ethiopia	-0.219***	-0.150***
	(0.019)	(0.016)
Nigeria	-0.141***	-0.032***
	(0.017)	(0.012)
Uganda	-0.217***	-0.133***
	(0.017)	(0.014)
Quintile 2	-0.004	-0.019
	(0.031)	(0.027)
Quintile 3	-0.064*	-0.012
	(0.032)	(0.026)
Quintile 4	-0.059**	0.004
	(0.030)	(0.025)
Quintile 5	-0.094***	-0.006
	(0.028)	(0.023)
Ethiopia-Nigeria	0.000	0.000
Ethiopia-Uganda	0.929	0.351
Nigeria-Uganda	0.000	0.000
Observations	8,846	8,847
R-squared	0.024	0.032

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent answered "yes" to the question of whether they were concerned that a household member may fall ill with COVID-19 or that the household would experience financial distress due to COVID-19. The binary variable is regressed on indicators for each country, with Malawi as the base case, and each pre-COVID-19 household annual per capita consumption quintile, with the lowest consumption quintile as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country or that the coefficient on one quintile indicator equals the coefficient on an indicator for a different quintile. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia, round 2 in Malawi and Uganda, and round 1 in Nigeria. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S21. Estimated total number of households that report suffering a COVID-19-related shock and average household incidence of suffering a COVID-19-related shock

	All Countries	Ethiopia	Malawi	Nigeria	Uganda
Total	24,885,908	5,177,274	1,167,996	15,045,319	3,495,319
	(594,983)	(276,409)	(66,812)	(466,172)	(128,117)
Mean	0.423	0.261	0.325	0.558	0.411
	(0.010)	(0.014)	(0.019)	(0.017)	(0.015)
Observations	8,721	3,058	1,646	1,790	2,227

Note: Each column reports the estimated total number of households that reported suffering a COVID-19-related shock and average household-level incidence of suffering a COVID-19-related shock. Data comes from the most recent wave (round) of data available. This is round 3 in Ethiopia and Nigeria, round 2 in Malawi, and round 1 in Uganda. Standard errors on the estimates are in parenthesis.

Table S22. Estimated total number of households using a coping strategy in response to COVID-19-related income loss and average household-level incidence of using a coping strategy

	Any Coping Strategy	Relied on Saving	Sale of Assets	Reduced Food Consumption	Reduced Non-Food Consumption	Received Assistance from Friends and Family	Received Any Assistance
Total	33,171,234	12,219,426	3,462,072	21,370,172	6,491,568	8,084,976	4,270,560
	(578,286)	(473,945)	(284,763)	(518,857)	(354,462)	(422,270)	(313,064)
Mean	0.564	0.294	0.083	0.514	0.156	0.194	0.073
	(0.010)	(0.011)	(0.007)	(0.012)	(0.009)	(0.010)	(0.005)
Observations	8,721	5,595	5,595	5,595	5,595	5,595	8,719

Note: Each column reports the estimated total number of households using a coping strategy in response to COVID-19-relaated income loss and average household-level incidence of using a coping strategy. Adoption of a strategy is condition on experiencing a COVID-19 related loss of income per Table S8. Data come from the most round of phone survey data available. This is round 3 in Ethiopia and Nigeria, round 2 in Malawi, and round 1 in Uganda. Standard errors on the estimates are in parenthesis.

Table S23. Strategies to cope with income lost due to COVID-19 pandemic

	Relied on Saving	Sale of Assets	Reduced Food Consumption	Reduced Non-Food Consumption	Received Assistance from Friends and Family	Received Any Assistance
Ethiopia	0.056**	-0.027**	0.126***	0.149***	-0.020	-0.020
	(0.027)	(0.011)	(0.022)	(0.017)	(0.016)	(0.012)
Nigeria	0.090***	0.070***	0.592***	0.125***	0.143***	0.018
	(0.024)	(0.014)	(0.021)	(0.014)	(0.019)	(0.014)
Uganda	0.228***	-0.017	0.182***	0.179***	0.141***	0.061***
	(0.026)	(0.011)	(0.022)	(0.018)	(0.021)	(0.014)
Ethiopia-Nigeria	0.205	0.000	0.000	0.224	0.000	0.002
Ethiopia-Uganda	0.000	0.236	0.026	0.187	0.000	0.000
Nigeria-Uganda	0.000	0.000	0.000	0.008	0.955	0.002
Observations	5,595	5,595	5,595	5,595	5,595	8,719
R-Squared	0.015	0.025	0.217	0.012	0.031	0.011

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent stated that the household relied on that strategy to cope with the loss of income and 0 if they did not. The binary variable is regressed on indicators for each country, with Malawi as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia and Nigeria, round 2 in Malawi, and round 1 in Uganda. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S24. Strategies to cope with income lost due to pandemic across rural/urban sector

	Relied on Saving	Sale of Assets	Reduced Food Consumption	Reduced Non-Food Consumption	Received Assistance from Friends and Family	Received Any Assistance
Urban	0.016	-0.061***	0.088***	0.017	0.046**	0.014
	(0.023)	(0.012)	(0.021)	(0.019)	(0.022)	(0.011)
Ethiopia	0.053*	-0.014	0.108***	0.146***	-0.030*	-0.022*
	(0.028)	(0.011)	(0.022)	(0.018)	(0.017)	(0.013)
Nigeria	0.088***	0.077***	0.581***	0.123***	0.137***	0.016
	(0.024)	(0.015)	(0.022)	(0.014)	(0.019)	(0.014)
Uganda	0.226***	-0.009	0.171***	0.177***	0.135***	0.059***
	(0.026)	(0.011)	(0.023)	(0.018)	(0.021)	(0.014)
Observations	5,595	5,595	5,595	5,595	5,595	8,719
R-Squared	0.015	0.035	0.223	0.012	0.033	0.011

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent stated that the household relied on that strategy to cope with the loss of income and 0 if they did not. The binary variable is regressed on indicators for each country, with Malawi as the base case, along with an indicator equal to 1 if the household was located in an urban area, as opposed to a rural area. Data come from the most recent round of phone survey data available. This is round 3 in Ethiopia and Nigeria, round 2 in Malawi, and round 1 in Uganda. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S25. Strategies to cope with income lost due to pandemic across gender of head of household

	Relied on Saving	Sale of Assets	Reduced Food Consumption	Reduced Non-Food Consumption	Received Assistance from Friends and Family	Received Any Assistance
Female Head	-0.105***	-0.021**	0.037	-0.068***	0.020	0.085***
	(0.022)	(0.009)	(0.028)	(0.021)	(0.024)	(0.018)
Round 2	-0.029	-0.004	0.090***	-0.003	0.000	0.014
	(0.024)	(0.010)	(0.022)	(0.019)	(0.016)	(0.010)
Round 3	-0.004	0.044***	0.146***	-0.040**	-0.009	-0.031***
	(0.021)	(0.011)	(0.020)	(0.017)	(0.018)	(0.010)
Female × Round 2	0.096**	0.013	-0.033	0.083**	0.079**	-0.057**
	(0.038)	(0.011)	(0.039)	(0.033)	(0.038)	(0.024)
Female × Round 3	0.027	0.007	-0.038	0.039	-0.008	-0.069***
	(0.038)	(0.022)	(0.043)	(0.030)	(0.038)	(0.024)
Ethiopia	0.014	-0.036***	0.093***	0.134***	0.004	-0.007
	(0.024)	(0.010)	(0.021)	(0.016)	(0.018)	(0.010)
Nigeria	0.088***	0.010	0.532***	0.191***	0.178***	0.058***
	(0.030)	(0.013)	(0.026)	(0.020)	(0.022)	(0.011)
Uganda	0.225***	-0.017	0.265***	0.201***	0.165***	0.061***
	(0.034)	(0.014)	(0.030)	(0.025)	(0.027)	(0.011)
Observations	10,618	10,618	10,618	10,618	10,618	22,664
R-Squared	0.021	0.022	0.204	0.014	0.042	0.022

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent stated that the household relied on that strategy to cope with the loss of income and 0 if they did not. The binary variable is regressed on indicators for each country, with Malawi as the base case, and round, along with an indicator equal to 1 if the household head is female, as opposed to male. Data come from all rounds of phone survey data in which FIES questions exist. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S26. Estimated total number of households without access to basic necessities and average household-level incidence of lack of access

	Unable to Access Medicine	Unable to Access Staple	Unable to Access Soap
Total	5,132,974	11,151,785	4,075,418
	(253,575)	(448,490)	(276,591)
Mean	0.204	0.243	0.124
	(0.010)	(0.010)	(0.008)
Observations	4,604	6,793	5,298

Note: Each column reports the estimated total number of households without access to basic necessities and average household-level incidence of lack of access. Inability or ability to access a basic necessity is conditional on the household needing the item or attempting to purchase the item. Note that the question regarding soap was not asked in Ethiopia. Data are only from the first phone survey round in each country. Standard errors on the estimates are in parenthesis.

Table S27. Lack of access to basic necessities by consumption quintile

	Unable to Access Medicine	Unable to Access Staple	Unable to Access Soap
Ethiopia	0.221***	0.009	
	(0.037)	(0.033)	
Nigeria	0.011	-0.034	0.018
	(0.024)	(0.032)	(0.019)
Uganda	0.217***	-0.129***	0.092***
	(0.024)	(0.030)	(0.019)
Quintile 2	0.004	-0.081*	-0.071*
	(0.043)	(0.047)	(0.039)
Quintile 3	0.001	-0.156***	-0.115***
	(0.042)	(0.043)	(0.036)
Quintile 4	-0.039	-0.121***	-0.099***
	(0.039)	(0.042)	(0.037)
Quintile 5	-0.113***	-0.218***	-0.138***
	(0.034)	(0.039)	(0.036)
Ethiopia-Nigeria	0.000	0.107	
Ethiopia-Uganda	0.919	0.000	
Nigeria-Uganda	0.000	0.000	0.000
Observations	4,604	6,792	5,297
R-squared	0.072	0.038	0.030

Note: Each column reports results from a single regression of a binary variable equal to 1 if the respondent answered "yes" to a question about the inability to access a basic necessity. Inability or ability to access a basic necessity is conditional on the household needing the item or attempting to purchase the item. The binary variable is regressed on indicators for each country, with Malawi as the base case, and each pre-COVID-19 household annual per capita consumption quintile, with the lowest consumption quintile as the base case. Note that the question regarding soap was not asked in Ethiopia. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S28. Estimated total number of school-aged children in households without educational engagement

	All Countries	Ethiopia	Malawi	Nigeria	Uganda
Total	68,465,008	31,681,834	6,116,277	24,741,134	5,925,768
	(1,797,619)	(614,013)	(156,190)	(1,489,912)	(313,951)
Observations	6,190	1,911	1,193	1,417	1,669

Note: Each column reports the estimated total number of school-aged children living in households that report their children have not been engaged in any sort of educational activity since schools closed. Data are only from the first phone survey round in each country. Standard errors are in parenthesis.

Table S29. Prevalence of engagement in educational activity by consumption quintile

	Education Activity
Ethiopia	0.011
	(0.024)
Nigeria	0.437***
	(0.028)
Uganda	0.439***
	(0.025)
Quintile 2	0.012
	(0.042)
Quintile 3	0.051
	(0.039)
Quintile 4	0.108***
	(0.038)
Quintile 5	0.179***
	(0.037)
Ethiopia-Nigeria	0.000
Ethiopia-Uganda	0.000
Nigeria-Uganda	0.931
Observations	6,316
R-squared	0.185

Note: The table reports the result from a single regression of a binary variable equal to 1 if the household has a school-aged child that has been engaged in some educational activity since schools closed and 0 otherwise. The question is asked conditional on the household containing a school-aged child. The binary variable is regressed on indicators for each country, with Malawi as the base case, and each pre-COVID-19 household annual per capita consumption quintile, with the lowest consumption quintile as the base case. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data are only from the first phone survey round in each country. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S30. Educational activity and food insecurity

	Moderate or Severe Food Insecurity	Severe Food Insecurity
Education Activity	-0.075***	-0.033
	(0.024)	(0.023)
Ethiopia	-0.118***	-0.054**
	(0.029)	(0.024)
Nigeria	0.112***	0.102***
	(0.029)	(0.027)
Uganda	-0.195***	-0.147***
	(0.028)	(0.021)
Ethiopia-Nigeria	0.000	0.000
Ethiopia-Uganda	0.005	0.000
Nigeria-Uganda	0.000	0.000
Observations	5,978	5,978
R-squared	0.089	0.074

Note: Each column reports results from a single regression of a continuous variable that measures the prevalence of moderate or severe food security, or just severe food insecurity among adult household members. The variable is regressed on indicators for each country, with Malawi as the base case, and a binary for educational activity. Educational activity is a binary variable equal to 1 if the household has a school-aged child that has been engaged in some educational activity since schools closed and 0 otherwise. The question is asked conditional on the household containing a school-aged child. The second panel reports p-values for Wald tests of the simple linear hypothesis that the coefficient on one country indicator equals the coefficient on an indicator for a different country. Data come from the most recent round of phone survey data available. This is round 2 in Ethiopia, Malawi, and Nigeria, and round 1 in Uganda. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).

Table S31. Engagement in educational activities over time

Panel A: Ethiopia

	Education Activity	Listened to Education Programs on Radio	Used Mobile Learning Apps	Watched Educational TV Programs	Meeting with Lesson Teacher
Round 2	0.130***	-0.110*	-0.043	-0.070**	0.119***
	(0.027)	(0.064)	(0.028)	(0.036)	(0.037)
Round 3		-0.117*	0.037	-0.051	0.041
		(0.063)	(0.038)	(0.038)	(0.031)
Observations	3,742	2,228	2,228	2,228	2,228
R-Squared	0.023	0.009	0.012	0.006	0.017

Panel B: Malawi

	Education Activity	Listened to Education Programs on Radio	Used Mobile Learning Apps	Watched Educational TV Programs	Meeting with Lesson Teacher
Round 2	0.054*	-0.053	-0.058*	0.087**	0.343***
	(0.030)	(0.077)	(0.030)	(0.043)	(0.057)
Observations	2,355	516	516	516	516
R-Squared	0.004	0.003	0.017	0.031	0.141

Panel C: Nigeria

	Education Activity	Listened to Education Programs on Radio	Used Mobile Learning Apps	Watched Educational TV Programs	Meeting with Lesson Teacher
Round 2	-0.012	0.267***	0.123***	0.141***	0.168***
	(0.033)	(0.038)	(0.028)	(0.032)	(0.034)
Round 3	-0.113***	0.291***	0.182***	0.242***	0.304***
	(0.034)	(0.038)	(0.032)	(0.035)	(0.036)
Observations	4,045	2,515	2,515	2,515	2,515
R-Squared	0.010	0.076	0.042	0.049	0.072

Note: Each column in each panel reports results from a single regression of a binary variable equal to 1 if the school-aged children in the household have engaged in the educational activity. The question is asked conditional on the household containing a school-aged child. Each panel reports results for a single country. Uganda is excluded as there is only one round of data. All rounds of all available data for a country are included in each regression. Robust standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.10).