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Three essays on the Covid-19 crisis on household food security

Evidence from Ethiopia, Uganda, and Mozambique

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Abstract

The COVID-19 pandemic brought about disruptive consequences to many people's livelihoods around the world. The package of restrictions to contrast the health crisis caused a contraction of income and employment, on the demand side, and a disruption of domestic and global value chains, on the supply side. In many low-income economies, the crisis exacerbated an already fragile situation, raising concerns in terms of food insecurity and malnutrition. However, given the peculiar characteristics of the COVID-19 shock, not all individuals are expected to be affected in the same way. Nevertheless, evidence of the ultimate impact on food security, and the mechanisms of transmission, is still scarce.

This thesis aims to address this literature gap, providing evidence for three African countries. Specifically, the study analyses the change in terms of food production and food consumption, as well as their relationship, in the aftermath of the COVID-19 outbreak, disentangling the heterogeneous impact over different types of households and different segments of the food value chain.

To answer the proposed research questions, the study uses the most appropriate econometric techniques, which include a longitudinal model with household fixed effects, a structural equation model, and a cross-sectional model. What emerges is that the COVID-19 crisis severely impacted both household employment and income in 2020, the more so the longer the time length from the pandemic onset. The shock operated through two main channels of transmission, namely food value chain disruption and job loss, ultimately affecting household food security and child nutrition.

The study also highlights the importance of considering the specific context under analysis and distinguishing between different types of households, specifically their market positioning when considering agricultural households.

Keywords— Covid-19 - Food security - Food value chain

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Introduction

Motivation

Covariate shocks can have significant consequences on food systems[1], ranging from food production, affecting the upstream segment of the value chain, to ultimate outcomes of food security and nutrition (Bakhtiar and Rabbani, 2021; Block et al., 2004; Diao and Roe, 2000; Dyer et al., 2006; Ferreira and Schady, 2009; Kavallari et al., 2014; Lin and Martin, 2010). However, the nature of the shock can lead to different effects among individuals, both in terms of magnitude and direction, so the final overall effect is often unpredictable. Covariate shocks indeed can be demand-driven, such as reduced demand for goods or services, or supply-driven, as is the case of an increase in prices due to production shortfall. An increase in prices, for instance, can positively affect producers, while it has a negative effect on consumers. This was the case for some commodity exporters, many from middle-income emerging economies, after the great recession of 2007-2008, who benefited from both high energy and food prices (Schmidhuber and Qiao, 2020), while at the same time high-income countries were suffering from the increase in prices.

At the micro level, this can be observed among households with different levels of integration in the food market. Additionally, several factors, both exogenous and endogenous, and other simultaneous shocks can influence the final total effect. Understanding the specific type of shock under analysis and the different factors that can affect its overall impact is then crucial.

The COVID-19 crisis presents some peculiarities that make it different from the previous covariate shocks experienced by the global economy (Schmidhuber and Qiao, 2020). Indeed, the COVID-19 crisis can be defined as a typical Keynesian supply shock (Guerrieri et al., 2020), which involves two recessive shocks simultaneously: a demand

[1] A food system includes "all the elements (environment, people, inputs, processes, infrastructures, institutions, etc.) and activities that relate to the production, processing, distribution, preparation and consumption of food, and the output of these activities, including socio-economic and environmental outcomes" (HLPE, 2017).

shock superimposed on a supply shock (Charles et al., 2021).

At the local level, this can be translated into a contraction of income on the demand side, and a disruption of domestic value chains on the supply side. During the lockdown, people were prevented from going to work, thereby reducing their income in the absence of welfare measures, and at the same time limiting their ability of spending on goods and services. Furthermore, the fear of contracting the virus prevented people from buying food in crowded markets or eating outside, intensifying the demand effect. At the same time, in many countries, non-essential businesses were forced to close, creating a cascade effect on transportation costs and input and output prices. Even when they were able to operate, they were directly hit by the collapse of external demand, especially if they were integrated into the global market, with repercussions in the domestic markets. As highlighted by Charles et al. (2021), the nature of the COVID-19 shock varies depending on the strictness of the restrictions. When non-essential businesses were completely closed, such as restaurants and bars, the shock was purely supply-side. If instead a certain level of activity was ensured, such as through takeaway food or food delivery, the shock occurred both on the supply and the demand. When the fear of contracting the virus prevented people from going out, forcing businesses to close down because of the demand contraction, people experienced a demand-side shock following a supply-side shock.

Additionally, while previous crises mainly affected only some countries, as happened during the 2007-2008 crisis, the COVID-19 crisis resulted in a truly global crisis (Schmidhuber and Qiao, 2020). The package of restrictions to contrast the health crisis has been implemented across all countries, although in different manners and at different timings. Economies were then directly affected by the restrictions implemented both on the domestic and global markets. Given the globalized economy, which is characterized by multiple, interlinked value chains and incomplete markets, each country has been also indirectly affected by the restrictions on international trade and the global value chain. As a result, not only high-income countries but also low and middle-income countries highly experienced the negative effects of the COVID-19 crisis.

In many developing economies, the crisis exacerbated an already fragile situation, where severe structural problems and other concurrent shocks, such as extreme weather events and conflicts, were already hitting the population, making food insecurity and malnutrition relevant issues for many people's livelihoods. It has been estimated that due to the COVID-19 crisis, over 140 million people, mainly in sub-Saharan Africa, fell into extreme poverty and suffered from food insecurity and hunger in 2020 (Laborde et al., 2020; Swinnen, 2020; Torero, 2020).

In many African countries, these impacts were channeled mainly through the loss/reduction of jobs and the disruption of food systems (Demeke et al., 2020; Devereux et al., 2020; ILO, 2020; UN-HABITAT and WFP, 2020), eventually leading to higher poverty rates and food insecurity (Kansiime et al., 2021). On the one hand, indeed, the government restrictions disrupted livelihood activities, specifically participation in the labor market, reducing household income (Abay and Tafere, 2020; Amare et al., 2021; Arndt et al., 2020). Informal and seasonal workers, which represent 60% of all workers in developing countries (ILO, 2018), were more likely to be affected (Gururaja and Ranjitha, 2022; Narula, 2020). On the other hand, the disruption of food markets and value chains undermined the access to food, reducing food security (e.g., (Aggarwal et al., 2022; Hirvonen et al., 2021; Mahajan and Tomar, 2021). As suggested by Devereux et al. (2020), the disruptions to food systems from the pandemic are negatively linked to food security. Evidence of this effect is emerging from different studies, with food accessibility resulting the most affected dimension of food security (Béné et al., 2021).

This is particularly true in the traditional food systems, where technologies used in time of lockdown, such as e-commerce (Reardon et al., 2021), are not well developed (Reardon and Timmer, 2012). Given that 74% of farmers in Sub-Saharan Africa are smallholders[2] (Lowder et al., 2021) who practice mainly subsistence agriculture, the impact on this region is expected to be higher, raising concerns about the livelihoods of many agri-food systems participants.

Understanding the specific context under analysis, as well as the type of restrictions and the level of stringency enforced in each country, is then important to identify the effect of the COVID-19 crisis and disentangle it from other factors. For this

[2] Small farms defined as those agricultural holdings that encompass fewer than two hectares of farmland (Lowder et al., 2021)

reason, this thesis analyzes the heterogeneous effects of COVID-19 in three different African countries separately, namely Ethiopia, Uganda, and Mozambique. In this way, the analysis can be adapted to the specific context. Indeed, although it is not intended as a comparative exercise, the results emerging in each country highlight the importance of considering the differentiated impact of the same shock over different contexts and different types of individuals and households.

Aim of the study

The purpose of this study is to investigate the economic impact of the COVID-19 crisis and the related restrictions implemented by governments on different aspects of the agri-food systems, ultimately affecting food security outcomes, using three African countries as case studies. The effect that this thesis aims to capture is the economic response to the COVID-19 crisis, rather than the health aspect of the pandemic.

Specifically, the study analyzes the heterogeneous impact on the agri-food system over different segments of the food value chain, as well as the implications in terms of food production on one side, and food consumption on the other side.

The first chapter investigates the change in income and labor participation as a consequence of the COVID-19 crisis on the different segments of the agri-food value chains (AFVCs). AFVC is decomposed into upstream (agricultural production and agricultural employment, including fisheries, forestry and hunting), midstream (manufacturing of food products, including processing; trade; and transport), and downstream (restaurants). In addition, four income sources/employment activities are considered: own production, on-farm wage, off-farm wage, and off-farm self-employment. The analysis also includes the identification of the main constraints households, and, specifically, agricultural households, faced in dealing with the crisis.

The second chapter focuses on the mechanisms of transmission of the impact, considering poverty and food security as the final outcomes. The hypothesis is that COVID-19 affected poverty and food security mainly through two channels, namely food value chain disruption, and job loss, but depending on the type of household and its market positioning, the net effect on welfare and the related underlying mechanisms can be different. Given that household welfare is simultaneously determined by production, consumption, and labor supply decisions (Barnum and Squire, 1979; Singh et al., 1986), it is important to analyze how each decision was affected by the crisis to disentangle the heterogeneous effect.For this reason, the analysis has been ran over different groups of households according to refugee status (refugee vs. host households), main income source (agricultural vs. non-agricultural households), and market position (food net-buyers vs. net-sellers vs. self-sufficient households).

The third chapter instead focuses on the effects of COVID-19 on the consumption side, considering different indicators of food security and dietary diversity at the household level, and anthropometric measures to state the child's nutritional status.

The thesis adopts a food system approach of the food security impacts of COVID-19. In this way, each element and each activity of the system in a given country can be considered. This allows recognizing the interlinkages between the different actors in the system, including trade-offs and feedbacks (Ericksen, 2008). Additionally, as highlighted by Devereux et al. (2020), it allows incorporating considerations of all aspects of the food value chains.

The main research questions addressed in this work are:

- Which segments of the AFVC (such as production, distribution, and retail) have been most affected by the crisis?
- What are the pathways linking COVID-19 shock to household food security?
- Whether and to what extent has COVID-19 influenced household food consumption and child nutrition?

The first research question considers the overall food value chain, and it is addressed mainly in the first chapter, with a focus on production and labor activities. The second chapter answers the second research question, considering the effects of the shock both on consumption and production. The third chapter instead mainly addresses the third research question, investigating the implications of the crisis in terms of food consumption and nutrition.

Literature gaps

Although three years have passed since the outbreak of the COVID-19 pandemic, empirical evidence of the effects of COVID-19 on different aspects of the agrifood systems[3] is still scarce, especially in developing countries. Additionally, even if some evidence, either anecdotal or empirical, of the COVID-19 related impacts at various stages of the economic system exists, it is not clear yet how the COVID-19 shock has been transmitted through the food system to eventually impact people's livelihoods. This can be mainly explained by a lack of data availability. The measurement of the specific variables needed to investigate this relationship indeed requires detailed surveys conducted through in-person interviews, which were mostly not possible during the pandemic. To overcome lockdown restrictions, many surveys moved to phone-based or online interviews, which revealed to be a powerful instrument in times when movement restrictions are in place since they help to understand some of the socioeconomic consequences of the pandemic, such as job and income losses (Gourlay et al., 2021). The World Bank launched the High-frequency phone surveys on COVID-19, a series of monthly phone surveys in 6 African countries, for a period of 12 months, to track the responses to and the socio-economic impacts of COVID-19. The LwC-Africa project collected 4 quarterly repeated cross-sectional phone-based surveys over 12 months to advance understanding of how the pandemic affected health, food, work, gender, and social cohesion outcomes in 5 Sub-Saharan Africa. Other institutions, such as IFPRI and Young Lives, also moved the data collection to phone-based interviews. Many researchers benefited from this data to track the effects of COVID-19 on food security and other socioeconomic outcomes, such as Amare et al. (2021); Ceballos et al. (2021); Dasgupta and Robinson (2022); Gaitán-Rossi et al. (2021); Hirvonen et al. (2021); Mahmud and Riley (2021). Few studies in low-income countries used online surveys (Kansiime et al., 2021; Pakravan-Charvadeh et al., 2021), while they revealed to be the method most used for collecting data during COVID-19 lockdowns in many high-income countries, especially for investigating adult eating behaviors (Adams et al., 2021; Ammar et al., 2020; Dondi et al., 2021; Herle et al., 2021; Maffoni et al., 2021; Molina-Montes et al., 2021; Robinson et al., 2020).

[3]The definition of agrifood system includes food and non-food agricultural products (FAO, 2021).

Other researchers used different techniques, based on simulations and projections, to predict the socio-economics consequences of the pandemic (Laborde et al., 2021a,b; Lakner et al., 2022; Sumner et al., 2020). Laborde et al. (2021b) used a global general equilibrium model linked to epidemiological and household models to assess the impact of COVID-19 on poverty, food insecurity, and diets, projecting 150 million people to fall into extreme poverty and food insecurity, especially in Africa South of the Sahara and South Asia. Although simulations are a powerful tool in anticipating the possible effects of crises and are highly useful for policymakers to deal with the immediate negative effects, evidence emerging from real data is needed to validate and confirm previous predictions. Additionally, empirical evidence helps to monitor the effects of the crisis and their evolution over time, to better target policies and interventions, and to guide long-term development plans.

Furthermore, different types of households are expected to be affected differently, based on their socio-economic characteristics, their sources of livelihood, and their integration into the market. It is important to disentangle the different mechanisms through which the COVID-19 impact has affected people's livelihoods.

Although literature has emerged on the effects of COVID-19 on household food security in developing countries, most of the studies investigated the ultimate impact of COVID-19 on specific indicators of food security. These include variables capturing households' experience of food insecurity, including the Food Insecurity Experience Scale (FIES) (Amare et al., 2021; Kansiime et al., 2021), Household Dietary Diversity Score (HDDS) (Hirvonen et al., 2021), food consumption (Mahmud and Riley, 2021; Hirvonen et al., 2021) or variables measuring food accessibility and affordability (Ceballos et al., 2021). Few studies investigated the socioeconomic determinants of food insecurity during the pandemic (Dasgupta and Robinson, 2022). None of the existing studies however systematically analyzed the mechanisms of transmission of COVID-19 to the final outcome and measured how much each possible pathway contributed to the overall effect.

Another issue caused by the limited data available is the difficulties to monitor the effects of the COVID-19 crisis, and their evolution, over time. Only phone-based and online surveys allow for repeated interviews over time, but some sets of questions were asked on a rolling basis, due to the limited time of the interview. Therefore, it is not always possible to track the same outcome over all rounds of interviews.

Contributions

This study aims to overcome the literature gaps in terms of: i) data availability, ii) understanding the mechanisms of the impact, and iii) tracking the evolution of the effect over time.

In terms of data availability, data used in the second and third chapters were collected through in-person interviews administered before and after the COVID-19 outbreak. In the second chapter, the data source is a longitudinal survey specifically designed for refugees and host households interviewed in 2019 and again in 2020. The third chapter is based on data collected through face-to-face interviews, including physical measurements of weight and height for children under 5 years old. Compared to the phone-based interviews, the in-person interviews collect broader and better-quality information about the household as a whole and for each household member. Furthermore, the in-person survey design includes also the population not having access to a phone.

For what concerns the heterogeneous effects and the mechanisms of transmission, all three chapters address this gap, although in different ways. The first chapter considers the heterogeneous impact of the shock on the different AFVC segments, and look at individuals and households based on their income source and employment activity. Throughout the thesis, different structural equation modeling (SEM) techniques are used to analyze the complex cobweb of relationships between the many factors potentially mediating the shock impact on household welfare dimensions. Specifically, the second chapter analyzes the different transmission mechanisms of the impact, starting from the effect on the labor market and on the food value chain. Additionally, the analysis was ran separately for different groups of households to test whether the same shock was transmitted differently. In the third chapter, a mediation analysis is employed to link the household food environment to child nutrition. The chapter also investigates which factors are associated with a greater likelihood of being worse off from the crisis.

The evolution of the impact over time is analyzed in the first and third chapters. In the first chapter indeed the data used is composed of six rounds of post-COVID longitudinal data collected every month, from April to September 2020. Although the time span is quite limited (seven months from the pandemic onset), it is still possible to track the evolving nature of the effect in the first months after the COVID-19 outbreak. This is also the period when immediate interventions are needed to prevent long-lasting consequences. In the third chapter instead, the effect of the shock is tracked over the trimesters of 2020.

Data

The first chapter takes advantage of a longitudinal data collected over seven rounds, which include a pre-pandemic face-to-face survey, used as the baseline, and six follow-up phone surveys, to provide an early empirical examination of the economic condition of households in the aftermath of the pandemic in Ethiopia. Pre-Covid data are taken from the 2018/19 Ethiopia Socioeconomic Survey (ESS), which is part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). It covers all regions of the country and is representative at national, urban/rural, and regional levels. The other six rounds of data are part of the COVID-19 High-Frequency Phone Survey of Households (HFPSH) 2020. This phone-based survey is a 15-minute questionnaire submitted to a subsample of the ESS 2018/19 households with access to a phone every month, from April to September. The World Bank team attempted to interview the same households in each round. This allowed tracking of the same set of households from 2019 to September 2020.

Data used in the second chapter come from the RIMA Uganda Refugee and Host Communities Panel Survey, a four-round longitudinal survey implemented through in-person interviews, representative of refugee and host communities in Uganda (d'Errico et al., 2021).This study uses only the second (December 2019) round as a baseline just before the COVID-19 outbreak, and the third one (December 2020, i.e. nine months after the COVID-19 outbreak in the country) as a follow-up in the aftermath of the pandemic.

The analysis of the third chapter uses cross-sectional data from the 2019/2020 household budget survey in Mozambique (Inquerito de Orcamento Familiar, henceforth IOF) collected by the National Institute of Statistics (INE). Data collection took place from December 2019 to December 2020 through face-to-face interviews, with a 3-months break from April to June due to the COVID-19 outbreak.

These datasets are extremely suitable for this study because interviews took place immediately before and after the COVID-19 outbreak, allowing observing the situation before the shock and estimating the effects in the immediate aftermath.

Methodology

Different econometric models, which take into consideration the systemic nature of the shock, have been used throughout the thesis. In the first chapter, the number of confirmed cases of COVID-19 over the population in each region of Ethiopia is used as a continuous treatment variable. The study uses a linear regression model with household and time fixed effects (also called two way fixed effects linear model), adapting the approach implemented by Amare et al. (2021).

In the second chapter, path analysis with household fixed effects is used to identify the main pathways for different groups of households according to refugee status, main income source, and market position. Path analysis is a precursor to and a subset of the vast SEM family of methods. This approach is better suited to model and test complex phenomena, measuring the influence of each variable in mediating direct and indirect effects on the final outcomes, than standard econometric techniques. So far SEM has been mainly used to investigate the psychological impact of the pandemic (Buttler et al., 2021; Chen et al., 2021; Lathabhavan and Vispute, 2021), but not the socio-economic one.

In the third chapter, the methodology used is a pooled OLS/probit over cross-sectional data, using different proxies of COVID-19, which include a simple time dummy before and after the COVID-19 outbreak, dummies for each trimester, the average stringency index by trimester, the number of confirmed COVID-19 cases over population and the positivity rate, by province and by trimester. By considering the trimesters it is possible to see if there has been an evolution of the effect over time and if the effect was higher in the aftermath of the pandemic or in a longer term. The stringency index allows looking at the intensity of the restrictions over time. The last two variables capture not only the variation over time but also across provinces.

Caveats and limitations

The overall study presents a series of limitations related mainly to the type of shock analyzed and the limited data availability. In terms of methodology, it is not possible to claim a causal impact of COVID-19 based on a robust and valid identification strategy. COVID-19 indeed, given its systemic and simultaneous nature, cannot fit a typical treatment/control setting. All individuals were impacted by the crisis, although with a different magnitude.

Additionally, the variable that captures the COVID-19 economic effect is not itself observable. Information on restrictions and testing within countries is most of the time not available, and even if it were, it would not capture spillover effects across areas in the countries and from the international market. For this reason, different proxies of the shock have been used throughout the study. These include the number of confirmed cases of COVID-19 in the first chapter and the time dummy in the second and third chapters. These variables are not able to fully capture the economic downturn caused by non-pharmaceutical interventions. The variable of the COVID-19 cases mainly captures the health effect of the pandemic, rather than the economic one. However, in the specific country analyzed, the two effects move in the same direction. Indeed, when using daily data retrieved from the Oxford COVID-19 Government Response Tracker (OxCGRT), the correlation between the COVID-19 cases and the stringency index is positive and significant. It is not the same in other contexts. In Mozambique, for instance, the two variables are not correlated, and this is also confirmed in the results obtained in the third chapter.

The time dummy, instead, could include other factors other than the COVID-19 crisis that have driven the evolution of outcomes over time. For instance, month-to-month seasonality can represent an issue when tracking agricultural production and food security outcomes and can report significant changes over a few months.

The type of data used also presents some limitations. In the first chapter, the use of phone interviews brings about possible biases in terms of the representativeness of the sample, especially in rural areas, and the reliability of the information collected through self-reported data. Telephone interviews indeed are much shorter than those in person (around 15/20 minutes), reducing the quantity and limiting the type of data collected (Dabalen et al., 2016), and they are based on self-reported answers provided by only one member of the household (Abate et al., 2021). As a result, they are not able to collect reliable measures of, for instance, diet quality and nutrition. Furthermore, some variables require physical measurement, as is the case of anthropometric measures; other variables require a detailed description of expenditures, with repeated interviews to avoid long recall periods. Abate et al. (2021) found evidence of survey fatigue occurring early on in phone interviews but not in in-person interviews, confirming that while the phone survey mode provides lower costs and it is easier to implement in times of crises, it cannot replace in-person surveys.

Additionally, phone-based surveys are representative only of those households that have access to phone. When the phone penetration is low, this represents a serious bias in terms of representativeness (Ambel et al., 2021; Ballivian et al., 2015; Brubaker et al., 2021; Demombynes et al., 2013; Gibson et al., 2017; Gourlay et al., 2021; Henderson and Rosenbaum, 2020; Kastelic et al., 2020). In Ethiopia for instance, about only 40% of rural households have access to a phone, compared to over 90% of urban households, and they are systematically different from those without (Ambel and Bundervoet, 2020).

In the third chapter instead, the use of cross-sectional data does not allow to control for time-invariant household and individual characteristics, which could be a source of possible endogeneity problems. Additionally, data used in this study were not intended to specifically track AFVC participants, therefore it is difficult to capture a representative picture of the actors across the different segments of the value chain.

Results

Although each chapter investigates different aspects of the COVID-19 crisis, some overall findings, as well as some main differences across countries, emerge. First, COVID-19 negatively impacted both household employment and income, the more so the longer the time length from the pandemic onset during the year 2020. In the first chapter, the analysis shows that COVID-19 negatively impacted employment activities in Ethiopia. All segments of the AFVC were negatively affected, with upstream being the one most affected. As for employment, also total income was negatively affected by the COVID-19 cases, although the effect took more time to occur. The negative effect is driven by income from agriculture, which is the income source most affected. The second chapter validates the hypothesis that COVID-19 disrupted the food value chain and reduced labor participation. Indeed, the results of the analysis confirmed that COVID-19 operated through these two channels of transmission to eventually affect total household income.

Second, COVID-19 ultimately affected both poverty and food security, both in terms of household food consumption and child nutrition. In the second chapter, the effect was found to be transmitted both directly and through total household income, ultimately affecting both poverty and food security, though the food consumption score (FCS) was impacted to a greater extent. In the third chapter, food consumption and caloric intake were found to decline in the aftermath of the pandemic in Mozambique. Additionally, the COVID-19 crisis contributed to further exacerbating stunting, which was already high in the country before the pandemic.

Third, the study shows the importance to monitor the evolution of the impact of the shock over time. When tracking the evolution of the effect in the first chapter, it emerges that farming, after an initial advantage, was the sector most affected. This result part is in line with previous studies that arose in the immediate aftermath of the pandemic, such as Bundervoet and Finn (2020); Reardon et al. (2020), which stated that farming was the less affected sector. However, tracking the impact over time allowed gaining a more complete picture, showing a reverse direction of the effect. In the third chapter, when unpacking the simple before-after COVID-19 onset comparison over time, it emerges that the effect was not immediate, but it mainly occurred in the last trimester of the year. This could suggest that in the aftermath of the pandemic people were using different coping strategies to offset the reduction in income, which however turned out to be insufficient over time.

Fourth, the study shows that access to formal institutions, as well as to cash transfers, played a key role in reducing the likelihood of income loss in the aftermath of the pandemic. In the first chapter indeed, the results of the analysis show that having access to formal insurance, credit, formal contract, and land ownership title are associated with a lower probability of income loss. In the second chapter, cash transfers and income sources diversification have proven to be key determinants of household disposable income, playing a positive role in offsetting the COVID-19 negative shock.

The study also highlights some differences across the three countries analyzed. In Ethiopia, the agricultural sector, and specifically farmer households operating upstream of the food value chain, were ultimately hit more than other sectors. In Mozambique instead, the analysis led to the opposite result. Households in urban areas indeed were affected more, although the result is not statistically significant, while farmers practicing subsistence agriculture were better off. In Uganda, the agricultural households more integrated into the market were able to counteract the negative effect of the COVID-19 crisis. These results show that the COVID-19 crisis did not occur in the same way across countries, and households were affected differently. They also highlight the importance of distinguishing the type of agricultural household. Indeed, the effect does not depend only if the household practices agriculture, but mainly on its position in the market and along the food value chain.

Although the study uses three countries as case studies, the findings contribute to the overall evidence of the effects of COVID-19 on food security. Specifically, it sheds light on which households have been affected more, and it analyzes the underlying mechanism of the impact. This is particularly relevant for policymakers because different interventions can be implemented to reduce food insecurity, but not all are equally effective. Understanding the available options to adapt to the "new normal" is then crucial for targeting appropriate food security and poverty responses. The findings of this study therefore would help policymakers to better design policy responses and implement effective and targeted interventions at the onset of similar shocks.

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Chapter 1

The impact of COVID-19 on household income and participation in the agri-food value chain: Evidence from Ethiopia

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Abstract

The COVID-19 pandemic brought about disruptive consequences on many people's livelihoods around the world. Domestic food supply chains have been severely affected, resulting in income reduction and job loss. Understanding the main constraints faced by the agri-food system participants is then key for targeting appropriate responses. Using Ethiopia as a case study, this chapter aims to assess the change in household employment and income in the aftermath of the pandemic at different segments along the agri-food value chain and identify the main determinants that mediate those impacts. Using both longitudinal and cross-sectional econometric models over a panel sample composed of a pre-COVID interview and 6 follow-up phone-based surveys, the study shows the crisis is associated with a reduction in both employment and income, with increasing negative impacts over time. Farming resulted the most affected sector in the agri-food value chain in the medium-long run. Access to formal institutions such as formal insurance, credit, formal contract, and land ownership title played a key role in reducing the likelihood of income loss.

JEL Classification: I15; O12; Q12

Keywords: COVID-19; food value chain; labor market; income loss

1.1 Introduction

The COVID-19 pandemic caused unexpected changes in supply and demand all over the world, and given the interlinked nature of the value chains in the global economy, it created significant disruption within them (Moosavi et al., 2022), both at domestic and global levels. Agri-food value chains (AFVCs) are no exception in this regard (Devereux et al., 2020). Although some segments of the chain, such as the upstream and specifically farming, have been initially less affected, other segments, especially downstream, such as food services, restaurants, and retail, and midstream, such as processing, logistics, and transportation, have been impacted more from the real onset of the crisis. Indeed, it has been reported that farming experienced less direct effects, except where hired labor was important, although interlinkages with the other segments of the chain may have caused revenue losses and production disruption (Swinnen, 2020). The general conclusion of early studies is that the COVID-19 impact is differentiated across different segments of the AFVC as well as within each segment of the value chain (Diao and Roe, 2000; Tamru et al., 2020; Tesfaye et al., 2020).

The pandemic and the related restrictions implemented by governments raised many challenges to individuals and households participating in the AFVC. The ability to absorb, adapt, and even transform the way a livelihood is gained by individuals and households – in short, their resilience capacity– is often limited by many constraints they face, such as access to technology, financial services, or social safety nets. Many of them have limited options to cope with the COVID-19 shock, resulting in income reduction or job loss, with consequent effects on poverty and food security. Understanding what are the constraints faced by participants in the AFVC and their available options to adapt to the "new normal" is then crucial for targeting appropriate food security and poverty responses.

This study aims at investigating what has been the differentiated impact of COVID-19 on different segments of AFVCs. Specifically, the research questions are the following:

- Which segments of the AFVC (such as production, distribution, and retail) have been most affected by the crisis, in terms of labor participation and income change, compared to other economic activities?

- Which determinants at the household level have most influenced the impact of COVID-19 on income, and specifically on farm income?

Ethiopia has been selected as a case study. This country is an interesting case for several reasons. Its economy is mainly based on agriculture which accounts for 34% of GDP [1], with smallholder farming accounting for 95% of agricultural production (Tigre and Heshmati, 2022) and 80% of the country's population depend on the sector for their livelihoods (FAO, 2016). However, new commercial and gig economy clusters are emerging in the country, as is the case of intensive vegetable cultivation in the central Rift Valley (Minten et al., 2020). These new activities challenge small farmers' and small enterprises' participation in the AFVC, compounding with the already existing constraints (Asfaw et al., 2011; Bryan et al., 2009; Croppenstedt et al., 2003). In such a situation, the COVID-19 outbreak could force additional family farmers and small and medium enterprises out of the market.

The first case of COVID-19 in the country was reported on March 13th, 2020 [2]. In the same month, the national government implemented a set of containment measures, such as school closure, social distancing, and restrictions on gathering and transportation (Baye, 2020). In April, a five-month state of emergency was declared, though economic activities continued to operate. The virus spread differently across regions. In particular, the Addis Ababa region reported the highest proportion of cases per million population, followed by Harar and Dir Dawa. Although farmers could continue working, they faced many challenges. With borders shut, imported inputs were more difficult to find and their price increased (Hirvonen et al., 2021a,b). Moreover, domestic travel restrictions made it almost impossible for farmers to reach the markets. The travel restrictions also doubled transport costs, with a further domino effect on production. Additionally, since many farmers could not store their goods – particularly perishable produce – they were forced to accept the low prices set by buyers (Ababulgu et al., 2022). Hired labor was also an issue. Many rural labor workers returned to their homes, and the few workers that remained available pushed up the costs of

[1] Source: https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=ET Accessed on 29/08/2020

[2] Source: https://www.afro.who.int/news/first-case-covid-19-confirmed-ethiopia

labor (Tesfaye and Habte, 2020). Effects were also driven by the fear of contagion. People associated raw vegetables with infection, reducing their purchases (Hirvonen et al., 2021a; Tamru et al., 2020) . This would likely lead to a heavy drop in production and sales, severely impacting food value chains in both export and local markets (Ababulgu et al., 2022).

Although anecdotal evidence exists on the impacts of COVID-19 on AFVC participation and income, rigorous empirical studies based on household-level survey data are still few. Amare et al. (2021) used panel data household survey to quantify the overall and differential impacts of COVID-19 on household food security, labor market participation, and local food prices in Nigeria. They found that households located in areas affected by higher cases or by more stringent mobility lockdowns experienced a significant increase in food insecurity, a reduction in labor market participation, and an increase in food prices.

Josephson et al. (2021) used phone-based surveys collected by the World Bank, the same used in this study, over 4 countries, including Ethiopia, to document the socioeconomic impacts of the pandemic. They found that 77% of households across the 4 countries have lost income since the onset of the pandemic. However, they are not able to measure how much of the loss can be directly attributable to the pandemic, given the descriptive nature of the analysis. The same data have been used by Rudin-Rush et al. (2022) to document trends in food security up to one year after the onset of the COVID-19 pandemic. The study reports a sharp increase in food insecurity in the aftermath of the pandemic, with a subsequent gradual decline. Households in rural areas experienced more the negative consequence of the pandemic in terms of food security than those in urban areas. Other organizations besides the World Bank conducted phone surveys in Ethiopia during the pandemic. IFPRI for instance conducted a series of monthly phone-based surveys between May and August 2020 (i.e. up to five months after the pandemic onset) of nearly 600 households in Addis Ababa (Hirvonen et al., 2021a). The data show that more than half of households reported a fall in income relative to their standard income at that time of the year (Hirvonen et al., 2020), and the percentage increased from May to July (Hirvonen et al., 2021a). Less-wealthy households were more likely to report income losses, with a significant worsening of household food security and nutritional status. Income loss and unemployment were identified as the most common shocks experienced by the respondents (de Brauw et al., 2020; Hirvonen et al., 2020; Abate et al., 2020). Related to the impact on the agri-food value chain, Hirvonen et al. (2021b) relied on a large value chain survey that IFPRI undertook in February 2020 and follow-up phone interviews collected in May 2020, to analyze the disruption of the vegetable value chain from the main producing areas in the Central Rift Valley to Addis Ababa, including changes in prices and adjustments in the marketing activities of the participants —from farmers to wholesalers and retailers. They found that nearly 60% of the smallholder farmers and more than 60% of the investors reported that they received less income than usual (Hirvonen et al., 2021a). They also found that the pandemic in Ethiopia disrupted trade not only between neighboring countries but also among sub-national regions, thus determining high volatility in agricultural prices (Hirvonen et al., 2021b). However, they found that the overall changes in wholesale and retail marketing margins were relatively low, suggesting a resilient response of the domestic food value chains during the pandemic in Ethiopia.

Although these studies provide important early estimates of the effects of the pandemic on relevant indicators of welfare, they present some limitations. Some of them are based on a limited and nonrepresentative sample. The study of Hirvonen et al. (2021b) for instance is focused on the vegetable value chain, while in Hirvonen et al. (2021a) food consumption levels and food security in the capital remained fairly constant between Sept 2019 and Sept 2020, but only households in Addis Ababa were interviewed. From a case study by Zhang et al. (2022), the population in the capital was not affected in terms of food security, despite income losses. However, other groups of individuals, especially at-risk groups such as refugees and people living in conflict affected regions, suffered significantly from food insecurity exacerbated by COVID-19. The majority of the existing studies are based on data collected a few months after the pandemic onset, and when more rounds of data were available, they consider few points in time, failing to capture the evolving impact of COVID-19 over time.

Other studies look at the impact on employment, such as in Khamis et al. (2021), but they do not specifically consider the different segments of the food value chain. This study addresses both limitations contributing to estimating the magnitude of food supply chain disruption caused by the COVID-19 outbreak in Ethiopia over a relatively longer time (seven months from the pandemic onset) and looking specifically at the differentiated impacts on various AFVC segments. It will also help to identify the main constraints faced by AFVC participants, which prevent them to ensure adequate levels of income. Although the data present some limitations in terms of representativeness, as discussed in Section 1.2, we think the findings emerging from this study can be relevant not only because they provide policy insights for the current crisis, but also because they contribute to building evidence for managing similar other crises.

The chapter is organized as follows: the next Section describes the data used and presents some descriptive statistics of relevant variables, in particular, related to employment and income; Section 1.3 describes the empirical strategy adopted; Section 1.4 presents the results of the analysis; Section 1.6 concludes.

1.2 Data and Descriptive Statistics

The analysis uses longitudinal data over seven rounds, which include a pre-pandemic face-to-face survey, used as the baseline, and six follow-up phone surveys. The availability of this longitudinal data that captures information before and after the start of the pandemic makes Ethiopia an ideal case for an early empirical examination of COVID-19's impacts.

Pre-COVID data are taken from the 2018/19 Ethiopia Socioeconomic Survey (ESS), which is part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). It covers all regions of the country and is representative at national, urban/rural, and regional levels. The other six rounds of data are part of the COVID-19 High-Frequency Phone Survey of Households (HFPSH) 2020. This phone-based survey is a 15-minute questionnaire submitted to a subsample of the ESS 2018/19 households with access to a phone every month, from April to September. The World Bank team attempted to interview the same households in each round. This allowed tracking the same set of households from 2019 to September 2020, leading to a balanced sample of 2,347 households[3].

[3] Each COVID-19 HFPSH survey has a slightly different number of observations, ranging from 2,704 to 3,249 households. In order to have a balanced panel we reduced the sample to 2,347 observations. For more information on sampling design please visit https://microdata.worldbank.org/index.php/catalog/3716

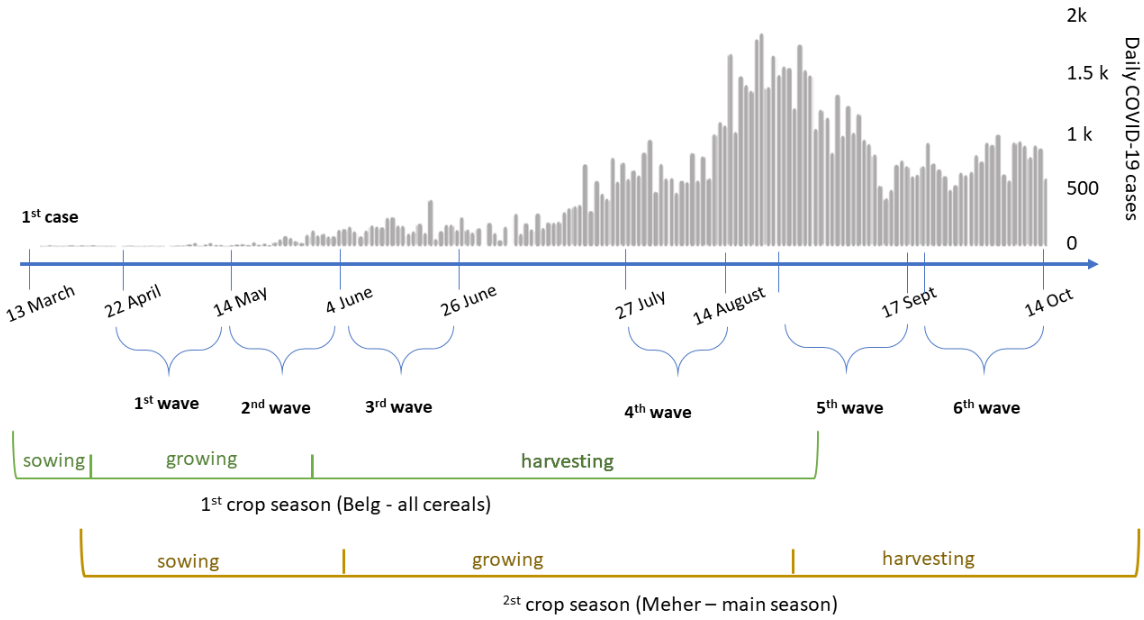
To obtain unbiased estimates, adjusted sampling weights at the household level have been used[4], to have a sample that is representative at the national and urban/rural levels. A major problem with the HFPSH surveys is that the phone penetration in rural Ethiopia is still low. Indeed, about only 40% of rural households have access to a phone, compared to over 90% of urban households, and they are systematically different from those without (Ambel et al., 2021). The data is indeed biased toward urban households and better-off rural households that have access to mobile phones (Ambel and Bundervoet, 2020).The sample of the HFPSH is therefore representative only of those households that have access to phones in urban and rural Ethiopia. Additionally, only one member per household, typically the household head or the spouse, has been interviewed. Household heads could systematically differ from other household members, undermining the representativeness of the sample at the individual level. Further discussion about this issue is presented in section 1.5.2. Figure 1.1 combines daily cases of COVID-19, the dates of the HFPSH data collection, and the crop seasons over a timeline.

A central methodological concern is that factors other than the COVID-19 crisis could drive the evolution of outcomes over time. Specifically, month-to-month seasonality could represent an issue, as it can report changes over a few months. Seasonality can be easily controlled by including month fixed effects. However, due to the time of the survey implementation used in this study, they cannot be applied. Looking at the labor outcome, the pre-COVID survey considers the employment activities over a year, including both planting and harvesting seasons. Questions on employment in the post-COVID rounds instead consider only the last 7 days. There could be then an underestimation of the farming-related employment rate. However, the months under analysis coincide with a sowing or a harvesting period of the two main crop seasons, as reported in Figure 1.1, which correspond to the periods of more intense workload. Looking at the crop calendar in the country [5], only two crops report neither planting nor harvesting in the period under analysis, which are sugarcane and taro. Therefore, although it is not possible to completely exclude problems of seasonality, we can assume that the problem is minimal.

[4] Sampling weights of the HFPSH were computed by the World Bank team, following the approach described in Himelein (2014).

[5] Source: https://cropcalendar.apps.fao.org//home?id=ETcrops=

Figure 1.1: Timeline with daily COVID-19 cases, surveys date, and crop seasons in Ethiopia



Source: data on COVID-19 daily cases retrieved from https://covid19.who.int/region/afro/country/et; information on crop seasons retrieved from https://www.prepdata.org/stories/ethiopia-climate-and-agriculture; date of COVID-19 HFPSH data collection retrieved from https://microdata.worldbank.org/index.php/catalog/3716.

In terms of farm income, farmers in the country usually run out of stock between July and September, with a consequent increase in food insecurity in many parts of Ethiopia (Dercon and Krishnan, 2000; Gilbert et al., 2017; Hirvonen et al., 2016). Agricultural production in the country largely follows seasonal cycles. There are two rainy season over the year: the small rainy season (belg), which occurs between March and May, and the main rainy season (meher), that takes place between June and September[6] (Hirvonen et al., 2016). Around 90% of the total crop production is done during the Meher season (Taffesse et al., 2013). Additionally, this shortage due to seasonality, although varying from crop to crop, is quite homogeneous across farmers, therefore it is plausibly captured by controlling for the aggregate time trend, as described in the next section.

Another factor to consider in the analysis is the desert locusts invasion. The desert locusts are the most destructive migratory pests in the world (Cressman, 2016; Lazar et al., 2016). They arrived in the Horn of Africa in the summer of 2019, when nu-

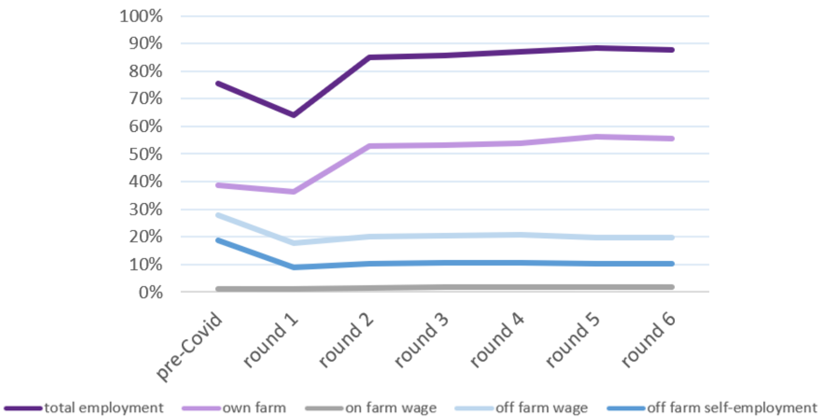
[6]this refers to the growing period of the season.

merous swarms from Yemen invaded Ethiopia, Djibouti, and northern Somalia. In the fourth [7] round of data, 45% of farmers self-reported to have experienced desert locusts on their farm, and 41% of households experienced locusts in their kebele. Desert locusts have negative consequences on income because they destroy the crops and the fodder for livestock. Additionally, labor time is required to spray the chemicals on the area under cultivation.

1.2.1 Employment

The questionnaire in the first post-COVID round asks if the individual did any work in the last 7 days, if he/she was working before the COVID-19 outbreak and if the current work is the same of the previous one before the pandemic. For the other rounds of data, the questions were the same, but related to the last call. As shown in Figure 1.2, the employment rate experienced a significant reduction in the aftermath of the COVID-19 outbreak. Considering overall employment, there has been a reduction of 11 percentage points. However, after the initial outbreak, it seems that labor activities recovered quickly, exceeding the employment rate before COVID-19. This increase seems to be driven by own farming activity.

Figure 1.2: Employment trends.



Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.

It is interesting to see the dynamics of labor mobility within the AFVC (Figure 1.1. The variable of labor participation has been decomposed into three segments of

[7]Information on desert locusts is available only in rounds 4 and 6. However in round 6 very few respondents answered the questions related to locusts, so it is not possible to produce reliable estimates.

the AFVC, namely upstream (agricultural production and agricultural employment, including fisheries, forestry and hunting), midstream (manufacturing of food products, including processing; trade; and transport), and downstream (restaurants). The upstream segment remained quite stable, with 83% of people that did not change occupation on average across the 6 post-Covid rounds. Among those that changed, the majority preferred to move out of the AFVC. A different scenario is presented for those people employed in the midstream. In this case, only 28% on average remained in the same segment, while 41% moved out of the chain, and 21% moved to upstream. A similar situation can be found in the downstream, with only 30% on average that did not change the segment of the AFVC. Here however people preferred to move to midstream. Finally, 65% of who was out of the chain remained out, and the rest split mainly between midstream and upstream.

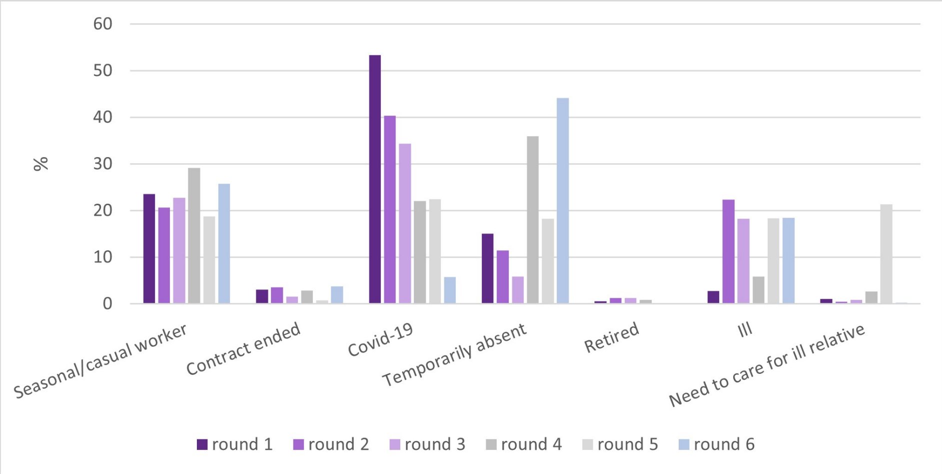
Table 1.1: Labor mobility along with segments of AFVC.

			Round 1				Round 6			
		N. obs.	**Downstream**	**Midstream**	**Upstream**	**Out of FVC**	**Downstream**	**Midstream**	**Upstream**	**Out of FVC**
Pre-Covid	**Downstream**	145	32.8%	47.5%	7.6%	12.2%	27.5%	48.5%	6.2%	17.8%
	Midstream	184	5.4%	34.0%	14.2%	46.3%	12.4%	26.0%	22.9%	38.8%
	Upstream	517	0.6%	5.3%	81.5%	12.5%	0.6%	3.6%	83.3%	12.1%
	Out of FVC	834	3.8%	12.2%	15.5%	68.4%	4.0%	14.4%	17.8%	63.9%

Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.
Note: Upstream = agricultural production and agricultural employment, including fisheries, forestry and hunting; Midstream = manufacturing of food products, including processing, trade, and transport; Downstream = restaurants; Out of FVC = all other employment activities. Statistis are reported for the first and the last rounds of data.

Employment changes, as previously mentioned, can be in part driven by seasonality. Indeed, seasonal migration in Ethiopia occurs both from rural to urban areas, used as a coping strategy during the dry season (Asefawu, 2022), and also towards northwest Ethiopia for temporary employment on large-scale agricultural farms during the rainy season (Schicker et al., 2015). However, when looking at the responses for the reason to stop working, the main reason is COVID-19, especially in the first rounds. Between April and May, more than half of individuals declared that the pandemic-related crisis caused their employment loss. In the last rounds instead, being “temporarily absent” is the main reason to stop working. This can be indirectly associated with the crisis because probably people temporarily left their job in the city to migrate to rural areas. Detailed information on the numbers of individuals that started to work again in each round, and the reason for having stopped working in the previous round is reported in the Appendix.

Figure 1.3: Reason to stop working, percentage.



Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.

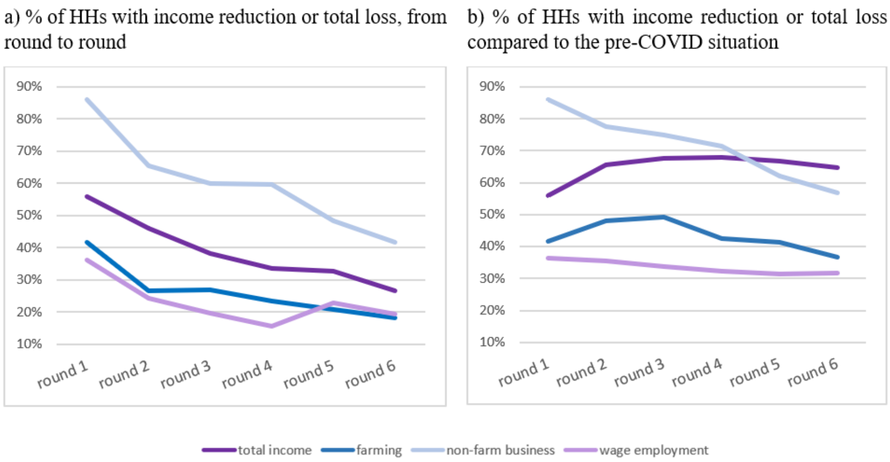
1.2.2 Income

In the phone-based surveys, respondents were asked to assess the income change the household has experienced, compared to the situation before the COVID-19 outbreak in the first round, and compared to the last call in the other rounds. The possible answers ranged from total loss to increase. The categorical nature of the question does not allow to compute precise estimates of the impact of COVID-19 on income, limiting the analysis to its incidence, but with few possibilities to look at its magnitude and severity (De Weerdt, 2008). Additionally, for what concerns farming income, the answer highly depends on the timing of the harvest by each farmer. Although the bulk of crop sales by farm households occurs between December and February, April usually records the largest sales (Hirvonen et al., 2016). At the time of the first wave therefore, farmers already started to sell their crops. Additionally, given that we consider the spatial heterogeneity of COVID-19 cases across regions rather than the temporal variation, the only concerns should be in terms of agroecological zones. But, since they are constant over time within each person interviewed, it is captured by the household fixed effects included in the model. If we look at the percentage of households that reported a reduction or a total loss between each round (panel a in Figure 1.4, we can see a decreasing trend for all sources of income. However, if we compare the income change to the situation before the COVID-19 outbreak[8] (panel b), the trend is

[8]The change of income is computed backwards up to the baseline. If, for instance, in round 2 income did not change compared to previous round, and in round 1 it increased compared to the baseline, in

substantially different. The percentage of households indeed increased, up to 9 percentage points. Comparing the two figures, it is evident how COVID-19 has drastically affected the livelihood of Ethiopian households.

Figure 1.4: Percentage of HHs with income reduction or total loss.



Source: Own elaboration from ESS 2018/2019 and HFPSH 2020.

Table 1.2 reports the descriptive statistics of employment and income variables used as outcomes of the analysis for each round. Specifically, the employment variables show the rate of people employed in each sector, while the income variables report the percentage of households that experienced a reduction in income or a total loss compared to the baseline.

round 2 it also increased compared to baseline. The change is assumed to occur with the same amount, therefore if a household first reports an increase, and then a reduction, the net effect is null. I am aware this is arbitrary, since the extent of the change could be different. For this reason, the analysis has been conducted also round by round, finding similar results, as reported in the Appendix.

Table 1.2: Descriptive statistics of employment and income outcomes.

	Round						
	0	**1**	**2**	**3**	**4**	**5**	**6**
Employment							
Total employment	0.75	0.64	0.85	0.86	0.87	0.88	0.88
Downstream	0.04	0.01	0.02	0.02	0.02	0.02	0.02
Upstream	0.40	0.37	0.55	0.55	0.56	0.58	0.57
Midstream	0.05	0.07	0.08	0.08	0.08	0.08	0.09
Out of FVC	0.25	0.18	0.20	0.21	0.21	0.20	0.20
Own farm	0.39	0.36	0.53	0.53	0.54	0.56	0.56
On farm wage	0.01	0.01	0.02	0.02	0.02	0.02	0.02
Off farm wage	0.28	0.18	0.20	0.20	0.21	0.20	0.20
Off farm self-employed	0.19	0.09	0.10	0.10	0.11	0.10	0.10
Income							
Total inome		0.56	0.67	0.70	0.72	0.72	0.71
Farming		0.42	0.50	0.51	0.47	0.45	0.41
Wage employment		0.36	0.36	0.34	0.35	0.36	0.33
Non-farm business		0.86	0.82	0.82	0.76	0.68	0.65

Note: Employment variables report the percentage of people employed in each round. Income figures show the percentage of households that reported an income reduction or a total loss compared to the baseline.

1.3 Empirical Strategy

To assess the impact of COVID-19 on income and employment we ran a linear regression model with household and time fixed effects (also called two way fixed effects linear model) and a continuous treatment variable, adapting the approach implemented in Amare et al. (2021). The dependent variables analyzed are two: participating in labor activities, considering any type of activity and specific sectors; and income change, looking at total income and different sources. Regarding employment, labor activities are grouped into own farm, on-farm wage employment, off-farm self-employment, and off-farm wage employment. Occupations can be also divided in terms of the segments of the AFVC, distinguishing between downstream, midstream, and upstream. Upstream includes labor activities related to direct production, namely own farm activities and agricultural workers. Midstream refers to those activities in the middle of the chain, such as manufacturing of food products, wholesale and retail trade, transportation, and distribution. Downstream instead concerns those activities where the food product is in its final form and it is ready to be sold, such as restaurants and bars. For each labor activity, we computed a dummy equal to 1 if the individual operated in that activity, and zero otherwise.

A major issue is that the information is provided only for one member of the household, the respondent. This implies that the individual sample could not be representative of the entire individual population. Looking at the descriptive statistics of some individual characteristics, some differences between the entire individual sample at baseline and the phone-based subsample, as reported in Table 1.3, emerge. Individuals belonging to the HFPS subsample are mainly located in urban areas, the majority are male, and the employment rate is higher. They are older, more educated and a higher share has a formal job contract. The rate of non-farm employment activities is higher compared to the baseline population. However, the rate of farm-related activities is similar. The same occurs for the employment rate along the food value chain.

Given these differences, the results of the analysis could not be generalized to the entire Ethiopian population. To check this issue, in section 1.5.2 we ran a robustness check using adjusted individual weights.

Table 1.3: Comparison of individual characteristics, baseline vs phone-based samples.

Variable	Baseline sample	Phone-based sample
Rural	0.72	0.64
	(0.45)	(0.48)
Sex=female	0.51	0.27
	(0.50)	(0.45)
Employed in any activity	0.75	0.85
	(0.43)	(0.35)
Age	30.69	38.33
	(16.38)	(13.76)
NEET	0.10	0.11
	(0.30)	(0.31)
Literacy rate	0.55	0.63
	(0.50)	(0.48)
Formal job contract	0.04	0.10
	(0.19)	(0.30)
Years of education	3.70	4.75
	(4.32)	(5.12)
Agricultural wage work	0.01	0.01
	(0.09)	(0.09)
Non-farm self-employment	0.10	0.15
	(0.29)	(0.36)
Non-farm wage work	0.12	0.22
	(0.32)	(0.42)
Own farm work	0.63	0.63
	(0.48)	(0.48)
Upstream of AFVC	0.63	0.64
	(0.48)	(0.48)
Midstream of AFVC	0.03	0.04
	(0.16)	(0.20)
Downstream of AFVC	0.01	0.01
	(0.10)	(0.12)
N. of observations	19,910	2,347

Note: sample weights are applied. Standard deviation in parenthesis. Children below 11 years old are excluded.

Regarding household income change, we consider total income and specific generating-income activities, namely family farming, non-farm family business, wage employment of household members, and other sources of income (pension, remittances, etc). The variables take the values -2 (total loss) -1 (reduction), 0 (no change) and 1 (increase).

The main variable of interest is the confirmed cases of COVID-19 over the number of inhabitants in each region[9]. The information has been retrieved from the Ethiopia COVID-19 Monitoring Platform [10] and weekly governmental bulletins[11]. This variable captures the evolution and the spread of the virus around the country. It also allows capturing behavioral effects associated with the fear of contagion. The variable has been transformed using the inverse hyperbolic sine (IHS) transformation, to account for zero cases in the first post-COVID survey. Regression results can be interpreted as the log transformation (Johnson, 1949; Burbidge et al., 1988).

The variable presents some limitations: firstly, the number of confirmed cases probably underestimates the real infection level due to the limited testing capacity of the country. Reporting the cases over the population can help to reduce the bias, as it controls for the population density, assuming the testing capacity is linked to that. Unfortunately, data on testing disaggregated at regional level are not available. Although the testing capacity is presumably unequal across regions, as access to basic health care in Ethiopia was highly unequal already before the pandemic (see e.g., Woldemichael et al. (2019)), the use of fixed effects in the model allows controlling for differences across regions that do not vary over time. Secondly, this variable does not completely reflect the real variation in terms of access to the market and restrictions imposed by the government, which in turn affect labor participation and income. However, one hypothesis is that as long as the number of confirmed cases increases in a region, both the restrictions imposed by the government and the self-imposed restrictions of individuals will increase. In Amare et al. (2021), variables of COVID-19 cases and government restrictions produced the same results for the case of Nigeria, confirming that the two variables were interchangeable in that specific context. Unfortunately, information on government restrictions at regional level is not available in Ethiopia. When using daily data at national level retrieved from the Oxford COVID-19 Government Response Tracker (OxCGRT), the correlation between COVID-19 cases and stringency index is positive and significant in Ethiopia[12]. This confirms our assumption that in the specific country analyzed, the health-related variable and the economic-related one move in the same direction. Although there could be a time lag between the im-

[9]Ethiopia is a federation subdivided into 11 ethno-linguistically based regional states and two chartered cities. The regions vary enormously in area and population

[10]Available at this link: https://www.covid19.et/covid-19/

[11]See https://www.ephi.gov.et/

[12]Correlation coefficient=0.35 significant at the 1% level.

plementation of the restrictions and the effect in terms of COVID-19 cases, this lag is shorter (7/14 days, depending on the type and stringency level of the restriction, and the rate of infection of the specific COVID-19 variant when the restriction is applied) than the period analyzed in each round (one month)- Therefore, the average effect of the restrictions over a month should be captured by the number of confirmed cases.

After having checked the consistency between COVID-19 cases and stringency at national level, it is important to consider the heterogeneity of the response across the regions. Indeed, although measures were coordinated at the national level, each regional state in Ethiopia had a Public Health Emergency Operations Centre (PHEOC) and had autonomy to implement the policies, which applied to their local situation[13]. For this reason, it is important to use a variable disaggregated at regional level.

Thirdly, it does not capture spillover effects that occurred at the national level. Indeed each region is treated as an independent entity, assuming that each one does not have any interaction with the rest of the country and that no aggregate impacts occurred. Bias can occur when two or more regions have strong trade relationships, when for instance a food value chain crosses over regional boundaries – e.g. a food item produced in a region and consumed in another – or workers commute between different regions. In these cases, if one region has been affected differently than others, the effect will affect not only people living in the specific region, but also in the geographically or commercially closest ones. However, as regions in Ethiopia are extended, hosting up to 35 million people, and as we are focusing on family farmers and individuals mainly working in the local economy, the spillover effect should be limited. Additionally, the Ethiopian political system based on Ethnic Federalism, where the regions have been identified on the basis of "settlement patterns, identity, languages" (Article 46.2 of the Ethiopian Constitution), eases the conceptualization of regions as separate economies. Evidence indeed shows that labor mobility and internal migration in Ethiopia is limited (Bundervoet, 2018) and migration across regional boundaries often creates social tensions and violence (Breines, 2020; Fessha and Dessalegn, 2020).

[13]Source: https://www.acceleratehss.org/wp-content/uploads/2022/03/Covid-Collaborative-Ethiopia-Case-Study.pdf

The baseline model is the following:

$$y_{hrt} = \alpha_h + \beta_0 \, Time_t + \beta_1 \, (Cases_r * Time_t) + \varepsilon_{hrt} \quad (1.1)$$

where y_{hrt} is the outcome variable, either labor or income, defined for each individual/household h in region r and round t. α_h captures individual/household fixed effects, allowing to control for unobserved time-invariant heterogeneity among individuals/households. $Cases_r$ is the number of confirmed COVID-19 cases per million population in each region. $Time_t$ is a dummy equal to 1 for the post-COVID round and 0 for the pre-COVID round. The parameter associated with this dummy captures aggregate time trends in the labor market and income composition. The interaction term between time and the number of cases allows capturing the differential impact of COVID-19 on labor participation and income change across regions with different exposure to the virus. ϵ_{hrt} is the error term. Although the analysis will focus on the differential effect of the crisis across regions, captured by the variable of COVID-19 cases, it is worth highlighting that the time-trend dummy $Time_t$ could also, at least partly, reflect the impact of COVID-19 at an aggregate level. However, given that it is not possible to isolate the aggregate effect of COVID-19 from the normal time trend, the differential effect provides a more precise measure of the effect of the shock. Given that the virus spreads differently among regions over time, we need to control for this. Regions that experienced the virus earlier are indeed more likely to report more cases than the other regions. A first specification of the baseline equation introduces the variable $Day1_r$, which reports the number of days that occurred from the first COVID-19 case at the national level to the first COVID-19 case registered in the region. The equation is the following:

$$y_{hrt} = \alpha_h + \beta_0 \, Time_t + \beta_1 \, (Cases_r * Time_t) + \beta_2 \, (Day1_r * Time_t) + \varepsilon_{hrt} \quad (1.2)$$

To differentiate the impact of the isolated interactions and the impact of the combined spatial and temporal variabilities, we introduce an additional specification of the model, which includes the interaction between the dummy of time, the number of confirmed cases per million population, and the variable $Day1_r$.

The corresponding specification of the model is the following:

$$\begin{aligned} y_{hrt} = \alpha_h + \ \beta_0 \ Time_t + \beta_1 \ (Cases_r * \ Time_t) + \beta_2 \ (Day1_r * \ Time_t) + \\ + \beta_3 \ (Cases_r * \ Day1_r * \ Time_t) + \epsilon_{hrt} \end{aligned} \tag{1.3}$$

As an additional specification, we include in (1.3) some control variables available in the phone-based post-COVID surveys, which are not captured by the fixed effects. These variables are the presence of another member in the household that lost a job in the aftermath of the pandemic, and if the household received any assistance since the outbreak of the pandemic. The analysis has been conducted for each post-COVID wave, comparing it with the baseline. In this way, it is possible to observe a possible evolution of the response to the crisis over time. We expect that regions more affected by the pandemic will report a higher reduction in labor participation and income and that the effect will increase with the intensification of the crisis over time. We also estimated the impact of COVID-19 from wave to wave, comparing the outcome with the previous interview. Results still hold and they are available in the Appendix. The analysis is undertaken over the balanced sample. However, given some attrition rates, we replicated the analysis over the unbalanced sample, finding consistent results, as reported in the Appendix.

To estimate the regression, we used a linear probability model with fixed effects. The advantage of this model compared to a logit or conditional logit model with fixed effects is the inclusion of all observations. Logit model with fixed effects indeed would drop the units with no variability in the dependent variable (Beck, 2020), drastically reducing the number of observations in case of small variability.

To investigate what are the main determinants that influenced the changes in income in the presence of COVID-19, we used a probability model with regressors in time t (pre-COVID) and the dependent variable in time t+1 (post-COVID). In this way we can estimate which factors that were in place in normal conditions are more likely to affect the outcome in the presence of the pandemic. The probability that the outcome variable takes a certain value is given by

$$Prob(y_{ht+1} = j) = x_{ht}^T \beta + u_{ht+1} \tag{1.4}$$

where h is the household, x is a column vector of observable variables, namely the factors in time t, u_{ht+1} is the error term, and j takes the value 1 if the outcome is dichotomous, or multiple values if it is categorical. The regressors include household characteristics, water and sanitation conditions of the dwelling, level of infrastructure and variables at the community level, employment and economic related variables, and agricultural-related variables when considering farm income. The dependent variable is the change in income at the household level. We have decided to not consider the employment status because there could be problems of endogeneity caused by omitted variable bias. This could occur mainly by external factors, for which information is not provided in the survey and which could affect the status of employment. An example could be the loss of an employee's job due to the closure of the company where he/she worked. In addition to econometric issues, given that the job loss mainly depends on factors beyond household or individual control, investigating the determinants at the household level of the loss of employment due to the COVID-19 crisis would make no sense and would not address the research questions of the study.

The estimation has been conducted through the maximum likelihood method, and we used the ordered probit model to account for the categorical nature of the dependent variable. However, given that the response rate for total loss and income increase was very low, we also created a dummy equal to 1 if income did not change or increase, and 0 otherwise. In this case, we used a probit model.

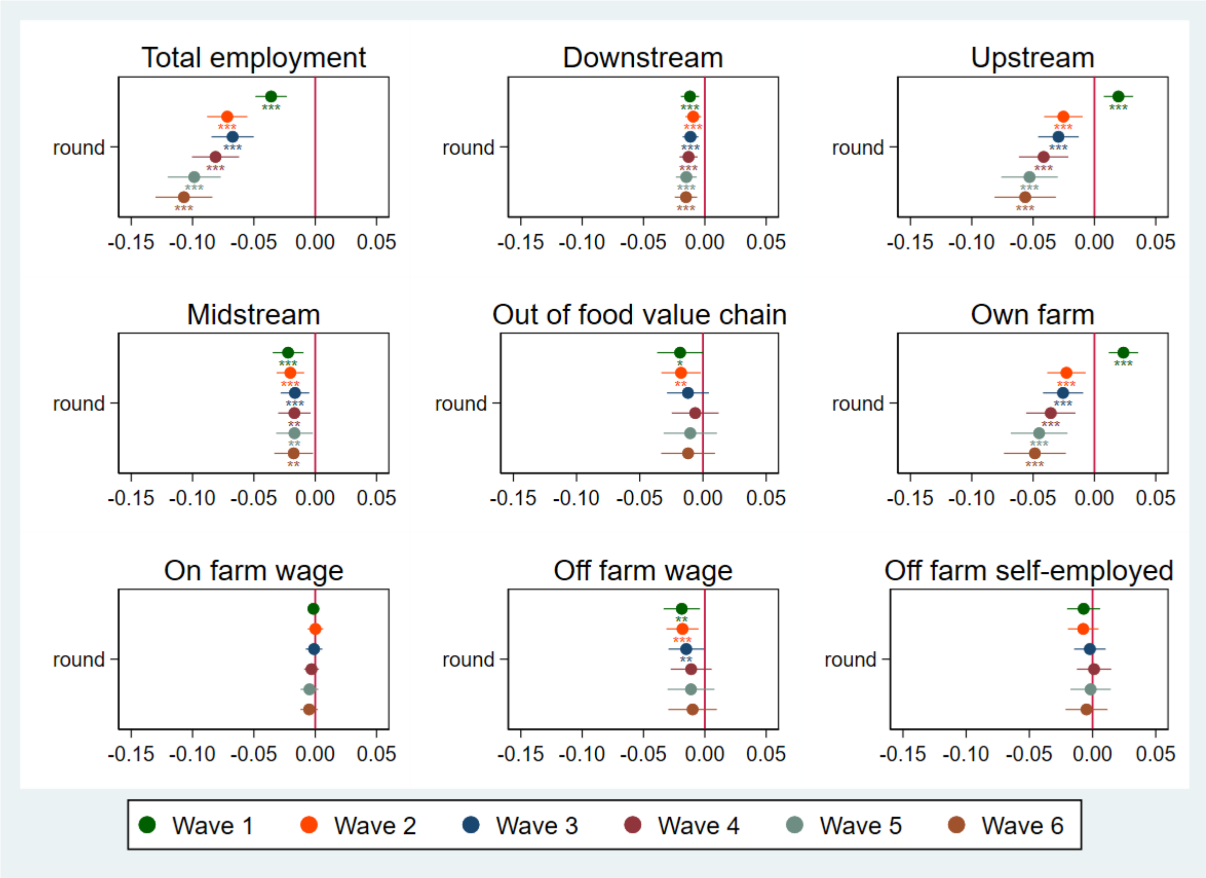
1.4 Results

1.4.1 Impact of the COVID-19 cases

Different model specifications have been considered, starting from a simple OLS over the pooled sample, to a more complex model, which includes all the variables related to COVID-19, their interaction terms, the individual/household fixed effects, and the controls. The regression tables are reported in the Appendix. Driven by theoretical considerations, the adjusted R-square, and the level of completeness, we selected the last model for the analysis. The advantage of the within estimator of the fixed effects model is that it is robust to many types of omitted variable bias. However, it is more inefficient than an OLS estimator, because it reduces the variation of the independent and dependent variables used for estimation. Indeed, it is more affected by measurement errors and by omitted variables which are not constant within household/individual.

In Figure 1.5 the coefficient of the interaction term between the time trend and the COVID-19 cases is reported for each round, firstly considering any labor activities and then looking at specific sectors or segments of the AFVC. These results show how COVID-19 negatively impacted employment activities in Ethiopia. They also show that the severity of the impact increased over time. Decomposing the impact along the AFVC, we can state that the segment most affected is the upstream. Although it had initially been relatively less affected, reported highly negative impacts in subsequent rounds. Downstream and midstream segments have also been negatively affected, but in this case, the impact remained constant over time. For those working out of the AFVC, after an initial negative impact, the coefficients became no longer significant from the third round onwards. This could mean that the COVID-19 cases did no longer have an impact, or that different occupations within this category experienced a contrasting effect. Among the off-farm self-employment occupations, for instance, construction and manufacturing reported a positive effect, while trade and restaurants, hotels, and bars showed negative coefficients.

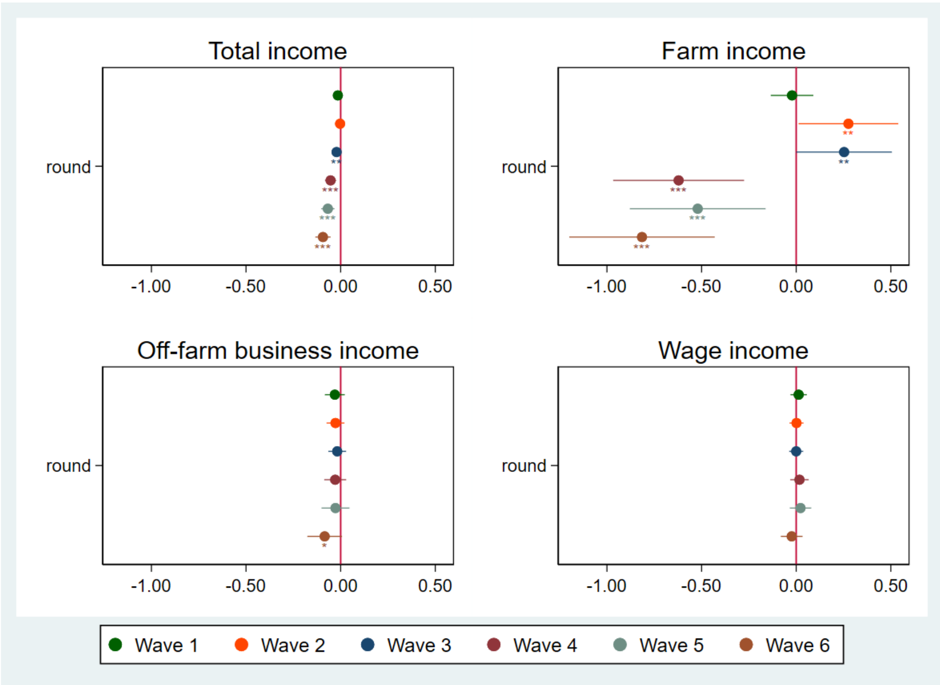
Figure 1.5: Impact of COVID-19 cases on employment over time.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if individual is employed. Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

In the case of income (Figure 1.6), the impact takes more time to occur, as expected. Households indeed can rely on different coping strategies in the short run, such as the sale of livestock or other assets, thus increasing income. However, from the third round onwards, total income has been negatively affected by COVID-19 cases, and the effect, as seen for employment, increases over time. Wage income and off-farm business income do not seem to have been significantly affected, while it is interesting to see the impact on farm family farming. After an initial positive effect, in the last three rounds, COVID-19 cases have significantly and negatively impacted farm income. This can be explained because initially, the virus spread in the cities, safeguarding farmers living in rural areas. But then the virus expanded all around the country, affecting also people located in remote areas. Additionally, if initially smallholders and subsistence farm households were more advantaged against the measures implemented by the government because they relied less on external inputs and markets, this advantage disappeared over time, because of the limited coping mechanisms available.

Figure 1.6: Impact of COVID-19 cases on income over time.



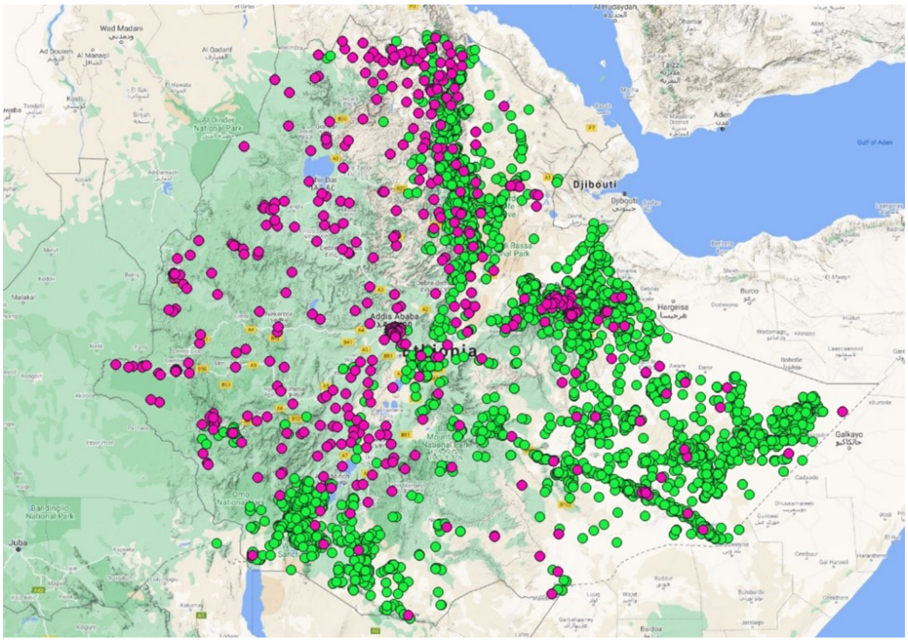
Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Dots are coefficients estimated from a linear probability model with household fixed effects. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Standard errors clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

In the same period, some regions of the country were invaded by desert locusts, with drastic consequences on production. For this reason, it is important to take into account also the presence of locusts in the farm. This information in the HFPH surveys is available only in the 4th wave[14]. In order to have information on locusts over all the time periods, we retrieved GIS data on desert locusts from the FAO Locusts Hub[15] and merged it with the households' location. Given that the household coordinates refer to the dwelling, and not to the parcel, and that they have been slightly modified for privacy reasons, we created a buffer of 3 km around the household centroid to account for these factors. On average the parcel is 1.7 km distant from the dwelling. Regarding the location of locusts, we considered the area surveyed, which is 580 hectares on

[14]Estimates computed using self-reported data are reported in the Appendix.
[15]https://locust-hub-hqfao.hub.arcgis.com/

average. Figure 8 reports the location of households (in purple) and where the desert locusts have been observed (in green) over the year 2020.

Figure 1.7: Map of households' location and locusts sites in 2020.



Source: own elaboration using data from FAO Locusts Hub and ESS 2018/2019.
Note: households' location are reported in purple; locusts sites are the green dots.

When using the georeferenced data, locusts do not show to have a significant impact on own farm labor activities. Instead, the impact is significant and negative for farm income. As reported in Table 5, having experienced locusts is negatively associated with an income increase. The effect seems higher in the 4th wave, which corresponds to the more damaging period for crops caused by locusts, given their level of maturity and aggregation. The inclusion of the locusts' data over all the six waves does not seem to affect the impact of COVID-19 cases on farm income. The coefficients indeed remained almost the same.

Although GIS data are usually more precise and reliable than self-reported data, in this case, many data gaps undermine the quality of the information. Firstly, household coordinates have been slightly modified, and although this change is minimal, it introduces some measurement bias. Secondly, the parcel could be far from the dwelling, and given that only the distance is available, and not the direction, it is not possible to know exactly where it is located. Thirdly, the information provided for locusts does not account for the movements that locusts have done from one point to the other over time, excluding crossed areas.

Table 1.4: Simultaneous impact of locusts (using GIS data) and COVID-19 on farm income change.

	wave 1	wave 2	wave 3	wave 4	wave 5	wave 6
Time	-0.377***	-0.981***	-1.163***	2.829***	3.007***	5.228***
	(0.0627)	(0.269)	(0.363)	(0.895)	(1.141)	(1.273)
Cases*Time	-0.0217	0.277**	0.254**	-0.620***	-0.519***	-0.815***
	(0.0564)	(0.134)	(0.129)	(0.174)	(0.182)	(0.196)
Days*Time	0.00110	0.0131**	0.0189**	-0.0531***	-0.0581**	-0.103***
	(0.00267)	(0.00638)	(0.00858)	(0.0169)	(0.0250)	(0.0273)
Cases*Days*Time	-0.00175	-0.00621**	-0.00654**	0.0104***	0.00923**	0.0153***
	(0.00185)	(0.00281)	(0.00272)	(0.00310)	(0.00365)	(0.00393)
Locusts dummy	-0.307***	-0.350***	-0.0973	-0.377***	0.0327	-0.00324
	(0.104)	(0.129)	(0.156)	(0.144)	(0.245)	(0.213)
Constant	0.00328	0.00398	0.00131	0.00455	-0.000442	4.29e-05
	(0.0114)	(0.0126)	(0.0111)	(0.0131)	(0.0163)	(0.0139)
Controls	yes	yes	yes	yes	yes	yes
FE	yes	yes	yes	yes	yes	yes
Observations	3,025	2,882	2,850	2,853	2,844	2,843
R-squared	0.386	0.415	0.384	0.225	0.102	0.099
Number of pid1	2,347	2,347	2,347	2,347	2,347	2,347

Note: Dependent variable: categorical variable of income change, ranging from -2 (total loss) to 1 (increase). Estimates are computed using a linear probability model with household fixed effects. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1.

1.4.2 Determinants of income change

In this section, the results of the regressions aimed to identify the main determinants of income change are presented. Regressors have been grouped into four categories: household characteristics, infrastructures, WASH variables, and economic-related variables. As dependent variables, we considered a change in total and in farm incomes. For illustrative reasons, we only report the results of the models where the dependent variable is dichotomous[16].

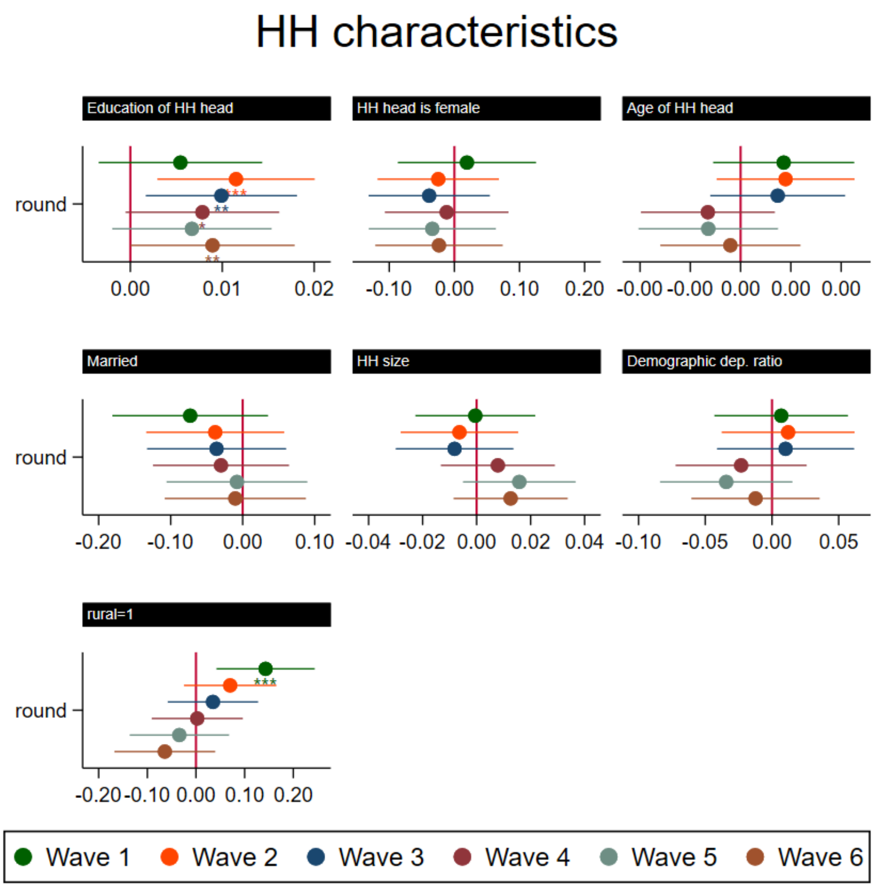
Total income

Figure 1.8 reports the estimated coefficients of household characteristics over the six rounds. The only significant variable here is the level of education of the household head. A higher level of education is positively associated with a higher probability

[16]For space constraints, estimates of the ordered probit model are not reported, but they are available upon request.

of having income increase or unchanged. Living in rural areas shows a positive and significant coefficient only in the first round. Indeed in the beginning rural areas were advantaged.

Figure 1.8: Effects of households' characteristics on total income change over rounds.



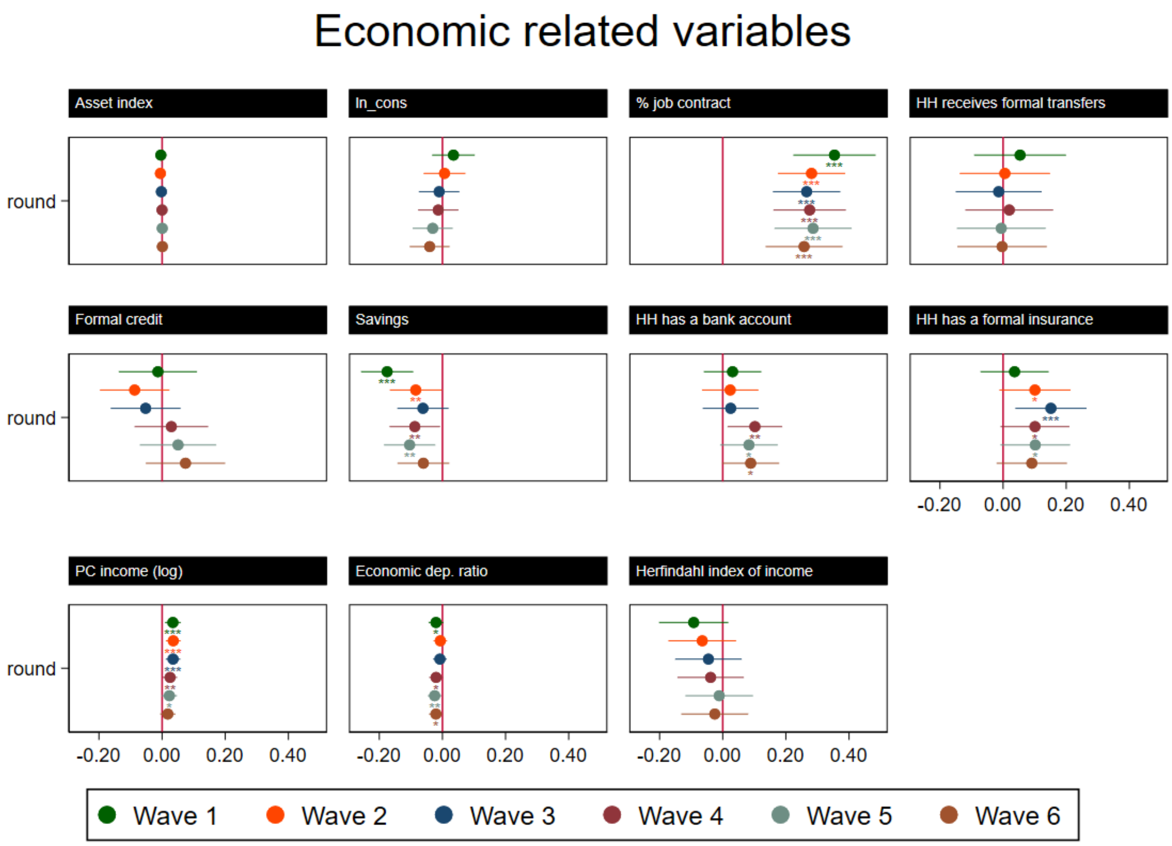
Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

For what concerns economic-related variables, Figure 1.9 shows some interesting patterns. Having a formal job contract is associated with a higher probability of income increase or unchanged. A similar relationship can be found with having a bank account and formal insurance, although the magnitude and the level of significance are lower. Formal insurance includes different insurance products, such as health or livestock. Therefore, a possible mechanism may be compensation from the insurance institution as a result of health problems related to the SARS-CoV-2 virus. This would directly increase household income. Having a bank account gives the household access to bank-related products and services, including access to loans or banking counseling, which can reduce the likelihood of experiencing income reduction compared to households without access. These results show that access to formal institutions is a winning strategy to contrast the negative consequences caused by the crisis. Savings[17] instead show an opposite trend. Given that savings represent a component of income, relying on savings in time of crisis translates into an income reduction. This can explain the negative coefficient. Per capita household income reports a positive relationship, meaning that as per capita income increases also the probability of not experiencing an income reduction increases. Richer households are then expected to suffer less from the crisis. However, the magnitude of the coefficient is quite small, suggesting that the differential effect between poorer and richer households is limited.

Regarding infrastructure and WASH-related variables, none of them report a substantial effect on total income. Being distant to the urban center, to the main road, or to the markets seems to be slightly positively associated, sometimes in a significant way, to the probability of income increase or unchanged. However, the coefficient is lower than 1%. The graphs of these two categories of variables are reported in the appendix.

[17]The variable of savings is defined as a dummy equal to 1 if the household saved some money in any way in the last 12 months.

Figure 1.9: Effects of economic-related variables on total income change over rounds.



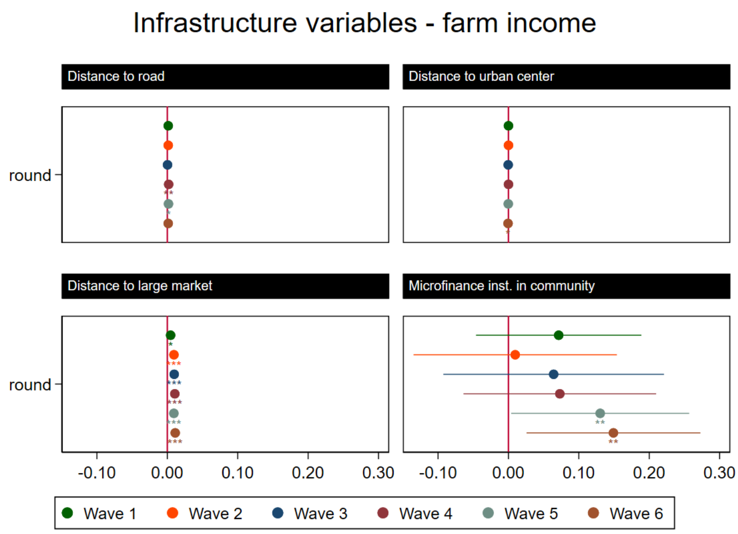
Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if total income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Agricultural income

The same variables considered in the previous section show in part different patterns when considering farm income. Looking at the household characteristics, the education of the household head no longer seems to play a relevant role, while the household size and the age of the household head are associated with a higher probability of income reduction, although the effect is statistically significant only in a few waves.

Even in the case of farm income (Figure 1.10), distance did not show significant patterns, except for distance to a large market, where it seems that the more distant the household is to the market and the higher is the probability of farm income unchanged or increase. The explanation could be that farther households had already put in place some strategies to account for the distance, so they were more advantaged than those farmers that were used to relying on markets. Additionally, given the travel restrictions, domestic food value chains could have reshaped to adapt to the new situation, shortening their lengths. In this way, people in remote areas could have directly bought products from the closest farmers instead of going to the market.

Figure 1.10: Effects of infrastructure variables on farm income change over rounds.

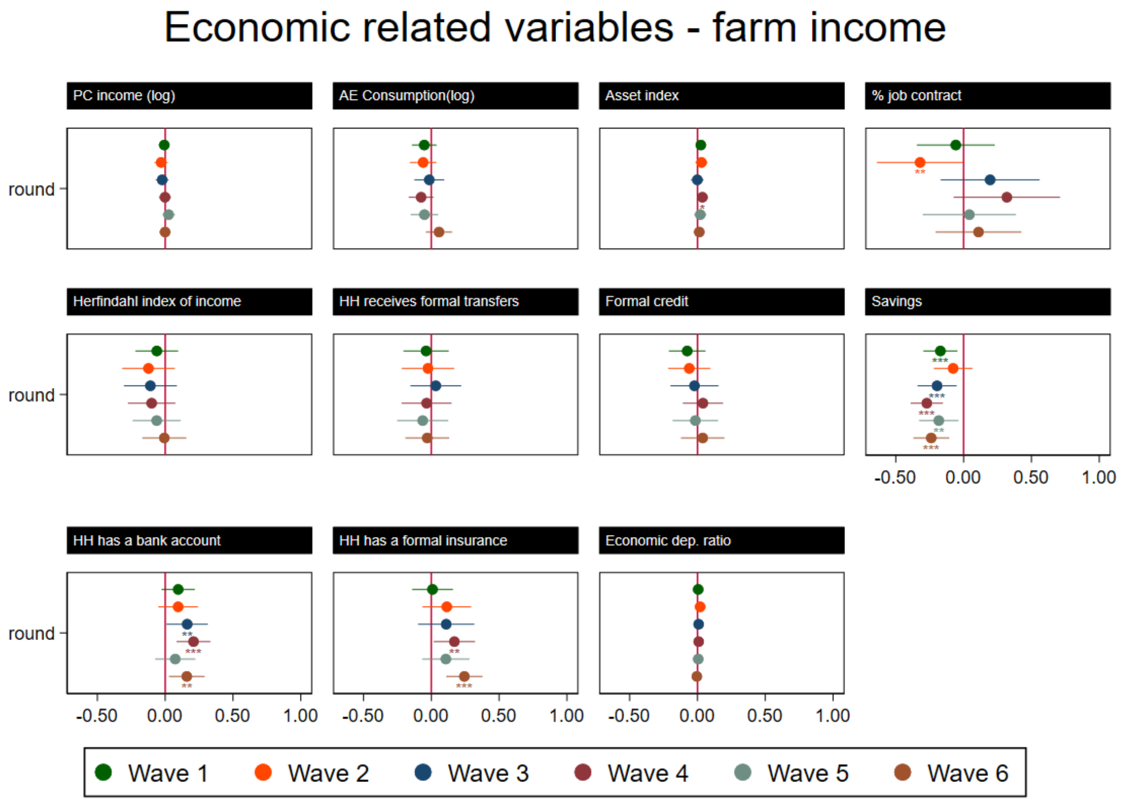


Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

The role of microfinance institutions in the community is interesting. Indeed, differently from total income, here it shows a positive coefficient, and in the last rounds, the effect is also statistically significant. This means that this type of institution is important in supporting farm livelihood in situations of crisis.

For what concerns economic-related variables (Figure 1.11), estimates for farm income are similar to the ones for total income, with few exceptions. Even in this case having a bank account and formal insurance rise the probability of income increase, while savings increases the probability of income reduction. Relying on savings was probably used as a coping strategy in the aftermath of the pandemic, shrinking in this way total disposable income. A different result regards having a formal job contract, where here it does not have a clear and significant effect. This is comprehensible given that the majority of households in Ethiopia run family farming on their land, so they do not participate in the labor market, although they conduct labor activities.

Figure 1.11: Effects of economic-related variables on farm income change over rounds.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

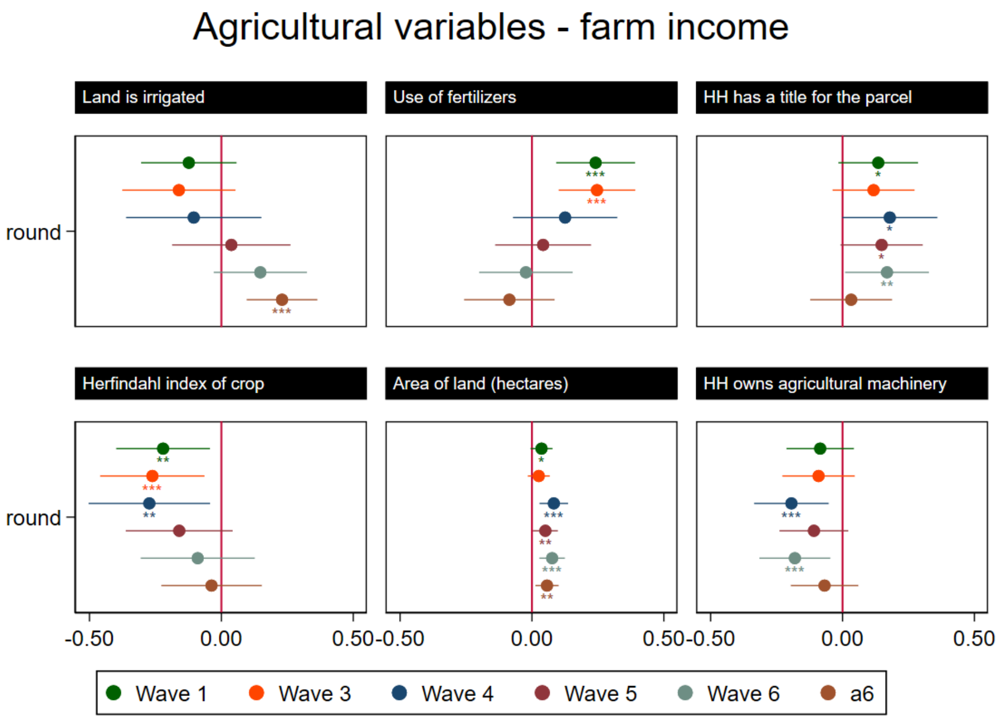
Regarding the agricultural-related variables, reported in Figure 1.12, results seem to suggest that farmers with larger areas of land have a higher probability of success compared to smallholders. The marginal effects of land size on the probability of farm income change being equal to 1, reported in Figure 1.13, confirm these findings. In all six rounds indeed the probability of not having an income reduction increases with land size.

Having a title[18] of ownership or holding the rights of use of the parcel is particularly relevant during the COVID-19 crisis, as they increase the probability of avoiding an income reduction. Households that use fertilizers and those that have agricultural

[18]Land title is defined based on how the family acquired the parcel and whether documentation is available to certify the acquisition.

machinery, although they initially experience a positive or insignificant effect, are subsequently negatively affected. This result can be the consequence of the mobility and trade restrictions, which increased prices and decreased the availability of inputs. A higher concentration of crop varieties represents a disadvantage for increasing agricultural income, but only in the first rounds, as reported by the coefficient of the Herfindahl index of crop[19].

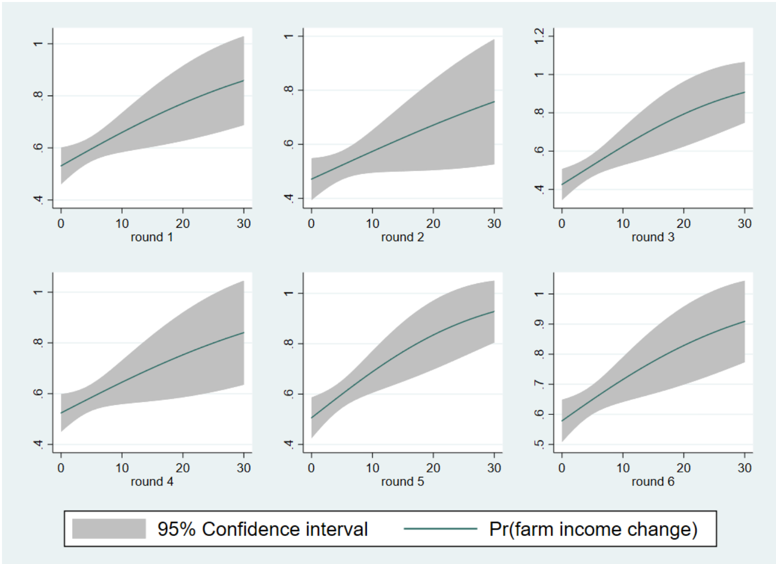
Figure 1.12: Effects of agricultural-related variables on farm income change over rounds.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: Dependent variable = dummy equal to 1 if farm income did not decrease compared to pre-Covid round. Dots are average marginal effects from a probit regression. Each post-COVID round is compared with the baseline. Bars are 95% confidence intervals. Sampling weights applied. Robust Standard errors. *** p<0.01, ** p<0.05, * p<0.1.

[19]The Herfindahl index is a measure of crop concentration. It is computed as the sum of square of the proportion of individual crop groups in a portfolio. The index decreases with an increase in diversification. It ranges from 0 (complete diversification) to 1 (complete Specialization) (Singh et al., 1986).

Figure 1.13: Marginal effects of land size on the probability that farm income change has not decreased.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.

1.5 Robustness checks

1.5.1 Placebo test

To test the validity of the treatment variable used in the analysis, we ran a placebo test, imputing the COVID-19 shock in the prior wave of the ESS, collected in 2015/2016, and considering as baseline the 2012/2014 ESS survey. If the variable of the number of COVID-19 cases correctly captures the impact of the COVID-19 shock, we should not find any significant effect, given that at that time the shock did not occur. Table 1.5 reports the results of the test, applied for the change of total income at the household level and the variable of total employment at the individual level. The variable is valid when applied to the model of household income, where none of the coefficients related to COVID-19 is significant. Instead, when running the same model on total employment, the coefficient of the interaction between time and COVID-19 cases is significant, as reported in column (1). However, the sign is positive, in contrast to the predicted effect that the shock should have. A possible explanation is that the variable of COVID-19 cases is in a way correlated with regional characteristics. For instance, as we know that COVID-19 has affected some economic sectors more than others, if a region is specialized in one, this correlation will be significant. If the employment rate was expanding between 2014 and 2016 in that specific sector, the correlation will be positive. Introducing regional income indeed leads the variable of COVID-19 cases to lose its significant effect. Regional income can capture the level of economic development of the region, which is in turn correlated with other factors, including the economic sector. Economies based on agriculture indeed are usually less developed than those based on services, as the latest already went through a process of structural transformation.

Table 1.5: Placebo test on ESS 2012/2014 and ESS 2015/2016.

Variables	Total income change	Total employment	
		(1)	(2)
Time	0.0852	-0.294***	-0.363**
	(0.154)	(0.0850)	(0.169)
Time*cases	0.0136	0.0258**	0.0419
	(0.0204)	(0.0113)	(0.0365)
Time*days	0.00274	0.00153	0.00192
	(0.00538)	(0.00295)	(0.00311)
Time*days*cases	-0.000364	-0.000233	-0.000312
	(0.000701)	(0.000386)	(0.000431)
Cases*regional income			-4.31e-07
			(9.34e-07)
Constant	-0.00491	0.601***	0.601***
	(0.0109)	(0.00583)	(0.00584)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
R-squared	0.023	0.050	0.050
Observations	9,760	21,289	21,289
Number of pid	4,887	11,368	11,368

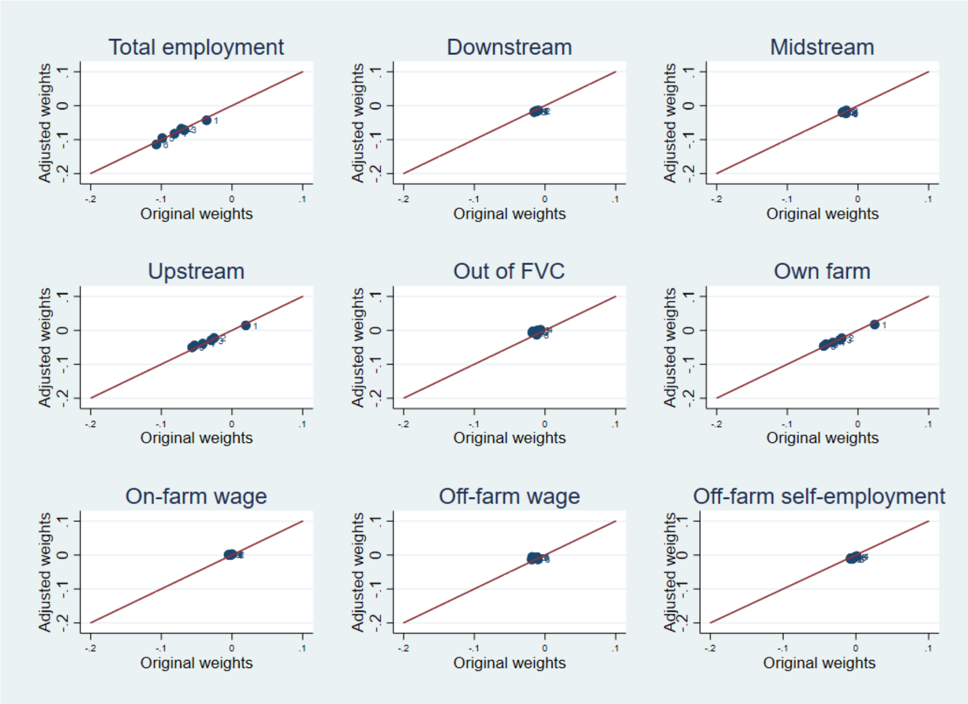
Note: Dependent variables: categorical variable of income change, ranging from -2 (total loss) to 1 (increase) (1st column), and dummy equal to 1 if individual is employed (2nd column). Income change is computed by comparing the amount of household income earned in each round.

1.5.2 Inverse probability weights

To address the problem of representativeness of the individual sample, as a robustness check we created individual-level adjusted weights using the inverse probability based on the ESS 2018/2019, and we compared the outcomes using these weights with the estimates previously presented. In this way, we create weights that make the HFPS subsample more aligned with the original sample of individuals in the ESS 2018/2019, based on a series of observable individual characteristics. A similar check has been implemented in Khamis et al. (2021), where the authors rely on the World Bank's Global Monitoring Database. Although they found similar results when applying the corrected weights compared to the original ones, they had a limited set of variables available to use for reweighting the estimates, undermining the effectiveness of the weights created. In this case, instead, we can consider more variables, increasing the ability to effectively adjust for the differences between the individuals in the subsample and the rest of the population.

We ran a logit regression to estimate the probability of being in the HFPS subsample over a set of variables at the individual level, weighted by the household weights of ESS 2019. Variables considered include age, gender, years of completed education, living in rural areas, income quintile, being employed, working in own farm activities, and NEET. Children below 12 years old have been excluded. The inverse of the estimated probability is the adjusted weight. This procedure gives greater weight to observations that appeared in the HFPS sample. Figure 1.14 reports the coefficients estimated with original weights vis-à-vis the adjusted ones. The correlation of the estimates using the two methods is very high, corresponding to 98%. This result is rather robust, suggesting that the labor market outcomes of the subsample of individuals are generally consistent with the outcomes of the entire working population.

Figure 1.14: Comparison of weighting methods.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.

1.6 Conclusions

The analysis showed that COVID-19 negatively impacted both household employment and income, the more so the longer the time length from the pandemic onset in 2020. Upstream activities, and specifically own farming, are the most affected segment of the AFVC. Indeed, despite an initial positive effect, the impact then became negative and increased in magnitude over time. This finding is partly in line with previous studies published in the immediate aftermath of the pandemic, such as Bundervoet and Finn (2020) and Reardon et al. (2021), who showed that farming was the sector less affected. However, tracking the impact over time allowed gaining a more complete picture, where farming, after a relatively less negative impact, has been severely affected by the disruption of the food value chain. The initial resilience capacity of the Ethiopian food marketing systems, as found in the case of vegetable value chain by Hirvonen et al. (2021b), therefore does not seem to persist over time. This highlights the importance to monitor the evolution of the impact of the shock over time. Indeed, considering only the initial effect could give an incomplete understanding of the actual situation.

The analysis also showed that small farming households are more exposed to the negative consequences of the crisis. There is the need then to target specifically this group of AFVC actors, especially in situations of crisis. To do this, AFVC participants need to access specific tools that allow them to overcome the constraints they currently face. Access to formal institutions, such as formal insurance, bank account, formal contract, and land title are all positively associated with a higher probability of income increase. The national government should then increase its effort in providing opportunities to access financial services as well as formal institutions also to individuals located in remote areas of the country.

However, it is important to notice that a reduction in employment and income does not always affect food security. Food security indeed is a multidimensional concept, and its level depends on different factors other that income. Especially when subjective estimates of income change are used, the relationship is not straightforward. In Hirvonen et al. (2021a), for example, self-reported income shocks did not appear to be associated with changes in the HDDS. At the same time, the HDDS is only one indicator of food security, and considering other measures could provide different results. Furthermore, other mechanisms may be in place that can influence food security, depending on the type of household considered and its integration in the food value chain, as found in Chapter 2.

The main limitations of this work are due to the type of data available, which reduces the internal and external validities of the findings, as described across the paper. Specifically, the variable of COVID-19 cases is not able to fully capture the infection rate and the economic downturn caused by the non-pharmaceutical interventions in the country. The fact that data are collected through phone interviews limits the representativeness of the sample, especially considering the low phone penetration in rural areas. Another bias can arise from measurement error, which is common in self-reported data. This is particularly relevant for the variable of income change, which is highly subjective to respondent's perception. Income data collected through more reliable measures are then needed to avoid major measurement errors. Additionally, data used in this study were not intended to specifically track AFVC participants. Usually, quantitative value chain studies rely on a representative sample of the whole value chain and conduct a cascading survey along it. Household surveys based on random sampling instead are typically unable to capture a representative picture of the actors across the different segments of the value chain. Less than 100 individuals for instance are employed in the downstream segment in each post-COVID round. Studies on specific value chains in Ethiopia have been conducted for the dairy value chain (Tesfaye et al., 2020), and the vegetable value chain (Hirvonen et al., 2021b; Tamru et al., 2020). Additional data that collect information on different food value chains in the country through a cascading survey is then needed to have a better understanding of the overall effect of the COVID-19 crisis on the aggregate food system in Ethiopia.

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Appendix

Table 6: N. of individuals that started to work again in each round, by reason for stop working in the previous round.

	N. of individuals that started working again				
Reason for stop working	**Round 2**	**Round 3**	**Round 4**	**Round 5**	**Round 6**
Seasonal/Casual worker	27	8	8	7	6
Contract ended	3	0	3	2	1
Covid-19	83	22	22	5	6
Temporarily absent	25	8	6	5	9
Retired	0	0	0	1	0
Ill	2	8	2	1	5
Need to care for ill relatives	1	1	1	0	0
Other	1	0	1	1	0
N/A	329	94	71	54	30
Total	**471**	**141**	**114**	**76**	**57**

Table 7: Regression results over different models, employment – wave 1

Dependent variable: individual employed in any activity					
Variable	(1)	(2)	(3)	(4)	(5)
Time	-0.0684***	-0.0758***	-0.0657***	-0.0658***	-0.0709***
	(0.0137)	(0.0127)	(0.0185)	(0.0193)	(0.0196)
Cases*Time	-0.0438***	-0.0353***	-0.0362***	-0.0361***	-0.0360***
	(0.00866)	(0.00577)	(0.00607)	(0.00651)	(0.00654)
Days*Time			-0.000395	-0.000386	-0.000364
			(0.000505)	(0.000644)	(0.000640)
Cases*Days*Time				-9.72e-06	-1.53e-06
				(0.000383)	(0.000383)
Constant	0.746***	0.746***	0.746***	0.746***	0.746***
	(0.0163)	(0.00507)	(0.00507)	(0.00507)	(0.00507)
Controls	No	No	No	No	Yes
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	4,694	4,694	4,694	4,694	4,694
R-squared	0.042	0.071	0.082	0.107	0.116
Number of pid		2,347	2,347	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1. Data refers to the 1st wave.

Table 8: Regression results over different models, income – wave 1

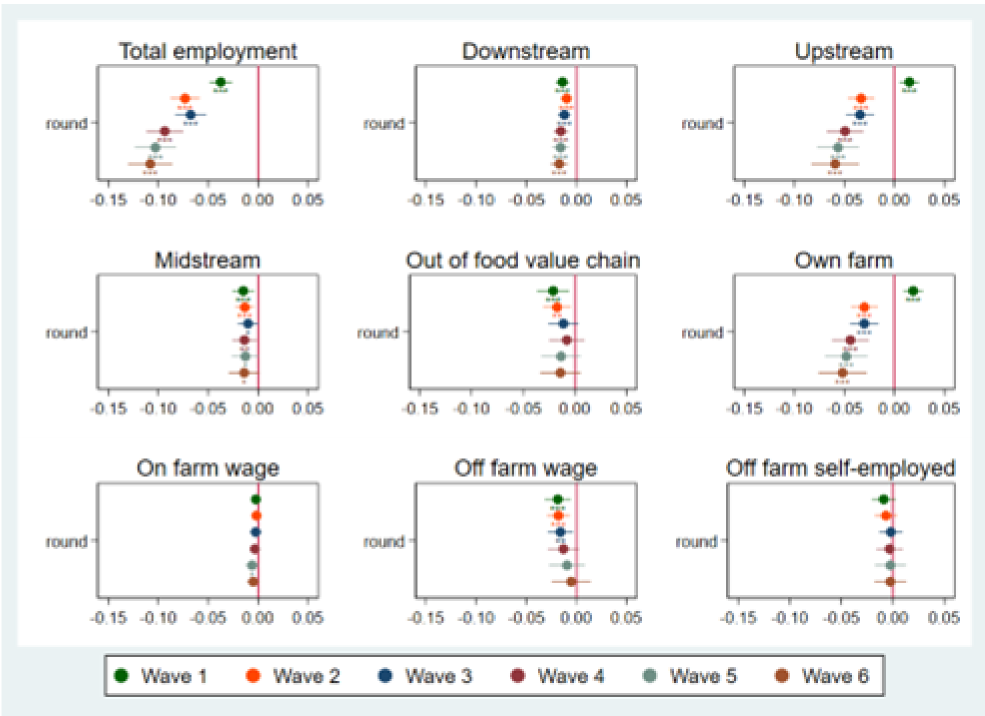
Dependent variable: change in total HH income					
Variable	(1)	(2)	(3)	(4)	(5)
Time	-0.567***	-0.567***	-0.544***	-0.558***	-0.549***
	(0.0274)	(0.0274)	(0.0374)	(0.0404)	(0.0412)
Cases*Time	-0.0246**	-0.0246**	-0.0266**	-0.0157	-0.0148
	(0.0112)	(0.0112)	(0.0114)	(0.0118)	(0.0119)
Days*Time			-0.000879	5.95e-05	1.58e-05
			(0.00110)	(0.00162)	(0.00161)
Cases*Days*Time				-0.000967	-0.000970
				(0.000864)	(0.000864)
Constant	0	-0	-0	-0	0
	(3.08e-10)	(0.0106)	(0.0106)	(0.0106)	(3.08e-10)
Controls	No	No	No	No	Yes
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	4,691	4,691	4,691	4,691	4,691
R-squared	0.336	0.503	0.503	0.504	0.505
Number of pid		2,347	2,347	2,347	2,347

Note: Estimates are computed using a linear probability model. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1. Data refers to the 1st wave.

Figure 15: Impact of COVID-19 cases on income change, wave by wave.

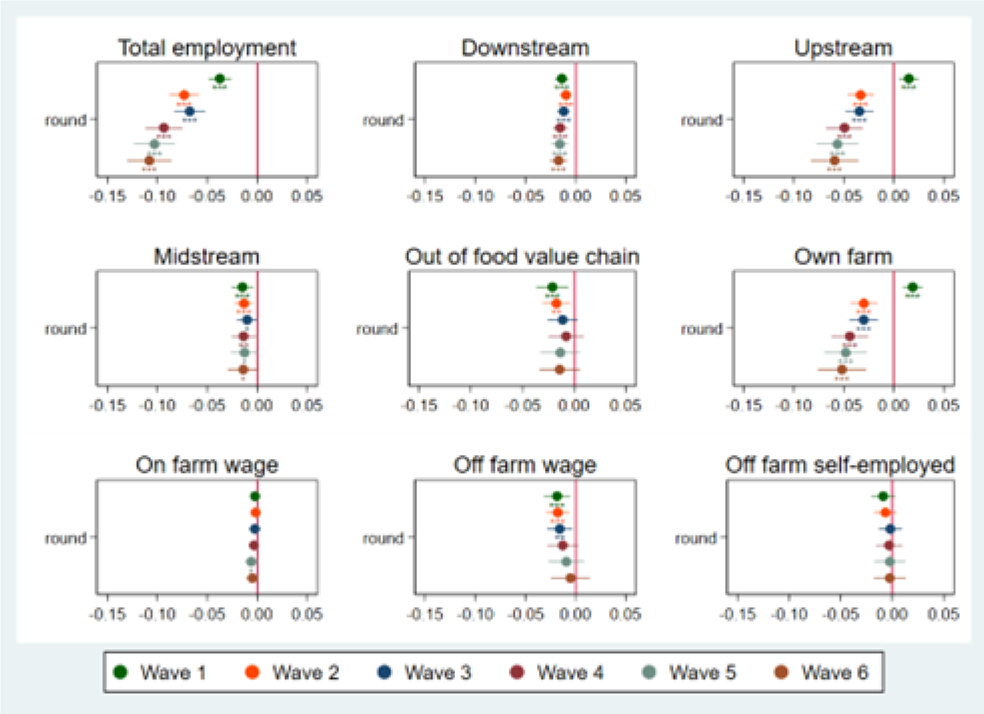
Source: Own calculation from ESS 2018/2019 and HFPSH 2020.
Note: previous call is considered the baseline.

Figure 16: Impact of COVID-19 cases on employment over time, unbalanced sample.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.

Figure 17: Impact of COVID-19 cases on total income over time, unbalanced sample.



Source: Own calculation from ESS 2018/2019 and HFPSH 2020.

Table 9: Simultaneous impact of self-reported locusts and COVID-19 on own farm employment activities and farm income change, 4th wave.

	Employed in own farm activities	Farm income change
Time	0.0489	5.242***
	(0.504)	(1.893)
Cases*Time	0.0216	-1.103***
	(0.0938)	(0.372)
Days*Time	-0.0237**	-0.0998***
	(0.0115)	(0.0350)
Days*Time*Cases	0.00333*	0.0194***
	(0.00200)	(0.00671)
Locusts in the farm	0.134*	-0.0244
	(0.0685)	(0.110)
Constant	0.542***	-0
	(0.00927)	(0.0111)
Controls	yes	yes

FE	yes	yes
Observations	2,961	2,639
R-squared	0.088	0.309
Number of pid1	2,347	2,347

Note: Dependent variables: dummy equal to 1 if employed in own farm activities (1st column) and categorical variable of income change, ranging from -2 (total loss) to 1 (increase) (2nd column). Estimates are computed using a linear probability model with household fixed effects. Sampling weights applied. Standard errors clustered at the household level.*** p<0.01, ** p<0.05, * p<0.1.

Chapter 2

Identifying the transmission channels of COVID-19 impact on poverty and food security in refugee-hosting districts of Uganda

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Abstract

This study[1] aims to identify the mechanisms through which COVID-19 affected poverty and food insecurity in refugee-hosting districts in Uganda. We use path analysis with household fixed effects to identify the main pathways for different groups of households according to refugee status (refugee vs. host households), main income source (agricultural vs. non-agricultural households), and market position (food net-buyers vs. net-sellers vs. self-sufficient households). The analysis shows that COVID-19 significantly affected labor participation and increased food value chain disruption, particularly worsening diet quality. Refugees have been affected more than hosts by the COVID-19 direct and indirect effects resulting in a higher negative impact on poverty. Host households benefited from an increase in food prices, while refugees were more affected through the effect on the labor market. As expected, net-buyers are the group most affected by food value chain disruption and, along with non-agricultural households, are the ones that were most affected in terms of food security.

JEL Classification: I15; O12; Q12

Keywords: Covid-19; food security; poverty; refugees

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2.1 Introduction

Many different shocks, such as extreme weather events, pest outbreaks, conflicts, price spikes, and, more recently, COVID-19, hit East African countries. These shocks compound with severe structural problems making poverty, hunger, and malnutrition a harsh reality for many countries in the region. Uganda is not an exception. Income levels are low, with 41.3% of people below the $1.9 poverty line[2] and a significant share of the population unable to meet their basic needs, including food, especially in the northern and eastern parts of the country (OPM et al., 2020). A fast-growing population, expected to reach 100 million by 2050, and the presence of the world's third-largest refugee population are other challenges the country faces.

Uganda hosts the largest refugee population in Sub-Saharan Africa, with more than 1.5 million refugees[3], originating from conflict-affected neighborhood countries such as South Sudan, the Democratic Republic of the Congo, and Burundi. The country has a very progressive refugee policy, promoting refugees' self-reliance and favoring a development-based approach to refugee assistance. Refugees are granted wide-ranging rights that include allocating land (from ¼ to 1 acre) for agriculture purposes, freedom of movement, and the right to seek employment. Nevertheless, the magnitude and speed of the refugee influx in recent years are critical challenges to the sustainability of this progressive policy. As the number of refugees grows, the size of the plots granted becomes gradually smaller (OPM et al., 2020), and the number of food-insecure households increases. Food insecurity in refugee settlements has recently peaked at 44% of households, that crucially depend on humanitarian assistance to meet their food needs (OPM et al., 2022).

The first case of COVID-19 in the country was registered on March 20th, 2020, and the government immediately implemented severe restrictions to limit the spread of the virus, which included the closure of schools, religious gatherings, nonessential businesses, and domestic as well as international travel restrictions. Many sectors received financial assistance to compensate for the lack of businesses (BMAU, 2020). In the agricultural sector, emergency procurement of planting materials, e.g. seeds and cassava cuttings, was undertaken. However, delays in input delivery were reported in most districts, due to the COVID-19 lockdown-related restrictions that affected input procurement and transportation (BMAU, 2020). Additionally, in April 2020 the refugee food rations were reduced from 100% to 70% of the recommended daily food basket (IPC, 2021).

[2]World Bank Open Data, available at https://data.worldbank.org/indicator/SI.POV.DDAY?locations=UG
[3]Source: https://data.unhcr.org/en/country/uga Retrieved on October 19, 2022.

Notwithstanding evidence of COVID-19 related impacts at various stages of the food system, it is not clear yet how the COVID-19 shock has been transmitted through it to eventually impact households' welfare. Furthermore, different types of households are expected to be affected differently, based on their socio-economic characteristics, their livelihood strategies, and their integration in the market. Hence, the overall objective of this study is to identify the mechanisms through which COVID-19 impacted different types of households. Specifically, the research questions addressed by this study are the following:

- What are the pathways linking COVID-19 shock to household poverty and food security?
- Did COVID-19 differently affect different types of households, and if so, how?

The COVID-19 impact on household poverty and food security is transmitted through two main channels. On the one hand, government restrictions disrupt livelihood activities, specifically participation in the labor market, reducing household income (Abay and Tafere, 2020; Amare et al., 2021; Arndt et al., 2020; World Bank, 2021). On the other hand, disruption of food value chains (FVCs) undermines access to food, reducing food security (e.g., Aggarwal et al. (2022); Hirvonen et al. (2021); Mahajan and Tomar (2021)). Therefore, the mediating role of these two channels is explored and analyzed to answer the first question. Addressing the second research question requires disentangling the heterogeneity of COVID-19 effects on household groups that differ for refugee status (i.e., refugee vs. host households), main income source (i.e., agricultural vs. non-agricultural households), and agricultural household's market position (i.e., net-buyers vs. net-sellers vs. self-sufficient households).

The contribution of this study is threefold. First, it sheds light on the transmission mechanisms of the COVID-19 shock. So far, research mainly focused on the COVID-19 overall impact, or on specific groups of households. Kansiime et al. (2021) assessed the implications of the COVID-19 pandemic on household income and food security in Kenya and Uganda, finding worsening levels of food security and dietary quality, especially among the poorest and non-agricultural households. Although this study considers the overall population in the two countries, it does not investigate the mechanisms behind the change in income and food security. Mahmud and Riley (2021) measured the economic and well-being impacts of the COVID-19 lockdown on a sample of households in rural Uganda, finding a large decline in household non-farm income, with a shift of household labor supply towards agriculture and livestock activities. The focus however is only on the rural areas of the country, where different mechanisms compared to other areas could occur. The World Bank, in collaboration with the Uganda Bureau of Statistics and UNHCR, conducted a series of phone surveys to track the socioeconomic impacts of COVID-19 among refugees in Uganda. Their findings show a reduction in labor participation, off-farm business activities, and total income, resulting in an increase in poverty and difficulties in buying main staple foods. Households were also less able to sell their products. Furthermore, they found that refugees fared substantially worse on key dimensions of welfare and their recovery was slower compared to Ugandans in general (Atamanov et al., 2021). Although this study is very comprehensive, as it compares refugee households with the local population and try to disentangle the different ways families have suffered from the crisis, it is mainly descriptive and not intended to estimate a causal effect.

Second, our study uses primary data from a survey specifically designed for refugees and host communities through in-person interviews administered before and after the COVID-19 outbreak. Compared to the phone-based interviews used during the pandemic by many organizations (e.g. Ambel and Bundervoet (2020); Atamanov et al. (2022); Chikoti et al. (2021); Egger et al. (2021); Siwatu et al. (2021), the in-person interviews collect broader and better-quality information about the household as a whole and for each household member. Furthermore, the in-person survey design includes the population not having access to a phone, thus eliminating one of the most serious biases of phone-based surveys (Ambel et al., 2021; Ballivian et al., 2015; Brubaker et al., 2021; Demombynes et al., 2013; Gibson et al., 2017; Gourlay et al., 2021; Henderson and Rosenbaum, 2020; Kastelic et al., 2020).

The third contribution is a methodological one. To analyze the complex cobweb of relationships between the many factors potentially mediating the shock impact on household poverty and food security, structural equation modeling (SEM) is used. So far, SEM has been mainly used to investigate the psychological impact of the pandemic (Buttler et al., 2021; Chen et al., 2021; Lathabhavan and Vispute, 2021), while the economic consequences of the shock have been mainly estimated through simulation exercises based on projections (Filipski et al., 2022; Younger et al., 2020; Laborde et al., 2021). In this study, instead, we use SEM techniques over real data to account for the different roles of the main transmission channels affecting poverty and food security at the household level. This is particularly relevant for policymakers because different interventions can be implemented to reduce poverty and food insecurity, but not all are equally effective. Therefore, identifying how and how much different households have been affected would help to better design policy responses.

The chapter is organized as follows. The next Section describes the data and presents some descriptive statistics of the outcome variables and meditating factors. Section 2.3 describes the SEM methodology. Section 2.4 presents the results of the analysis. Section 2.5 concludes.

2.2 Data

Data used in this study come from the RIMA Uganda Refugee and Host Communities Panel Survey, a four-round longitudinal survey representative of refugee and host communities in the country (d'Errico et al., 2021), implemented by the Uganda Office of Prime Minister (OPM), the Uganda Bureau of Statistics (UBOS), the Food and Agriculture Organization of United Nations (FAO), the World Food Program (WFP) and the United Nations' Children Fund (UNICEF). The main objective of this survey is to monitor the implementation of the Refugee Response Plans and to inform on the living conditions of refugees and host communities in eleven refugee-hosting districts. The host communities have been identified as the closest communities living in the same sub-county. In this study, we use only the second round (December 2019, i.e. just before the COVID-19 outbreak) as a baseline, and the third one (December 2020, i.e. nine months after the COVID-19 outbreak in the country) as a follow-up in the aftermath of the pandemic[4]. The fact that the interviews took place in the same month in the two rounds allows for time comparability, ruling out crop production seasonality problems. The final balanced sample includes 2,969 households per year.

The dataset contains a wide range of information on household socio-demographic and economic status, including food security, shocks experienced, assistance received, employment status, agricultural and livestock production. The 2020 round also contains COVID-19 related questions, such as having experienced COVID-19 symptoms or the reasons why the household experienced problems in getting food. The households were selected using a stratified two-stage cluster sampling, with refugee households' settlement blocks (or the villages close to the settlement for the host households) as the primary sampling units, and randomly selected households as the second sampling units.

2.2.1 Outcome variables

The two outcome variables considered in this analysis are poverty and food security. We estimated a relative poverty line equal to half the median of per capita daily expenditure distribution in 2019, i.e. USD 0.13 in 2011 PPP[5] . We used a relative rather than an absolute poverty

[4]While this facilitates the analysis of COVID-19 impact, it is worth emphasizing that the results of the analysis crucially depend on the time frame of data collection: a longer reference period could lead to different results and different policy implications.

[5]The national annual poverty line was UGX 46,233.65 in 2016/2017 (UBOS, 2019), which corresponds to a daily poverty line in 2011 PPP of USD 0.10, very close to the relative poverty line used in this study.

line because the consumption module does not include all required items to estimate an expenditure measure comparable to the one provided by official statistics. However, it allows for comparability across waves. We used the Food Consumption Score (FCS) [6] as a proxy for food security (WFP, 2008). Although the FCS is an indicator that captures primarily the quality of household diet, it is highly correlated to food intake as well (IFPRI, 2006).

2.2.2 COVID-19 and other shocks

The COVID-19 variable is proxied by a time dummy equal to 0 in 2019 and 1 in 2020. Given the short time span between rounds and the fact that there were no other significant shocks, or shocks already present in the territory did not increase in intensity and frequency during the analyzed period [7], we can assume that any changes that have occurred between these two years can be attributed to COVID-19. However, to control for any other possible shocks over the same period, we look for systemic and idiosyncratic shocks affecting the surveyed households. Among systemic shocks, drought and flood are the most frequently experienced, affecting respectively 25% and 26.6% of households in the two years. In particular, intense rainfalls triggered localized but significant flooding between September and November 2020 in the districts of Adjumani, Moyo, Lamwo, and Arua (FAO, 2020). Therefore, a dummy for having experienced a flood[8] has been included in the model.

Among the idiosyncratic shocks, only 5% of respondents reported that some household members suffered from COVID-19 symptoms. This suggests that COVID-19 affected households primarily through the pandemic's indirect consequences on the economy rather than directly via the respondent's infection. To distinguish between these two associations, a dummy equal to 1 if at least one household member suffered from COVID-19 symptoms has been included in the analysis. However, we must take into account that the fear of getting infected can affect household demand. This has been proxied by a dummy equal to 1 if any members of the household did not access medical care because of being afraid of getting infected while going out. Although this variable only addresses those households that needed medical service since March 2020, it is plausible that at least a member of the household needed some types of medical service in the last 9 months. Indeed, 70% of households reported that they needed

[6] the FCS is "a score calculated using the frequency of consumption of different food groups consumed by a household during the 7 days before the survey (WFP, 2008). 8 food groups have been used to compute the FCS in this analysis.

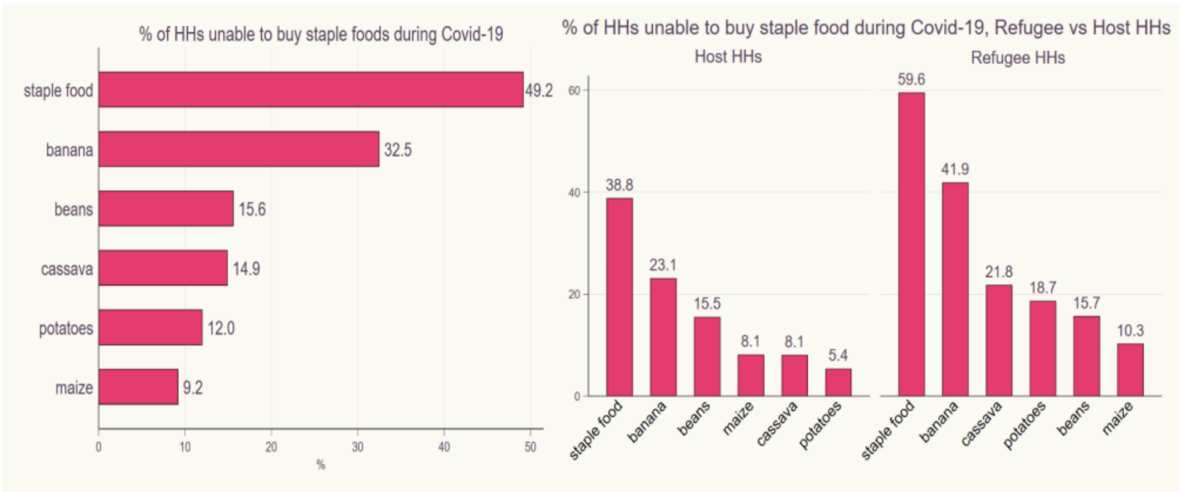
[7] Events such as droughts and floods are common in the country, however they did not increase or change in intensity between 2019 and 2020.

[8] Shock impact intensity ranks from 1 (Least Severe) to 4 (Very Severe). The flood dummy is equal to 1 if the household experienced at least intensity 2 (Moderate).

medical assistance. It is worth highlighting that all these variables are based on self-reported data, therefore, although they are used as proxy for different shocks, they could have problems in terms of measurement error.

The change in household employment status was measured as the change in the share of employed household members, excluding children under the age of six. The proxy of FVC disruption was built as a count variable summing up the reasons for not being able to buy the main staple foods[9]. The higher the count the higher the level of FVC disruption. Almost 10% of households in 2020 reported at least one type of FVC disruption[10], with the closure of local markets being the most frequent one. Roughly half of the households were unable to buy staple food during COVID-19 and refugee households generally reported more difficulties in buying staple food than host households (Figure 2.1).

Figure 2.1: Percentage of households unable to buy food by food item, whole sample, and refugee vs. host households



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

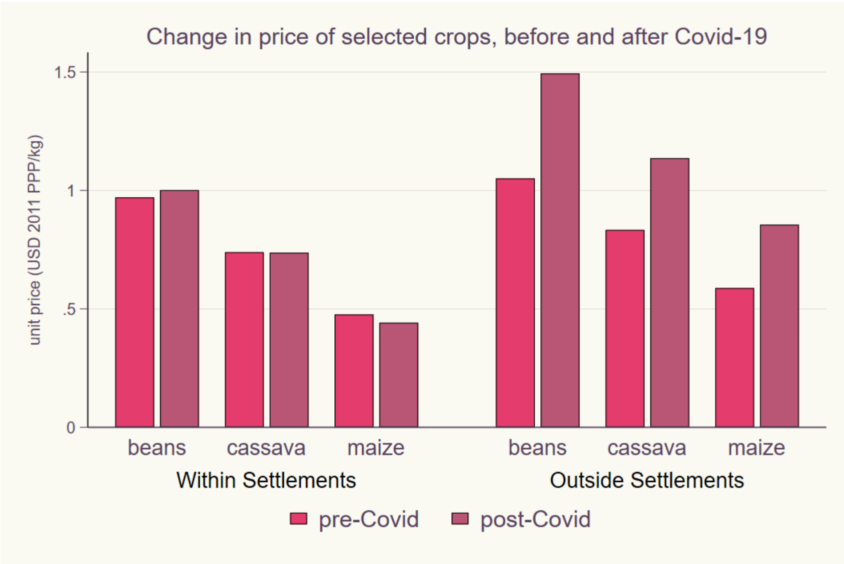
Among other reasons for not being able to buy foods, lack of affordability and price increase are the most frequent responses. Indeed, the price of the main crops increased between 2019 and 2020, although this change was much less pronounced within refugee settlements than outside settlements (Figure 2.2). However, spatial and temporal variations in prices occurred, especially in more integrated markets (Dietrich et al., 2022), with the retail price of

[9]The reasons considered are: "shops have run out of stock", "local market closed", "limited/no transportation", "restriction to go outside". Other reasons, such as "increase in price" and "cannot afford it", were not included in the index because they refer to the consequences of the FVC disruption rather than to the disruption per se.

[10]The percentage is lower than the rate of households that were unable to buy staple food because the indicator of FVC disruption does not include all the reasons available.

beans and maize significantly higher amidst panic-buying and trade disruptions (FAO, 2020; FEWS NET, 2021).

Figure 2.2: Price of selected crops in $2011 PPP, 2019 vs. 2020, and within vs. outside settlements ($/kg)



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

2.2.3 Household types

The analysis has been conducted for the whole sample as well as separately for different household types (see Appendix for household type definition). Both refugee and host households are among the poorest households in the country (World Bank, 2019). However, differences in terms of socioeconomic characteristics exist between the two groups (Appendix 2.5). Refugee households are characterized by a younger head, more frequently a female, and are less educated on average as compared to host households. The per capita daily expenditure of hosts is two thirds higher than that of refugees. Although decreasing with the years since arrival in the country, cash and food transfers remain the main source of livelihood for refugees[11] (Figure 2.3). The land size operated by refugee households is much smaller compared to that of host households (on average 0.4 acres vs. 3.6 acres, respectively).

Furthermore, refugees' future is more uncertain than hosts': despite the welcoming asylum policy, many refugees are not able to acquire Ugandan citizenship[12], thus exacerbating

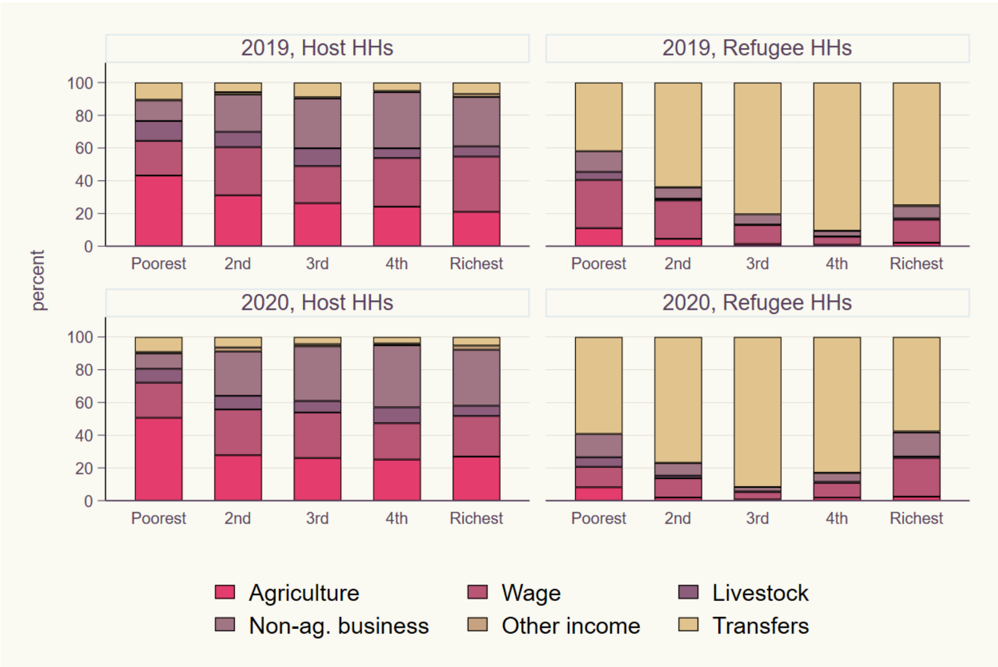
[11]Transfers are still the main source of income for 37% of refugees more than 5 years after their arrival in Uganda (World Bank, 2019).

[12]This applies also to the children of refugees born in Uganda (even when one parent is Ugandan) and their future offspring. As a result, refugees can neither repatriate nor resettle elsewhere (Watera et al.,

isolation (Hovil, 2016) and hindering the refugees' ability to obtain political representation in Uganda (Zakaryan and Antara, 2018). This situation is mirrored in the refugees' poor labor market participation. Indeed, refugees are 35 percentage points less likely than Ugandan nationals to be employed and earn on average 32% less than Ugandan nationals with similar education. Many refugees accept jobs that are below their skill level, and refugees with higher education are more likely to be unemployed (Beltramo et al., 2021).

Agricultural households are defined as households that report some agricultural production in the twelve months prior to the survey (EUROSTAT, 1995; FAO, 2015).

Figure 2.3: Income composition of refugee vs. host households, 2019 and 2020



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Furthermore, considering the COVID-19 induced food price changes, it is important to break agricultural households down into net-buyers, net-sellers, and self-sufficient households. Indeed, a food price increase lowers the welfare of a net-buyer household (and of a non-agricultural household), while may or may not improve the welfare of a net-seller household according to how large marketed surplus is relative to household consumption. On average, net-seller households are better-off: they report higher incomes and higher agricultural revenues in the pre-pandemic period; they own more land and are more educated than other groups; they also report a higher FCS (see Appendix). Self-sufficient and non-agricultural households are the poorest groups. Non-agricultural households are also the group with a

2017).

higher share of income from transfers. Net-buyers instead report the highest level of labor participation and, together with non-agricultural households, are the groups that spend more of their income on food.

The various household groups are distributed differently between refugees and hosts (Table 2.1). Most refugee and host households were net-buyers in 2019 (and to a lesser extent in 2020). However, substantial differences occur between the two groups. Host households generally show a higher share of net-sellers (27-33%) than refugees (7-9%). Refugees report a much higher share of non-agricultural households compared to hosts (more than one-fourth of households). These two results suggest that, although refugees receive a piece of land as part of the Uganda Refugee Policy, many of them are not able to produce an agricultural surplus.

Table 2.1: Distribution of households over the different household types, 2019 and 2020.

	2019			2020		
	Host HHs	Refugee HHs	Total	Host HHs	Refugee HHs	Total
Categories	%	%	%	%	%	%
Net-buyer	40.94	37.34	39.07	31.28	33.49	32.42
Net-seller	26.97	6.79	16.51	32.96	8.88	20.49
Self-sufficient	24.3	26.11	25.24	30.15	31.27	30.73
Non-agricultural	7.79	29.77	19.18	5.61	26.37	16.36
Total	100.0	100.0	100.0	100.0	100.0	100.0

Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

The transition matrix among the different household types (Table 2.2) shows that between 2019 and 2020 many households shifted to agriculture, i.e. 64.8% of total non-agricultural households vis-à-vis only 34.1% moving the other way around, which can be viewed as a coping strategy in response to the COVID-19 shock. At the same time, moving from self-sufficient and net-seller categories to net-buyers (28.5% and 31.1%, respectively) suggests a significant vulnerability to food insecurity among those households that made this shift.

Table 2.2: Transition matrix of agricultural and non-agricultural households.

			2020				
			Net-buyer	Net-seller	Self-suff.	Non-ag	N. observations
2019	Net-buyer	%	37.7	21.0	30.2	11.1	1152
	Net-seller	%	31.1	40.5	21.2	7.2	486
	Self-suff.	%	28.5	17.1	38.7	15.8	745
	Non-ag	%	28.2	7.1	29.5	35.2	563
	Total	%	32.5	20.6	30.7	16.3	2946

Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

2.3 Methodology

2.3.1 Path analysis

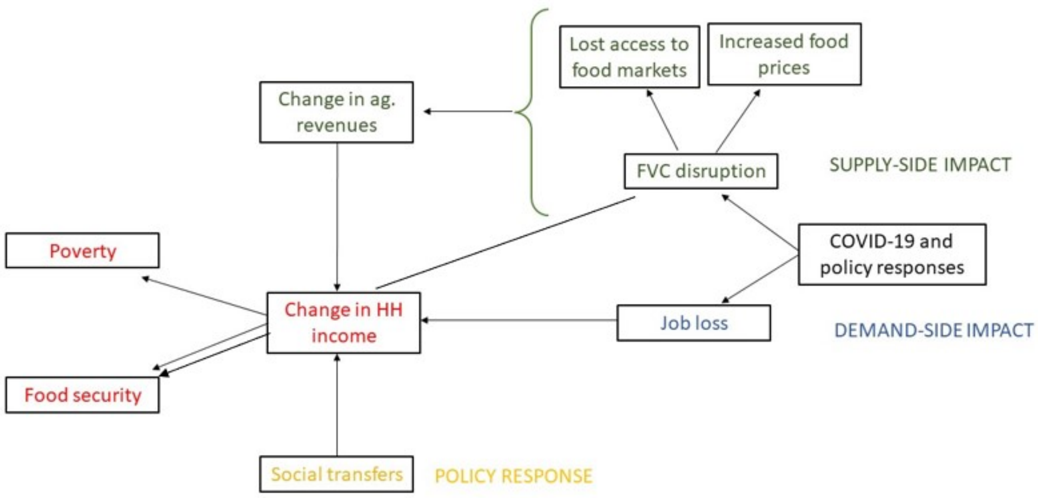
We use structural equation modeling (SEM) (Duncan et al., 1975; Jöreskog, 1970; Wiley, 1973) to answer our research questions. This approach is better suited to model and test complex phenomena, measuring the influence of each variable in mediating direct and indirect effects on the final outcomes, than standard econometric techniques. Specifically, we conduct a path analysis, a precursor to and a subset of the vast SEM family (Kaplan, 2001). Unlike other SEM methods, such as principal component analysis, path analysis does not include a measurement component to estimate latent variables. Therefore, all variables are assumed to be observed. Through path analysis, it is possible to decompose effects into direct, indirect, and total effects, which is extremely important to understanding the main pathways linking the COVID-19 shock to the final outcomes[13]. The total impact of the shock on a given variable along the path is then the sum of (i) the direct effects on that variable, i.e. immediately upstream to the considered variable, and (ii) indirect effects, that are the cumulative impact of all other variables included in the model that are indirectly linked to the considered variable.

The first step in path analysis is the model specification. Path analysis indeed is always theory-driven, meaning that it estimates the effects among the variables once the model has been a priori specified (Vehkalahti, 2011). Therefore, it is essential to have some priors about the causal relationships among the variables under consideration. The conceptual framework on which the path diagram is based (Figure 2.4) has been developed considering the economic theory, early evidence on the effects of COVID-19, and logical relationships among variables.

[13]Throughout the chapter, the use of the term "effect" is not intended to refer to any causal relationship.

Some adjustments have been made in the model, based on modification indices[14].

Figure 2.4: Conceptual framework



Source: own elaboration based on Filipski et al. (2022).

The agricultural household model (Barnum and Squire, 1979; Singh et al., 1986), which posits that household welfare is simultaneously determined by production, consumption, and labor supply decisions, is the reference theoretical framework for the development of our model. According to it, the household total income comprises the production profit, which in turn depends on the marketed surplus in the case of agricultural households, and the earning from labor activities. Total income determines consumption decisions of food and non-food goods, thus affecting both household food security and poverty. The restrictions implemented to contrast the spread of the COVID-19 infection increased transaction costs, the uncertainty on food availability, and eventually the difference between producer and consumer prices of food and agricultural inputs. Under these circumstances, it is more likely that separability does not hold and consumption and production decisions are taken simultaneously (de Janvry et al., 1991). However, it must be noticed that the situation analyzed considers different time frames: when COVID-19 broke out, production decisions related to the growing crops were already taken by the households, while consumption decisions could still be changed. For this reason, a change in price caused by COVID-19 is not expected to directly affect the quantity produced in the model. Nevertheless, it could affect the quantity sold and the agricultural revenues.

[14]Modification indices are score tests that guide modifying a model to obtain a better fit. If a parameter is added based on a large modification index, it is called a "post hoc model modification" and represents a data-driven modification of the original hypothesized model (Mueller and Hancock, 2008)

Early evidence shows that COVID-19 directly affected household welfare in two ways. On the one hand, the closure of local markets, movement restrictions, limited transportation, and closure of international borders determined a disruption of the food value chains. On the other hand, the suspension of economic activities due to lockdown and other restrictions meant also layoffs and closure of businesses (Younger et al., 2020), directly affecting household income. The disruption of the food value chain had a direct impact on prices (UN-HABITAT and WFP, 2020). Therefore, the prices of three crops have been included in the model, namely cassava, maize, and beans[15], which represent the typical staple, intermediate, and cash crops in Uganda, respectively. The change in the quantity of crops sold along with the change in prices affect the agricultural household revenues. The COVID-19-induced change in employment opportunities, which might translate into a reduction of household wage income, along with the change in agricultural revenue, determine a change in total income[16]. This eventually affect poverty and food security. Poverty can also be affected by the level of food prices, as price increases determine a reduction of households' purchasing power. Food security instead can also be directly affected by the FVC disruption, which constrains households' food availability.

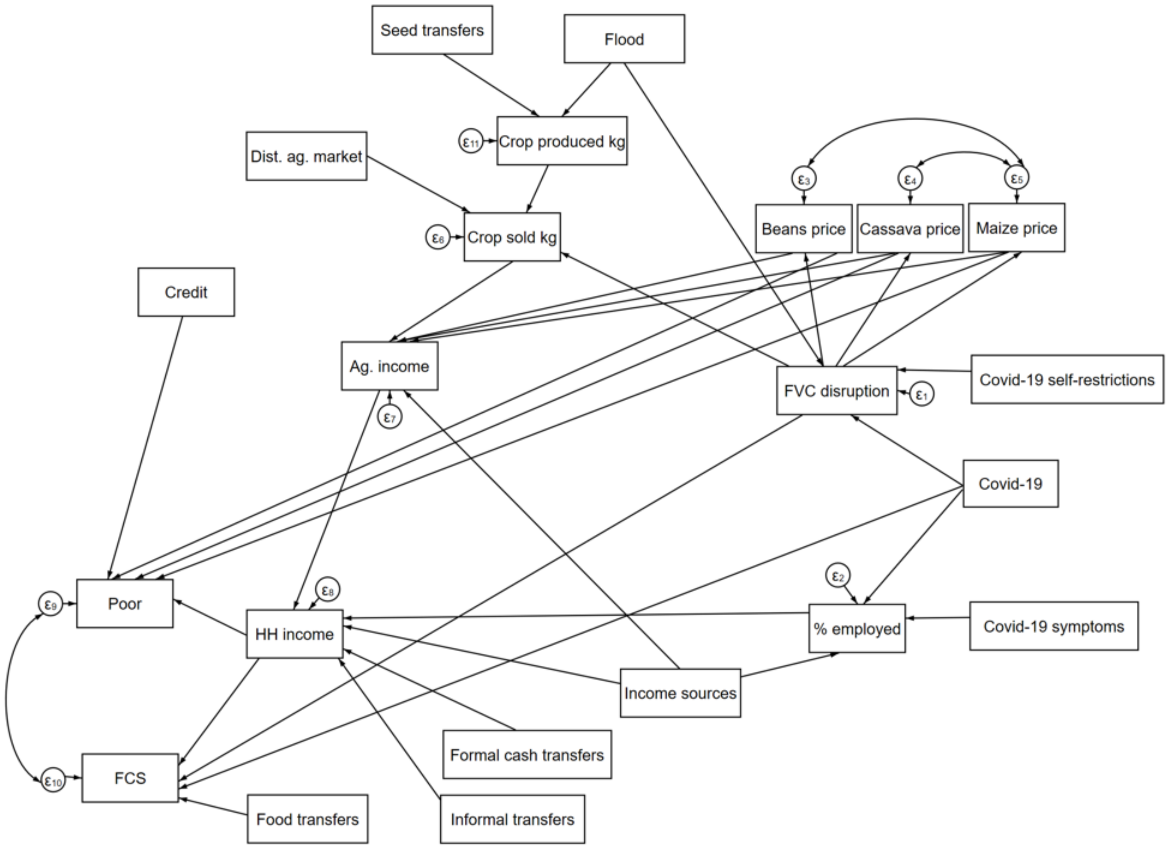
The pattern of relationships among the variables described above is summarized in the path diagram in Figure 2.5. Straight arrows linking two variables indicate the directions of the causal relationships between them. Curved, double-headed arrows instead indicate covariance among variables. This could in principle be the case of poverty and food security, where the two variables are positively correlated, or of price variables, that could reflect substitution or complement relationships. The initial hypotheses of the possible covariances reported in the final model have been generally confirmed by modification indices. These indices also highlighted a possible endogeneity problem caused by omitted variable bias in the relationship between FVC disruption and FCS. Adding the direct association of COVID-19 on FCS solved the problem. This means that the omitted variable was the effect of the pandemic on food security not mediated by the two main channels of transmission but caused by other channels, not explicitly accounted for by our model. Possible channels are for instance the effect of the pandemic on consumption from own production. Indeed, the model explicitly accounts for the effect on agricultural revenues, but it does not take into account the agricultural production used for own consumption. Another possible channel not explicitly reported in the model is

[15]Other relevant staple foods, such as cooking banana (matoke), have not been included because there were too few observations to compute a reliable unit price for this commodity.

[16]Total income is computed as the sum of agricultural revenues, livestock revenues, wage, non-farm business profit, transfers, and other incomes, such as earnings from renting land, house and other durable goods. Income does not include the monetary value of the agricultural production used for own consumption, but it only includes the value of the quantity sold. We therefore refer to cash income

on non-farm self-employment business.

Figure 2.5: Path diagram of the base model.



Some control variables have been included in the model, namely the COVID-19 self-restrictions and the COVID-19 symptoms, flood shock, the number of income sources, transfers, credit, and distance to the nearest agricultural market. The variable of income sources is an indicator of the household income diversification capacity, which is linked to agricultural income and employment opportunities, as well as to total household income. On the one hand, income diversification may be positively linked to the household's income because relying on different sources of income increases the likelihood that some members of the household are involved in the labor market and agricultural activities and helps in managing risk (Ersado, 2006). On the other hand, income diversification could be negatively linked to agricultural income when agriculture is a family business and requires the use of family labor.

Transfers are broken down into: food transfers[17], which directly affect the level of food security; formal cash transfers received by the government; informal transfers from friends and

[17]The commodities included in the General Food Assistance (GFA) basket are maize grain, beans, vegetable oil and salt (WFP, 2020)

family members (including remittances); and the provision of seeds and equipment, which may increase agricultural production and potentially the share of output sold. The household marketed surplus is also affected by the distance to the market, especially in the case of movement restrictions during the COVID-19 outbreak. Finally, access to credit is a key tool to cope with shocks, thus we expect that higher access to credit tends to reduce poverty all other things equal.

2.3.2 Model structure

The model is designed as a recursive model, i.e. with no feedback loops, and it is estimated using maximum likelihood methods, assuming joint normality[18] and homoscedasticity of the error terms. To satisfy this assumption, robust standard errors have been used in estimating the model. Household fixed effects have been added to control for unobserved time-invariant heterogeneity among households. This identification strategy is similar to a classical event study, where all observations are treated. Compared to a mere cross-sectional before-after comparison, as in Egger et al. (2021), the use of fixed effects and control variables allows us to increase our identification strategy. However, since the study is based on a before-and-after comparison, where it is not possible to distinguish between a treatment group and a comparison group, limitations to make causal statements of the findings are required.

The adopted system of equations is as follows, where α_h captures household fixed effects:

$$\begin{cases} FVC\ disruption : y_{1ht} = \alpha_h + \beta_0 Covid_t + \beta_1 Flood_{ht} + \beta_2 Covid\ self\ rest._{ht} + \epsilon_{ht} \\ Job\ loss : y_{2ht} = \alpha_h + \beta_4 Covid_t + \beta_4 Income\ sources_{ht} + \beta_5 Covid\ symptoms_{ht} + \epsilon_{ht} \\ Prices : y_{3ht} = \alpha_h + \beta_6 y_{1yt} + \epsilon_{ht} \ \ where\ y_{3ht} = \{\text{price of beans, cassava and maize}\} \\ Harvested\ quantity : y_{4ht} = \alpha_h + \beta_7 y_{1ht} + \beta_8 Seeds\ transfers_{ht} + \beta_9 Flood_{ht} + \epsilon_{ht} \\ Quantity\ sold : y_{5ht} = \alpha_h + \beta_{10} y_{1ht} + \beta_{11} y_{4ht} + \beta_{12} Distance\ ag.\ market_{ht} + \epsilon_{4ht} \\ Ag.\ income : y_{6ht} = \alpha_h + \beta_{13} y_{5ht} + \beta_{14} y_{3ht} + \beta_{15} Income\ sources_{ht} + \epsilon_{ht} \\ HH\ income : y_{7ht} = \alpha_h + \beta_{16} y_{6ht} + \beta_{17} y_{2ht} + \beta_{18} Formal\ transfers_{ht} + \\ \qquad\qquad + \beta_{19} Informal\ transfers_{ht} + \beta_{20} Income\ sources_{ht} + \epsilon_{ht} \\ Poverty : y_{8ht} = \alpha_h + \beta_{21} y_{7ht} + \beta_{22} y_{3ht} + \beta_{23} Credit_{ht} + \epsilon_{ht} \\ Food\ security : y_{9ht} = \alpha_h + \beta_{24} y_{7ht} + \beta_{25} Covid_t + \beta_{26} Food\ transfers_{ht} + \beta_{27} y_{1ht} + \epsilon_{ht} \end{cases} \tag{2.1}$$

[18]The assumption of multivariate normality is particularly important for maximum likelihood estimation. If the data follow a continuous and multivariate normal distribution, then maximum likelihood yields normal, unbiased, and efficient estimators (Kaplan, 2001)

The goodness of fit of the model has been tested using common fit indexes, such as Chi-square, Tucker Lewis Index (TLI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The Chi-square is a likelihood ratio chi-square that compares the fitted model with a saturated (just-identified) model that perfectly fits the data. If the Chi-square is large and the p-value is small, the model should be rejected.

However, there is a general consensus in the literature that the Chi-square test is highly sensitive to sample size, in that the test statistic tends to be statistically significant in large samples. Indeed, with a large sample, the Chi-square is almost always statistically significant (Barrett, 2007). For instance, the test over the whole sample reports a Chi-square=587.32 with 120 degrees of freedom (df) and p-value=0.000. This means that the model tends to overfit. Another issue with this test is that it does not take into account the df. Indeed, the saturated one used for the comparison is defined with zero df. When instead we run alternative measures of fit that compensate for the effect of the model complexity, such as the RMSEA test, the model shows a good fit. Acceptable values for the other goodness of fit tests are RMSEA < 0.05; SRMR ≤ 0.08; TLI and CFI > 0.9 (Lei and Wu, 2007; Schreiber et al., 2006).

2.3.3 Descriptive statistics

Table 2.3 reports the descriptive statistics of the model variables in 2019 and 2020 and the level of significance of the t-test of the difference in means. Most of the variables show a statistically significant difference between the two years. Specifically, FCS has decreased in 2020 compared to the previous year, while poverty increased. Among the endogenous variables, it is worth noting the increase in the price of beans and cassava, and the reduction in employment. The reduced distance to the nearest agricultural market in 2020 could derive from a reposition of markets as a consequence of the COVID-19 restrictions. None of the transfers instead reported a significant change between the two years, suggesting that households did not receive additional assistance on average as a response to the COVID-19 crisis. This however refers to the entire sample. When decomposing between refugee and host households, changes in transfers could occur, especially among refugees.

Table 2.3: Descriptive statistics of variables included in the model, by year, and t-test of difference in means.

Variables	2019		2020		Mean difference
	Mean	SD	Mean	SD	
Endogenous variables					
FVC disruption	0.00	0.00	0.15	0.51	***
% employed	15.87	24.92	14.80	23.36	*
Bean unit price ($/kg)	1.01	0.48	1.24	3.14	***
Maize unit price ($/kg)	0.53	0.81	0.64	3.45	
Cassava unit price ($/kg)	0.78	0.94	0.93	2.44	**
Crop sold (kg)	2004.17	67414.14	1408.08	39198.51	
Ag. annual income	111.59	315.39	141.01	422.58	**
Per capita HH income	196.96	238.39	202.23	220.17	
Poverty headcount	0.26	0.44	0.29	0.45	*
FCS	46.18	15.21	40.57	14.83	***
Exogenous variables					
COVID-19	0.00	0.00	1.00	0.00	
COVID-19 self-restrictions	0.00	0.00	.034	.181	***
COVID-19 symptoms	0.00	0.00	.055	.228	***
Flood	.22	.417	.238	.426	
N. income sources	1.78	1.03	1.94	1.07	***
Distance to ag. market (km)	2.83	2.75	2.57	2.64	***
Per capita credit amount	14.94	57.89	19.03	104.03	
Per capita informal transfers	3.28	24.93	3.74	26.77	
Per capita food transfers	47.43	182.98	40.94	87.66	
Per capita seeds transfers	.538	6.75	.497	4.14	
Per capita formal cash transfers	52.13	141.65	53.23	145.81	

Note: all monetary values are expressed in USD 2011 PPP; income-related variables are computed as year income. * p<0.05, ** p<0.01, *** p<0.001

2.4 Results

In this section, we first present the results of the whole sample and then for all other household types. The basic model is the one described in Section 2.3.1. This model has been adjusted to account for specific household characteristics in the case of other household groups. Path diagrams report the standardized estimates of direct effects, while the estimates of indirect and total effects have been computed separately[19]. The statistically significant relationships at $p < 0.1$ are drawn as black arrows, with green estimated values if positive and red if negative, while when the relationship is non-statistically significant the arrow is grey. Almost all estimated models show quite good goodness of fit .

[19]While the breakdown into direct, indirect and total effects has been carried out for all household types and informs the comment of results, the table reporting estimates for indirect and total effects is included only for the whole sample because of space limit. However, these estimates are available upon request to the authors.

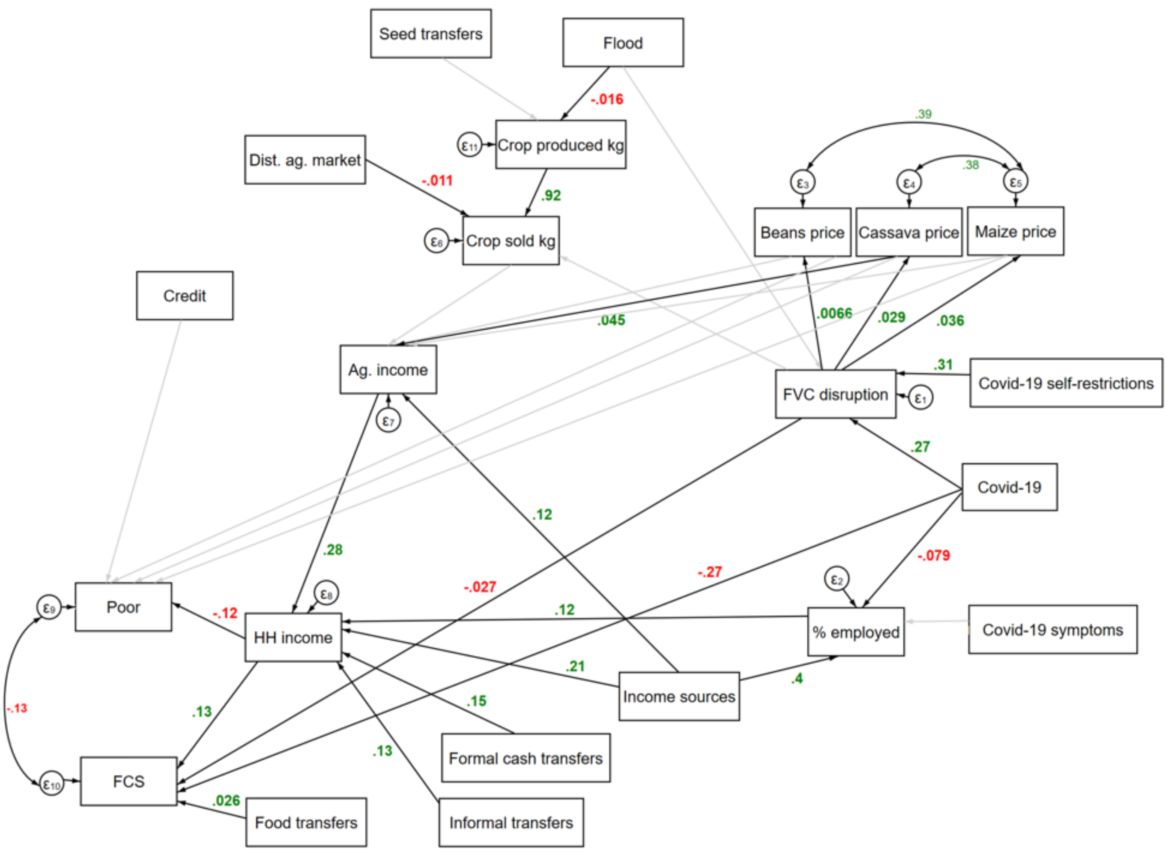
2.4.1 Whole sample

The path diagram for the sample as a whole (Figure 2.6) shows that our initial hypotheses about the COVID-19 transmission channels have been confirmed: COVID-19 determined the disruption of FVC and a reduction of employment. It also directly affected food security, reducing the FCS. Disruptions along the FVC were determined by supply problems as well as by changes in customers' and workers' behavior who adopted self-restrictive practices. An environmental shock such as a flood does not significantly affect the FVC. This suggests that COVID-19 was probably the main shock significantly affecting FVC in 2020. However, the information about having experienced flood is retrieved from self-reported data and might suffer from measurement error and selection bias due to the underreporting of those households who have successfully implemented coping mechanisms. Indeed they are unlikely to be conditionally randomly distributed across the population. The use of geo-referenced data on flooding would help reduce these issues. FVC disruption is associated with a reduction of FCS as well as an increase in food prices. However, the positive effect of FVC disruption on prices is then transmitted to agricultural income[20] in a significant way only through the price of cassava. Although cassava is mainly produced for own consumption rather than for selling, some substitution effects with other crops from the demand side could explain this result. Distance to the agricultural market matters in determining the quantity of crops sold: the farther the market the lower the agricultural output sold. As expected, floods determine a lower harvest, while the greater the harvest the greater the marketed surplus. Transfers, both formal and informal, income diversification, the share of employed household members, and agricultural income are all positively associated with total household income. Income diversification is also linked to a higher probability of having some members of the household still employed during COVID-19 and to a higher income from agriculture. Instead, having members of the household experiencing COVID-19 symptoms does not seem to produce a significant change on employment. Household income is key in determining the level of poverty and food security: an increase in household income reduces poverty and increases the FCS. Although these findings were expected, they confirm specific outcomes. For poverty, an increase in income allows households close to the poverty line to cross it. This result is highly relevant for policymakers. Furthermore, the fact that income is positively linked to food security makes clear the role of financial access in defining the level of food security. Another important variable affecting the final outcomes is food assistance, which improves food security. The goodness of fit of the model over the whole sample

[20]agricultural income, as well all other monetary values, have been divided by 1000 for scaling reasons.

of households has been validated by different tests[21].

Figure 2.6: Standardized estimates of path analysis - all households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Table in Appendix 5 complements Figure 2.6 by reporting the estimates of indirect and total effects. Some interesting results emerge from this decomposition. For instance, household total income is directly positively affected by agricultural income and indirectly negatively affected by the COVID-19 shock mostly through the loss/reduction of employment. However, the total COVID-19 impact on household income is negative, meaning that the negative effect mediated by employment more than offset the positive effect of an increase in agricultural income. Both indirect effects of income diversification on household income are positive, with the agricultural income accounting for roughly 40% of the overall indirect effect on household income, while the pathway mediated by employment accounts for the remaining 60%. The effect of income diversification is then transmitted to the final two outcomes, reducing poverty and increasing FCS.

Cash transfers, both formal and informal, alleviate poverty and enhance food security.

[21] RMSEA = 0.025; CFI = 0.972; TLI = 0.965; SRMR = 0.019

Looking at the total effects of transfers on the two main outcomes, we find that food assistance is highly associated with FCS, while formal cash transfers are relevant in reducing poverty.

Overall, COVID-19 affected more food security than poverty. The most important pathway is mediated by FVC disruption, which accounts for 85.6% of the overall indirect effect. The effect on employment accounts for 14.5%, while the food price increase reduces the negative effects by 0.15% only. Interestingly, COVID-19 self-restrictions show a significant negative relationship with food security only. Finally, while labor market participation affects both poverty and food security, FVC disruption affects only food security, as expected.

2.4.2 Refugee vs. host households

The models for refugee and host households have been slightly changed to account for specific characteristics of the two subsamples (Figures 2.7 and 2.8, respectively). To increase the fit of the model, as suggested by the modification indices and confirmed by the different tests for the goodness of fit, the covariance between employment and agricultural income has been added in both models. Indeed, the two variables are highly correlated with a negative sign. This means that households specialized in agriculture are less likely to participate in the labor market, and vice-versa. In addition, a direct effect of cash transfers on poverty has been added to the refugees' model to capture the refugees' dependency on transfers.

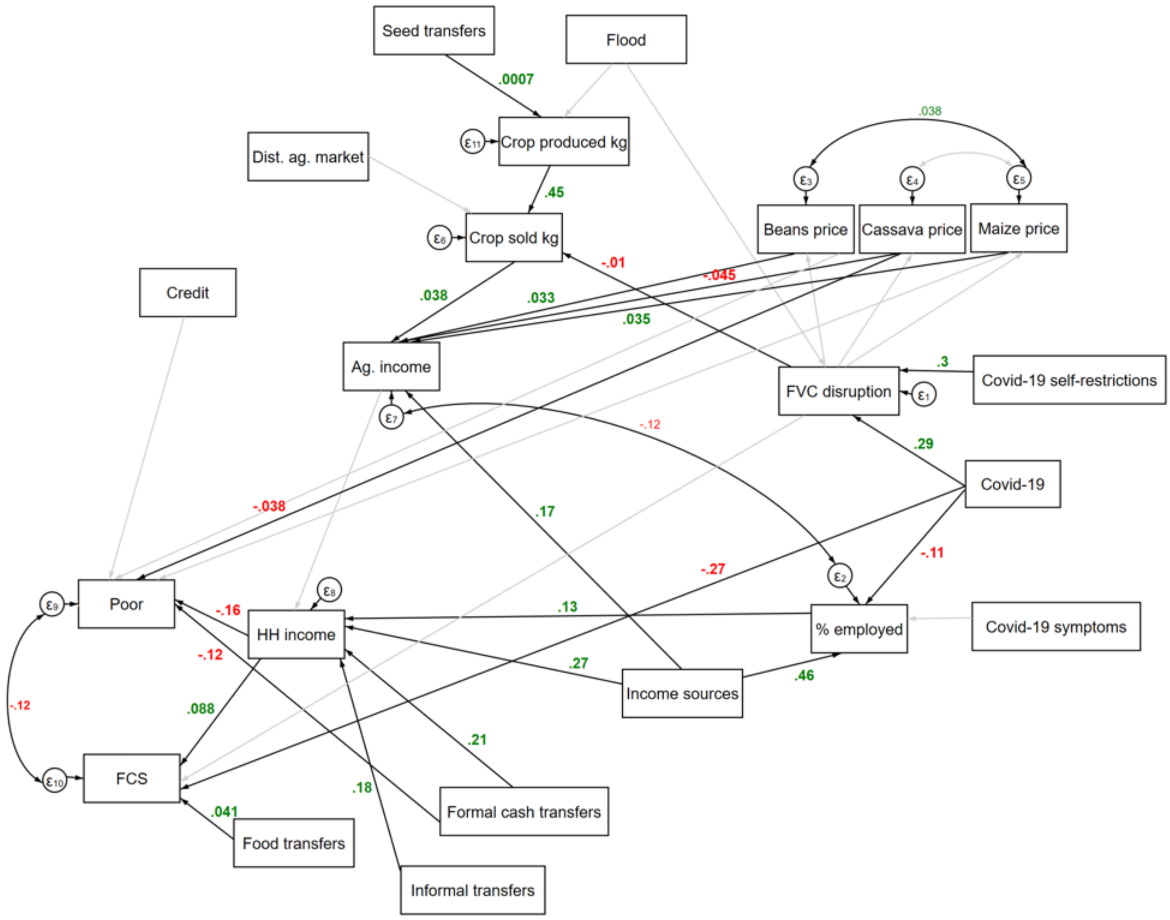
Comparing the two groups, COVID-19 shows a higher direct impact on employment for refugee households. Both types of households instead perceive a similar effect of self-restrictions on FVC. Host households perceive more the effect of FVC disruption on prices. This is expected, given that prices significantly increased outside the settlements (cf. Figure 2.2). Additionally, hosts are more integrated into the market, and therefore they are more responsive to shocks in the food value chain. It is interesting to see how the change in prices of different crops differently affects the two groups. For hosts, COVID-19-induced food price increase is transmitted to agricultural income, and in turn to household income, through the price of cassava. Refugees instead report an opposite relationship: an increase in the cassava price is linked to a reduction in agricultural income, while a positive change in the prices of beans and maize is associated with an increase in income. The different effects on prices between refugees and hosts are also confirmed in their covariances: for hosts, beans and maize and maize and cassava are positively correlated; for refugees instead, the sign is negative though not significant between maize and cassava.

This can be explained by the different composition of crop production between refugees and hosts, by the difference in price changes within and outside settlements, and possibly by substitution effects that occurred on the demand side due to the change in prices. Cassava is mainly produced for own consumption, and only 1.5% of refugee households sell it in the market. Instead, 39% of refugees that consume cassava rely on their own production. The rest mainly purchases it. For maize and beans, they mainly rely on food assistance, with only 25% of households considering their own production as the main source of consumption. Conversely, more than 60% of host households rely on their own production for their consumption of maize, cassava, and beans.

Agricultural income did not have a significant effect on refugees' total income, given that their main livelihood source is transfers. Indeed, estimates for cash transfers on income are significantly higher for refugees than for hosts. Formal transfers are also important to reduce the level of poverty among refugees. For hosts instead, agricultural income significantly matters in determining total household income. COVID-19 had an indirect negative effect on household income, but higher for refugees. This is not only because the magnitude of the relationship is higher for refugees, but also because the negative change on hosts' employment was partly mitigated by the positive effect on agricultural income. Total income is more important in reducing poverty for refugees, while it is highly relevant for food security for hosts. This can be explained by the different sources of food consumption among the two groups. Generally, refugees produce to self-consume and highly rely on food assistance for their food consumption, thus depending less on income. Additionally, refugees report a higher volatility in poverty dynamics than hosts, suggesting that many of them are close to the poverty line. Instead, hosts produce for selling their products in the market and do not receive food aid, so they need to rely more on their income to have an adequate and diversified diet. The use of an indicator of dietary diversity to proxy the level of food security also plays a role in determining these results. Indeed, it does not only look at the minimum adequate caloric intake required, which would suit more for poor households, but it also considers the composition of the diet, which implies additional requirements in terms of money, time, and food availability. Other measures of food security therefore could produce different results. The total final effect of COVID-19 on FCS is similar among refugees and host households, while on poverty the effect is higher for refugees. Both models show a good fit[22].

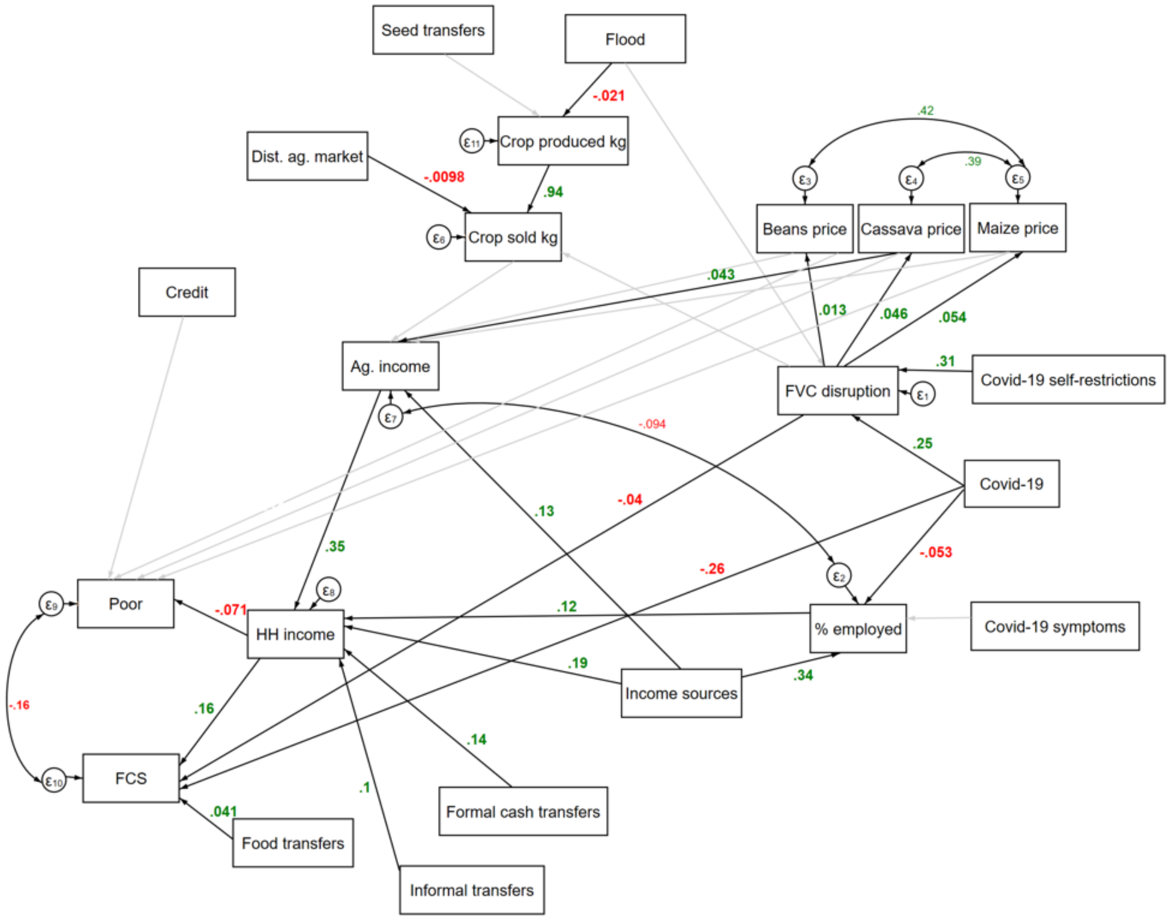
[22]For refugees: RMSEA = 0.023; CFI = 0.938; TLI = 0.921; SRMR = 0.021; overall R-squared = 0.53; for hosts: RMSEA = 0.031; CFI = 0.960; TLI = 0.949; SRMR = 0.027; overall R-squared = 0.40.

Figure 2.7: Standardized estimates of path analysis - refugee households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Figure 2.8: Standardized estimates of path analysis - host households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

2.4.3 Agricultural households

The market position of agricultural households – i.e. being self-sufficient, net-buyer, or net-seller – matters in the transmission of COVID-19 shock. Compared to net-sellers and net-buyers (Figures 2.9 and 2.10, respectively), the model for self-sufficient households has a much more simplified cobweb of relationships (Figure 2.11), typically lacking mediation of the market. For these households, the FVC disruption does not affect crop production, income is quite relevant in defining the level of FCS, while it has no significant effects on poverty. This result could suggest that the change in income for those households was not enough to cross the poverty line, or that the change in income did not translate into a change in expenditure.

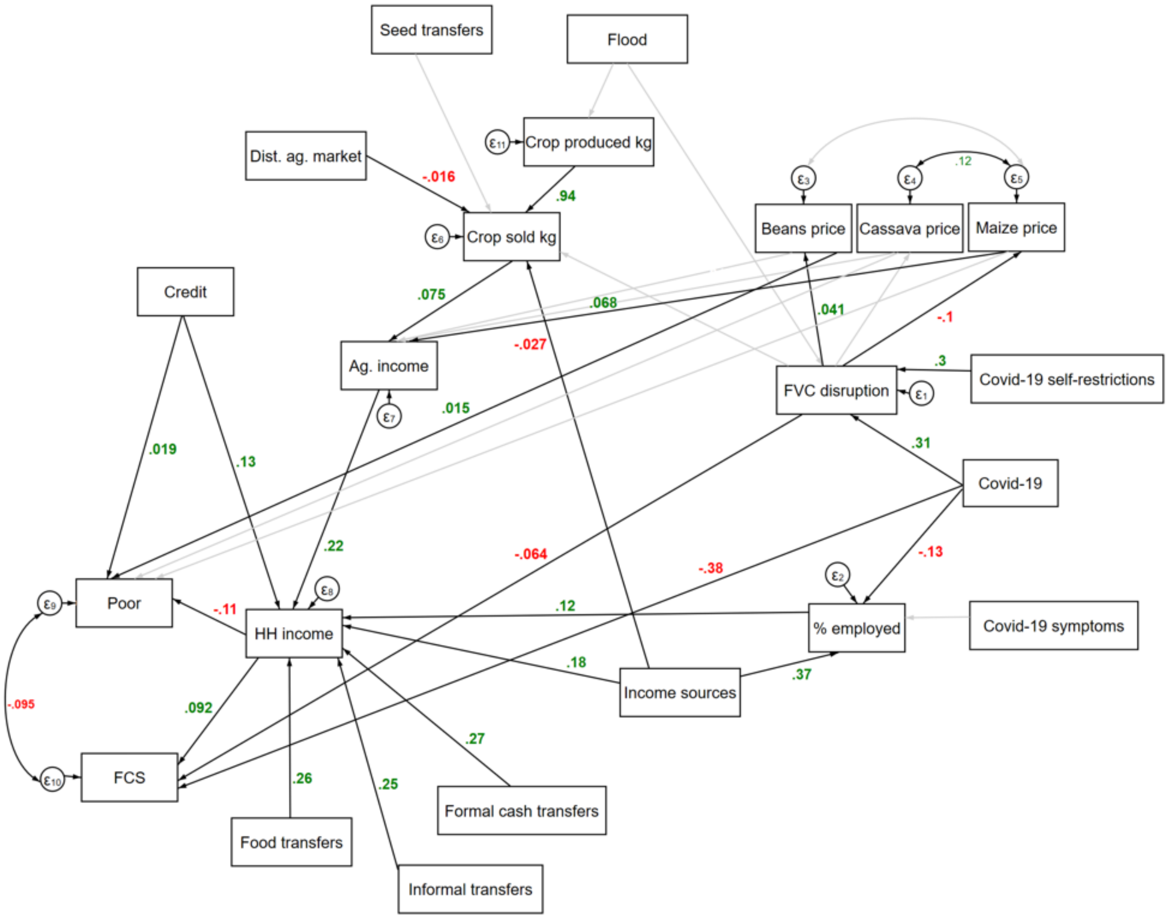
Net-sellers and net-buyers are heavily impacted by COVID-19 through the mediation of the market. An increase in the FVC disruption leads to an increase in the price of beans for both groups. However, while net-seller households transmit this positive effect to agricultural income and eventually to total income, the net-buyer households are negatively hit both on the production and the consumption side. The FVC disruption determines a reduction of the price of maize, and, considering that this price is positively associated with net-buyers' agricultural income, this means a reduction of their revenues. Furthermore, the beans price increase negatively affects net-buyers' welfare, thus increasing poverty.

Net-buyers are much more affected in terms of employment than net-sellers because the formers rely more on wage income and remittances, and even more so for refugee than host net-buyers. The combined negative effect of COVID-19 on employment and production (through the reduction of the price of maize), determines an indirect negative effect on net-buyers' total income. However, the indirect effect is disproportionately channeled through employment (97% of total), while the price of maize reduction contributes only marginally (3% of the indirect effect). Income sources and transfers have a positive role in household income for both net-sellers and net-buyers, eventually affecting poverty and food security. Both income sources and transfers – especially formal and food transfers – are particularly relevant in reducing poverty and increasing food security among net-buyer households, while they are key in increasing food security for net-sellers. The total effect of COVID-19 on FCS is much higher for net-buyers (-.40) than for net-sellers (-.15), while it does not have a significant effect on poverty for both types of households.

All tests for the goodness of fit report acceptable values for both groups, except the RMSEA for net-seller households[23].

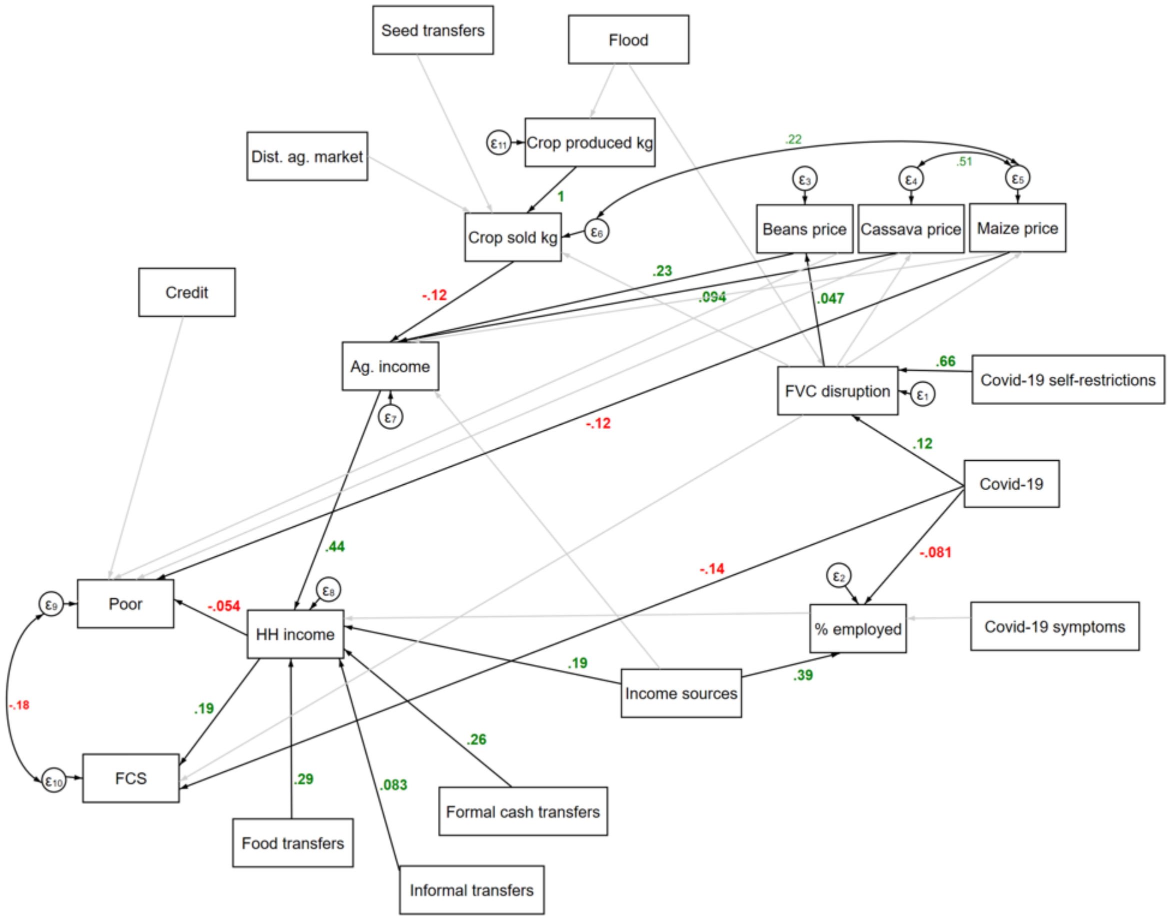
[23]For net-buyers: RMSEA = 0.038; CFI = 0.942; TLI = 0.926; SRMR = 0.037; for net-sellers: RMSEA = 0.070; CFI = 0.945; TLI = 0.931; SRMR = 0.056.; For self-sufficient households: RMSEA=0.036; CFI=0.937; TLI=0.911; SRMR=0.033

Figure 2.9: Standardized estimates of path analysis - Net-buyer households.



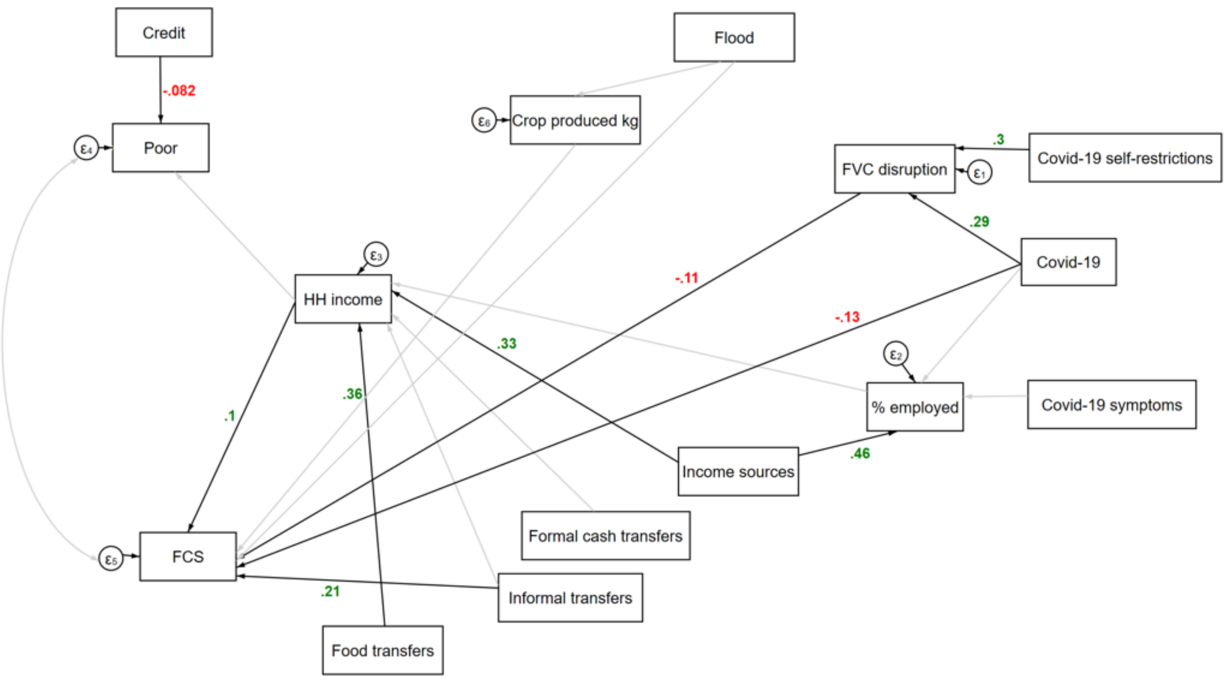
Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Figure 2.10: Standardized estimates of path analysis - Net-seller households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Figure 2.11: Standardized estimates of path analysis - Self-sufficient households.



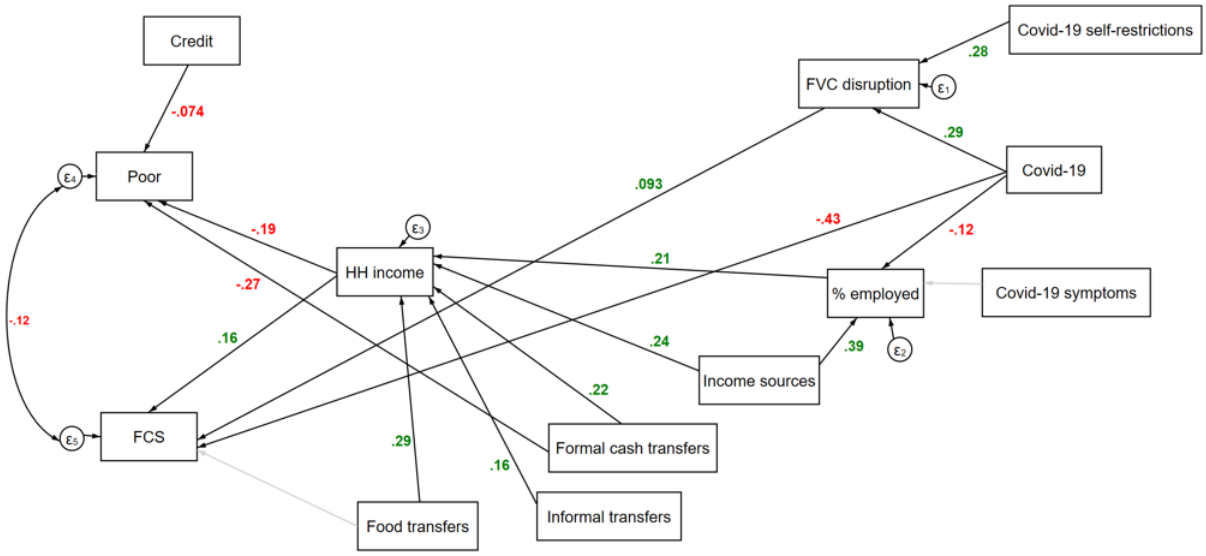
Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

2.4.4 Non-agricultural households

The model for non-agricultural households does not include food prices (Figure 2.12. Indeed, these households are not affected by price changes induced by FVC disruption because they are not involved in agricultural production, while the effect on the consumption side is already captured by the FVC disruption. Being not involved in FVC as farmers, they rely on labor income for their own livelihood: therefore, non-agricultural households perceive the negative effect of COVID-19 through employment more than other types of households. This is also confirmed by the relationship between employment and total income, which is relatively more important for non-agricultural households than for other types of households. They also perceive more the direct negative effect of COVID-19 on FCS.

The indirect effect of COVID-19 mediated by the FVC disruption instead is positive. They probably benefit from the reduction of the maize price, resulting in a positive effect of FVC disruption on food security. Household income plays an important role in reducing poverty and improving FCS. The final total effect of COVID-19 on FCS and poverty is higher for non-agricultural households than for the other types of households. Even in this case, the tests for the goodness of fit of the model report acceptable values[24].

Figure 2.12: Standardized estimates of path analysis - Non-agricultural households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

2.4.5 Robustness check

The attrition rate is significant in our data, amounting to 25.48% between the considered rounds. It is therefore important to check whether our estimates are still representative of the original population (Baulch and Quisumbing, 2010). First, we need to check whether the attrition is random. If this is the case, we do not need to correct for it. To do this we use two tests. The first consists of running an attrition probit with the attrition dummy as the dependent variable and some explanatory variables at baseline that could affect the outcome variable and the probability to drop out from the sample (Fitzgerald et al., 1998). The pseudo R-squared from the attrition probit in Table 2.4 suggests that observable variables explain 8.75% of panel attrition, with half of the variables being significant predictors of attrition. A Wald test of whether these variables are jointly equal to zero confirms that they are significant predictors of attrition (Chi-square(24) = 706.07, Prob > Chi-square = 0.0000).

[24] RMSEA=0.048; CFI=0.936; TLI=0.900; SRMR=0.039

Table 2.4: Attrition probit.

Probit regression		Number of obs.= 6227	
		Wald chi2(24)=706.07	
Log pseudolikelihood = -3911.99		Prob >chi2= 0.000	
		Pseudo R2= 0.0875	
Variables at baseline	Coef.	Robust Std. Err.	P-value
Age of household head	0.007	0.001	0.000
Dep. Ratio	-0.191	0.135	0.157
N. of male adults	0.011	0.029	0.708
N. of female adults	-0.004	0.027	0.877
N. of children<5	0.016	0.023	0.478
Avg years of adult education	-0.006	0.005	0.239
household head is female	-0.065	0.038	0.087
Drought shock	0.115	0.057	0.041
Flood shock	-0.018	0.036	0.619
Refugee	-0.007	0.047	0.890
Wealth index	0.294	0.065	0.000
District=2	-0.956	0.081	0.000
District=3	0.008	0.090	0.927
District=4	-0.041	0.101	0.682
District=5	0.312	0.109	0.004
District=6	-0.757	0.092	0.000
District=7	-0.461	0.087	0.000
District=8	-0.610	0.087	0.000
District=9	-1.071	0.090	0.000
District=10	-0.675	0.093	0.000
household size	0.018	0.015	0.214
Land (acres)	0.038	0.013	0.003
Income sources	-0.062	0.018	0.000
FCS	0.000	0.001	0.904
Constant	0.080	0.154	0.602

The second approach uses pooling tests, in which the equality of coefficients from the baseline sample with and without attritors is tested (Becketti et al., 1988)[25]. Even in this case, the F-test of the joint significance of the attrition dummy and the interaction variables rejects the null hypothesis that attrition is random (F(24), 6179) = 2.19 Prob > F = 0.0007). Given that both tests indicate that attrition is non-random, we proceed by using inverse probability weights that give more weight to observations that remained in the panel than an unweighted regression would (Baulch and Quisumbing, 2010).

Following (Wooldridge, 2010), we ran a probit regression to estimate the probability of being in the panel subsample over a set of variables at baseline (see Table 2.4). The inverse of the estimated probability is the adjusted weight. Table in Appendix 6 reports the coefficients of the path analysis over all households, estimated with original weights vis-à-vis the adjusted ones. Inspection of the left and right-hand sides of the table reveals that the signs, values, and significance of the estimated coefficients are fairly similar.

2.5 Conclusions

This study aims to understand how COVID-19 has impacted poverty and food security of refugee and host households in Uganda. The initial hypothesis was that the main transmission channels are the food value chain disruption and job loss/reduction. Our analysis confirmed that COVID-19 increased FVC disruption and reduced the share of employed people within the household. Experiencing direct COVID-19 symptoms did not have a significant impact on employment, while self-imposed restrictions contributed to exacerbating FVC disruption. This affected food prices, which in turn affected agricultural revenues and total household income. As expected, the reduction of household members' employment negatively impacted household income. Food prices could work either way, depending on the importance of agricultural revenues in total income and on the relative position of the household in the food market, i.e. being net-buyer or net-seller. Cash transfers and income diversification have proven to be key determinants of household disposable income, playing a positive role in offsetting the COVID-19 negative shock. COVID-19 ultimately affected both poverty and food security, though FCS was impacted to a greater extent.

The comparison of refugee and host households shows that the former has been more

[25]The Becketti et al. test involves regressing an outcome variable from the first wave of a survey on household and community variables, an attrition dummy, and the attrition dummy interacted with the other explanatory variables. F-test of the joint significance of the attrition dummy and the interaction variables is then conducted to determine whether the coefficients from the explanatory variables differ between households who are retain or drop from the panel (Baulch and Quisumbing, 2010)

affected than the latter both directly and indirectly. Host households, that feature a higher share of agricultural income, benefited from the COVID-19 induced food price increase, while refugees were negatively affected through the impact on the labor market, i.e. the loss of casual employment opportunities, significantly compromising the diet of refugee households (IPC, 2021). Cash transfers were key in offsetting the negative consequences of COVID-19 on refugees' total income and eventually on poverty, while food assistance was crucial in ensuring food security.

Looking at the results among the three agricultural household subgroups, net-buyers are the group most affected by both transmission channels, with a final negative impact on FCS higher than on poverty. Net-buyer households were negatively affected as producers as well as consumers. Vice versa, the impact on net-seller households was mixed. Furthermore, agricultural net-buyer households, along with non-agricultural households, are the most affected groups through the employment channel, being highly dependent on off-farm incomes.

These findings suggest several policy insights. First, the fact that refugees generally do not sell food prevents them to take advantage of the food price increase, while they are significantly negatively affected by the job loss/reduction. Four main reasons explain why refugees are not able to profit from participating in agricultural market transactions:

(a) Refugee households usually operate too small pieces of land that are not large enough to generate a marketed surplus;

(b) Refugees face more constraints than locals in accessing the market because of the loss of social and human capital after fleeing their home country, language and communication barriers, and physical isolation from the rest of the country's economy;

(c) A fast-increasing refugee population faces increasingly limited off-farm employment opportunities, resulting in limited labor market participation.

The determinants of refugees' limited participation in market transactions can be targeted by policy interventions aiming at fostering their integration into the market. For instance, more off-farm employment opportunities could contribute to a more efficient agricultural production by distributing land only to those really interested in farming while providing a larger piece of land to the recipient households, and would allow a better use of refugees' human capital in the country, thus improving the local economy (Filipski et al., 2022). In addition, while transfers can be an important tool to manage/cope with a negative shock (Daidone et al., 2019; Hoddinott et al., 2018), it is well known that they are not that good at serving more developmental, longer-term objectives. They should be coupled with interventions that can help overcome the emergency-development dichotomy, such as promoting agricultural investment or extension services[26]. This would prove helpful, especially in a recovery phase, as investing in infrastructure increases returns to assets currently available.

A second important finding of this study is the vulnerability of the labor market, especially for refugees. Wage income represents the second most important source of income for refugees after transfers. Safeguarding labor participation in the wake of significant shocks is key to ensuring the livelihood of vulnerable groups. This can be done through: (i) short-run (i.e. emergency) social welfare programs to alleviate the negative consequences of the loss of employment; and (ii) medium-long run interventions aiming at guaranteeing equal and stable opportunities of work for both refugees and Ugandan citizens. In particular, refugees are mostly employed in casual jobs that systematically do not match their skills and are paid less than nationals[27] (Beltramo et al., 2021; Loiacono and Vargas, 2019). Several activities can be undertaken to improve refugees' access to formal better-paid jobs, including assessing refugees' skills and facilitating job matching soon after arrival, providing timely training to improve their skills, and facilitating the recognition of certificates and degree equivalence. The lack of decent employment for refugees not only represents an inefficient use of resources, in terms of human capital, but, as shown in this analysis, it also increases the refugees' vulnerability to shocks, resulting in humanitarian assistance dependence and possibly poverty traps.

Finally, our analysis also highlights the importance to take measures specifically targeted to contrast the negative impact of COVID-19 on food security. This is particularly relevant for those households with reduced or no access to self-produced food such as non-agricultural and net-buyer households. This result suggests that food assistance should be better targeted to support those households that cannot rely on their own production as a coping strategy, especially non-agricultural households, for whom food transfers have the highest indirect effect on FCS than other types of transfers.

[26]Only 30% of refugee households received training in 2019. COVID-19 restrictions further decreased this share to 16% in 2020.

[27]According to Loiacono and Vargas (2019), discrimination in the labor market towards refugees, inconsistency, cost of compliance with local regulations and employers" lack of information about the legal status of refugees are all determinants of the refugees' poor market participation.

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Appendix

Household classification

Households are classified according to different criteria, namely: a) refugee status, b) main income source, and c) market position.

(a) *Refugee status*: A household is classified as a refugee as per natural classification based on the answer to the question related to the household type: refugee Uganda national.

(b) *Main income source*: A household is classified as agricultural when it has some positive crop production, measured in terms of quantity. Otherwise, it is considered a non-agricultural household.

(c) *Agricultural household market position*: Agricultural households are classified as net buyers, net sellers, and self-sufficient households according to the following procedure:

   (1) Compute the monetary value of staple food production, sales, and purchases. We focused on staple foods because are (i) typically marketed and produced; (ii) relevant for food security and (iii) relevant for the expected food insecure livelihood groups (WFP 2009). Staple food includes cereals, white tubers and roots, pulses/legumes, seeds and nuts;

   (2) Compute the value of household staple food consumption as production + purchases – sales;

   (3) Identify a ratio x = ((purchases - sales) / consumption) according to which households are considered:

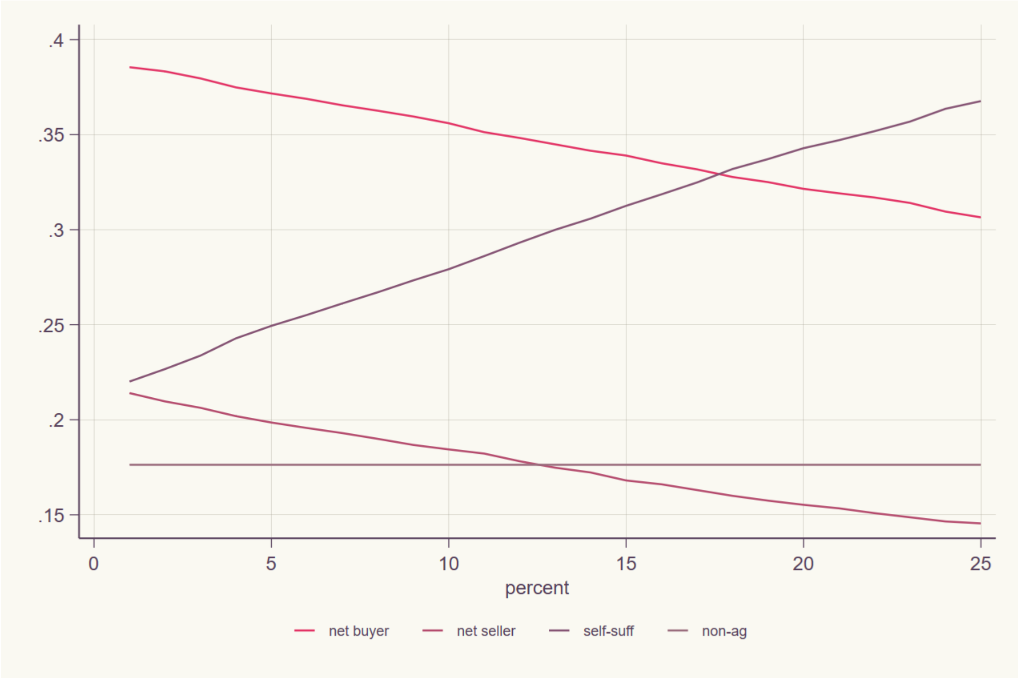
   • self-sufficient: if ((purchases – sales) / consumption) < |x|;

   • net-buyer: if ((purchases – sales) / consumption) x;

   • net-seller: if ((purchases – sales) / consumption) -x.

We explored the change in the subgroup sample size varying parametrically x in the range x = 0.01,..., 0.25 (Figure 13). Considering a reasonably low x and a sufficiently large sample size in each sub-group, we eventually picked a threshold of |x| = 10%. This threshold gives a share of households in the self-sufficient group similar to other countries (WFP 2009).

Figure 13: Change of household categories over different "x".



Descriptive statistics, pre-pandemic.

Variables	Total	Agricultural categories Non-ag.	Ag.	Net-buyers	Net-sellers	Self-sufficient	Refugee status Refugees	Hosts
Age of household head (years)	43.61	42.4	43.9	43.67	46.36	42.76	40.64	46.84
Household head is female	0.36	0.44	0.34	0.36	0.26	0.36	0.48	0.22
Household size	6.31	5.92	6.4	6.46	6.33	6.32	6.19	6.43
Dependency ratio	0.49	0.48	0.5	0.49	0.52	0.49	0.47	0.52
Education of household head (years)	5.81	5.22	5.95	5.85	6.41	5.83	5.29	6.37
% employed in the household	0.16	0.15	0.16	0.17	0.14	0.16	0.17	0.15
Distance to ag. market (Km)	2.83	2.2	2.98	2.74	3.02	3.3	2.45	3.25
N. income sources	1.78	1.37	1.88	1.84	2.3	1.67	1.75	1.82
Crop produced (Kg)	1987	0	2456	631	8437	1412	550	3547
Crop sold (Kg)	1438	0	1778	290	7920	94	81	2910
Ag. revenues (USD $ in 2011 PPP)	112	13	135	64	399	74	19	212
Per capita household income (USD $ in 2011 PPP)	197	187	199	201	245	169	224	168
FCS	46.2	42.2	47.1	46.5	50.8	45.8	42.2	50.5
Poverty headcount	0.26	0.4	0.23	0.11	0.18	0.44	0.4	0.11
Household experienced flood	0.24	0.14	0.26	0.27	0.33	0.22	0.21	0.28
Household experienced drought	0.24	0.16	0.26	0.25	0.26	0.27	0.16	0.32
Maize unit price (USD $ in 2011 PPP/kg)	0.53	0.46	0.55	0.51	0.58	0.6	0.48	0.59
Cassava unit price (USD $ in 2011 PPP/kg)	0.8	0.77	0.8	0.76	0.8	0.86	0.74	0.85
Beans unit price (USD $ in 2011 PPP/kg)	1.01	0.93	1.03	0.99	1.17	1.00	0.97	1.05
Per capita seeds transfer (USD $ in 2011 PPP)	0.54	0.14	0.63	0.45	0.78	0.83	0.39	0.7
Per capita food transfers (USD $ in 2011 PPP)	58.18	133.88	40.31	24.84	22.63	74.62	110.54	1.37
Per capita formal cash transfers (USD $ in 2011 PPP)	52.13	57.06	50.96	80.79	24.95	22.69	95.53	5.04
Per capita informal transfers (USD $ in 2011 PPP)	3.29	2.64	3.44	4.59	2.65	2.07	2.1	4.58
Per capita credit amount (USD $ in 2011 PPP)	14.94	7.13	16.78	15.46	30.39	10.22	5.79	24.87
Per capita daily expenditure	0.37	0.33	0.38	0.47	0.39	0.24	0.28	0.46
Wealth index	0.03	-0.29	0.11	0.05	0.53	-0.07	-0.29	0.38
Land size (acres)	1.93	0.71	2.22	1.93	3.17	2.07	0.41	3.58
Ag. income share	0.16	0.02	0.19	0.13	0.43	0.13	0.03	0.31
Wage income share	0.21	0.18	0.21	0.23	0.17	0.21	0.15	0.27
Livestock income share	0.05	0.03	0.05	0.05	0.08	0.04	0.01	0.09
Non-ag. business income share	0.15	0.11	0.16	0.17	0.13	0.16	0.07	0.24
Transfer income share	0.43	0.65	0.38	0.42	0.17	0.45	0.74	0.08
Other income share	0.01	0	0.01	0.01	0.01	0.01	0	0.01
Obs.	2969	563	2383	1152	486	745	1545	1424

Note: all monetary values are expressed in USD 2011 PPP; income-related variables, including transfers, are annual values. Descriptive statistics refer to 2019.

Indirect and Total effects of the model over all households.

Indirect effects	Std. Coef.	*Total effects*	Std. Coef.
Beans price		FVC disruption	
Flood	-0.0001	Flood	-0.016
COVID-19 self-restrictions	0.0021**	COVID-19 self-restrictions	0.3106***
COVID-19	0.0018**	COVID-19	0.2738***
Cassava price		% employed	
Flood	-0.0005	COVID-19	-0.0785***
COVID-19 self-restrictions	0.0091*	COVID-19 symptoms	-0.0021
COVID-19	0.0080*	Income sources	0.3986***
Maize price		Beans price	
Flood	-0.0006	Flood	-0.0001
COVID-19 self-restrictions	0.0111*	COVID-19 self-restrictions	0.0021**
COVID-19	0.0098*	FVC disruption	0.0066**
Crop sold (Kg)		COVID-19	0.0018**
Flood	-0.0143*	Cassava price	
COVID-19 self-restrictions	-0.0004	Flood	-0.0005
COVID-19	-0.0004	COVID-19 self-restrictions	0.0091*
Seeds transfer	0.0037	FVC disruption	0.0293*
Ag. income		COVID-19	0.0080*
Crop produced (Kg)	-0.0266	Maize price	
FVC disruption	0.0013*	Flood	-0.0006
COVID-19	0.0004*	COVID-19 self-restrictions	0.0111*
COVID-19 self-restrictions	0.0004*	FVC disruption	0.0358*
Distance ag. market (Km)	0.0003	COVID-19	0.0098*
Flood	0.0004	Crop produced (Kg)	
Seeds transfer	-0.0001	Flood	-0.0156*
Pc household income		Seeds transfer	0.0041
FVC disruption	0.0004*	Crop sold (Kg)	
Beans price	0.0043	Crop produced (Kg)	0.9188***
Cassava price	0.0125***	FVC disruption	-0.0013

Maize price	-0.001
Crop sold (Kg)	-0.0081
Crop produced (Kg)	-0.0074
COVID-19	-0.0094***
Income sources	0.0807***
Distance ag. market (Km)	0.0009
COVID-19 self-restrictions	0.0001*
COVID-19 symptoms	-0.0003
Flood	0.0001
Seeds transfer	-0.00003
FCS	
FVC disruption	0.00005*
% employed	0.0157***
Beans price	0.0006
Cassava price	0.0016***
Maize price	-0.0001
Crop produced (Kg)	-0.001
Crop sold (Kg)	-0.0011
Ag. income	0.0365***
COVID-19	-0.0085**
Income sources	0.0385***
Distance ag. market (Km)	0.00001
Seeds transfer	-0.000004
Formal cash transfer	0.0190***
Informal transfer	0.0170***
COVID-19 self-restrictions	-0.0082**
COVID-19 symptoms	-0.00003
Flood	0.0004
Poor	
FVC disruption	-0.0008
% employed	-0.0146***
Beans price	-0.0005
Cassava price	-0.0015***
Maize price	0.0001

COVID-19	-0.0004
Distance ag. market (Km)	-0.0111**
Flood	-0.0143*
COVID-19 self-restrictions	-0.0004
Seeds transfer	0.0037
Ag. income	
FVC disruption	0.0013*
Beans price	0.0155
Cassava price	0.0448***
Maize price	-0.0035
Crop produced (Kg)	-0.0266
Crop sold (Kg)	-0.0289
COVID-19	0.0004*
Income sources	0.1166***
Distance ag. market (Km)	0.0003
Flood	0.0004
COVID-19 self-restrictions	0.0004*
Seeds transfer	-0.0001
Pc household income	
FVC disruption	0.0004*
% employed	0.1207***
Beans price	0.0043
Cassava price	0.0125***
Maize price	-0.001
Crop produced (Kg)	-0.0074
Crop sold (Kg)	-0.0081
Ag. income	0.2795***
COVID-19	-0.0094***
Income sources	0.2951***
Distance ag. market (Km)	0.0001
Flood	0.0001
COVID-19 self-restrictions	0.0001*
COVID-19 symptoms	-0.0003
Seeds transfer	-0.00003

Crop produced (Kg)	0.0009
Crop sold (Kg)	0.001
Ag. income	-0.0338***
COVID-19	0.0009***
Income sources	-0.0356***
Distance ag. market (Km)	-0.00001
Seeds transfer	0.000004
Formal cash transfer	-0.0176***
Informal transfer	-0.0158***
Flood	-0.000001
COVID-19 self-restrictions	-0.00025
COVID-19 symptoms	0.00003

Formal cash transfer	0.1460***
Informal transfer	0.1304***
FCS	
FVC disruption	-0.0265**
% employed	0.0157***
Pc HH income	0.1304***
Beans price	0.0006
Cassava price	0.0016***
Maize price	-0.0001
Crop produced (kg)	-0.001
Crop sold (kg)	-0.0011
Ag. income	0.0364***
COVID-19	-0.2806***
Income sources	0.0385***
Flood	0.0004
COVID-19 self-restrictions	-0.0082**
COVID-19 symptoms	-0.00003
Distance ag. market (Km)	0.00001
Seeds transfer	-0.000004
Food transfer	0.0261***
Formal cash transfer	0.0190***
Informal transfer	0.0170***
Poor	
FVC disruption	-0.0008
% employed	-0.0146***
Pc HH income price	-0.1208***
Beans price	-0.0036
Cassava price	-0.0007
Maize price	-0.0211
Crop produced (Kg)	0.0009
Crop sold (Kg)	0.001
Ag. income	-0.0338***
COVID-19	0.0009***
Income sources	-0.0356***

Credit	-0.0049
Distance ag. market (Km)	-0.00001
Flood	-0.000001
COVID-19 self-restrictions	-0.0002
COVID-19 symptoms	0.00003
Seeds transfer	0.000004
Formal cash transfer	-0.0176***
Informal transfer	-0.0158***

Note: * p<0.05, ** p<0.01, *** p<0.001

Standardized estimates of path analysis over all households, without and with attrition weights.

	Without attrition weights			With attrition weights		
	Std. Coef.	Robust Std. Err.	P-value	Std. Coef.	Robust Std. Err.	P-value
FVC disruption						
COVID-19	0.274	0.006	0	0.282	0.007	0
Flood	-0.016	0.011	0.154	-0.033	0.014	0.015
COVID-19 self-rest.	0.311	0.013	0	0.287	0.014	0
Constant	0.013	0.019	0.467	-0.001	0.021	0.961
% employed						
COVID-19	-0.079	0.012	0	-0.065	0.014	0
COVID-19 symptoms	-0.002	0.013	0.867	0.002	0.014	0.913
Income sources	0.399	0.01	0	0.404	0.011	0
Constant	0.084	0.033	0.012	0.016	0.038	0.669
Beans price						
FVC disruption	0.007	0.003	0.026	0.008	0.003	0.007
Constant	0.705	0.088	0	0.777	0.101	0
Cassava price						
FVC disruption	0.029	0.015	0.056	0.04	0.02	0.041
Constant	0.659	0.082	0	0.604	0.076	0
Maize price						
FVC disruption	0.036	0.021	0.084	0.029	0.019	0.135
Constant	0.321	0.056	0	0.341	0.067	0
Crop produced (Kg)						
Flood	-0.016	0.008	0.063	-0.014	0.007	0.053
Seed transfers	0.004	0.003	0.24	0.004	0.003	0.164
Constant	0.079	0.022	0	0.073	0.023	0.001
Crop sold (kg)						
FVC disruption	-0.001	0.003	0.599	-0.001	0.002	0.591
Crop produced (Kg)	0.919	0.046	0	0.924	0.045	0
Dist. Ag. market (Km)	-0.011	0.005	0.038	-0.013	0.006	0.039

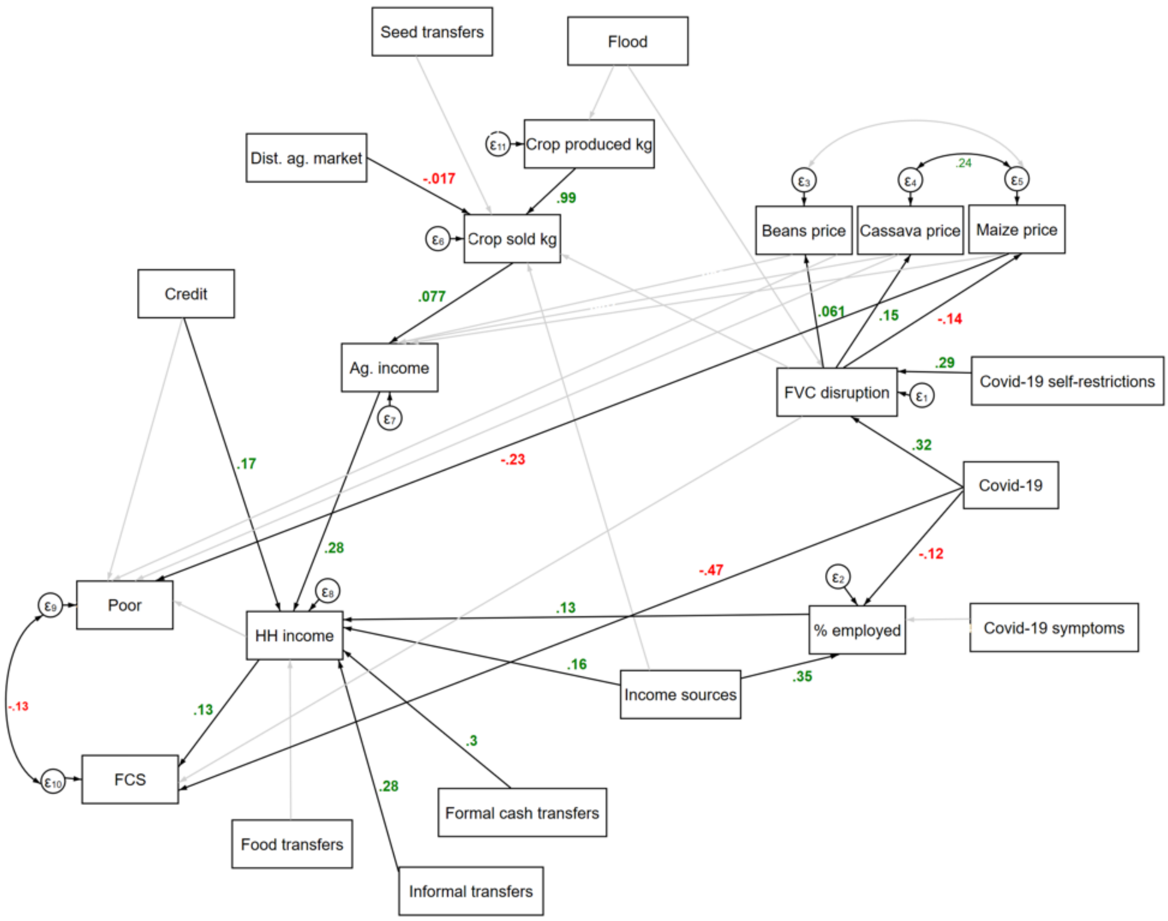
Constant	-0.003	0.011	0.776	-0.001	0.012	0.938
Ag. income						
Crop sold (Kg)	-0.029	0.039	0.454	-0.049	0.044	0.265
Beans price	0.016	0.015	0.296	0.013	0.011	0.234
Cassava price	0.045	0.009	0	0.047	0.009	0
Maize price	-0.004	0.012	0.774	0	0.01	0.981
Income sources	0.117	0.013	0	0.112	0.013	0
Constant	0.195	0.04	0	0.259	0.037	0
Pc HH income						
Ag. income	0.28	0.019	0	0.247	0.021	0
% employed	0.121	0.019	0	0.127	0.02	0
Income sources	0.214	0.016	0	0.198	0.018	0
Formal cash transfers	0.146	0.029	0	0.111	0.03	0
Informal transfers	0.13	0.014	0	0.147	0.019	0
Constant	0.35	0.042	0	0.345	0.045	0
FCS						
FVC disruption	-0.027	0.013	0.042	-0.012	0.015	0.41
Pc HH income	0.13	0.012	0	0.134	0.014	0
COVID-19	-0.272	0.013	0	-0.259	0.014	0
Food transfers	0.026	0.008	0.002	0.036	0.008	0
Constant	4.539	0.051	0	4.534	0.054	0
Poor						
Pc HH income	-0.121	0.011	0	-0.115	0.012	0
Beans price	-0.003	0.013	0.807	-0.013	0.013	0.326
Cassava price	0.001	0.009	0.928	-0.006	0.009	0.513
Maize price	-0.021	0.015	0.157	-0.017	0.015	0.257
Credit	-0.005	0.008	0.55	-0.011	0.009	0.241
Constant	1.142	0.025	0	1.135	0.027	0
Cov(FCS,Poor)	-0.13	0.012	0	-0.139	0.014	0
Cov(Beans price, Maize price)	0.393	0.117	0.001	0.333	0.109	0.002
Cov(Cassava price, Maize price)	0.382	0.152	0.012	0.395	0.154	0.01

Agricultural categories across refugee and host households

To better understand the specific effects of COVID-19 over the different types of households for refugees and hosts, we should carry out the analysis combining each agricultural household category with the subsamples of host and refugee households. Unfortunately, two household categories, specifically net-seller refugees and non-agricultural hosts, have too few observations to run the model. However, the comparison between hosts and refugees is still possible for net-buyers and self-sufficient households.

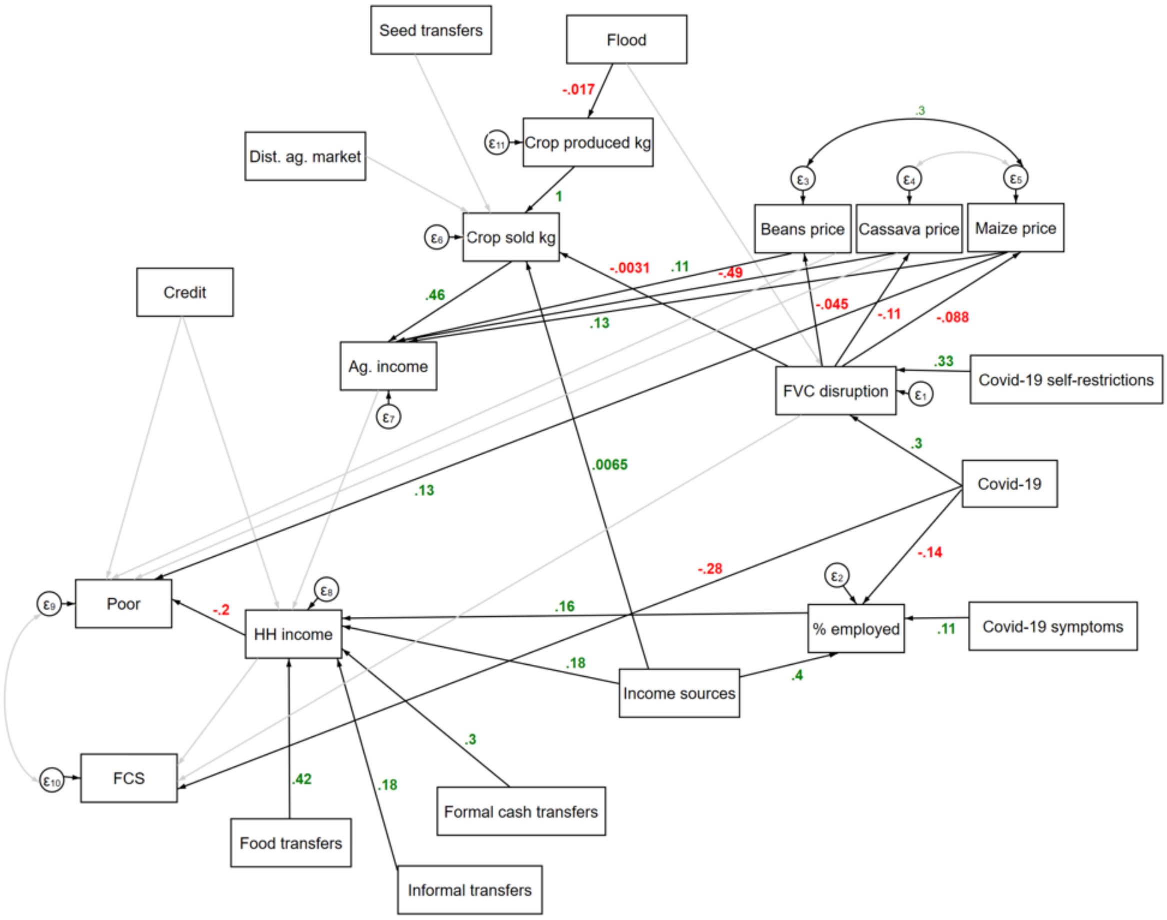
Figures 14 and 15 report the estimates for the net-buyer category. We can see that COVID-19 significantly affects employment both for refugees and for hosts, though the effect is stronger among the former. Both groups experience a reduction in the price of maize due to the FVC disruption. However, for hosts, this reduction is offset by the increase in the prices of cassava and beans. Refugees, on the contrary, experience a reduction in the price of all three crops. For them, the reduction of the price of maize positively affects consumption, but it is detrimental on the production side because it is associated with lower agricultural revenues. For hosts instead, a reduction in maize price is linked to a poverty increase. This increase however is artificially produced by the use of expenditure to compute the level of poverty. Maize indeed is a basic food item which cannot be easily substituted, therefore if its price increases, households are forced to spend more to buy the same amount. This is expected to mainly occur among net-buyers and non-agricultural households, which cannot rely on their own production. Agricultural income is an important component of household income for hosts. Agricultural income has no significant effect on the total income of refugees, which largely depends on food transfers for gaining their own livelihood. Total household income is important in reducing the level of poverty for refugees, while it is more important to increase FCS for hosts.

Figure 14: Standardized estimates of path analysis - Net-buyer host households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

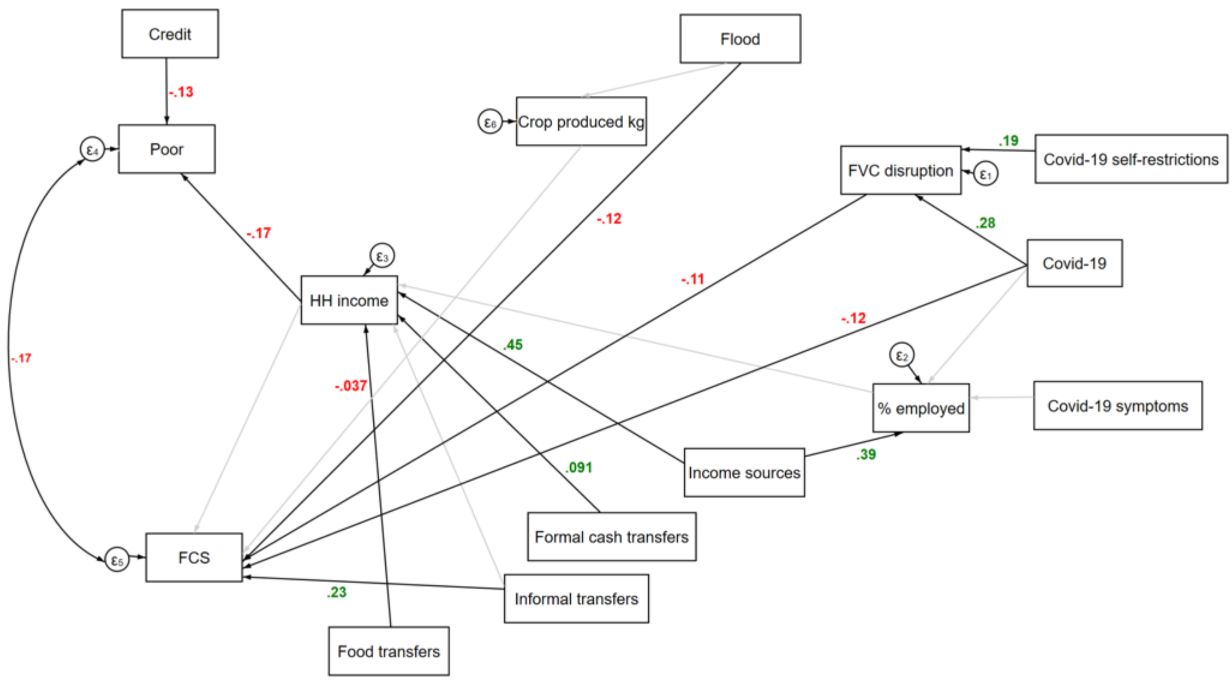
Figure 15: Standardized estimates of path analysis - Net-buyer refugee households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

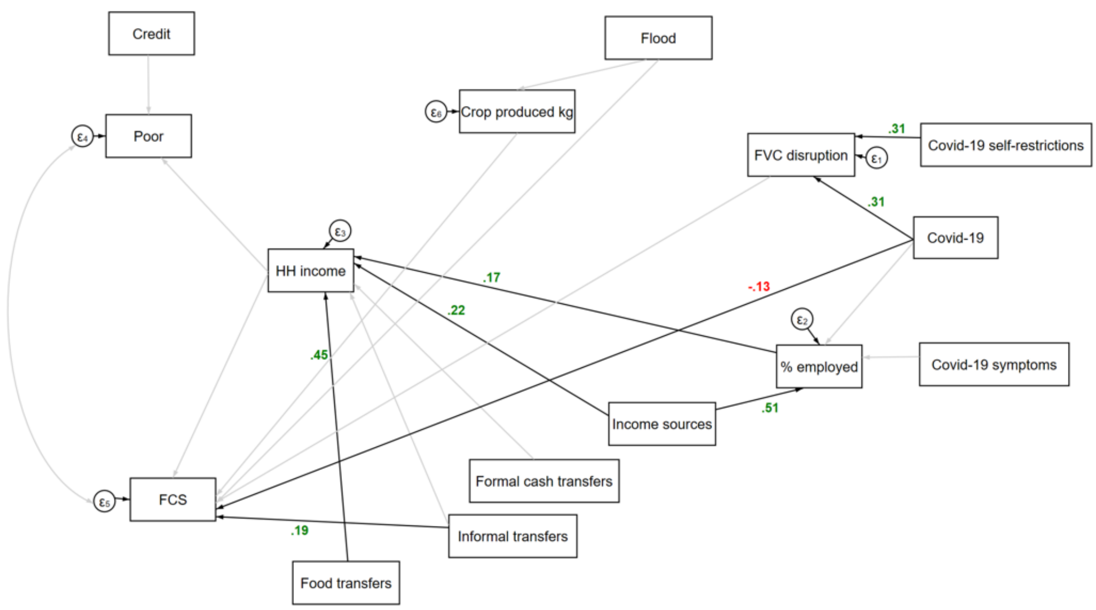
The comparison between refugees and hosts among self-sufficient households is reported in Figures 16 and 17. In this case, we can find some important differences between the two subgroups. First, for hosts, the negative impact on FCS is driven by FVC disruption and floods. Refugees confirm their dependency on food aids and employment in determining household income, which however is not relevant neither for poverty nor for food security. Informal transfers instead play a key role in achieving food security for both groups. For hosts, total income is important in reducing the level of poverty.

Figure 16: Standardized estimates of path analysis - Self-sufficient host households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Figure 17: Standardized estimates of path analysis - Self-sufficient refugee households.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.

Chapter 3

Effects of the COVID-19 crisis on household food consumption and child nutrition in Mozambique

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Abstract

The study investigates the impact of COVID-19 and related restrictions on household food consumption and children's nutritional outcomes in Mozambique. Specifically, this study aims at understanding how the socio-economic effects of the crisis have in turn affected nutritional and food security outcomes. Due to the economic downturn caused by the pandemic, households are expected to adjust their food choices both in terms of food quality towards cheaper and unhealthier food and in terms of quantity, with a consequent reduction in diet diversification and a higher exposure to malnutrition, mainly of children. Empirical evidence on the effects of COVID-19 on child nutrition is still scarce, mainly due to lack of data. Relying on household survey data from 2019/2020, which includes anthropometric measures for under-5 children and detailed food consumption data, this study aims to fill this evidence gap. We take advantage of repeated cross-sectional wave of the survey to estimate the variation in household food consumption and child nutrition before and after the pandemic. Results show that there has been a significant reduction in household food consumption and per capita caloric intake, and an increase in stunting, especially among newborn children.

JEL Classification:

Keywords: COVID-19; food security; nutrition

3.1 Introduction

During the COVID-19 pandemic in Mozambique, the government implemented a series of restrictions that negatively affected employment and income, which could translate into higher exposure to food insecurity and malnutrition (Barletta et al., 2022; Betho et al., 2022). However, evidence of the effects of COVID-19 on food consumption or nutritional status is still scarce. This is because the measurement of these variables requires detailed in-person surveys, which were mostly not possible during the pandemic. Therefore, many surveys moved to phone-based or online interviews, which revealed to be a powerful instrument in times where movement and lockdown restrictions are in place, since they help to understand some of the socioeconomic consequences of the pandemic, such as job and income losses (Gourlay et al., 2021).

However, these findings are all based on crude measures (Abate et al., 2021), given that phone interviews are much shorter than the in-person ones (around 15/20 minutes), and they are based on self-reported and concise answers. As a result, they are not able to collect reliable measures of diet quality and nutrition. Some variables indeed require physical measurement, for example anthropometric measures; other variables require a detailed description of expenditures and consumption, with repeated interviews to avoid long recall periods, as is the case of caloric intake and dietary diversity indexes. While the phone survey mode provides lower costs and it is easier to implement in times of crises, it cannot replace in-person surveys for food consumption and anthropometric measurement.

Other researchers tried to overcome this issue using different techniques, based on simulations and predictions (Laborde et al., 2021b,a; Lakner et al., 2022; Sumner et al., 2020). In particular, Osendarp et al. (2021) used three different models over three different scenarios (pessimistic, moderate, and optimistic) to predict the effect of the COVID-19 crisis on child stunting, wasting and mortality, maternal anemia, and children born to women with a low body mass index in 118 low and middle-income countries, finding that an additional USD 1.2 billion per year will be needed to mitigate the negative consequences on children and women health. An analysis conducted by the "Standing Together for Nutrition" consortium suggests there could be a 14·3% increase in the prevalence of moderate or severe wasting among children younger than 5 years due to COVID-19. This would translate to an additional estimated 6·7 million children with wasting in 2020 compared with projections for 2020 without COVID-19 (Headey et al., 2020). However, without real data, it is impossible to state if these predictions proved to be correct.

This study will contribute to the current literature by estimating the change in household food consumption and child nutrition in the aftermath of the pandemic based on data collected through face-to-face interviews, including physical measurement of weight and height for children under 5 years old. The analysis aims to assess the extent to which the pandemic affected these outcomes, comparing it to previous predictions, and provide evidence to define adequate interventions against malnutrition and food insecurity.

COVID-19 can increase malnutrition in different ways: through a reduction in household incomes, changes in the availability and affordability of nutritious foods, and interruptions to health, nutrition, and social protection services (Headey et al., 2020). Our hypothesis is that, as a consequence of the COVID-19 crisis, households are forced to adjust their food choices in terms of food quality, towards cheaper and unhealthy food (McDermott and Swinnen, 2022), and in terms of quantity, reducing in these ways diet diversification and increasing the exposure to malnutrition.

The implications of poor nutrition are particularly critical for children under 5 years of age, as nutritional deficiencies can exert a strong influence on their subsequent growth and development (DNEAP, 2010). For this reason, alongside the analysis on the overall household food consumption, we also look at the change in malnutrition among young children.

Specifically, the research questions are:

- Whether and to what extent has COVID-19 influenced household food consumption?
- How have children's nutritional outcomes changed due to the COVID-19 crisis?

Some studies investigated the effects of the COVID-19 crisis on adult nutrition (Pakravan-Charvadeh et al., 2021; Gaitán-Rossi et al., 2021; Lamarche et al., 2021), and on children nutrition and lifestyle behaviors (Androutsos et al., 2021; Kim et al., 2021; van der Berg et al., 2020; Zemrani et al., 2021). It is however important to link the simultaneous effects of the COVID-19 crisis on adults and children within the same household. The household food environment and the parental dietary style indeed are critical factors in child nutrition (Benton, 2004). Parents act on child's nutrition in two ways: directly, as they are the members of the household that take food consumption decisions for the entire family; and indirectly, through modeling, namely that children model the behavior of their parents and act accordingly (Bandura, 1977). Studies have shown parent-child correspondence in the intake of foods and drinks, particularly for mothers (e.g., Cooke et al. (2004); Fisher and Birch (2002); Fisk et al. (2011); Grimm et al. (2004); Sonneville et al. (2012); Wroten et al. (2012)). At the same time, the impact of shocks on households can have unequal effects on individual household members (Alderman, 1995; Hoddinott, 2006). In an attempt to answer the proposed research questions, we also take into consideration the influence that the household food environment plays in affecting the response to the COVID-19 crisis on child nutrition.

We use a cross-sectional econometric analysis over a sample of households representative at geographical as well as temporal (trimester) levels to look at the variation in different indicators of household food consumption and child nutrition before and after the pandemic. The design of the sample and the timing of the shock, which occurred in the middle of the data collection, allow us to conduct the intended impact assessment. We perform a heterogeneity analysis to understand which factors may be associated with a greater likelihood of being worse off from the crisis. Finally, we conduct a mediation analysis to investigate the mediating effect the household food environment plays on child nutrition.

Results show that there has been a significant reduction in household food consumption and caloric intake in the aftermath of the pandemic, especially in the last trimester of 2020, and an increase in stunting, especially among newborn children. The economic consequences of the crisis were mainly driven by the government restrictions and their level of enforcement, rather than by the health impact of the pandemic. Households located in the South of the country seem to be affected more, confirming the findings of previous simulations. Households practicing subsistence agriculture were more effective in maintaining a certain degree of dietary diversity compared to other households. Wealthier families in general have been hit relatively harder. The robustness checks suggest that the real effect is potentially underestimated, although, when correcting for multiple hypothesis testing, it loses significance except for stunting. The sensitivity analysis confirms that the findings persist even when excluding the provinces of Cabo Delgado and Maputo City, treated as possible outliers.

The chapter is organized as follows. Section 3.2 provides an overview of the COVID-19 situation in the country during the period under analysis, including the interventions implemented by the government and their association with the rate of infection. Section 3.3 describes the data used and presents some descriptive statistics of relevant variables. We introduce the methodology in Section 3.4. Section 3.5 presents the main results of the analysis. Section 3.6 concludes.

3.2 Context

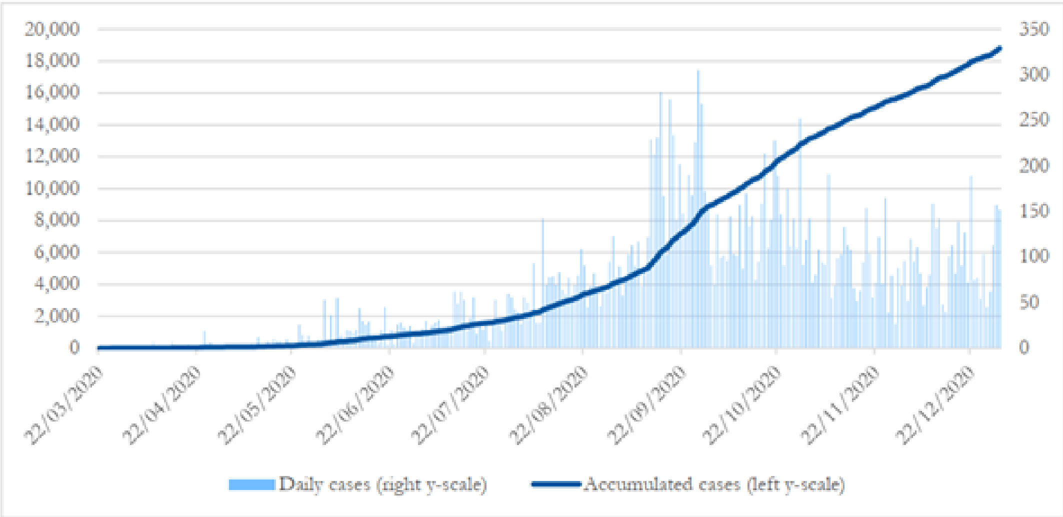
This analysis looks at the COVID-19 crisis in Mozambique during the year 2020, which corresponds to the first phase of the pandemic. The first case of COVID-19 in the country was registered on the 20th of March. However, preventive measures were already in place since the beginning of the month, enabling the population to protect against the spread of the virus at an early stage. The government measures targeted travel restrictions including quarantine, import and export restrictions, early border closure, sanitary measures, an economic recovery plan, a support plan for businesses, and a support plan for exporters.

Four different levels of alert were defined in the country, with gathering restrictions that moved from 300 people in level 1 to 10 people in level 3 (Ministério da Saúde, 2020). This last one was the most stringent one implemented in the country, in place at the end of March. At the same time, President Filipe Nyusi announced the state of emergency. The first 120 days focused on preventing the spread of the disease, while the latest stage of emergency/calamity seemed to accept both the existence of the virus and the need for envisaging a 'new normal' combined with a slow opening of the economy. The alert level 4, which corresponds to a complete lockdown, was never put in place.

In this way, during the so-called first wave of infection, from March to June 2020, the country experienced relatively few cases. This continued to be so for a few more months until September 2020, when numbers increased and plateaued at a slightly higher level, as reported in Figure 3.1.

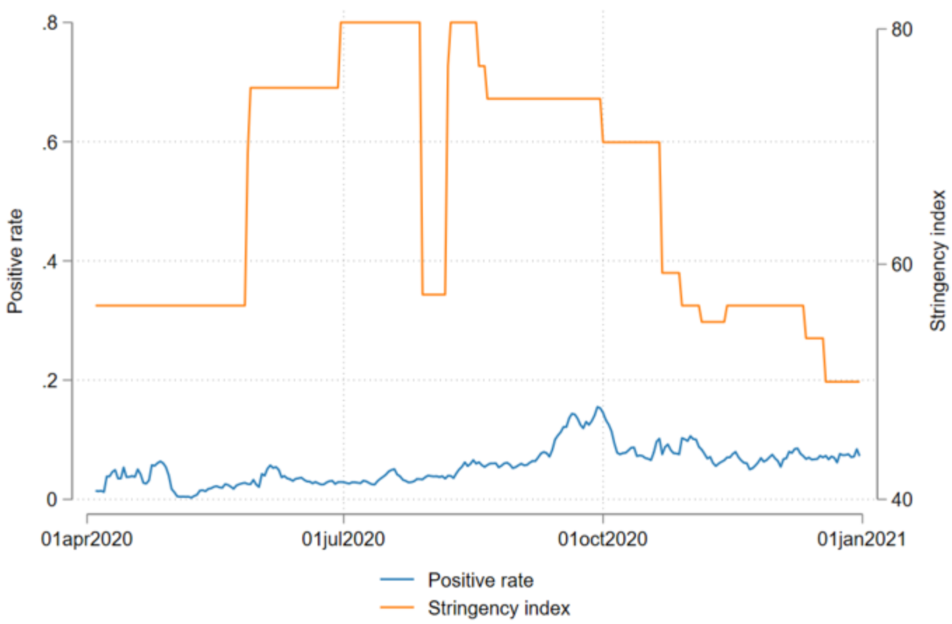
The year 2020, therefore, corresponds to the period with the highest stringency level and the lower positivity rate, as shown in Figure 3.2. Given that the short-run effect on food consumption and nutrition is expected to be mainly driven by the economic downturn caused by the COVID-19 restrictions rather than the direct health effect, our study focuses on 2020.

Figure 3.1: COVID-19 cases registered in Mozambique in 2020, daily and cumulative.



Source: Ministério da Saúde (2020).

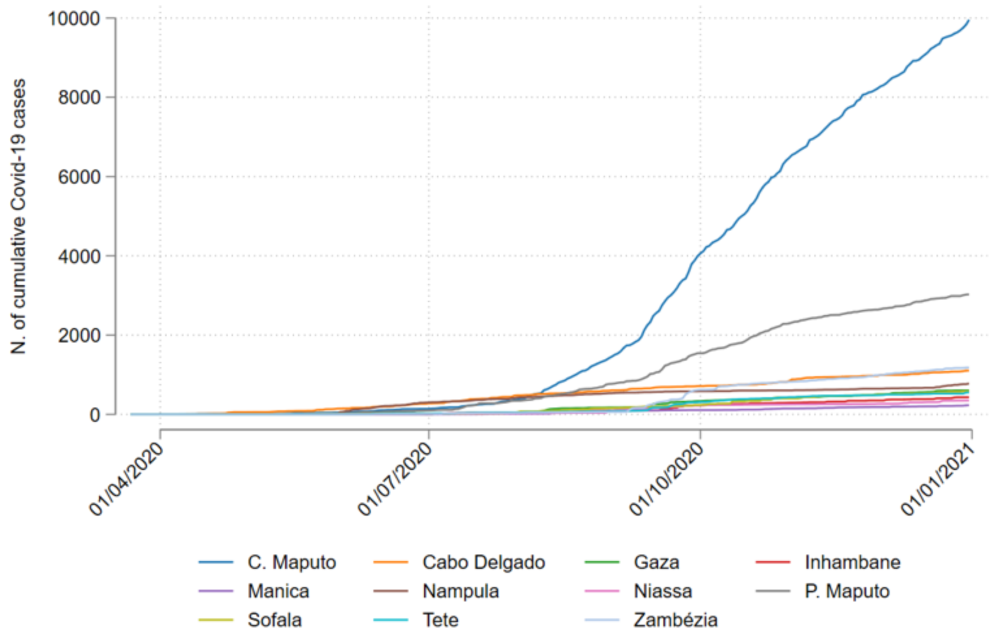
Figure 3.2: Stringency index and positivity rate in 2020.



*Note:*The stringency index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 (low stringency) to 100 (high stringency) (Hale et al., 2021).
Source: Authors' elaboration from Oxford COVID-19 Government Response Tracker (OxCGRT).

Although the cases were quite low during this period, the spread of the virus was different across the country, with some provinces experiencing more COVID-19 cases than others. This is particularly true for the province of Maputo and the city of Maputo, as shown in Figure 3.3. The different geographic spread can be explained by several factors, including population density, level of enforcement and rate of testing. Additionally, different economic activities and a higher inflow of foreign travelers could favour a higher rate of infection. The geographic as well as the temporal differences are therefore important aspects to be taken into account when analyzing the various consequences of the COVID-19 crisis.

Figure 3.3: Cumulative COVID-19 cases by province.



Source: Authors' elaboration compiled from daily bulletins by the Ministry of Health.

The socioeconomic impact of COVID-19 affected the entire country, although some individuals and sectors have been hit more than others, depending on the different channels of transmission. According to the study by Betho et al. (2022), the hardest-hit sectors through the channel of foreign demand decline are mining, trade, and hospitality. The last two sectors, together with construction and manufacturing, were also affected by the lower domestic demand. The effect on labor participation primarily affected urban informal workers and the hospitality sector. Household consumption in Mozambique has been affected by COVID-19 mainly through lower demand for employment, which translated into a reduction in disposable income. Household consumption was estimated to have dropped by 10% (Barletta et al., 2022; Betho et al., 2022; World Bank, 2021), but the effect was stronger in urban areas where the density of people restricted movement proportionally more under social distancing rules. Among urban workers, private enterprises and self-employed individuals, especially small traders, show the highest reduction in consumption (Betho et al., 2022).

The Index of Confidence and Economic Climate (*Indice de Confiança e de Clima Económico*

(ICCE)) reported that employment was down by 10% and 8% in Q2 and Q3, respectively, compared with Q1 in 2020 (INE, 2021a). Simulations on poverty instead found that people working in subsistence agriculture in rural areas are more exposed to an increase in poverty, with about 2 million people expected to enter poverty in less than a year (Barletta et al., 2022; World Bank, 2021). Reduction in consumption and increase in poverty can expose households to food insecurity, worsening an already fragile situation. On the supply side, the disruptions in food supply chains and blockages in transport routes, which are particularly obstructive to fresh food, can result in increased levels of food waste and loss, which in turn can reduce food availability and increase food prices. Retail prices of white maize for instance, despite a decrease between March and June 2020 due to the increased post-harvest production, were on average over 15% higher than their year-earlier values (FAO, 2020).

Other concurrent shocks can deteriorate food security in specific areas of the country. The production shortfalls in the South for instance are likely to negatively affect households' food supplies and to reduce the income-generating opportunities from crop sales in rural areas. In the North instead, the resurgence in violence in the province of Cabo Delgado in the first half of 2020 has resulted in the internal displacement of about 250,000 people and has severely hampered the delivery of humanitarian assistance, worsening the already high levels of food insecurity (FAO, 2020).

In this situation, vulnerable groups are expected to suffer the most. Among them, Mozambican children were already struggling with adequate levels of nutrition before COVID-19. Indeed, the country has already registered extremely high levels of chronic malnutrition among children aged 0–4 years (UNICEF, 2020), with 53% of children between 6-59 months stunted in 2021 (WFP, 2021). This rate can be further exacerbated by the food insecurity caused by reduced income and disrupted food chains, with a consequent life-long impact on child well-being and cognitive development.

Child nutrition is also directly affected by the interruption of school-feeding programs and a reduced access to health facilities. Following the closure of schools across the country on 23 March, 235,000 children no longer had access to critical school feeding. UNICEF estimated that 67,500 children would need treatment for malnutrition in the next nine months after the COVID-19 outbreak (UNOCHA, 2020).

Additionally, the continuity of health essential services, such as vaccination, treatment of acute malnutrition, and vitamin A supplementation, has declined across the country. According to routine immunization data from the Ministry of Health, Cabo Delgado recorded the highest decline in Expanded Vaccination Program coverage from 100% in 2019 to 59% in 2020 (UNICEF, 2020).

3.3 Data and descriptive statistics

Data used for this study come from the 2019/2020 household budget survey in Mozambique (*Inquérito de Orçamento Familiar*, henceforth IOF) collected by the National Institute of Statistics (INE). Data collection took place from December 2019 to December 2020 through face-to-face interviews, with a 3-months break from April to June due to the COVID-19 outbreak. The sample was designed through a probabilistic strategy using a multi-stage stratified sampling plan based on the General Census of Population and Housing 2017. It has been designed to be representative at national, urban and rural, and province levels as well as for each quarter, meaning that in each quarter, all provinces, as well as urban and rural areas were visited. This allows capturing temporal and geographic variations of expenditure, income, and other socio-economic characteristics during the year. The survey contains information about general household characteristics, employment, income, daily and monthly expenditures, and household food consumption. It also includes a module with anthropometric data for children under 5 years old, collected in collaboration with UNICEF. The units of analysis are the household and its respective members. Each selected household was visited every 2 days for 14 continuous days (approximately a fortnight) in a quarter to reduce recall bias in the food expenditure module.

This dataset is extremely suitable for our analysis for three main reasons. First, interviews took place immediately before and after the COVID-19 outbreak, allowing to observe the situation before the shock and to look at the effects in the immediate aftermath. Second, given that it has been designed to be a survey with an independent sample for each quarter, this allows us to have representative samples before and after the shock. Third, it represents one of the few existing data that has been collected through face-to-face interviews during the pandemic, including the collection of anthropometric measures. This is particularly relevant for this analysis, given that anthropometric measures, which are our main outcome variables for child nutrition, cannot be collected remotely.

In the cleaning of the data, we decided to eliminate those households interviewed in March. These households indeed were interviewed before the first case of COVID-19 was registered in the country, but when the preventive measures were already in place. In this way, we entirely dropped the trimester from March to May, ending up with a sample over three trimesters[1]: the first one, which corresponds to the period before the COVID-19 outbreak, namely from December 2019 to February 2020; the second one from June to August; and the third one from September to early December 2020. The final sample is composed of 11,836 observations at the household level, and 8,524 observations for children under-5. Table 3.1 reports the distribution of households before and after COVID-19, and over trimesters. The design of the sample was based on this trimester subdivision, and not on the standard definition of trimesters (which considers a calendar year starting from January).

Table 3.1: Distribution of households over trimesters

		N.	%
Before COVID-19	Trimester 1	3,326	28.10
After COVID-19	Trimester 2	3,792	32.04
	Trimester 3	4,718	39.86
	Total	11,836	100.00

3.3.1 Outcome variables

The outcome variables used in this analysis can be divided into two groups: on one side we consider the food consumption patterns at the household level. On the other side, we focus on the nutritional status of children, using anthropometric measures.

Food consumption

IOF 2019/2020 includes a specific module on daily food consumption. Questions refer to the quantity of food purchased or consumed from own production. The data have been collected over a 14-days period[2], with interviews happening every 2 days. This allowed reducing the measurement error of recalling the food purchased and eaten. From this module, different indicators of household food consumption and dietary quality can be computed. In this analysis we look at different aspects of food consumption: in economic terms, we consider the monetary value of per capita food consumption; in terms of food quantity, we look at the per capita

[1] In the text we refer to the second and third trimesters as the periods after the COVID-19 outbreak, compared to the first trimester used for the baseline. Therefore the numbering does not correspond to the calendar breakdowns.

[2] We checked the difference between food consumption reported in the first 7 and the last 7 days and there is no sign of fatigue.

caloric intake[3]; in terms of dietary diversity, we compute the Household Dietary Diversity Score (HDDS), and Shannon and Simpson dietary diversity indexes.

The HDDS measures the number of different food groups consumed by each household, based on 12 food groups[4] (Anne and Bilinsky, 2006). The HDDS serves as a standard indicator of households' economic access to food (Lovon and Mathiassen, 2014; Kennedy et al., 2011; Ruel, 2003), and it is found to be highly correlated with household-level calorie intakes (Hoddinott and Yohannes, 2002) and individual micro-nutrient intakes (Fongar et al., 2019; Hatløy et al., 1998; Mekonnen et al., 2020). However, this indicator does not provide any information on the quantity consumed in each food group.

Shannon and Simpson indexes instead move from a simple count of food aggregates consumed, to measure the concentration of food consumption in each food aggregate over total food consumption. Both indexes were firstly developed in ecology as measures of entropy to reflect the number of different species and how evenly the individuals are distributed among those species (Kiernan, 2014), and it can be easily applied to food diversity. The Shannon index takes into account the number of food groups consumed (richness) and their relative abundance (evenness). The Simpson index gives the probability that any two food items randomly selected from an infinitely large food basket will belong to the same food group. The Simpson index is defined as $\sum_{i=1} w_i^2$, where w_i is the share of expenditure on different food subgroups and i = 1, 2, . . . , n are the categories of food subgroups. The Shannon index instead is defined as $-\sum_{i=1} w_i ln(w_i)$. The Simpson index ranges between 0 and 1, while the Shannon index ranges between 0 and ln(n), where a higher value corresponds to higher dietary diversity. Although the two indexes are highly correlated, the main difference is that, unlike the Simpson index, the Shannon index gives lower weights to food subgroups with a higher share of food expenditure, such as cereals and staple food, and comparatively higher weight to food subgroups with a lower share of food expenditure, such as meat (Sharma and Chandrasekhar, 2016). Both indexes are widely used in literature to examine the determinants of dietary diversity, as for instance in Karamba et al. (2011), Nguyen and Winters (2011) and Sharma and Chandrasekhar (2016).

A problem already highlighted in the 4th National Poverty Assessment of Mozambique and observed in previous IOF surveys is a degree of under-reporting of food consumption, especially in the urban South (DEEF, 2016). This is probably due to the existence of more

[3]We decided to consider a per capita measure instead of per adult equivalent to be consistent with official national statistics, as reported in the 4th National Poverty Assessment (DEEF, 2016)

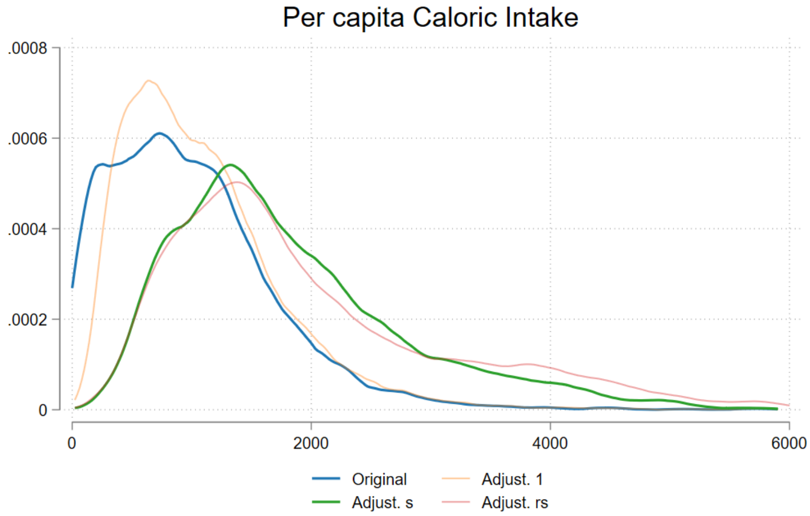
[4]Cereals, root and tubers, vegetables, fruits, meat, eggs, fish, pulses and legumes, milk and dairy products, oils, sugar, and miscellaneous.

diversified diets in these areas and greater food consumption made away from home, which is not captured in the food consumption module. These factors increase the probability of non-sampling error in food consumption reported by the surveyed households. Indeed, in none of the areas in the country, the caloric intake reaches the minimum daily energy requirement of 1,800 calories per person per day set by FAO (Bassett and Winter-Nelson, 2010).

To correct for this, we applied an adjustment based on the meals description module of the IOF survey, following the methodology applied in the 4th Poverty Assessment (DEEF, 2016). The methodology imputes the adjustment based on the description of the three main meals, namely breakfast, lunch, and dinner. When households reported having eaten a certain food category in the meal description module but did not report that same category in the own consumption or daily expenses, the amount of food of the specific category is then imputed and added in the calculation of total consumption. This amount is determined from the median of the quantity consumed per person per day for each category of food in each spatial domain. To be even more cautious, the amount that is imputed for each food category is equivalent to half the median amount, here interpreted as a small portion. The adjustment can be made in three different ways: imputing i) one quantity per week (1); ii) one quantity per day (s); iii) one quantity per meal (rs). The final consumption will be clearly higher when we apply options (ii) and (iii) than in case (i). Figure 3.4 shows how the distribution of caloric intake changes from the original data to the three different ways of adjustment.

As expected, the distribution shifts to the right, especially with adjustments (s) and (rs). In this analysis, we used the adjustment per day (s). In this way, the per capita caloric intake moves from the original 872 calories to the adjusted 1704 calories. The increase is particularly high in the urban areas (150%) and the South (175%), as expected. Food consumption includes both purchases and the monetary value of food consumed from own production. Value has been adjusted using a spatial price index to correct for differences in purchasing power across provinces and between rural and urban areas. Both variables of food consumption and caloric intake have been transformed using the inverse hyperbolic sine (IHS) transformation to account for zeros while preserving a similar interpretation as the log transformation (Johnson, 1949; Burbidge et al., 1988).

Figure 3.4: Caloric adjustment based on meal description.



Source: Own elaboration from IOF 2019/2020.

Child nutrition

We rely on the anthropometric module of IOF 2019/2020 to compute measures for child nutrition. These data were collected by the Ministry of Health and the Technical Secretariat for Food and Nutrition Security, under the supervision and coordination of UNICEF Mozambique (INE, 2021b).

Measures of malnutrition focus on the distance of a given indicator for a child (e.g., height for age) relative to the reference population. Specifically, for each child, a Z-score can be calculated as: $Z_i = (h_i - H_r)/\sigma_r$, where h_i refers to an anthropometric indicator for child i, H_r the median value for that indicator in the reference population, and σ_r is the standard deviation in the reference population (DNEAP, 2010). The reference population comes from the WHO's 2006 data and it is produced from globally representative data to provide a single international standard that best represents the expected distribution of the growth of children under five years of age. Thus, the lower the level of the Z-score, the higher the level of malnourishment. Using this definition, the WHO recommends that children should be considered malnourished if they have a Z-score of negative two or less in relation to a given anthropometric index. Weight, height, and age are used to calculate three standard anthropometric indices: weight-for-age, height-for-age, and weight-for-height. Each index indicates different aspects of malnutrition and addresses specific deficits and possible future implications. Height-for-age, for instance, reflects the cumulative effects of under-nutrition and infections, and it indicates poor environmental conditions and long-term restriction of a child's growth potential (DNEAP, 2010).

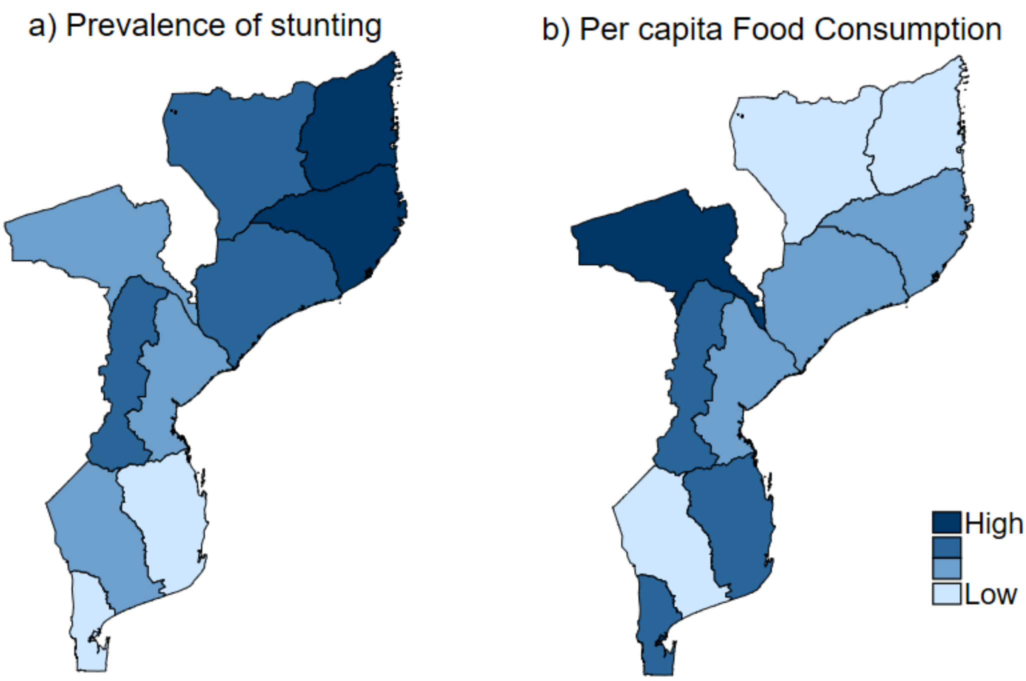
Weight-for-height indicates acute weight loss, which is a deficit in the amount of tissue and fat compared to the amounts expected for children of the same height. Weight-for-age instead may be driven by short-term factors, such as recent illness or moderate seasonal fluctuations in the food supply, as well as longer-term deficiencies in access to adequate foods.

Based on the Z-score of these three variables, we computed dummies of malnutrition, equal to 1 when the Z-score is below (or above, in the case of overweight) two, and zero otherwise. Specifically, we considered stunting from height-for-age, wasting and overweight from weight-for-height, and underweight from weight-for-age. Stunting is a physical manifestation of long-term malnutrition, and it represents a risk factor that contributes to infant mortality, and can be also used as a marker of inequalities in human development (Development Initiatives, 2020). Although it is responsive to shocks in the short run (as found in Akresh et al. (2011) for instance), it brings along long-terms effects in terms of malnutrition and human capital (Deshpande and Ramachandran, 2022). Therefore, it allows investigating not only the immediate effect of the shock, as mainly captured by the indicators of food consumption, but also long-run effects (Carter and Maluccio, 2003). Wasting is caused by individual's inability to consume or absorb nutrients, and it might be the result of inadequate food intake or a recent episode of illness (DNEAP, 2010). Regarding overweight, this form of malnutrition results from a very low calorie consumption in relation to the amount taken, and this increases the risk of developing non-communicable diseases later in life. The use of the dichotomous variables of malnutrition vis-a-vis the continuous variables of the Z-score makes it possible to specifically analyze the critical levels of nutrition of children, rather than considering the entire distribution. The latter indeed could provide mixed and misleading results.

Among the different indicators of malnutrition, the country suffers most from high levels of stunting. INE estimated that the prevalence of stunting in 2019/2020 was 38% at the national level, which, according to WHO and UNICEF (2019), is classified as "very high". The rate is higher for children over 12 months of age, male children, and children living in rural areas. Provinces in the central and northern regions show higher levels of stunting, with the province of Nampula reporting the highest prevalence. Wasting and underweight instead report lower rates, with a national average of 4.5% and 15.2%, respectively (INE, 2021b).

The situation before the COVID-19 outbreak indicates a higher prevalence of stunting in the North of the country, where the levels of food consumption are lower. It is evident indeed an inverse correspondence between the level of stunting and the level of food consumption, as shown in Figure 3.5.

Figure 3.5: Pre-pandemic situation of malnutrition and food security across the country.



Source: Authors' elaboration from IOF 2019/2020.

3.3.2 Summary statistics

Table 2 reports the summary statistics of the main outcome variables and covariates used in the analysis. A full description of the variables considered in the analysis is available in Appendix 3.6. We can see that, on average, food consumption and caloric intake slightly reduced after the pandemic, while indicators for dietary diversity seem to have remained unchanged. All controls appear quite stable over time, except for tropical livestock units (TLUs), which have declined on average in the aftermath of the COVID-19 crisis, and a slight increase in the percentage of households that practice subsistence agriculture. This could suggest a return to agriculture caused by the crisis, while the sale of livestock may have been used as a coping strategy.

Table 3.2: Summary statistics

	All sample		pre-Covid		post-Covid		Mean diff.
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Outcome variables							
Pc Food consumption	35.9	39.3	37.8	38.1	35.3	39.8	***
Pc Caloric intake	1576	1168	1599	1285	1568	1124	
HDDS	5.94	1.91	5.88	2.07	5.96	1.85	*
Simpson index	0.51	0.20	0.50	0.22	0.52	0.20	***
Shannon index	2.08	0.47	2.06	0.50	2.09	0.46	***
Stunting	0.35	0.48	0.32	0.47	0.36	0.48	***
Wasting	0.04	0.19	0.04	0.20	0.04	0.19	
Underweight	0.13	0.34	0.16	0.36	0.12	0.33	***
Overweight	0.05	0.22	0.03	0.18	0.06	0.23	***
Control variables							
HH size	4.81	2.46	4.80	2.49	4.81	2.45	
HH head is female	0.28	0.45	0.27	0.45	0.28	0.45	
Asset index	1.12	3.74	1.14	3.90	1.12	3.68	
Dep. ratio	1.13	1.00	1.15	1.01	1.13	0.99	
HH has children	0.85	0.35	0.85	0.36	0.86	0.35	
% employed	0.61	0.30	0.61	0.30	0.61	0.30	
Head has primary educ.	0.50	0.50	0.50	0.50	0.50	0.50	
HH owns land	0.78	0.41	0.78	0.41	0.78	0.41	
TLU	0.50	8.43	0.71	15.97	0.43	2.47	
HH is subsistence ag.	0.62	0.48	0.61	0.49	0.63	0.48	
Rural	0.66	0.47	0.66	0.47	0.66	0.47	
Social assistance	0.03	0.18	0.04	0.19	0.03	0.18	
Access to city (hours)	2.58	2.07	2.72	2.41	2.53	1.94	***
% of land=Savannas	47.41	29.03	48.77	28.59	46.92	29.16	***
% of land=Grasslands	28.49	27.03	27.93	26.81	28.70	27.11	
% of land=Braidleaf forest	7.36	10.42	7.22	10.16	7.41	10.51	
% of land=Urban	3.93	9.59	3.83	9.41	3.97	9.65	

Note: household sampling weights applied. Data on access to city was developed by the Stochastic frontier analysis FAO-HiH task force (2021). Data on land cover was retrieved from Friedl (2019).

3.4 Methodology

3.4.1 Main analysis

We quantify the change in household food consumption and child nutrition during the COVID-19 crisis using a pooled OLS/probit, depending on whether the dependent variable is continuous or dichotomous, with province and month fixed effects to account for geographical differences and seasonality. We included a series of control variables, and we clustered standard errors at the district level to correct for possible heteroskedasticity. Household sampling weights are applied to obtain representative estimates. We use the term “effect” but we acknowledge that we are not identifying a causal mechanism with our estimation strategy. The general specification of the model is the following:

$$y_{hpt} = \alpha_0 + \beta_1 * Covid_{pt} + \beta_2 * Controls_{hpt} + \phi_m + \mu_p + \epsilon_{hpt} \tag{3.1}$$

Where the subscripts h and t respectively denote household/child and time (year/trimester), while p refers to the province; y_{hpt} is the outcome variable, namely the variables for food consumption and child nutrition; $Covid_{pt}$ is the variable used to capture the effect of COVID-19. Different definitions of the shock have been applied and are discussed below; $Controls_{hpt}$ includes a set of covariates for household (and child) characteristics; ϕ_m is the set of month dummies to account for seasonality; μ_p are province fixed-effects, and ϵ_{hpt} is the error term. It is important to include the month dummies, because otherwise seasonality effects would be included in the year/trimester variables. At the same time, these dummies could capture monthly variation of the COVID-19 impact. However, as reported in Section 3.5, when including the month dummies, all the variables used as a proxy for COVID-19 turn significant, and the coefficients for the month dummies also report a significant level. Specifically, we can observe a trend over the year, which goes in the opposite direction to the coefficient of the COVID-19 proxies. This should reassure us that the month dummies are capturing seasonality and not COVID-19-related effects. For the full set of results, please refer to Appendix 3.6.

To identify the effects of COVID-19 and related restrictions, different variables have been considered. First, a simple time dummy equal to 1 from July 2020 onwards, and zero otherwise, was computed to account for the effect before and after the outbreak of the pandemic. In this case, we assume that nothing else except COVID-19 occurred during the period under analysis. To look more in-depth at the variation over time, we then considered the dummies for each trimester. In this way, we are able to see if there has been an evolution of the effect over time, and if the effect was higher in the immediate aftermath of the pandemic or in a longer term. Additionally, to look at the intensity of the restrictions over time, we computed the average level of the government stringency index, retrieved from the OxCGRT dataset, by trimester. Finally, we computed two other variables: the number of confirmed COVID-19 cases over population by province and trimester, and the positivity rate, i.e. cases over tests, by province and trimester. These two variables capture not only the variation over time but also across provinces. The positivity rate is a more accurate variable because it reduces measurement error across areas in the country. Indeed we would expect an under-reporting in the number of COVID-19 cases in rural and remote areas rather than in the main cities, where the enforcement and testing capacity was higher. Assuming the same level of under-reporting for the COVID-19 tests, we would expect that the ratio between cases and tests is a reliable measure.

3.4.2 Heterogeneity analysis

To better understand possible channels and to identify which households and individuals have been affected more than others, we conducted a heterogeneity analysis. This is done by interacting the variable used as a proxy for the aggregate COVID-19 shock with the variable of interest for the heterogeneity. The model is specified as follow:

$$y_{hpt} = \alpha_0 + \beta_1 * Covid_t + \beta_2 * (Covid_t * C_{hpt}) + \beta_3 * C_{hpt} + \beta_4 * Controls_{hpt} + \phi_m + \mu_p + \epsilon_{hpt} \quad (3.2)$$

We are interested in the coefficient β_2 of the interaction term, where C_{hpt} is the household/child characteristic of interest. We consider different variables. At the household level, we look at the gender of the household head, the location of the household (if rural/urban, and South/Center/North), the level of education of the household head, if the household practices subsistence farming[5], if the household has children, if the household lives in a district with high levels of malnutrition[6], and the wealth level (poor vs rich households)[7]. At the child level, we consider whether the child is the firstborn, the age cohorts, specifically newborn children, and the gender of the child.

3.4.3 Mediation analysis

To explore the role the household food environment in affecting children's diets and disentangle the direct effect of COVID-19 from the one mediated by the household food consumption, we computed a mediation analysis (Baron and Kenny, 1986). The household food environment and the parental dietary style indeed are critical factors in child nutrition (Benton, 2004). Parents act on child's nutrition in two ways: directly, as they are the members of the household that take food consumption decisions for the entire family; and indirectly, through modeling, a cognitive process through which individuals observe others' behaviors and create their own beliefs based on them (Bandura, 1977). Studies have shown parent-child correspondence in

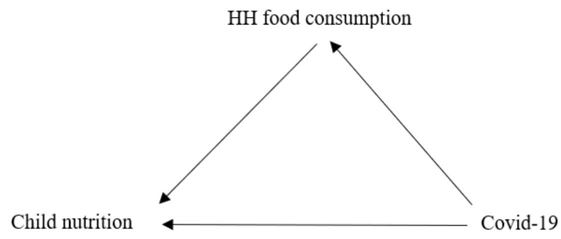
[5]A household is defined to practice subsistence agriculture when the share of food consumption from own production over total food consumption is >50%.

[6]Malnutrition here is proxied by the median prevalence of stunting at district level computed at baseline to capture the pre-pandemic situation.

[7]Wealth is defined in terms of assets. The asset index is computed with Principle Component Analysis using indicators of housing quality and access to public service infrastructure, such as sanitation and electricity. A household is defined poor if it belongs to the first and second lowest wealth quintiles.

the intake of foods and drinks, particularly for mothers (e.g., Cooke et al. (2004); Fisher and Birch (2002); Fisk et al. (2011); Grimm et al. (2004); Sonneville et al. (2012); Wroten et al. (2012)). At the same time, the impact of shocks on households can have unequal effects on individual household members (Alderman, 1995; Hoddinott, 2006). The graphical model representing the relationship between household food decisions and child nutrition in the impact of COVID-19 is shown in Figure 3.6.

Figure 3.6: Diagram path of mediation analysis



In the figure, we can see that the impact of COVID-19 on child nutrition can be both direct and mediated by the effect of the household food environment. In this way, it is possible to separate the two avenues, isolating the role that the household food consumption plays in mediating the effect on child nutrition. The corresponding system of equations is the following:

$$\begin{cases} FoodConsHH_{hpt} = \alpha_0 + \beta_1 * Covid_t + \beta_2 * ControlsHH_{hpt} + \phi_m + \epsilon_{1hpt} \\ ChildNutrition_{ihpt} = \alpha_1 + \beta_3 * Covid_t + \beta_4 * FoodConsHH_{hpt} + \\ \qquad\qquad + \beta_5 * ControlsChild_{ipt} + \phi_m + \epsilon_{2ihpt} \end{cases} \tag{3.3}$$

We considered the same set of control variables used in (3.1), specific for households and children. The second equation in the system includes the direct effect of COVID-19, the direct effect of household food consumption, and the indirect effect of COVID-19 mediated by the household food environment on child nutrition. For the sake of simplicity, we considered the time dummy as a proxy for COVID-19. We had to exclude province fixed effects because of convergence problems.

3.5 Results

3.5.1 Main results

Table 3.3 reports the results of the pooled OLS with per capita caloric intake as dependent variable (used as an example), over different specifications. For the sake of simplicity, we use the time dummy as the proxy for the aggregate COVID-19 shock. In Figure 3.7 instead, we show the estimated coefficients using the alternatives to proxy the shock. Model (1) is the simplest one, where no controls and no fixed effects are included. Model (4) instead is the most complex one and corresponds to the one reported in Equation 3.1. As shown in the table, it is important to include month fixed effects. Indeed, when we include month fixed effects, the coefficient of the time dummy becomes negative and significant, suggesting that seasonality highly affects the level of food consumption over the year. Also the adjusted R-squared increases, suggesting that model (4) is the most suitable to explain variation in food consumption. We can also verify that most covariates correlate with the quantity of food consumption as expected. For example, larger households with relatively more dependents in rural areas have on average lower levels of caloric intake, whereas asset-rich households and those with an employed household head have higher levels.

Table 3.3: Pooled OLS, different specifications.

Variables	(1)	(2)	(3)	(4)
Time dummy	0.0390	0.0350	0.0428	-0.368***
	(0.0522)	(0.0530)	(0.0502)	(0.101)
HH size		-0.0554***	-0.0542***	-0.0533***
		(0.00717)	(0.00583)	(0.00590)
HH head is female		-0.0651**	-0.00803	-0.00730
		(0.0296)	(0.0281)	(0.0282)
Asset index		-0.0156	0.0220**	0.0224**
		(0.0100)	(0.00883)	(0.00863)
Dep. ratio		-0.0525***	-0.0604***	-0.0587***
		(0.0170)	(0.0157)	(0.0150)
HH has children		-0.0703	-0.116**	-0.119***
		(0.0452)	(0.0455)	(0.0449)
% employed		0.109*	0.129**	0.138***
		(0.0625)	(0.0549)	(0.0526)
Head has some primary educ.		-0.0282	-0.0513*	-0.0521*
		(0.0316)	(0.0267)	(0.0265)
HH owns land		0.0728	0.0605	0.0682
		(0.0562)	(0.0423)	(0.0419)
TLU		0.000442	0.000791**	0.000813**
		(0.000629)	(0.000397)	(0.000390)
HH is subsistence ag.		0.109	0.0745	0.0798
		(0.0972)	(0.100)	(0.0998)
Rural		-0.276***	-0.135*	-0.141*
		(0.0863)	(0.0708)	(0.0727)
HH receives social assistance		-0.119*	-0.0950	-0.0975
		(0.0672)	(0.0666)	(0.0648)
Access to city (in hours)		-0.00553	-0.00265	-0.00116
		(0.0168)	(0.0145)	(0.0146)
% of land=Savannas		-0.00237	-0.00361*	-0.00348
		(0.00225)	(0.00218)	(0.00224)
% of land=Grasslands		-0.00185	0.000200	0.000344
		(0.00271)	(0.00222)	(0.00225)
% of land=Braidleaf forest		0.000910	-0.00462	-0.00423
		(0.00547)	(0.00501)	(0.00495)
% of land=Urban		-0.0139**	-0.00590*	-0.00593*
		(0.00573)	(0.00332)	(0.00335)
Constant	7.693***	8.337***	7.721***	7.701***
	(0.0526)	(0.217)	(0.185)	(0.192)
Province FE	no	no	yes	yes
Month FE	no	no	no	yes
Observations	11,836	11,836	11,836	11,836
R-squared	0.000	0.064	0.139	0.144

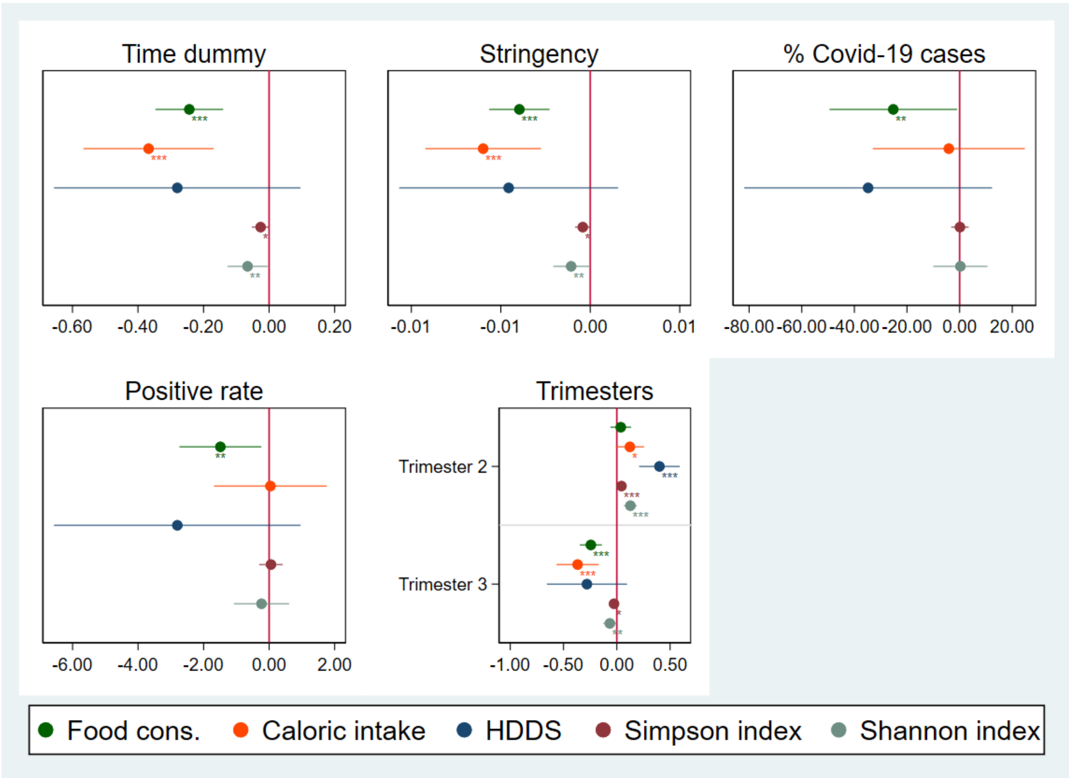
Notes: Dependent variable: per capita caloric intake. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

When looking at the coefficient of different definitions of the COVID-19 shock on different household food consumption variables, reported in Figure 3.7, we see some interesting patterns. The time dummy is always negatively associated with the variables of food security, suggesting that after the COVID-19 outbreak there has been a reduction both in the quantity of food consumption and in the quality.

The stringency index reports similar results, suggesting that the change in household food consumption is linked to the restrictions imposed by the government, and specifically to their level of stringency. Therefore, as expected, more stringent measures correspond to a reduction in food consumption, caloric intake and dietary diversity. Instead, the two variables related to the COVID-19 cases seem to have a similar effect on food consumption, but a null effect on dietary diversity. This would suggest that variables more related to the health side of the pandemic are not perfect predictors of the economic consequences of the crisis. A higher number of COVID-19 cases could be also the result of lower enforcement of the restrictions.

Interesting dynamics instead emerge when looking at the effects over time (trimesters). Indeed, we notice that the effect is not immediate, but it mainly occurs in the third trimester. This could suggest that in the aftermath of the pandemic people were using different coping strategies to offset the reduction in income, such as relying on savings or selling assets. However, these strategies turned out to not be sufficient and sustainable over time.

Figure 3.7: Coefficients of different proxies for COVID-19 - Household level.

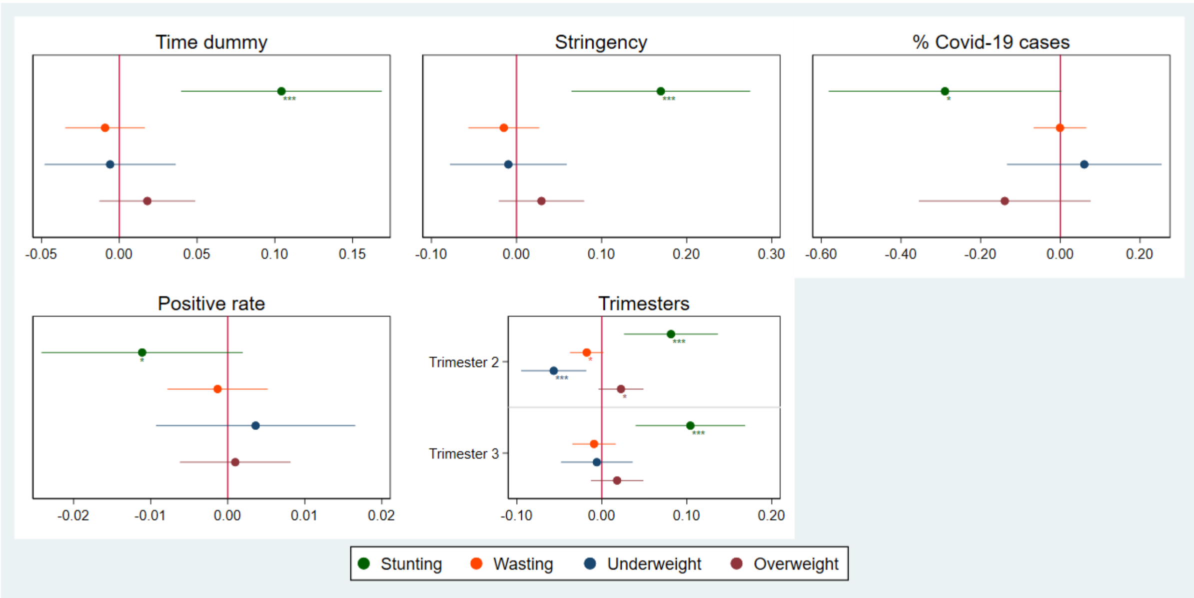


Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are coefficients estimated from a linear regression. Bars are 95% confidence intervals.

In terms of child nutrition, we find that only stunting seems to have significantly increased in the aftermath of the pandemic, as reported in Figure 3.8. Stunting usually captures long-term developmental challenges. However, given that the prevalence of stunting was already very high before the crisis, we expect many children to have been at risk of being stunted. The results suggest that stunting therefore is more sensitive to negative shocks than the other anthropometric measures. Indeed, it is positively and significantly correlated with the time dummy, the level of stringency, and the trimester dummies. As in the previous figure, we see an opposite effect when considering the COVID-19 cases and the positivity rate.

We do not see a path over time similar to the one observed for the variables of food consumption. In this case indeed, the sign of the estimated coefficients is similar in the second and the third trimester. Specifically, stunting immediately reported an increase, and the effect seems to intensify in the third trimester.

Figure 3.8: Coefficients of different proxies for COVID-19 - Child level.



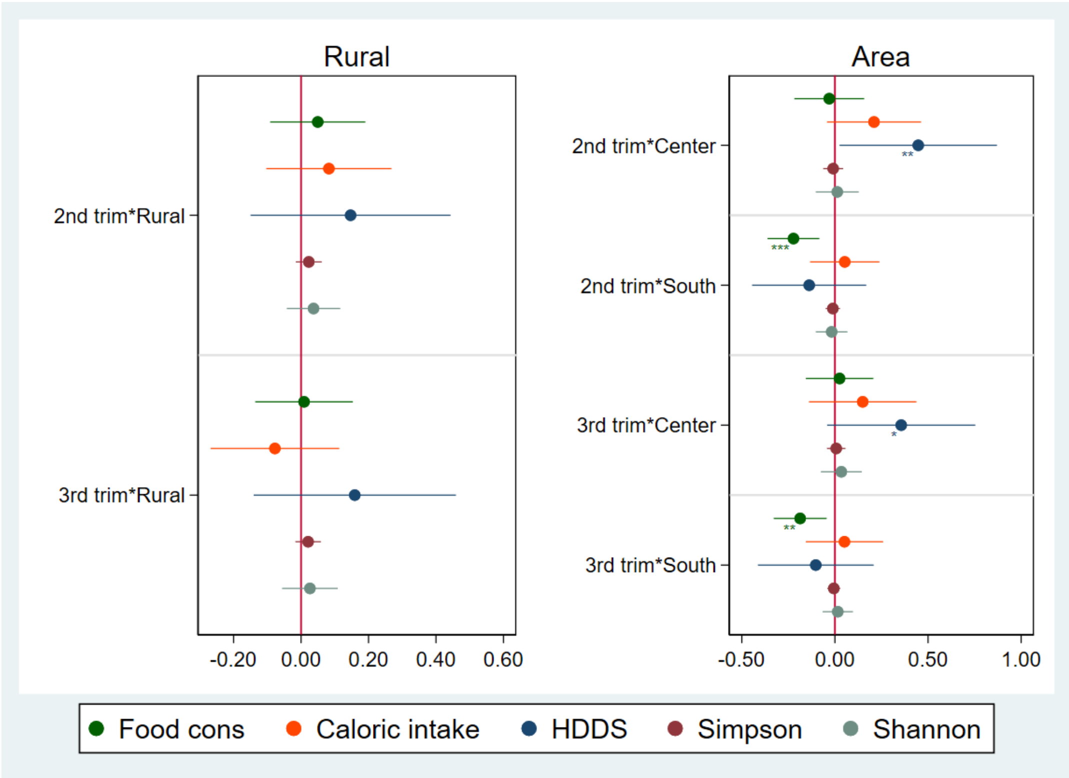
Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are average marginal effects estimated from a probability regression. Bars are 95% confidence intervals.

3.5.2 Heterogeneous effects

When we consider the differentiated effect over different household characteristics, some interesting patterns emerge. At the geographical level (Figure 3.9), we find that being placed in rural areas is positively correlated with food quantity and diet diversity in the aftermath of the pandemic, although not in a significant way. The opposite occurs for households located in the South, especially in terms of food consumption. Compared to the Northern region (used as reference), the Southern presents a negative and significant effect in terms of food consumption.

These results confirm what was simulated in Betho et al. (2022), namely that households in urban areas and in the South of the country were hit more by the COVID-19 crisis than households in the rest of the country. Movement restrictions and the trade shock were more prevalent in the urban centers of the South of Mozambique.

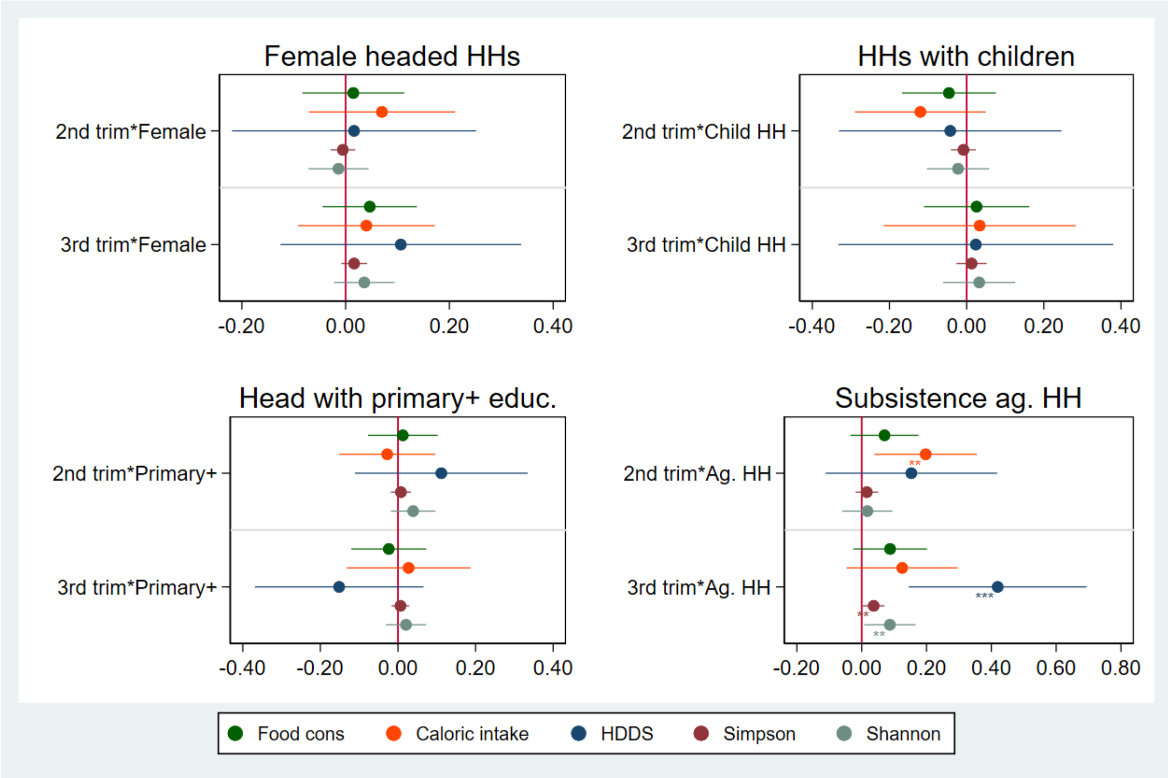
Figure 3.9: Heterogeneity analysis: geographical variables



Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are coefficients estimated from a linear regression. Bars are 95% confidence intervals.

In terms of household characteristics, we do not see a different pattern between female and male headed households, and between households with and without children (see Figure 3.10). A similar result can be found when considering the level of education of the household head. Instead, households that practice subsistence agriculture are better off compared to the other households in the aftermath of the COVID-19 outbreak. This is particularly true in terms of dietary diversity. Indeed, the coefficients of HDDS, Simpson index and Shannon index are positive and significant in the third trimester. Subsistence agriculture might enable these households to maintain a certain quantity and quality of food independent of market interruptions.

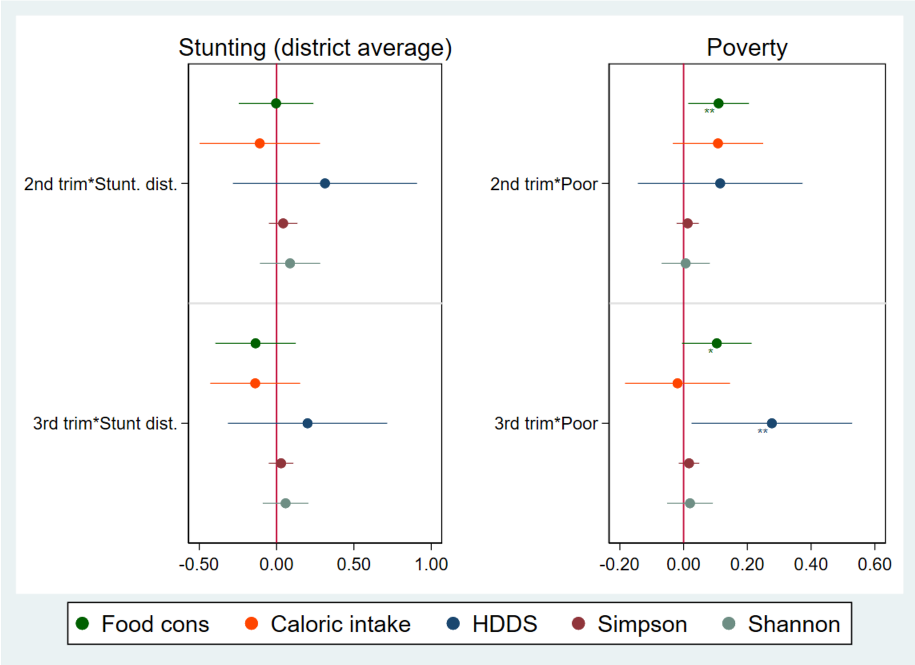
Figure 3.10: Heterogeneity analysis: household characteristics



Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are coefficients estimated from a linear regression. Bars are 95% confidence intervals.

Living in a district with a high level of malnutrition (proxied by the prevalence of stunting) does not seem to be a determinant factor in having a change of food consumption due to the COVID-19 crisis (Figure 3.11). Instead, the poorest households seem to have been less affected than richer ones. Although this could appear controversial, this result is aligned with the other findings emerging in this analysis and in other studies. Indeed, the magnitude of the effect of the aggregated COVID-19 shocks in absolute monetary terms is expected to be higher for wealthier people, but the relative effect is higher for the poor (Barletta et al., 2022).

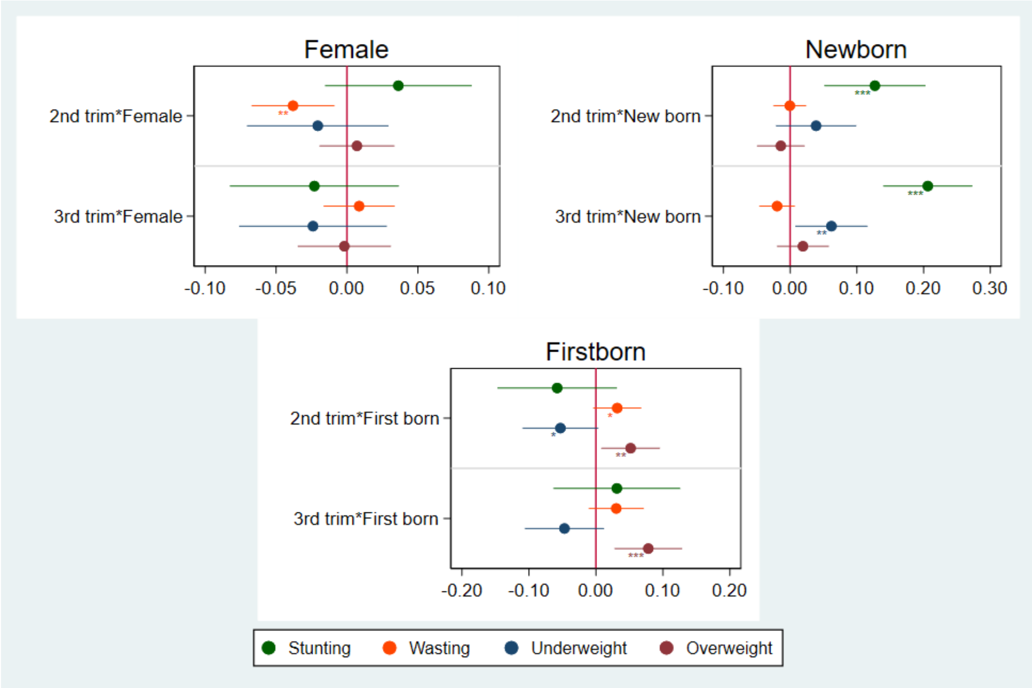
Figure 3.11: Heterogeneity analysis: malnutrition and poverty



Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are coefficients estimated from a linear regression. Bars are 95% confidence intervals.

In terms of the heterogeneous effect of COVID-19 on nutrition over different child characteristics, the first finding that emerges from Figure 3.12 is that there is not a gender effect. This means that girls and boys experienced a similar effect on nutrition in the aftermath of the pandemic. Instead, newborn children have been more negatively affected than older children. This is particularly true for stunting and in part for underweight. This confirms the expectation that younger children, especially the ones born immediately before the pandemic, could suffer more than the others. In the early stages of life, in particular during the first 1,000 days, nutrition has a crucial role in shaping the immunological, cognitive and physical development of the individual (Larson-Nath and Goday (2019); Mayneris-perxachs and Swann (2019)), with long-term health consequences, increasing the risk for developing diseases later in life Walker et al. (2007) and leading to poor school and work achievement Alderman et al. (2006). The firstborn children instead report a positive and significant coefficient of overweight. This result could suggest that there has been a redistribution of food among children, with parents prioritizing the firstborn over the other children.

Figure 3.12: Heterogeneity analysis over child characteristics



Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are average marginal effects estimated from a probability regression. Bars are 95% confidence intervals.

3.5.3 The mediating role of the household food environment

We conducted a mediation analysis to disentangle the direct from the indirect effects of the COVID-19 crisis on child malnutrition. Our interest lies on the role of the household food environment in channeling some of the crisis effect. For example, if a household consumes less food due to the government restrictions, how does this influence malnutrition outcomes of the children in this household? Table 3.4 reports for each outcome of child nutrition (columns) the direct effects of the household food environment (food consumption, caloric intake, HDDS, Shannon and Simpson index), the direct effect of COVID-19 (time dummy), and the indirect effect of COVID-19 mediated by the household food environment variable.

We observe that the direct effect of COVID-19 on child nutrition is always negative, as found in the previous analysis. Specifically, we see a significant increase in stunting and underweight. The direct effect of household food security and dietary diversity on child nutrition is only significant for food consumption. There is also a weak negative relationship between the Shannon index of dietary diversity and stunting. The lack of a significant relationship could be due to two factors. The first explanation is an unequal distribution of food within the family, so that the per capita value does not state what the children really consume. The other explanation relies on the limitations of some of the indicators. The amount of caloric intake is not an indicator of the quality of diet in terms of micronutrients. At the same time, the HDDS does not consider the quantity consumed in each food group.

Concerning the indirect effects of the household food environment on child nutrition outcomes in the context of the COVID-19 crisis, results are mixed. When we look at food consumption, the link is clear: given that COVID-19 led to a reduction in food consumption, which is systematically associated with an increase in child malnutrition, COVID-19 indirectly increased all forms of child malnutrition through a reduction in household food consumption (panel a). This is particularly relevant for wasting and underweight, where the effect is statistically significant. Since the direct effect on the different forms of malnutrition is not significant for other household food environment variables, as a consequence, also the indirect effect does not report a statistically significant coefficient. For what concerns the indicators of dietary diversity, we find an opposite result for the Shannon index. Its indirect effect on stunting is negative. This might be because for the sample of children with information on anthropometrics, being in the aftermath of the pandemic is associated with an increase in the Shannon index (see figure X). Given that the index is negatively correlated with stunting, this translates into an indirect better outcome.

Table 3.4: Direct and indirect standardized effects, mediation analysis.

	Stunting	Wasting	Overweight	Underweight
Panel (a)				
Direct effects				
PC Food Cons.	-0.028*	-.045**	-.007	-.056***
Time dummy	0.230***	-.003	.032	.119***
Indirect effects				
Time dummy	0.003	.004**	.001	.005**
Panel (b)				
Direct effects				
PC Caloric Intake	.021	-.008	-.000	-.014
Time dummy	.240***	-.001	.032	.121***
Indirect effects				
Time dummy	-.007	.003	.000	.005
Panel (c)				
Direct effects				
HDDS	.013	.020	-.002	-.006
Time dummy	.228***	-.005	.033	.127***
Indirect effects				
Time dummy	.004	.007	-.001	-.002
Panel (d)				
Direct effects				
Shannon	-.024*	-.001	-.008	-.004
Time dummy	.238***	.002	.034	.126***
Indirect effects				
Time dummy	-.005*	-.000	-.002	-.001
Panel (e)				
Direct effects				
Simpson	-.022	.000	-.009	.008
Time dummy	.235***	.001	.033	.125***
Indirect effects				
Time dummy	-.002	0.00	-.001	.001

Notes: Sampling weights applied. Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

3.5.4 Robustness checks

In this section we conduct some tests to assess the robustness of our results. Specifically, we ran 3 different analyses/tests: i) a coefficient stability test (Oster, 2019), to exclude possible omitted variable bias caused by unobservables; ii) Bonferroni and Holm corrections and Romano-Wolf correction to control for family-wise error rate (FWER), when considering the whole family of simultaneous tests instead of treating a single comparison for each outcome; iii) a sensitivity analysis, where we exclude some provinces considered possible source of outliers, which could bias the result of the overall sample.

Omitted variable bias

Since we do not have longitudinal data, it is not possible to use fixed effects to control for time-invariant unobserved characteristics that could create problems of endogeneity. Although we included observed controls to reduce the possibility of omitted variable bias, these could be incomplete proxies for the true omitted factor (Oster, 2019). It is then important to test if the bias arising from the observed controls is informative about the overall bias, including the unobserved components. Based on the method of Altonji et al. (2005), Oster (2019) developed an approach that combines coefficient stability with information about R-squared movements. With this test, we can examine the extent to which different assumptions regarding omitted variable bias affect our estimates.

The test consists of running the full model, with all observed controls, and the restricted one, with only the treatment variable. In our case, the variable of interest is the proxy of COVID-19. Here we present the results of the test using the dummy for the third trimester as the treatment. The tests conducted using the other proxies of COVID-19 are reported in the Appendix. We then compute consistent estimates of the bias-adjusted treatment effect under two assumptions: a value for the maximum R-squared (Rmax) and a value for the relative degree of selection on observed and unobserved variables (δ). Rmax is equal to 1 when the treatment and the set of controls can fully explain the outcome. When we assume an equal selection relationship between unobservables and observables, meaning that they are equally related to the treatment, δ is equal to 1. We apply different bounding values for Rmax and δ and compare the adjusted βs with our original estimate. We consider three different combinations: i) Rmax=0.75 & δ=0.5; ii) Rmax=1 & δ=0.5; and iii) Rmax=1 & δ=1.

The results of the test show that all adjusted betas confirm the sign of the original estimates for all outcome variables (see Table 3.5). Additionally, we can notice that the greater the values of Rmax and δ, the greater the magnitude of the coefficient. This suggests that the original estimates potentially underestimate the real effect.

Multiple Hypothesis Correction

When regressing the effect of a treatment or, as in this case, a shock, over a series of outcomes, it is likely to make erroneous inferences due, for instance, to sampling error. Our confidence that a result will generalize to independent data should generally be weaker if it is observed as part

Table 3.5: Comparison of original and adjusted estimated coefficients of the dummy of 3rd trimester.

	Original beta	Adjusted beta: Rmax=0.75 and δ=0.5	Adjusted beta: Rmax=1 and δ=0.5	Adjusted beta: Rmax=1 and δ=1
Pc food cons.	-0.243	-0.339	-0.399	-0.554
Caloric intake	-0.368	-1.015	-1.282	-2.195
HDDS	-0.280	-0.388	-0.443	-0.605
Shannon	-0.066	-0.094	-0.108	-0.150
Simpson	-0.026	-0.040	-0.046	-0.066

Note: household sampling weights applied. Clustered standard errors with 100 bootstrap repetitions.

of an analysis that involves multiple comparisons, rather than an analysis that involves only a single comparison. In this analysis, we have 5 outcomes at household level and 4 outcomes at child level, which implies 9 hypothesis tests. If we just test the hypotheses one by one, then the probability to get one or more false rejections when using a critical value of 0.05 is 23% and 18.5% at household and child levels, respectively. In order to reduce the likelihood of these false rejections, we need to adjust for the fact that we are testing multiple hypotheses.

Bonferroni (1935) developed the first technique to account for multiplicity in hypothesis testing, but many other procedures have been implemented over the years. Among them, we use the the Romano-Wolf multiple hypothesis correction, described in Romano and Wolf (2005a,b, 2016), to calculate the step-down adjusted p-values robust to multiple hypothesis testing. This program follows the re-sampling algorithm described in Romano and Wolf (2016), and provides a p-value that controls the family-wise error rate (FWER), i.e. the probability of committing any Type I error among all of the hypotheses tested, and allows for dependence among p-values by bootstrapping during the re-sampling process. The Romano-Wolf correction presents many advantages and improvements compared to earlier procedures, including more power and the elimination of the subset pivotality assumption (see Clarke et al. (2020) for a full discussion). We also compute the Holm multiple hypothesis correction and we compare the model p-value with the Romano-Wolf and Holm corrections. When correcting for multiple-hypothesis testing, the effect of COVID-19, proxied by the dummy of the third trimester, loses significance on the various outcome variables except for stunting, which instead remain significant at the 5% level using both types of correction. The p-value for per capita food consumption increases but remains at a low level (around 15%).

Table 3.6: Multiple hypothesis corrections.

Outcome Variable	Model p-value	Romano-Wolf p-value	Holm p-value
Pc Food Consumption	0.000	0.139	0.158
Caloric Intake	0.000	0.218	0.475
Shannon index	0.036	0.257	0.495
Simpson index	0.058	0.257	0.257
Stunting	0.002	0.010	0.040
Wasting	0.488	0.812	1.000
Underweight	0.785	0.812	0.753
Overweight	0.251	0.673	0.772

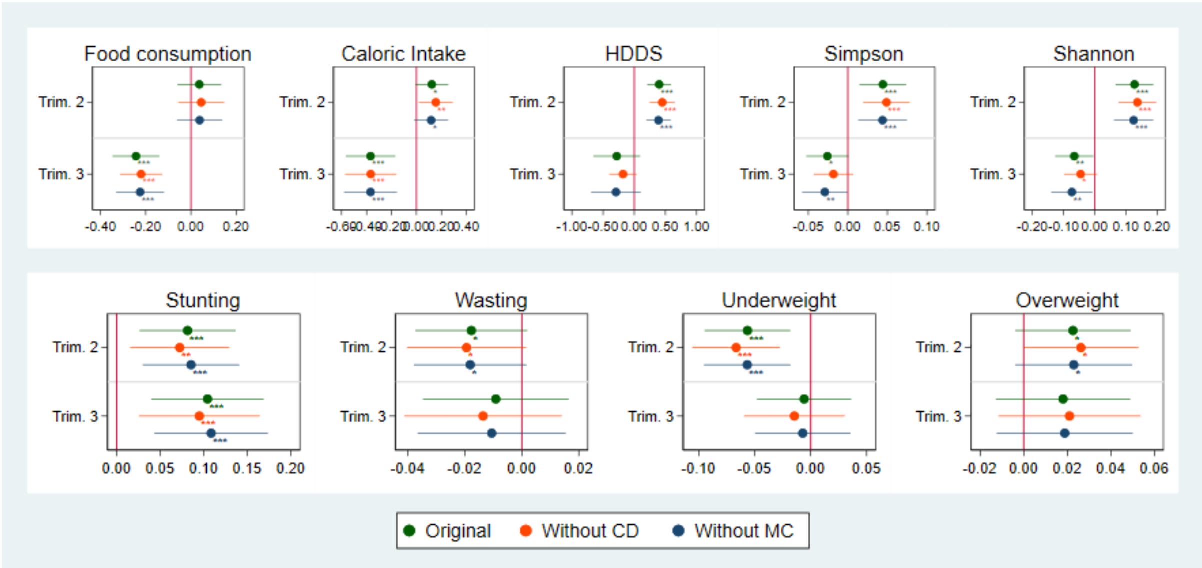
Note: column 2 reports the p-value estimated through the original model. Column 3 reports the step-down adjusted p-values robust to multiple hypothesis testing, based on the resampling algorithm described by Romano and Wolf (2016). It provides a p-value corresponding to the significance of a hypothesis test where S tests have been implemented, providing strong control of the FWER. The algorithm constructs a null distribution for each of the S hypothesis tests based on Studentized bootstrap replications of a subset of the tested variables. Number of replications = 100. Full details of the procedure are described by Romano and Wolf (2016). Column 4 reports the p-values corresponding to the Holm multiple hypothesis correction. Household sampling weights applied. Clustered standard errors at the district level.
Source: authors' elaboration based on data from IOF 2019–20.

Sensitivity analysis

Although provinces in Mozambique are quite heterogeneous, two of them are particularly different from the rest of the country. These are the city of Maputo and the province of Cabo Delgado. The first one diverts from the rest of the country because it is the main urban center, where the economy is much more developed and whit the highest level of welfare (70% of households in this province belongs to the 5th wealth quintile).

In Cabo Delgado instead a conflict began in October 2017, disrupting many people's livelihoods and forcing people to displace to other areas of the country. As a result, households living in this province are among the poorest in the country (DEEF, 2016). Additionally, the ongoing conflict makes the data collection difficult, causing possible problems of measurement error. Therefore, the inclusion of these two provinces could falsify the results. To check this, we ran again the analysis excluding each of the two provinces one by one. From the comparison of the original results with the new ones, reported in Figure 3.13, we can see that the coefficients do not differ substantially. Thus, we conclude that our results are not driven by these specific sample outliers.

Figure 3.13: Sensitivity analysis excluding provinces of Cabo Delgado and Maputo City



Source: Authors' elaboration from IOF 2019/2020.
Note: Dots are coefficients estimated from a linear regression (first row) and average marginal effects estimated from a probability regression (second row). Bars are 95% confidence intervals.

3.6 Conclusion

This study aims to understand how COVID-19 has affected food consumption and nutritional outcomes of households and children in Mozambique. The advancements that this work provides to the current literature are mainly two. First, it confirms some of the predictions early made in other studies based on simulation exercises. Here indeed we used real data collected through face-to-face interviews, including physical measurement of weight and height for children under 5 years old and detailed data of food consumption. Second, it tries to shed light on the mechanisms of the effect, looking at the different household and child characteristics, and trying to find a link between the household food environment and the child nutritional status.

We found that after the COVID-19 outbreak household food consumption and diet quality declined on average. This however did not occur in the immediate aftermath, suggesting that at the beginning households could rely on different coping mechanisms to offset the negative consequences of the crisis. We also see that a higher stringency level corresponds to a lower caloric intake and dietary diversity. This result suggests that measures aimed to alleviate food insecurity, such as food and cash transfers, are needed in conjunction with the non-pharmaceutical interventions implemented by the government to contrast the spread of the virus.

From the heterogeneity analysis, we are able to confirm and validate some of the predictions made in other studies. Specifically, as predicted in Betho et al. (2022), households located in the South have been affected more than the households living in the rest of the country. This can be explained by the higher level of enforcement of restrictions in the cities, more prevalent in the South, and the higher food market dependence. This result is also confirmed when we look at the differential effect between rural and urban households, although the effect is not significant, and between households practicing subsistence agriculture vis-a-vis the other households.

Wealthier households are the ones more affected by the COVID-19 crisis, as emerges from the heterogeneity analysis. This result can be explained through the Engel's Law and a non-linear income elasticity of the food demand, as the share of food expenditure over the total expenditure decrease (increases) in relation to the level of income. Indeed, the richest households are able to reduce their food expenditure more than the poorest ones. For the latter, instead, since they were already consuming at the subsistence level, it is much more difficult to further shrink their food consumption when experiencing a negative shock.

Before the pandemic, the country was already suffering from high levels of stunting, especially in the North, and the COVID-19 crisis contributed to further exacerbating this type of malnutrition. This is an alarming trend that cannot be ignored, and immediate actions need to be taken. This requires a joint effort of the public institutions, including the Ministry of Health, international organizations operating in the country, including UNICEF and WFP, and the involvement of local communities. This is particularly relevant for newborn children, which resulted to be the group most affected.

This is the first study that looks at the consequences of the COVID-19 crisis on food consumption and nutrition in Mozambique, and it is one of the few existing studies that rely on detailed and accurate data in the aftermath of the pandemic. Despite the rich quantity and quality of information contained in the data, the type of data itself imposes some limitations in the analysis. Cross-sectional data indeed does not allow to control for time-invariant household and individual characteristics, which could be a source of possible endogeneity problems. Additionally, the type of shock analyzed does not allow to have a robust and valid identification strategy that allows using experimental or quasi-experimental models usually employed to measure the impact of exogenous shocks. Indeed, the COVID-19 shock, given its aggregate and simultaneous nature, cannot fit a typical treatment/control setting. For this reason, we are not able to claim a causal impact of COVID-19 on food consumption and nutrition. However, we are confident that the findings emerging from this analysis have highlighted important patterns and may help steer policymakers towards better targeted and more effective interventions in the aftermath of this pandemic and the onset of similar undesirable future crises in Mozambique.

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Appendix

Data description

Variable	Description
Pc Food consumption	Per capita household food expenditure (food purchased + monetary value of food consumed from own production)
Pc Caloric intake	Per capita daily calories consumed in the household
HDDS	Household Dietary Diversity Score based on 12 food groups
Simpson index	Simpson dietary diversity index based on 15 food groups
Shannon index	Shannon dietary diversity index based on 15 food groups
Stunting	Dummy equal to 1 if height-to-age Z-score<2
Wasting	Dummy equal to 1 if weight-to-height Z-score<2
Underweight	Dummy equal to 1 if weight-to-age Z-score<2
Overweight	Dummy equal to 1 if weight-to-height Z-score>2
HH size	N. of members in the household
HH head is female	Dummy equal to 1 if the household head is female, zero otherwise.
Asset index	Asset wealth index constructed using principal component analysis based on the DHS approach.
Dep. ratio	Percentage of individuals under 15 and over 64 within the household.
HH has children	Dummy equal to 1 if at least a member of the household is less than 18 years old.
% employed	Percentage of members over 6 years old that worked for at least one hour in the last 7 days, including agricultural activities.
Head has primary educ.	Dummy equal to 1 if household head had completed primary education.
HH owns land	Dummy equal to 1 if household owns a piece of land (machamba).
TLU	N. of Tropical Livestock Units owned by the household.
HH is subsistence ag.	A household is defined to practice subsistence agriculture if the share of food consumption from own production over total food consumption is >50%
Rural	Dummy equal to 1 if household is located in a rural area.
Social assistance	Dummy equal to 1 if household received some social assistance from the government in the last 12 months
Access to city (hours)	Hours required to access main urban centers (>50,000 inhabitants)
% of land=Savannas	Percentage of land covered by Savannas
% of land=Grasslands	Percentage of land covered by Grasslands
% of land=Braidleaf forest	Percentage of land covered by Deciduous Braidleaf forest
% of land=Urban	Percentage of land covered by Urban and built-up land

Full regression results

Table 7: Full regression - Household level.

Variables	Food Cons.	Caloric Intake	HDDS	Simpson	Shannon
2nd Trimester	0.0373	0.123*	0.400***	0.0443***	0.127***
	(0.0491)	(0.0671)	(0.0964)	(0.0149)	(0.0307)
3rd Trimester	-0.243***	-0.368***	-0.280	-0.0259*	-0.0657**
	(0.0523)	(0.101)	(0.190)	(0.0135)	(0.0310)
HH size	-0.0704***	-0.0533***	0.0671***	-0.00254*	-0.00109
	(0.00496)	(0.00590)	(0.0129)	(0.00149)	(0.00380)
HH head is female	-0.0735***	-0.00730	-0.161***	-0.00500	-0.0109
	(0.0187)	(0.0282)	(0.0494)	(0.00637)	(0.0154)
Asset index	0.0771***	0.0224**	0.0856***	0.00665***	0.0168***
	(0.00585)	(0.00863)	(0.0194)	(0.00217)	(0.00583)
Dep. ratio	-0.0544***	-0.0587***	-0.0609**	-0.0102***	-0.0227***
	(0.00960)	(0.0150)	(0.0254)	(0.00311)	(0.00646)
HH has children	-0.213***	-0.119***	0.310***	0.0111	0.0557***
	(0.0273)	(0.0449)	(0.0741)	(0.00859)	(0.0201)
% employed	0.245***	0.138***	0.240**	-0.00767	0.00200
	(0.0496)	(0.0526)	(0.101)	(0.0103)	(0.0256)
Head has primary educ.	0.0197	-0.0521*	0.155***	0.0206***	0.0491***
	(0.0172)	(0.0265)	(0.0472)	(0.00636)	(0.0137)
HH owns land	-0.00833	0.0682	-0.0623	0.00825	0.0130
	(0.0305)	(0.0419)	(0.0889)	(0.00917)	(0.0220)
TLU	-0.000800	0.000813**	0.000769	-7.78e-05	-0.000246
	(0.000690)	(0.000390)	(0.000575)	(7.23e-05)	(0.000158)
HH is subsistence ag.	-0.0144	0.0798	-0.667***	-0.0878***	-0.216***
	(0.0475)	(0.0998)	(0.140)	(0.0121)	(0.0314)
Rural	-0.0168	-0.141*	-0.551***	-0.0180	-0.0584**
	(0.0410)	(0.0727)	(0.107)	(0.0123)	(0.0272)
HH receives social assistance	-0.125***	-0.0975	-0.0559	0.00408	0.0125

	(0.0412)	(0.0648)	(0.106)	(0.0143)	(0.0291)
Access to city (in hours)	0.0151	-0.00116	-0.0590***	-0.00256	-0.00680
	(0.00928)	(0.0146)	(0.0183)	(0.00265)	(0.00508)
% of Savannas	-0.00195	-0.00348	-0.00367	-0.000346	-0.00139
	(0.00148)	(0.00224)	(0.00362)	(0.000405)	(0.000920)
% of Grasslands	0.000405	0.000344	-0.00154	-0.000625	-0.00186
	(0.00172)	(0.00225)	(0.00396)	(0.000562)	(0.00126)
% of Braidleaf forest	0.000610	-0.00423	-0.00499	-0.000293	-0.00213
	(0.00285)	(0.00495)	(0.00701)	(0.000815)	(0.00181)
% of Urban land	-0.00120	-0.00593*	-0.0165**	-0.000912	-0.00300*
	(0.00188)	(0.00335)	(0.00764)	(0.000733)	(0.00169)
Province=CD	0.481***	0.999***	1.906***	0.0440	0.0697
	(0.0831)	(0.0928)	(0.325)	(0.0316)	(0.0788)
Province=GZ	-0.165	-0.194	-1.147***	-0.0947***	-0.312***
	(0.103)	(0.133)	(0.327)	(0.0321)	(0.0784)
Province=IN	0.259***	0.422***	0.424	0.0335	0.0792
	(0.0817)	(0.121)	(0.275)	(0.0257)	(0.0648)
Province=MA	0.894***	0.881***	0.672**	-0.118***	-0.307***
	(0.0776)	(0.135)	(0.295)	(0.0304)	(0.0713)
Province=MP	0.109**	-0.108	-0.166	-0.0109	-0.0114
	(0.0456)	(0.0685)	(0.172)	(0.0148)	(0.0381)
Province=NI	-0.0410	0.648***	1.460***	-0.0193	-0.0636
	(0.0843)	(0.0911)	(0.261)	(0.0311)	(0.0769)
Province=NP	0.648***	1.055***	1.366***	-0.0777**	-0.186**
	(0.0751)	(0.0907)	(0.277)	(0.0320)	(0.0767)
Province=SF	0.544***	0.419***	0.675**	0.00574	-0.0422
	(0.0984)	(0.135)	(0.292)	(0.0280)	(0.0687)
Province=TT	0.816***	0.461***	0.154	-0.111***	-0.297***
	(0.0813)	(0.155)	(0.302)	(0.0283)	(0.0672)
Province=ZA	0.528***	0.746***	0.651**	-0.00442	-0.101
	(0.0876)	(0.118)	(0.272)	(0.0304)	(0.0771)
Month= February	-0.00176	-0.0661	-0.167	-0.00738	-0.0120
	(0.0546)	(0.0777)	(0.139)	(0.0175)	(0.0392)
Month= August	-0.00140	-0.0294	-0.232**	-0.00832	-0.0464*

	(0.0452)	(0.0565)	(0.108)	(0.0123)	(0.0272)
Month= September	0.170**	0.325**	0.425*	0.0524**	0.126***
	(0.0768)	(0.138)	(0.237)	(0.0204)	(0.0475)
Month= October	0.189**	0.387***	0.300	0.0289	0.0671
	(0.0801)	(0.125)	(0.239)	(0.0207)	(0.0470)
Month= November	0.225***	0.378***	0.460***	0.0330**	0.0859***
	(0.0461)	(0.0607)	(0.145)	(0.0138)	(0.0307)
Month= December	0.139*	0.147*	0.743***	0.0689***	0.177***
	(0.0716)	(0.0870)	(0.148)	(0.0160)	(0.0355)
Constant	4.131***	7.701***	5.659***	0.637***	2.419***
	(0.133)	(0.192)	(0.375)	(0.0462)	(0.110)
Observations	11,836	11,836	11,836	11,836	11,836
R-squared	0.348	0.144	0.261	0.184	0.229

Note: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 8: Full regression - chil level.

Variables	Stunting	Wasting	Underweight	Overweight
2nd Trimester	0.0814***	-0.0178*	-0.0566***	0.0226*
	(0.0282)	(0.0100)	(0.0196)	(0.0135)
3rd Trimester	0.104***	-0.00914	-0.00587	0.0180
	(0.0329)	(0.0131)	(0.0215)	(0.0157)
HH size	0.00799***	0.000346	0.00131	-0.000492
	(0.00285)	(0.00152)	(0.00203)	(0.00101)
HH head is female	0.0209	0.0116	0.0126	-0.0257***
	(0.0213)	(0.00725)	(0.0160)	(0.00967)
Asset index	-0.0386***	-0.00107	-0.0209***	0.000840
	(0.00589)	(0.00270)	(0.00521)	(0.00208)
Dep. ratio	0.0152	0.00155	0.0154***	-0.00239
	(0.00963)	(0.00364)	(0.00573)	(0.00395)
% employed	0.0332	-0.00139	0.0133	-0.0178
	(0.0336)	(0.0134)	(0.0238)	(0.0118)

Head has primary educ.	-0.0186	-0.00699	-0.0134	-0.0141*
	(0.0139)	(0.00630)	(0.0124)	(0.00829)
HH owns land	0.0361	0.000773	0.0140	-0.0147
	(0.0396)	(0.0148)	(0.0345)	(0.0183)
TLU	-0.00185	-0.00144	-3.72e-05	2.16e-05
	(0.00274)	(0.00153)	(0.000404)	(8.45e-05)
HH is subsistence ag.	0.000512	0.00981	8.39e-05	0.0102
	(0.0228)	(0.00978)	(0.0153)	(0.00950)
Rural	-0.00412	-0.00125	-0.00493	0.0199*
	(0.0212)	(0.00891)	(0.0206)	(0.0109)
HH receives social assistance	-0.00364	0.0310*	-0.00427	-0.0336
	(0.0304)	(0.0176)	(0.0409)	(0.0226)
Child is female	-0.0609***	0.000591	-0.0308**	-0.00711
	(0.0136)	(0.00527)	(0.0130)	(0.00682)
Child is newborn	-0.227***	0.0417***	-0.0174*	-0.00373
	(0.0144)	(0.00528)	(0.0104)	(0.00769)
Child is firstborn	0.0230	-0.00458	0.0242	0.00265
	(0.0210)	(0.0108)	(0.0170)	(0.0108)
Access to city (in hours)	-0.0104**	-0.00112	-0.00471	0.00105
	(0.00486)	(0.00166)	(0.00356)	(0.00177)
% of Savannas	0.000395	2.09e-05	0.000392	0.000171
	(0.000631)	(0.000241)	(0.000623)	(0.000347)
% of Grasslands	0.000720	5.55e-05	0.00101	-0.000174
	(0.000764)	(0.000241)	(0.000702)	(0.000414)
% of Braidleaf forest	0.00174	8.47e-05	0.00107	0.000210
	(0.00132)	(0.000450)	(0.00102)	(0.000459)
% of land=Urban	0.000251	8.24e-05	-0.00123	0.000234
	(0.00145)	(0.00108)	(0.00178)	(0.000540)
Province=CD	0.0969**	-0.0179	-0.0268	-0.00497
	(0.0469)	(0.0360)	(0.0670)	(0.0205)
Province=NI	0.100**	0.0357	0.0298	0.0208
	(0.0480)	(0.0366)	(0.0705)	(0.0222)
Province=NP	0.0547	0.00704	-0.0346	0.0290

	(0.0480)	(0.0373)	(0.0704)	(0.0208)
Province=ZA	0.0494	-0.00844	-0.000572	-0.0176
	(0.0464)	(0.0359)	(0.0696)	(0.0225)
Province=TT	0.000343	-0.00352	-0.0574	0.00843
	(0.0535)	(0.0381)	(0.0701)	(0.0228)
Province=MA	0.0379	-0.0214	-0.0514	-0.00229
	(0.0505)	(0.0372)	(0.0690)	(0.0207)
Province=SF	-0.0184	-0.00507	-0.0535	0.00376
	(0.0520)	(0.0355)	(0.0684)	(0.0214)
Province=IN	-0.120**	-0.0167	-0.125*	0.0192
	(0.0503)	(0.0381)	(0.0681)	(0.0206)
Province=GZ	-0.0645	-0.00593	-0.0988	0.0347
	(0.0576)	(0.0369)	(0.0716)	(0.0234)
Province=MP	-0.224***	-0.0147	-0.0887	0.0151
	(0.0375)	(0.0345)	(0.0577)	(0.0169)
Month= February	0.0389	0.00858	0.0249	-0.0180
	(0.0305)	(0.0108)	(0.0214)	(0.0162)
Month= July	0.0339	-0.00567	0.0375*	0.0115
	(0.0269)	(0.0118)	(0.0216)	(0.0115)
Month= October	8.05e-05	0.00213	0.00411	0.00864
	(0.0324)	(0.0118)	(0.0249)	(0.0166)
Month= November	-0.0318	0.00868	-0.0168	-0.00685
	(0.0331)	(0.0131)	(0.0211)	(0.0151)
Month= December	0.0295	-0.0122	-0.0686**	-0.00469
	(0.0364)	(0.0159)	(0.0339)	(0.0206)
Observations	6,581	6,566	6,578	6,566

Note: Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1