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

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

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Abstract

The COVID-19 pandemic and the related restrictions implemented by the Ugandan government placed severe limitations on labor mobility, inputs availability, and market access. This negatively impacted poverty and food insecurity, especially in refugee-hosting districts, which were already suffering a fragile situation. While worsening levels of food security and dietary quality in the country have been documented by several authors, it is still unclear how the COVID-19 impact was transmitted to the final outcomes. This paper aims to identify the mechanisms through which COVID-19 affected poverty and food insecurity in refugee-hosting districts in Uganda.

Starting from the two main transmission channels– i.e., food value chain disruption and job loss – we use path analysis with household fixed effects to identify the main pathways for different groups of households according to refugee status (i.e. refugee vs. host households), main income source (agricultural vs. non-agricultural households) and agricultural household's market position (i.e. net-buyers vs. net-sellers vs. self-sufficient households). The role of responses that can offset the COVID-19 shock, such as assistance received or access to credit, and exogenous factors, such as environmental shocks or distance to market, have also been accounted for.

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 were impacted mostly by food prices and agricultural income, while refugees were more affected through labor market mediated effects. 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.

Keywords: COVID-19, food value chain, labor market participation, income loss.
JEL Codes: I15, O12, Q12

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. 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 existing 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[1] and a significant share of the population unable to meet their own basic needs[2], including food, especially in the northern and eastern parts of the country (OPM, WFP, UNHCR, & DP, 2020). A fast-growing population, expected to reach 100 million by 2050, and the presence of the world's third-largest refugee[3] population are other challenges the country faces.

Uganda indeed hosts the largest refugee population in Sub-Saharan Africa, with almost 1.5 million refugees, mainly originating from conflict-affected neighborhood countries such as South Sudan, the Democratic Republic of the Congo, and Burundi (UNHCR, 2021; IPC, 2021). Uganda 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 the 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, WFP, UNHCR, & DP, 2020), and the number of food-insecure households increases. Food insecurity in refugee settlements has recently peaked at 47% of households that crucially depend on humanitarian assistance to meet their food needs (UNHCR, 2021).

The COVID-19 outbreak exacerbated an already fragile situation. The first case of COVID-19 in the country was reported on March 20th, 2020. Just two days after the government imposed severe restrictions such as border closure, lockdown of schools, religious gatherings and non-essential businesses, and domestic as well as international travel restrictions. Many sectors got 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

[1] World Bank Open Data, available at https://data.worldbank.org/indicator/SI.POV.DDAY?locations=UG
[2] The World Bank (2020) estimates that the multi-dimensional poverty incidence was at 60% in 2016/2017.
[3] United Nations High Commissioner for Refugees, Uganda Comprehensive Refugee Response Portal.

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). The enforcement of these measures significantly impacted economic activities as well as people's life.

Reports show that in many East African countries, including Uganda, these impacts were channeled mainly through the loss/reduction of jobs and the disruption of food systems (Demeke & Kariuki, 2020; ILO, 2020; UN-Habitat & WFP, 2020), eventually leading to higher poverty and food insecurity rates (Kansiime et al., 2021). COVID-19 related restrictions indeed have impacted all stages of the food supply chains, from production to consumption (Siche, 2020; Torero, 2020) and there is some evidence that food prices increased by 8%-10% in the region between April 2019 and April 2020 (UN-Habitat &WFP, 2020).

Despite anecdotal evidence of these COVID-19 related impacts at various stages of the economic system, it is not clear yet how the COVID-19 shock has been transmitted through the food system to eventually impact households' welfare. Furthermore, different types of households are expected to be affected differently, based on their socio-economic characteristics, their sources of livelihood, and their participation to market transactions. 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 paper are the following:

a) What are the pathways linking COVID-19 shock to household poverty and food security?
b) Whether COVID-19 differently affected different types of households and, if so, how?

The effects of COVID-19 on household poverty and food security can occur through two main channels. On the one hand, government restrictions disrupt livelihood activities, specifically participation in the labor market, reducing household income (Abay et al., 2020; Amare et al., 2020; Arndt et al., 2020; World Bank, 2020). On the other hand, disruption of food markets and value chains undermines access to food, reducing food security (e.g., Aggarwal et al., 2020; 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 different household groups according to 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 uses primary data from a survey specifically designed for refugees and host communities through in-person interviews administered before, during, and after the COVID-19 outbreak. Compared to the phone-based interviews used during the COVID-19 outbreak by many organizations (e.g. Ambel et al., 2020; Atamanov et al.,2022; Chikoti et al., 2022; 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 also 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; Henderson & Rosenbaum, 2020; Himelein et al., 2020; Zezza et al., 2021).

The second contribution refers to the study focus, i.e., the transmission mechanisms. So far research just focused on the COVID-19 overall impact 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. Mahmud and Riley (2021) measured the economic and well-being impact 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 World Bank, in collaboration with the Uganda Bureau of Statistics (UBOS) and UNHCR, conducted a series of phone surveys to track the socioeconomic impacts of COVID-19 among refugees in Uganda. Preliminary 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 (World Bank, 2021). Furthermore, there is evidence that refugees fared substantially worse on key dimensions of welfare and their recovery was slower compared to Ugandans in general (Atamanov et al., 2021). None of these studies, however, look at how the impact was transmitted to the final outcomes through possibly different pathways.

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 welfare dimensions, i.e., poverty and food security, structural equation modeling (SEM) is used. So far SEM has been mainly used for investigating the psychological impact of the pandemic (Chen et al., 2021; Buttler et al., 2021; Lathabhavan & Vispute, 2021), while the economic consequences of the shock have been mainly estimated through simulation exercises based on projections (Younger et al., 2020; Laborde et al., 2021; Filipski et al., 2022). In this study, instead, we use 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 paper is organized as follows. The next section describes the data used and presents some descriptive statistics of the outcome variables and meditating factors. Section 3 describes the SEM methodology. Section 4 presents the results of the analysis. Section 5 concludes.

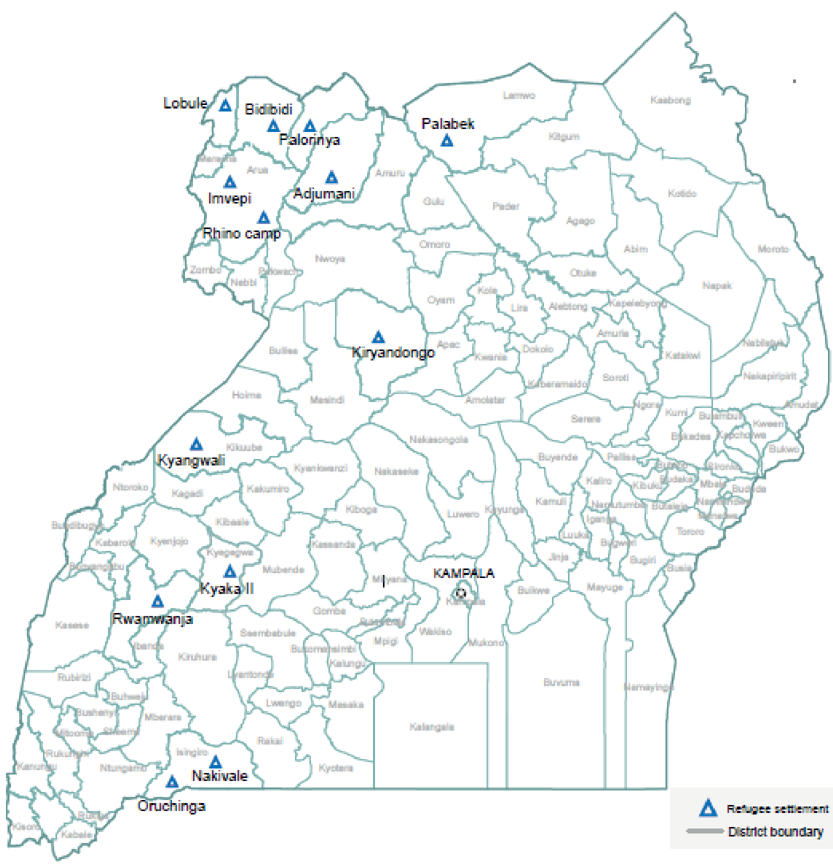
. Data

Data used in this study come from the RIMA Uganda Refugee and Host Communities Panel Survey, a three-round longitudinal survey representative at the national level, 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 (Figure 1). The host communities have been identified as the closest communities living in the same sub-county.

The survey provides a unique panel dataset representative of refugee and host communities in the country (Mastrorillo et al., 2021), which includes detailed information on households living within and in proximity to settlements. The dataset indeed contains a wide range of information on household socio-demographic and economic status, including food security, shocks, assistance, employment, agricultural and livestock production, with the 2020 round containing also COVID-19-related questions, such as the reasons why the household experienced problems in getting food.

The first round of data was collected during three different periods in 2017, 2018, and 2019; the second one in December 2019; and the third one in December 2020, nine months after the COVID-19 outbreak in the country. In this study, only the second and the third rounds are considered, i.e. a baseline just before the COVID-19 outbreak and a follow-up in the aftermath of the pandemic. The fact that the interviews took place in the same month in the two rounds allows for time comparability, especially for what concerns crop production and seasonal patterns. The final balanced sample includes 2,969 households per year. The households were selected using a stratified two-stage cluster sampling, with refugee households' settlement blocks (or the villages close to the settlement for host households) as the Primary Sampling Units, and randomly selected households as the Second Sampling Units. The probability of selection is proportional to the size of the settlement or sub-county (d'Errico et al., 2021).

Figure 1. Map of the refugee settlements in Uganda



Note: The survey covers the following settlements across eight districts: Palabeck settlement in Lamwo district; Palorinya in Moyo; Bidibidi in Yumbe, the namesake settlements in Adjumani and Kiryandongo districts; Imvepi and Rhino in Arua, Kyaka II in Kyegegwa and Rwamwania in Kamwenge. In each district, only one settlement and the closest host community are included in the sample, except for Arua and Adjumani districts, where respectively two (Imvepi and Rhino) and six settlements are sampled. Small changes in district boundaries exist from one year to another.
Source: Mastrorillo et al. (2021).

.. *Outcome variables*

The two outcome variables considered in this analysis are poverty and food security. For poverty, a relative poverty line was constructed, taking half of the median of per capita daily expenditure distribution in 2019, which corresponds to USD 0.13 (in 2011 PPP)[4]. Under this poverty line, 26% of households in 2019 are poor, while in 2020 the share increases to 29%. The use of a relative vis-à-vis an absolute poverty line is due to data constraints. The consumption module of the questionnaire is not comprehensive enough to compute an adequate measure of expenditure that can be compared to official statistics. Therefore, using international or national absolute poverty lines would have led to incorrect poverty levels. The consumption module used in the questionnaires in 2019 and 2020 however is the same, allowing for comparability across waves. For this reason, we opted for a relative measure of poverty. The Food Consumption Score (FCS) has been used as a proxy for food security[5]. Although the FCS is an indicator that captures the quality of household diet, it is highly correlated also to quantitative measures of food consumption (IFPRI, 2006). Even for food security, the situation worsened in 2020, with an average reduction of 5.6 percentage points. The changes for both poverty and FCS are statistically significant.

.. *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 between rounds and the absence of significant shocks occurring between the two rounds, we can assume that any change that occurred can be attributed to COVID-19.

[4] The national annual poverty line was UGX 46,233.65 in 2016/2017 (UBOS, 2019), which corresponds to daily poverty line in 2011 PPP of USD 0.10, very close to relative poverty line used in our study.
[5] The FCS is an indicator based on the number of days specific food groups are consumed in the seven days preceding the survey. The FCS is a continuous score where a value less than or equal to 45 or between 45 and 62 respectively indicate poor or borderline food consumption. This value is obtained by assigning a specific weight to each food group in accordance to its contribution to dietary quality (WFP, 2008).

However, to control for any other possible shocks hitting the surveyed communities over the same period, we look for any systemic and idiosyncratic shocks affecting the surveyed households. Among systemic shocks, respondents reported that drought and flood are the most frequently experienced agricultural shocks, affecting 25% and 26.6% of households respectively. Indeed, 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[6] has been included in the model, affecting the quantity of crop produced and the FVC disruption.

Among the idiosyncratic shocks, only 5% of respondents reported that some household members suffered from COVID-19 symptoms. This suggests that the COVID-19 impacts do not depend directly on the respondent's infection, but rather on the pandemic's indirect consequences on the economy. To discriminate between the economic effects and the direct health effects, a dummy equal to 1 if at least one household member suffered from the COVID-19 symptoms has been included in the model. However, we must consider that the fear of getting infected can affect the 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.

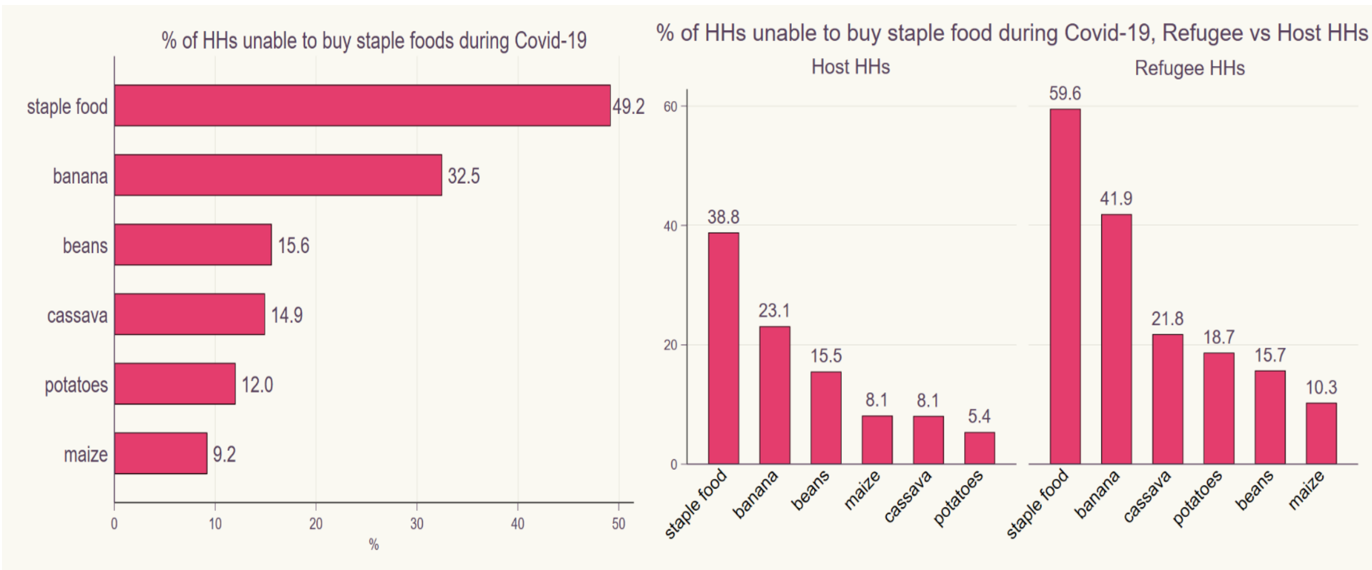
The two main transmission channels – i.e., job loss and food value chain (FVC) disruption – have been proxied by two other variables. The change in household employment was proxied by the change in the share of employed household members, excluding children under the age of six[7]. The FVC disruption proxy was built as a count variable summing up the answers to the questions on the reasons for not being able to buy main staple foods[8]. The higher the number the higher the level of FVC disruption.

Almost 10% of households in 2020 reported at least one type of FVC disruption, with the closure of local markets the most frequent one. Roughly half of the households were unable to buy staple food during COVID-19, with bananas being the most reported food (32% of respondents).

[6] 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).
[7] Six years is the age limit considered in the employment module of the RIMA Uganda Refugee and Host Communities Panel Survey questionnaire.
[8] The answers include: "shops have run out of stock", "local market closed", "limited/no transportation", "restriction to go outside", "increase in price", "no access to cash and cannot pay with credit card", "cannot afford it". we computed an index ranging from 0 to 4, indicating the household severity experienced in getting food, by summing up the first four answers. The last other three options were not included in the index because they refer to the consequences of the FVC disruption rather than to the disruption per se.

In general, refugee households report more difficulties in buying all types of food than host households (Figure 2). Among the reasons for not being able to buy staple foods, lack of affordability and price increase are the most frequent responses.

Figure 2. Percentage of households unable to buy staple foods by food item, overall and refugees vs. hosts



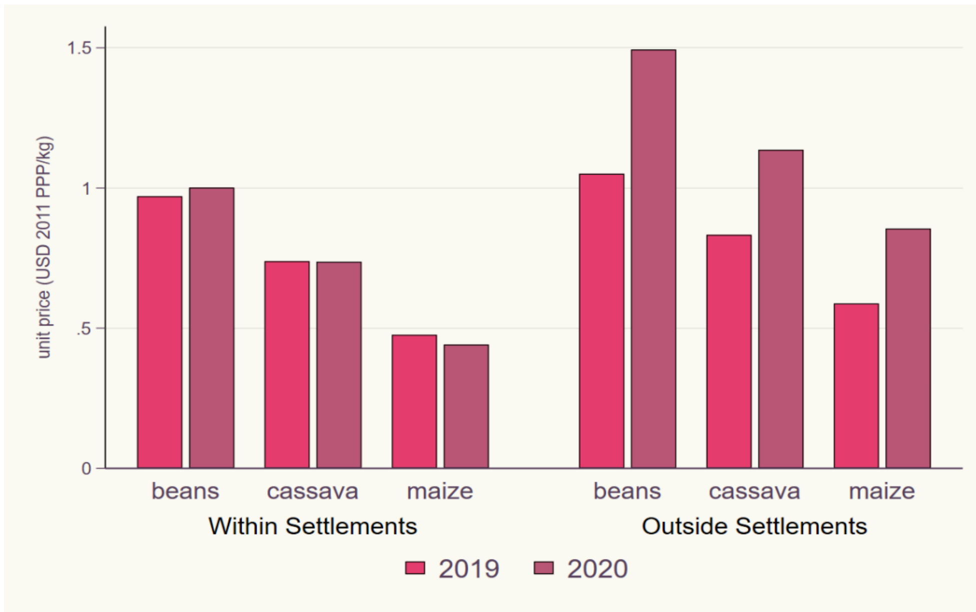
Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2020.

Indeed, a price increase between 2019 and 2020 has been observed for selected crops, although different trends exist within and outside refugee settlements (Figure 3). Within the settlements, prices remained quite stable, as confirmed by the WFP market price monitoring system[9], while outside settlements, i.e. where host households live, prices significantly increased compared to 2019.

However, spatial and temporal variations in prices occurred, especially in more integrated markets (Dietrich et al., 2021), The Famine Early Warning Systems Network (FEWS NET, 2020) confirms an increase in the retail price of beans compared to the previous year. The price of maize increased to high levels in April and May amidst panic-buying and trade disruptions (FAO, 2020), but then there was a reduction between May and August in all markets as the commercialization of the first season harvest increased market availability (Figure 4).

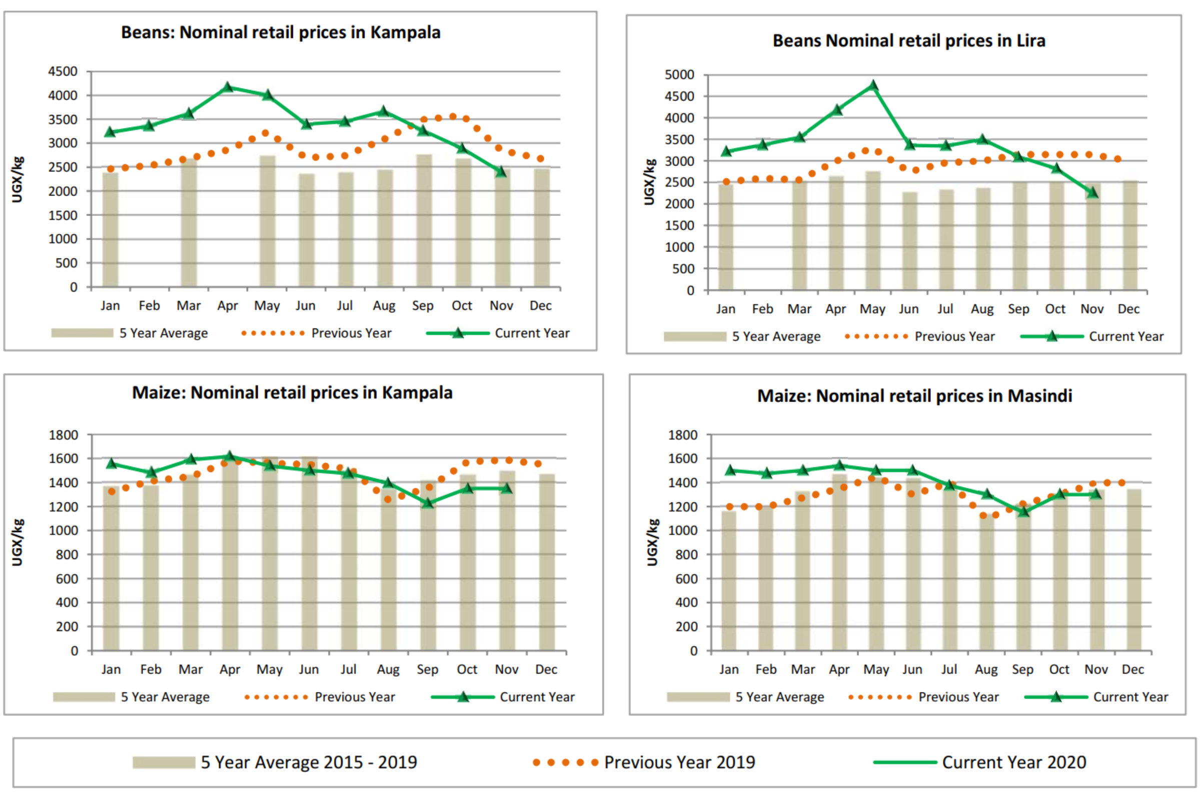
[9] Cf.
https://reliefweb.int/sites/reliefweb.int/files/resources/USAID_WFP_MM_Factsheet_15_March2021_round.pdf.

Figure 3. 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.

Figure 4. Monthly prices of beans and maize in selected local markets.



Source: FEWS NET (2020).

.. *Household types*

Households included in the RIMA Uganda Refugee and Host Communities Panel Survey are highly heterogeneous. Therefore, the analysis has been conducted for the pooled sample as well as separately for different household types. These types refer to the household community of origin – refugees vs. hosts – and the household‘s main livelihood source – i.e. agriculture vs. non-agriculture[10].

Households living in refugee-hosting areas, both refugees and hosts, are among the poorest in the country, especially in the Southwest and West Nile regions (World Bank, 2019). However, differences in terms of socioeconomic characteristics exist between the two groups. Refugee households are characterized by a younger head, more frequently a female, and less educated head as compared to host households. Per capita daily expenditure of refugees is almost half that of hosts. Although decreasing with tenure, cash and food transfers remain the main source of livelihood for refugees[11] (Figure 5). Most refugees are granted a piece of land, but the land size operated by refugee households is much smaller compared to the land size 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 isolation in their host country (Hovil, 2016) and depriving them of voting rights 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 employment that is below their skills level, and refugees with higher education are more likely to be unemployed (Beltramo et al., 2021).

Agricultural households are defined as households that reported some agricultural production in the twelve months prior to the survey[13]; the opposite is true for non-agricultural households.

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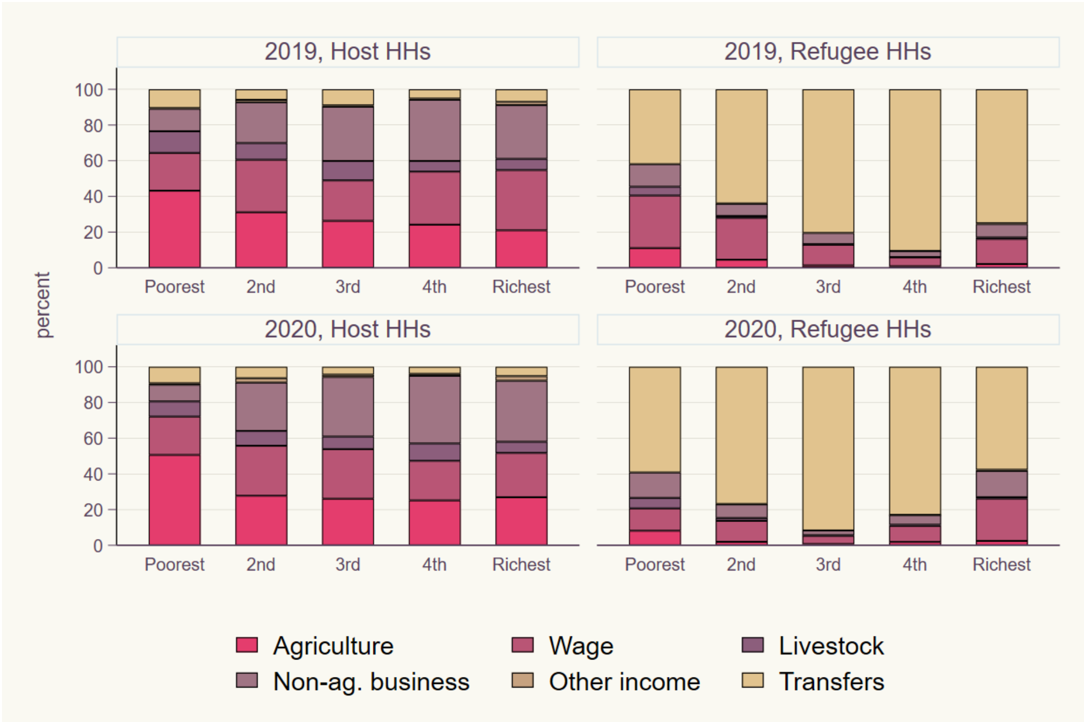
[10] The definitions of the various household groups are reported in Annex 1.
[11] Transfers are still the main source of income for 37% of refugees more than 5 years after refugees' arrival (World Bank, 2019).
[12] This apply also to the children of refugees born in Uganda (even if one parent is Ugandan) and their future offspring. As a result, refugees can neither repatriate nor resettle elsewhere (Watera et al., 2017).
[13] In accordance with the "broad" definition of agricultural households in Eurostat's statistics on income of agricultural households sector (Eurostat, 1995) and the FAO's definition of an agricultural holding (FAO, 2015).

Figure 5. 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.

However, agricultural households are a very heterogenous group that could be classified as:

a) net-buyer, when the value of household food production is less than household food consumption;

b) net-seller, when the value of household food production exceeds the household food consumption, thus being able to market the surplus; and

c) self-sufficient, when the household food production and consumption are balanced, i.e. they neither sell nor purchase in the market.

These features are crucial in face of food price movements. Agricultural households engage simultaneously in production, consumption, and work decisions. As a result, 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 is marketed surplus relatively to household consumption. Therefore, considering the significant food price changes determined by the COVID-19, it is important to distinguish between agricultural and non-agricultural households and, within the former group, between net-buyers, net-sellers, and self-sufficient households.

Among these groups, net sellers are the wealthiest (Annex 2). On average net-seller households report a higher income, higher agricultural revenues, and a higher score in the wealth index. This is probably due to a higher level of physical and human capital. Indeed, they own more land and are more educated than other groups. They also eat better than other groups, as shown by the higher FCS. Self-sufficient households and non-agricultural households are the poorest groups. Non-agricultural households in particular report the lowest wealth index. They are also the group with a higher share of income from transfers. Net-buyers instead report the highest level of labor participation among members of the households 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 1). Most of both refugee and host households were net-buyers in 2019. However substantial differences occur between the two groups. Host households are more integrated into the market than refugees, with 27% of host households being net-sellers in 2019 compared to only 7% of refugees. In 2020 the share increased for both groups, although the increase was higher for hosts (6 percentage points more than in the previous year). Refugees instead report a much higher share of non-agriculture households compared to hosts (more than one-fourth of households) and a very low share of net-sellers (7-8% 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 and/or marked an agricultural surplus.

Table 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.

Table 2 shows how households in the four agricultural and non-agricultural categories in 2019 have been distributed in 2020. What emerges is that many households shifted to agriculture, mostly as self-sufficient or net-buyer agricultural households. Indeed, we see that more than 28% of households falling in the net-seller and self-sufficient categories in 2019 moved to net-buyers in 2020. Instead, 30% of net-buyers and almost the same share of non-agricultural households in 2019 moved to self-sufficiency in 2020. This result suggests a transition of non-agricultural households to farming (in the aggregate, 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 in these households.

Table 2. Transition matrix among different household types

			2020				
			Net-buyer	**Net-seller**	**Self-suff.**	**Non-ag**	**Total**
2019	**Net-buyer**	Freq.	434	242	348	128	1152
		%	37.67	21.01	30.21	11.11	100
	Net-seller	Freq.	151	197	103	35	486
		%	31.07	40.53	21.19	7.2	100
	Self-suff.	Freq.	212	127	288	118	745
		%	28.46	17.05	38.66	15.84	100
	Non-ag	Freq.	159	40	166	198	563
		%	28.24	7.1	29.48	35.17	100
	Total	Freq.	956	606	905	479	2,946
		%	32.45	20.57	30.72	16.26	100

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

. Methodology

.. Path analysis

To answer the research questions proposed in this paper a structural equation model (SEM) (Duncan, 1975; Jöreskog, 1970; Wiley, 1973; Wright, 1934) has been used. While basic statistical methods such as regressions and analysis of variance only use a limited number of variables that are not capable of dealing with all different factors and their interactions involved in complex phenomena, SEMs are able to statistically model and test complex phenomena. This allows disentangling the different transmission channels and identifying the mediating factors. Indeed, the main difference of SEM, and specifically path analysis, as compared to uni-equational models is that the former look not only at the direct effects, but also at the indirect and total effects, and measures the influence of each variable in mediating these effect on the final outcomes. Therefore, SEM is a more suitable approach than standard econometric techniques to address the proposed research questions.

The major assumptions in structural equation modelling include multivariate normality, no systematic missing data, sufficiently large sample size, and correct model specification. Specification errors can occur when relevant variables are omitted in the model, resulting in a substantial parameter estimate bias (Kaplan, 2001). 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).

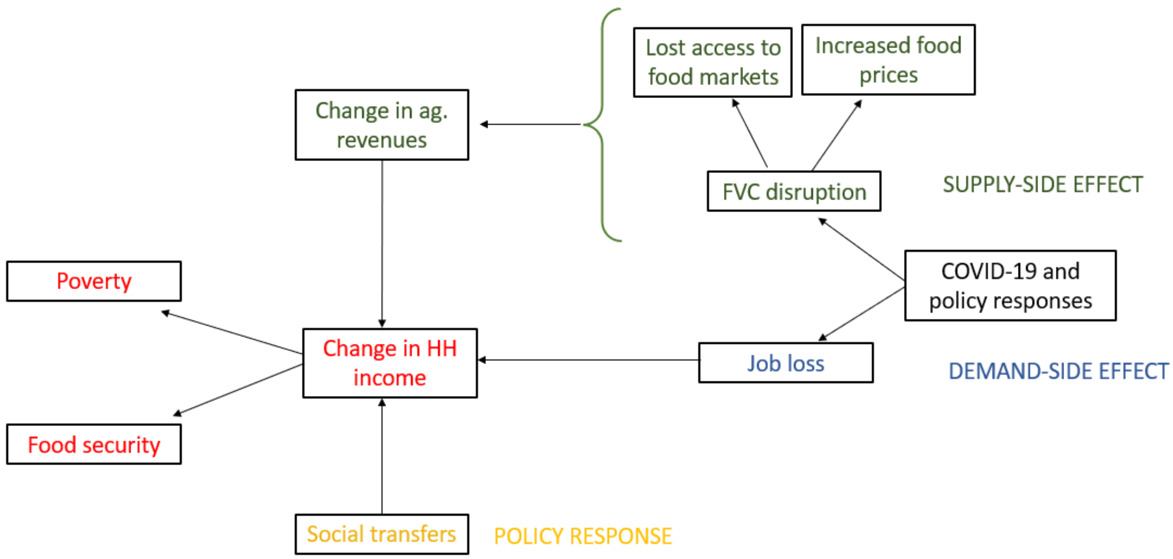
Specifically, we conduct a path analysis, a precursor to and a subset of the vast SEM family of methods that allows for measuring causal effects. Unlike principal component analysis, path analysis does not include a measurement component to estimate latent variables. Therefore, all variables are assumed to be observed. It is based on a closed system of nested relationships among variables that are represented statistically by a series of structured linear regression equations and allows for assessing the effects of a set of variables acting on specified outcomes via multiple causal pathways.

Path analysis allows also for the decomposition of effects into direct, indirect, and total effects, which is extremely important to understanding the main pathways linking the COVID-19 shock and the final outcomes. The total impact of the shock on a given variable along the path is the sum of (i) the direct effects on that variable, i.e. the impact of each immediately upstream variable linked to the considered variable, and (ii) indirect effects, i.e. the cumulative impact of all other variables included in the model that are indirectly linked to the considered variable (all pathways affecting each the immediately upstream variables).

The first step in path analysis is the model specification. Path analysis indeed is always theory-driven, meaning that it does not provide a way to specify the model, but rather 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 preliminary conceptual framework on which our analysis is based (Figure

6) has been developed considering four elements, namely: the economic theory, early evidence on the effects of COVID-19, logical relationships among variables, and adjustments suggested by modification indices[14].

Figure 6. Conceptual framework



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

The agricultural household model (Barnum & Squire, 1979; Singh et al., 1986), positing that the household welfare is simultaneously determined by production, consumption, and labor supply decisions, is the reference theoretical framework for the development of our SEM. According to it, total household income comprises the production profit, which in turn depends on the farm marketed surplus in the case of agricultural households, and the earning from labor activities. Total household income determines consumption decisions of food and non-food goods, thus affecting both household food security and poverty. Furthermore, the restrictions implemented to contrast the spread of the virus increased transaction costs, uncertainty on food availability, and eventually the difference between selling and buying prices of food and agricultural inputs. Under this circumstance, it is more likely that separability does not hold and

[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 & Hancock, 2008).

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 the COVID-19 is not expected to directly affect the quantity produced in the model. Nevertheless, it could affect the quantity sold and agricultural income.

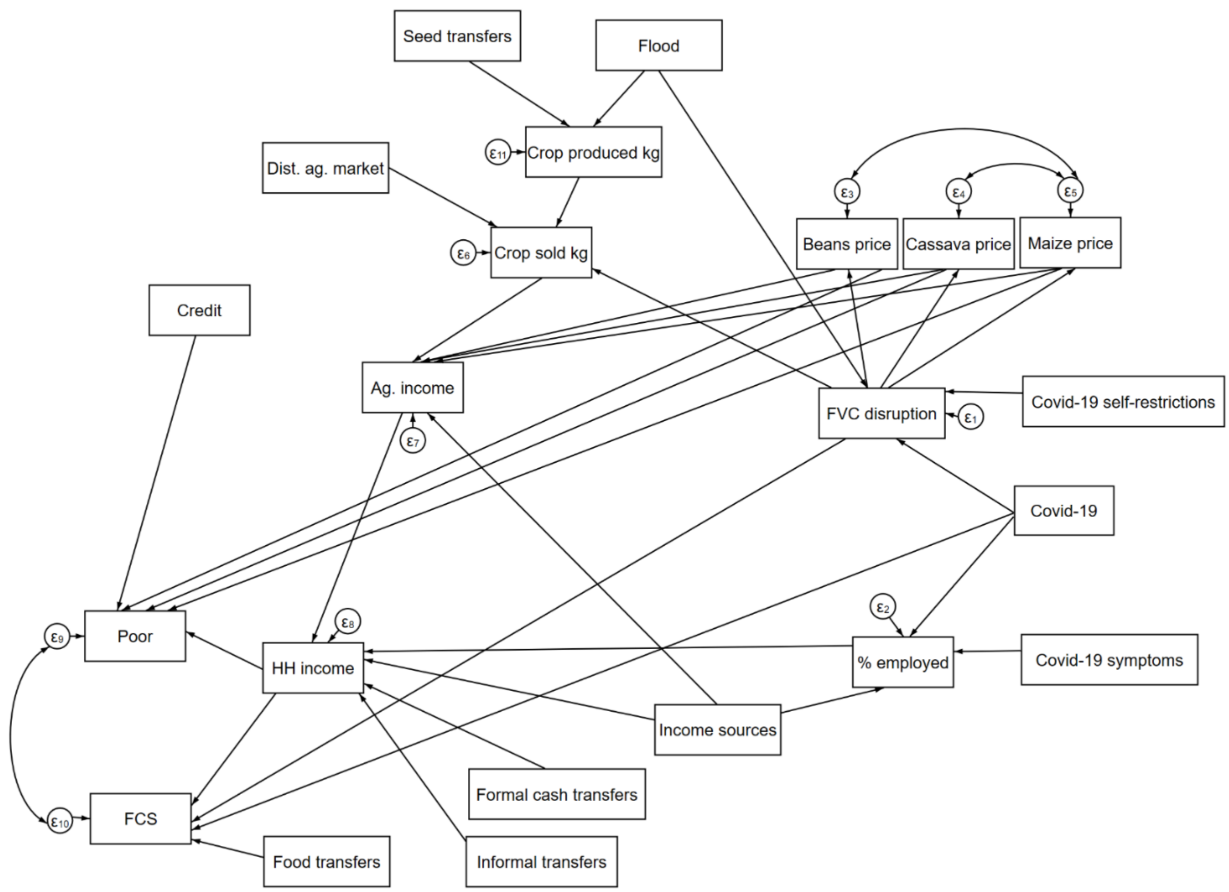
Early evidence shows that COVID-19 directly affected household welfare in two ways. On the one hand, the closure of local markets, movement restrictions, limited transportation, and closure of international borders determined a disruption of the food value chains. On the other hand, the suspension of economic activities due to lockdown and other restrictions have also meant 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 & 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 affected the agricultural household revenue. 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, determined the change in total household income. This eventually affected poverty and food security. Poverty was also affected by the level of food prices as price increases determine a reduction in households' purchasing power. Food security instead was directly affected also by the FVC disruption, which constrained households' food availability.

The pattern of relationships among the variables described above is summarized in the path diagram in Figure 7. 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

[15] Other relevant staple foods, such as cooking banana (matoke), have not been included because there were not enough observations in the data to compute a reliable unit price.

and FCS. Specifically, the modification indices highlighted the presence of a variable, not included in the model, that was affecting both FVC disruption and FCS. Adding the direct effect 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.

Figure 7. Path diagram of the base model



Some control variables have been included in the model such as the COVID-19 self-restrictions and the COVID-19 symptoms in any of the household members, flood shocks, the number of income sources, transfers, credit, and distance to the nearest agricultural market. The income sources variable is an indicator of the household income diversification capacity, which is linked to agricultural income and employment opportunities and therefore to overall 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, 2016). On the other hand, income diversification could be negatively linked to agricultural income when agriculture is a family business and requires the use of the family labor force. Transfers are broken down into food transfers, which directly affect the level of food security, formal cash transfers received by the government, informal transfers from friends and family members (including remittances), which are linked to household income, and the provision of seeds and equipment, which may increase the level of production and potentially the share of output sold. The household marketed surplus is also affected by the distance to the market, because the farther the market the more difficult to sell the household outputs, especially in case of movement restrictions such as the ones introduced during the COVID-19 outbreak. Access to credit is a key tool to cope with shocks and we expect that higher access to credit tends to reduce poverty all other things equal.

.. 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 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 used to control for unobserved time-invariant heterogeneity among households in running the model over the longitudinal sample. This identification strategy is similar to a classical difference-in-difference approach, though in this case all observations are treated. Compared to a mere before-after comparison, as in Egger et al. (2021), the use of fixed effects and control variables allows to better identify the causal relationship.

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

$$\begin{cases}
\text{FVC disruption: } y_1 = \alpha_h + \beta_0 Covid_t + \beta_1 Flood_{ht} + \beta_2 Covid\ self_restrictions_{ht} + \varepsilon_{ht} \\
\text{Job loss (\% employed): } y_2 = \alpha_h + \beta_3 Covid_t + \beta_4 Income\ Sources_{ht} + \beta_5 Covid\ symptoms_{ht} + \varepsilon_{ht} \\
\text{Prices: } y_3 = \alpha_h + \beta_6 y_{1,ht} + \varepsilon_{ht} \text{ where } Y_3 = [price\ of\ beans, price\ of\ maize, price\ of\ cassava] \\
\text{Harvest (Kg produced): } y_4 = \alpha_h + \beta_7 y_{1,ht} + \beta_8 Seeds\ transfer_{ht} + \beta_9 Flood_{ht} + \varepsilon_{ht} \\
\text{Ag. surplus (Kg sold): } y_5 = \alpha_h + \beta_{10} y_{1,ht} + \beta_{11} y_{4,ht} + \beta_{12} Distance\ ag.market_{ht} + \varepsilon_{ht} \\
\text{Ag. income: } y_6 = \alpha_h + \beta_{13} y_{5,ht} + \beta_{14} Y_{3,ht} + \beta_{15} Income\ sources_{ht} + \varepsilon_{ht} \\
\text{HH income: } y_7 = \alpha_h + \beta_{16} y_{6,ht} + \beta_{17} y_{2,ht} + \beta_{18} Formal\ transfer_{ht} + \beta_{19} Informal\ transfer_{ht} + \\
\qquad \beta_{20} Income\ sourcces_{ht} + \varepsilon_{ht} \\
\text{Poverty: } y_8 = \alpha_h + \beta_{21} y_{7,ht} + \beta_{22} Y_{3,ht} + \beta_{23} Credit_{ht} + \varepsilon_{ht} \\
\text{Food security (FCS): } y_9 = \alpha_h + \beta_{24} y_{7,ht} + \beta_{25} Covid_t + \beta_{26} Food\ transfer_{ht} + \beta_{27} y_{1,ht} + \varepsilon_{ht}
\end{cases}$$

.. Descriptive statistics

Descriptive statistics of the model variables in 2019 and 2020 and the level of significance of the t-test of the difference in means are reported in Table 3. 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 highlighting the beans and cassava price increase, and the reduction in employment.

Table 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	58.18	613.68	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	

* p<0.05, ** p<0.01, *** p<0.001

Note: all monetary values are expressed in USD 2011 PPP; income-related variables are computed as year income.

The model goodness of fit 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 comparing 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 Chi2-test is highly sensitive to sample sizes in that Chi2-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 model complexity, such as the RMSEA test, the model shows a good fit. Accepted values for the other goodness of fit tests are RMSEA < 0.05; SRMR ≤ 0.08; TLI and CFI > 0.9 (Schreiber et al., 2006; Lei & Wu, 2007).

.. Testing for parallel trend

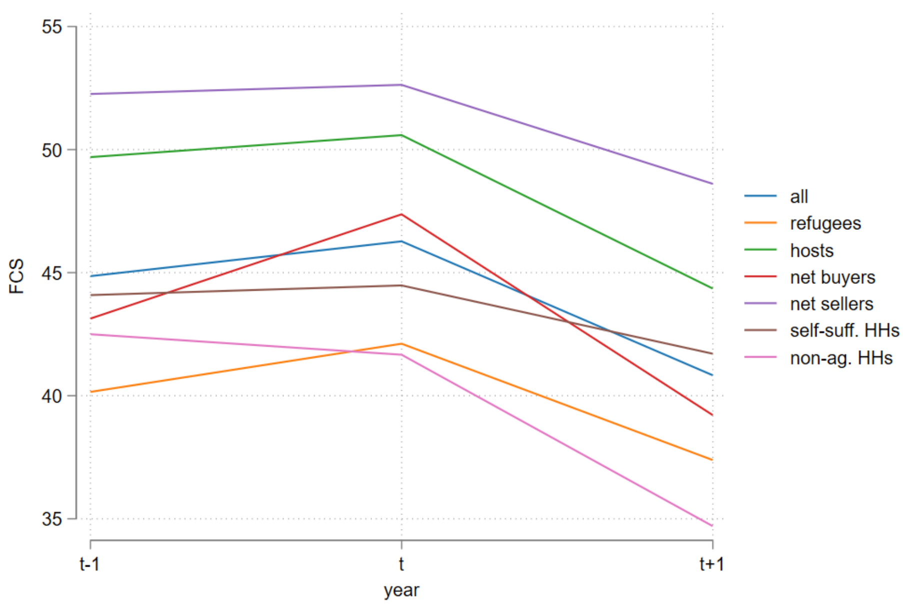
To rule out that factors other than the COVID-19 outbreak could drive the observed change in household welfare, we tested the parallel trend assumption on FCS[16] including the previous round of data collected between 2017 and 2019.

[16] Due to some differences in the questionnaire on the items included in the expenditure module in the initial round of data (collected between 2017 and 2019) compared to the next rounds (used in this analysis), it is not possible to compute a comparable measure of expenditure for poverty for the first round of data. Therefore, the assumption will be tested only on the proxy of food security.

Figure 8 shows that in the first round of data (year t-1) the level of FCS was lower than in 2019 (year t) for almost all types of households. Only non-agricultural households show a higher level, but the difference is not statistically significant. Almost all household types report a similar trend over time. From a visual inspection, the parallel trend assumption seems to hold, except for net-buyers and non-agricultural households.

To formally test the parallel trend assumption over the different subsamples, a difference-in-difference (DiD) over year t-1 and year t has been run on FCS, considering each household type as the treatment, and the rest of the sample as the control group. If the DiD estimator is not significant, it means that the difference in FCS over treatment and control groups between the two periods is null, validating the parallel trend. The DiD estimator is non-significant for all household groups report, except agricultural net-buyer households (Table 4)[17].

Figure 8. The trend of FCS for each household type.



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2017, 2018, 2019acrei, 2019, and 2020.

[17] More detailed results of the DiD are available in the Annex 3.

Table 4. Diff-in-diff estimation results over year t-1 and year t, by household types

Household types	Diff-in-Diff estimator	S. Err.	|t|	P>|t|
Refugees	1.151	0.755	1.52	0.128
Hosts	-1.078	0.755	1.43	0.153
Agricultural net-buyers	3.222	1.124	2.87	0.004***
Agricultural net-sellers	-1.094	1.558	0.70	0.483
Agricultural self-sufficient	-0.973	1.327	0.73	0.463
Non-agricultural	-2.201	1.585	1.39	0.165

. Results

The path analysis has been conducted over different subsamples to understand how COVID-19 impacted different household types. Specifically, in this section, we will present the results of the model starting with the whole household sample, proceeding with refugee and host households, and then analyzing agricultural household types – i.e., net-buyer, net-seller, and self-sufficient households – as well as non-agricultural households. Finally, we also compare refugee and host households within selected agricultural household groups, namely net-buyers and self-sufficient households[18].

The model used to analyze the whole household sample is the one described in Section 3. This model has been adjusted to account for specific household characteristics in the case of other household groups, as reported in the path diagram of each subsample. The statistically significant relationships at $p < 0.1$ are drawn as black arrows, while when non-statistically significant the arrow is grey. For the former, the estimated values are reported in green if positive and red if negative.

[18] Agricultural net-seller households have not been reported due to insufficient number of observations among refugee households.

.. ***Whole sample***

The standardized estimates of the path analysis over the total balanced sample are reported in Figure 9. Our initial hypotheses about the COVID-19 transmission channels have been confirmed: COVID-19 determined the disruption of FVC and a reduction of employment. COVID-19 also directly affects food security, reducing the FCS. This direct effect can be explained by other factors of the pandemic that are not captured by the two channels identified in the model.

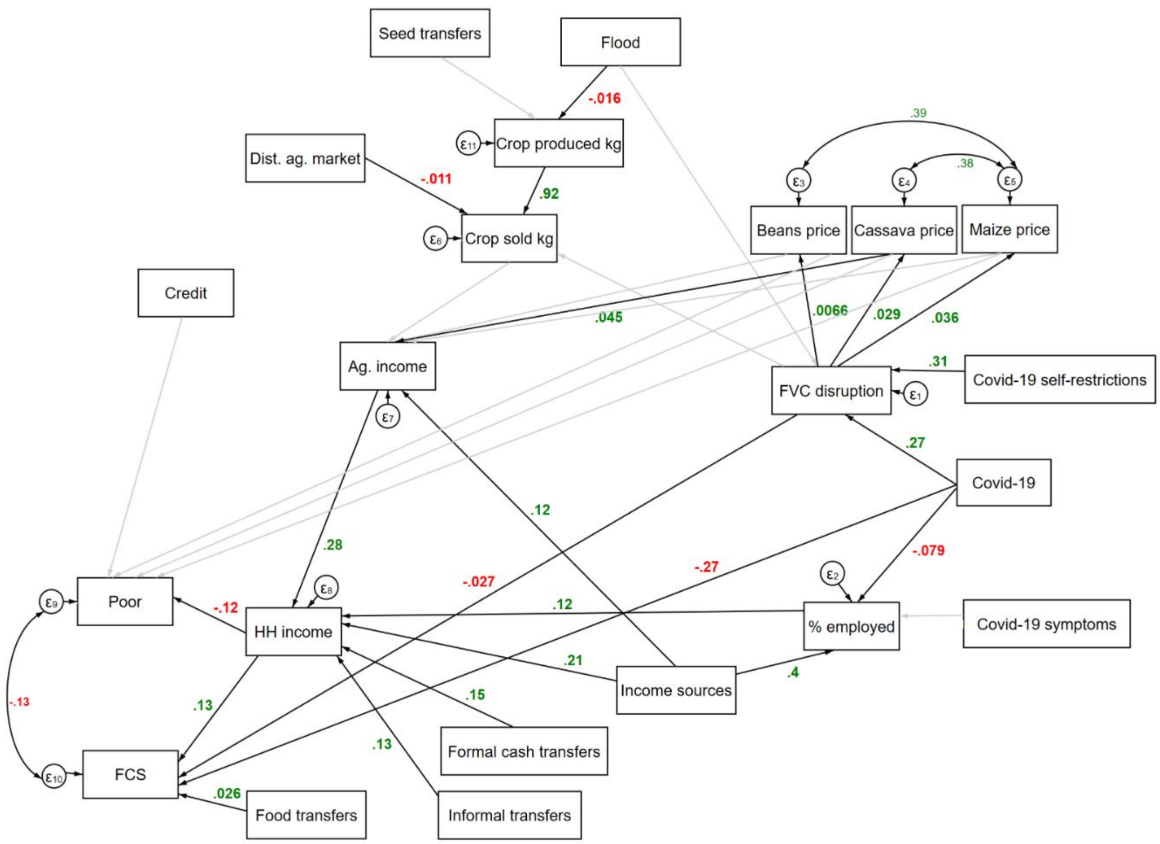
Disruptions along the FVC are determined by supply problems as well as by changes in customers' and workers' behavior who adopted self-restrictive practices being afraid of getting infected while going out. An environmental shock such as a flood does not significantly affect the FVC: this confirms that COVID-19 was the main and only shock significantly affecting FVC in 2020. FVC disruption is associated with a reduction of FCS as well as an increase in food prices. However, only cassava price positively affects agricultural income.

Distance to the agricultural market matters in determining the quantity of crops sold: the longer the distance to the market the lower the agricultural output sold. As expected, floods determine a lower harvest, while the higher the harvest the higher the marketed surplus. Quite surprisingly, the amount of crop sold does not have significant effects on the agricultural income.

Transfers, both formal and informal, income diversification, the share of employed 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 have a significant effect on employment, probably because only a few households have been directly affected by the virus[19].

[19] Only 5.5% of surveyed households reported symptoms (cf. Table 3).

Figure 9. Standardized estimates of path analysis - all households



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

Household income is key in determining the level of poverty and food security: an increase in household income reduces poverty and increases the FCS. Another important variable affecting the final outcomes is food assistance, which improves food security. Conversely, access to credit does not have a statistically significant effect on poverty.

The tests that measure the goodness of fit show acceptable values of fit[20]. The overall R-squared is 0.44.

Path analysis can be used to decompose the effects into direct, indirect, and total effects. The direct effects are the ones reported in the path diagram (Figure 8), while Table 4 reports the estimates of indirect and total effects.

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

Table 4. Indirect and total effects of the model over all households

Indirect effects

	Std. Coef.
Beans price	
Flood	-0.0001
COVID-19 self-restrictions	0.0021**
COVID -19	0.0018**
Cassava price	
Flood	-0.0005
COVID-19 self-restrictions	0.0091*
COVID-19	0.0080*
Maize price	
Flood	-0.0006
COVID-19 self-restrictions	0.0111*
COVID-19	0.0098*
Crop sold (Kg)	
Flood	-0.0143*
COVID-19 self-restrictions	-0.0004
COVID-19	-0.0004
Seeds transfer	0.0037
Ag. income	
Crop produced (Kg)	-0.0266
FVC disruption	0.0013*
COVID-19	0.0004*
COVID-19 self-restrictions	0.0004*
Distance ag. market (Km)	0.0003
Flood	0.0004
Seeds transfer	-0.0001
Pc household income	
FVC disruption	0.0004*
Beans price	0.0043
Cassava price	0.0125***
Maize price	-0.0010
Crop sold (Kg)	-0.0081
Crop produced (Kg)	-0.0074

Total effects

	Std. Coef.
FVC disruption	
Flood	-0.0160
COVID-19 self-restrictions	0.3106***
COVID -19	0.2738***
% employed	
COVID-19	-0.0785***
COVID-19 symptoms	-0.0021
Income sources	0.3986***
Beans price	
Flood	-0.0001
COVID-19 self-restrictions	0.0021**
FVC disruption	0.0066**
COVID-19	0.0018**
Cassava price	
Flood	-0.0005
COVID-19 self-restrictions	0.0091*
FVC disruption	0.0293*
COVID-19	0.0080*
Maize price	
Flood	-0.0006
COVID-19 self-restrictions	0.0111*
FVC disruption	0.0358*
COVID-19	0.0098*
Crop produced (Kg)	
Flood	-0.0156*
Seeds transfer	0.0041
Crop sold (Kg)	
Crop produced (Kg)	0.9188***
FVC disruption	-0.0013
COVID-19	-0.0004
Distance ag. market (Km)	-0.0111**
Flood	-0.0143*

COVID-19	-0.0094***
Income sources	0.0807***
Distance ag. market (Km)	0.00090
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)	-0.0010
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
Crop produced (Kg)	0.0009
Crop sold (Kg)	0.0010
Ag. income	-0.0338***
COVID-19	0.0009***
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	-0.0010
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
Formal cash transfer	0.1460***
Informal transfer	0.1304***
FCS	
FVC disruption	-0.0265**

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

% employed	0.0157***
Pc HH income	0.1304***
Beans price	0.0006
Cassava price	0.0016***
Maize price	-0.0001
Crop produced (Kg)	-0.0010
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	-0.1208***
Beans price	-0.0036
Cassava price	-0.0007
Maize price	-0.0211
Crop produced (Kg)	0.0009
Crop sold (Kg)	0.0010
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***

Some interesting results emerge from this analysis. For instance, we can see that total household 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 potentially induced by the food price increase[21]. Figure 8 shows that income diversification affects household income both directly and indirectly, through its effect on the share of employed members and on agricultural income. Both indirect effects are positive, with the pathway linking income diversification to total household income via 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. Looking at the total effects of transfers on the two main outcomes, we can see that food assistance is the most relevant for FCS, while formal cash transfers are most important in reducing poverty.

Overall, COVID-19 affected more food security than poverty. The overall impact on FCS is mainly due to the direct effect, which accounts for 97% of the total negative impact. 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%. Interestingly, COVID-19 symptoms in any of the household members do not have any significant impact on the two outcomes, while COVID-19 self-restrictions show a significant negative effect only on food security, but no significant effect on poverty. Finally, while labor market participation by household members affects both poverty and food security, FVC disruption affects only food security, as expected.

[21] In fact, this price mediated effect contributed to reducing the negative indirect effect on household income by only 1.08%.

.. *Refugee vs. host households*

To explore how COVID-19 has differently affected refugee and host households, the models have been slightly changed to account for specific characteristics of the subsamples. To increase the fit of the model, the covariance between employment and agricultural income has been added in both models. In addition, a direct effect of cash transfers on poverty has been added to the refugees' model. This link highlights the refugees' dependency on transfers. The standardized estimates of the path analysis for the two groups are reported in Figures 10 and 11.

Comparing the two subsamples, the first finding is that 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 of the settlements (cf. Figure 3). 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, the positive effect of FVC disruption caused by COVID-19 on food prices is transmitted to agricultural income, and in turn to household income, through the price of cassava. Refugees instead report an opposite effect: 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.

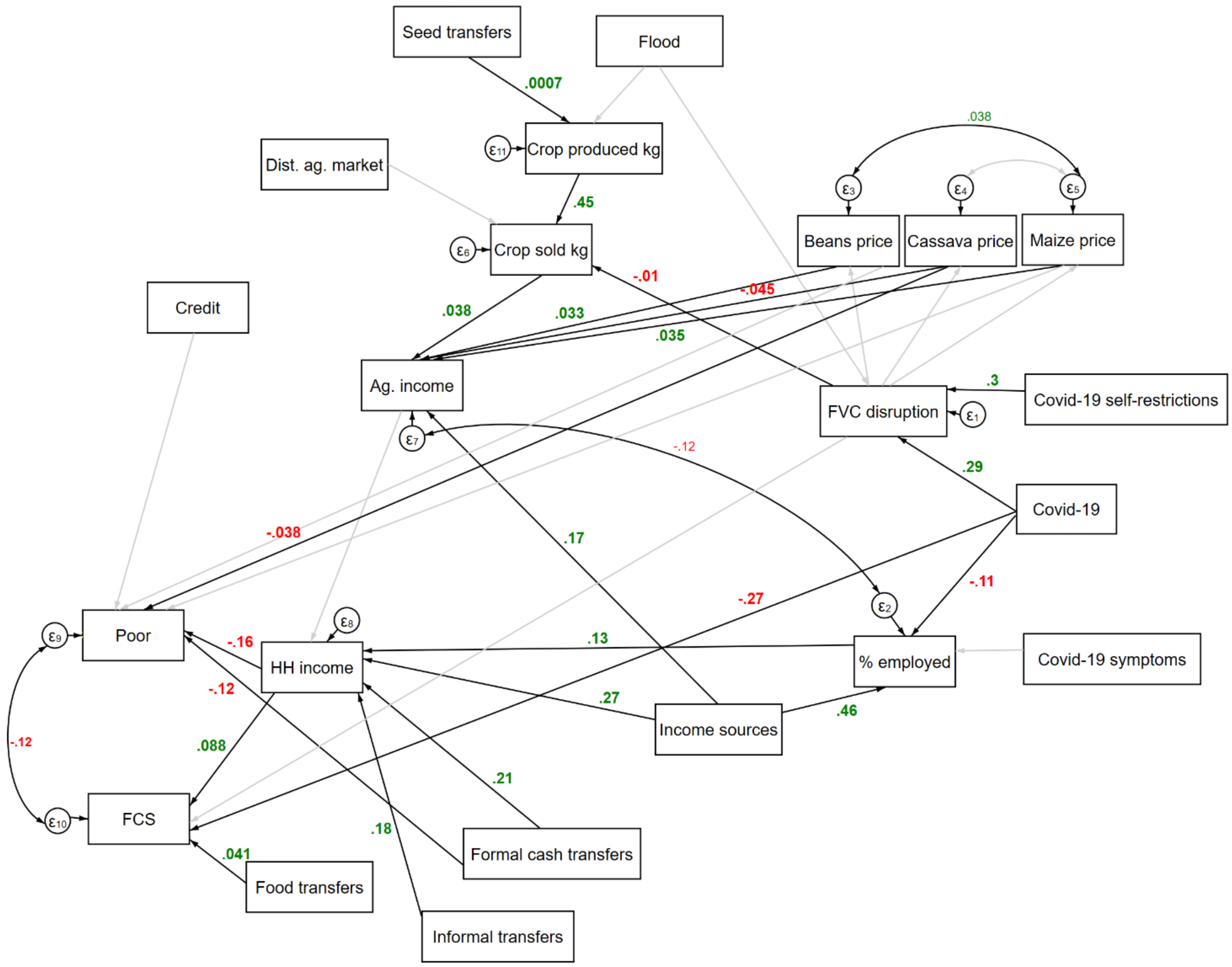
This can be explained by the different composition of crop production between refugees and hosts, by the difference in price changes within and outside settlements, and by possible substitution effects that occurred on the demand side due to the change in prices. Cassava is mainly produced for own consumption, 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. On the contrary, 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 total household income for refugees, given that their main livelihood source is transfers. Indeed, estimates for cash transfers on income report a higher value for refugees than for hosts, as expected. 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. Both for refugees and hosts COVID-19 has an indirect negative effect on household income, but for refugees, it is higher. This is not only because the magnitude of the effect is higher for refugees, but also because for hosts the negative effect on the employment side was partly mitigated by the positive effect on agricultural income. Total income is more important in changing the level of 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. Refugees produce mainly for their own consumption, and they mainly rely on food assistance for their food consumption, thus depending less on income. 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. As a result, the total final effect of COVID-19, that is the sum of direct and indirect effects, 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].

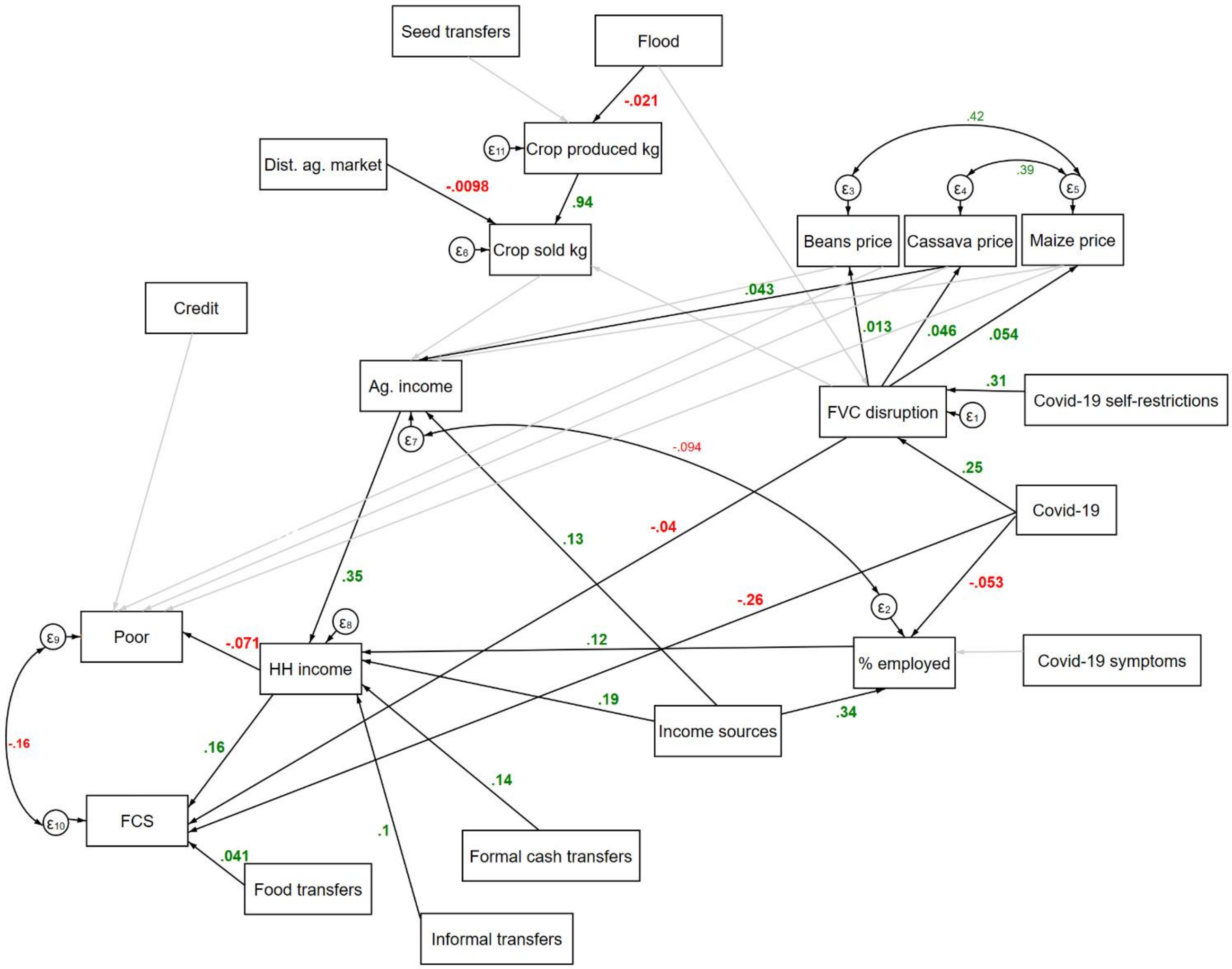
[22] For refugees: RMSEA = 0.023; CFI = 0.938; TLI = 0.921; SRMR = 0.021; overall R-squared = 0.53; for hosts: RMSEA = 0.031; CFI = 0.960; TLI = 0.949; SRMR = 0.027; overall R-squared = 0.40.

Figure 10. Standardized estimates of path analysis - Refugee households



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

Figure 11. Standardized estimates of path analysis - Host households



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

Although the analysis over refugee and host households provides interesting findings related to agricultural market exposure and the transmission of the COVID-19 effects through the different food system components, the results are also affected by the position of each household towards the market. Therefore, now we turn to analyze the different agricultural household types.

.. Net-buyer vs. net-seller households

The adjustments made on the models for the net-buyers and net-sellers are reported in Figures 12 and13. Both groups of agricultural households show an increase in FVC disruption due to COVID-19, but net-buyer are more affected than net-seller households.

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 of maize is positively associated with net-buyers' agricultural income, this means a reduction of the agricultural income. Furthermore, the beans price increase negatively affects their consumption, increasing the net-buyers' level of poverty.

Household income plays a key role for these two categories. However, while for net-sellers household income is relatively more important in determining the household food security status rather than the level of poverty, for net-buyers total income is important for both FCS and poverty, with a slightly higher effect on poverty.

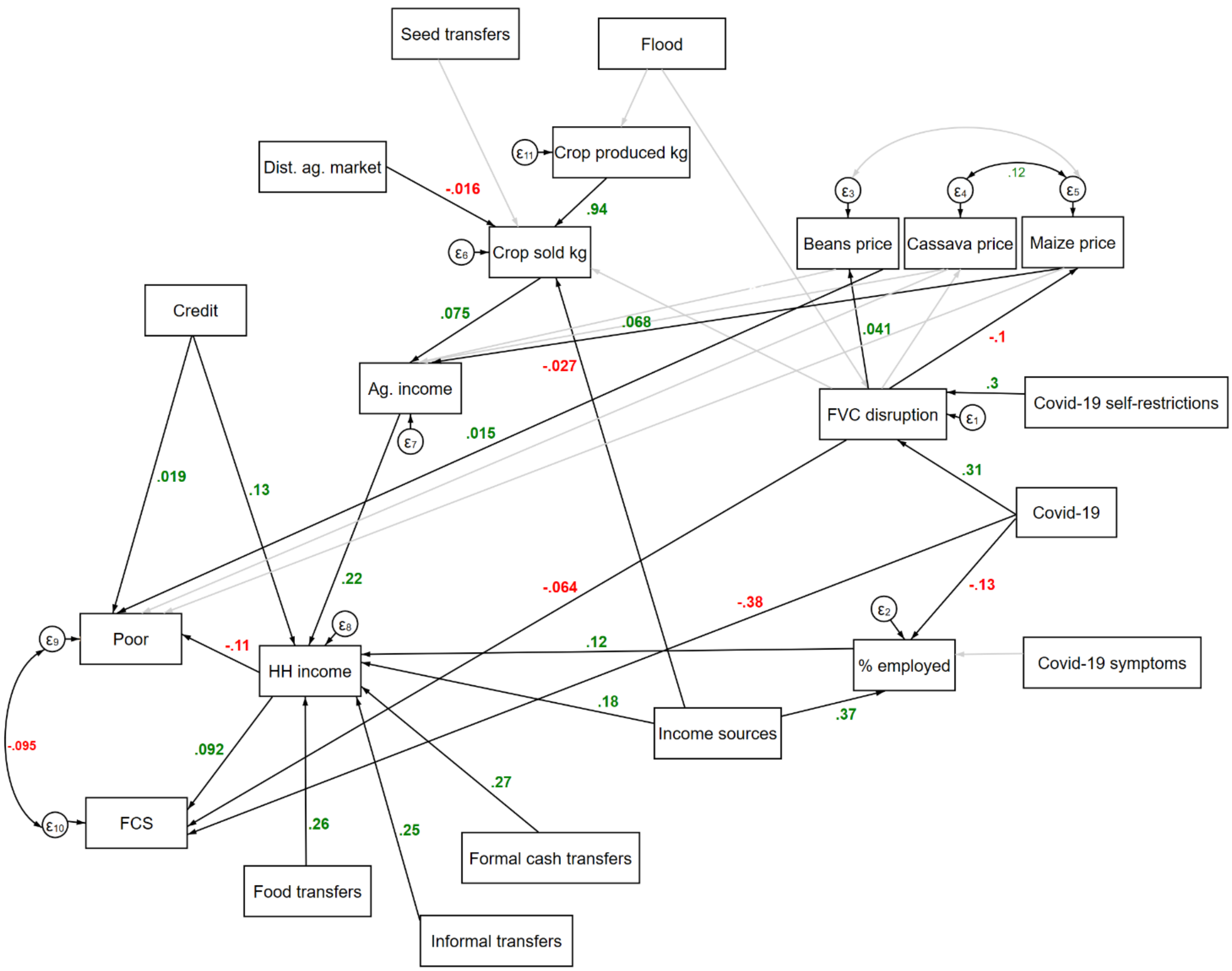
Net-buyers are much more affected in terms of employment than net-sellers. This is because net-buyers rely more on sources of income other than agricultural income, such as employment and remittances, which are important contributors to the household total income. The combined negative effect of COVID-19 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 disproportionally 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 on household income for both types of agricultural households, eventually affecting poverty and food security. Both variables, and among 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. Credit plays a double role for net-buyers: it directly increases poverty, possibly because of the cost of interest, but it is also positively associated with household income. As a result, the overall credit effect on poverty is not significant.

In conclusion, the total effect of COVID-19 on FCS is much higher for net-buyers (-.4001) than for net-sellers (-.1467), while it does not have a significant effect on poverty for both types of households. Net-buyers indeed are among the agricultural categories, the group most affected in terms of the direct impact of COVID-19 on FCS.

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

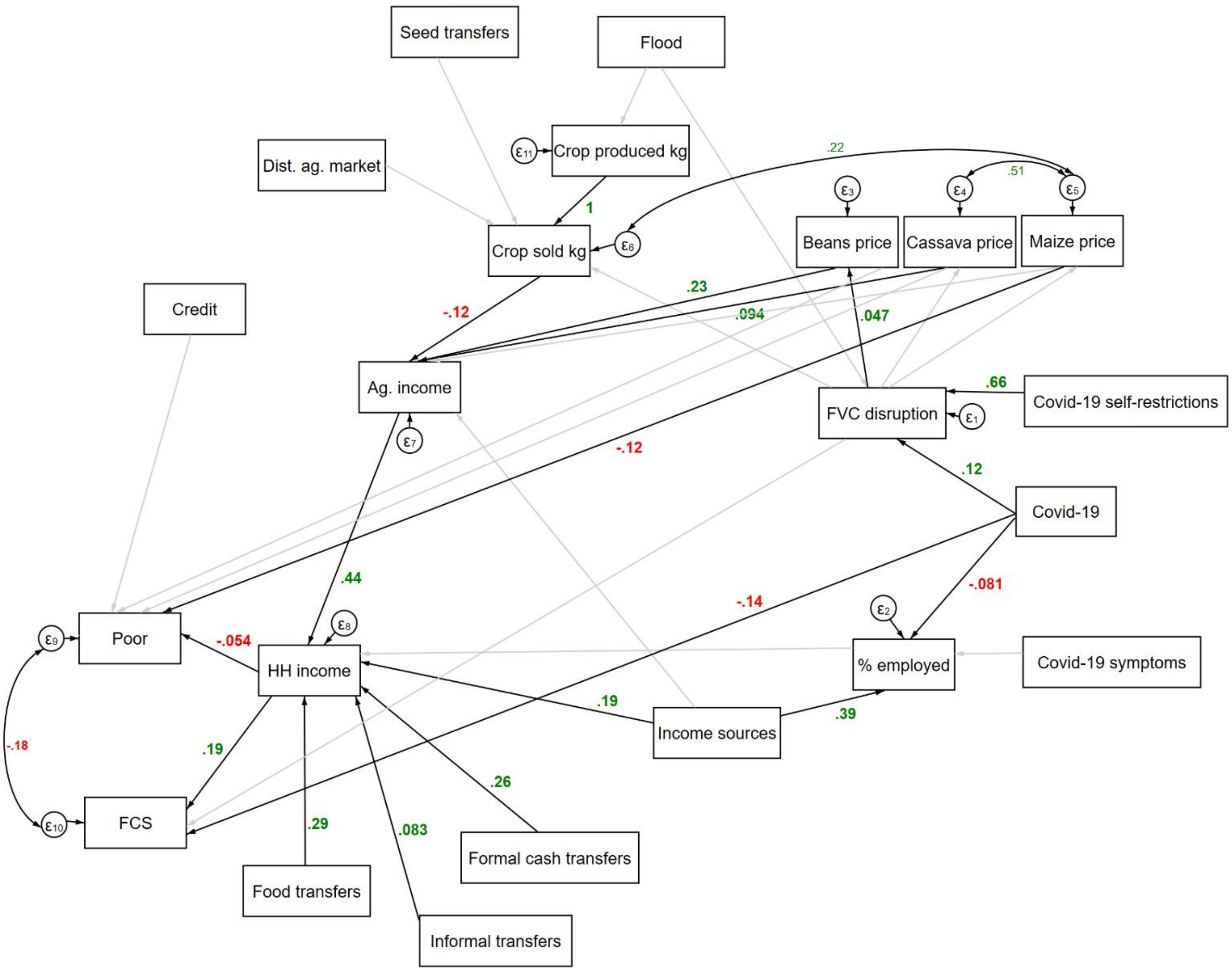
Figure 12. Standardized estimates of path analysis - Net-buyer households



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.
Note: the balanced subsample for net-buyers is composed of 434 households per year.

[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.

Figure 13. Standardized estimates of path analysis - Net-seller households



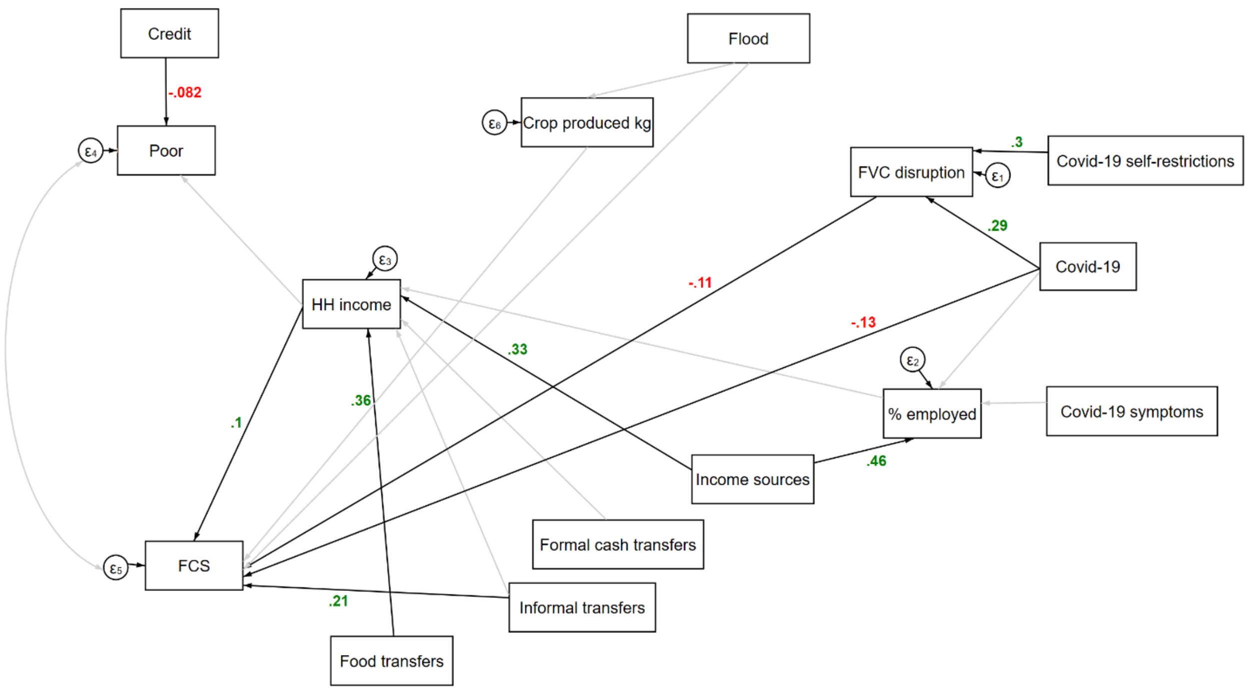
Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.
Note: the balanced subsample for net-sellers is composed of 197 households per year.

.. *Self-sufficient households*

Since this type of household is not integrated into the food market, prices have been removed from the model. The quantity of crop produced was included instead of the quantity sold. Although crop production is not affected by the disruption of the FVC, climatic shocks such as floods could affect the output quantity, which in turn could influence the level of food security in the household. However, as shown in Figure 14, the shock is not that important to affect crop production. FVC disruption instead has a negative effect on food security.

For this type of household, income is more relevant to defining the level of FCS, while it has no significant effects on poverty. Tests for the goodness of fit report acceptable values[24].

Figure 14. Standardized estimates of path analysis - Self-sufficient households



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.
Note: the subsample for self-sufficient households is composed of 288 households per year.

.. *Non-agricultural households*

Also the model for non-agricultural households does not include food prices. This is because they are not able to perceive the effect on prices coming from the FVC disruption, since they are not involved on the production side, and the effect on the consumption side is already captured by the variable of FVC disruption. Non-agricultural households perceive more the negative effect of COVID-19 through the employment compared to other types of households. This makes sense given that they are not involved in FVC as producers: they rely on labor income for their own livelihood. This is also confirmed in the relationship with total income, where employment is more

[24] RMSEA=0.036; CFI=0.937; TLI=0.911; SRMR=0.033

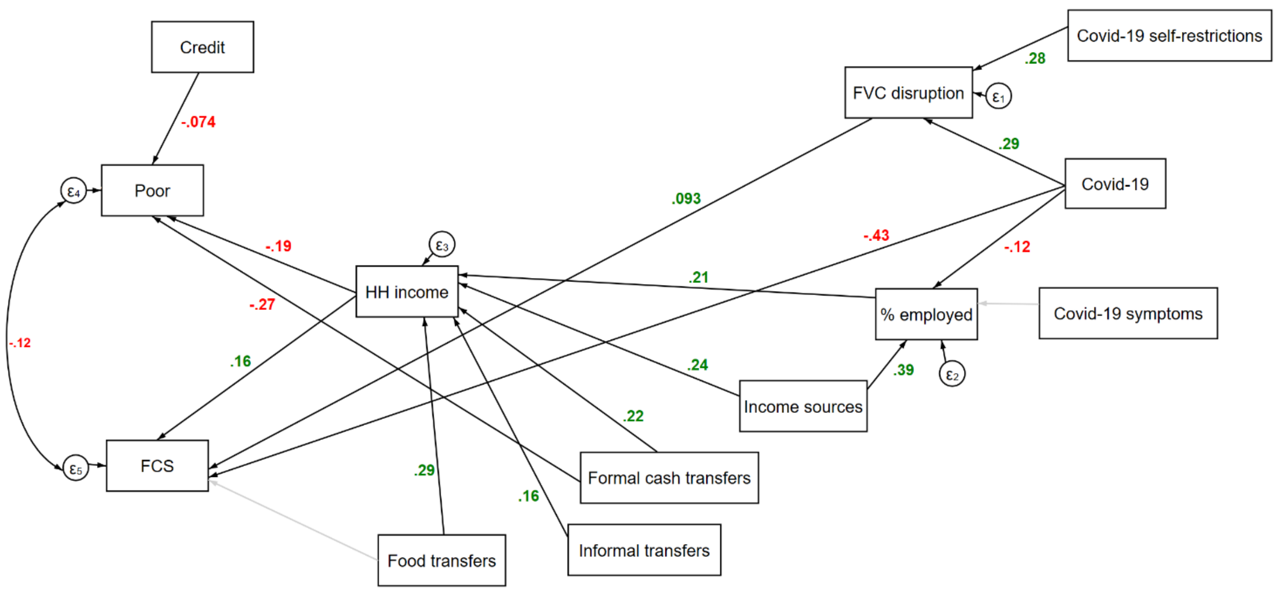
important in defining the level of household income for non-agricultural households compared to other types of households.

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 at the same time 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[25].

Figure 15. Standardized estimates of path analysis - Non-agricultural households



Source: Own elaboration on RIMA Uganda Refugee and Host Communities Panel Survey data, 2019 and 2020.
Note: The subsample of non-agricultural households is composed of 198 households per year.

.. *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, it would be interesting to carry out the analysis of each agricultural household category and non-agricultural household conducted splitting them into two

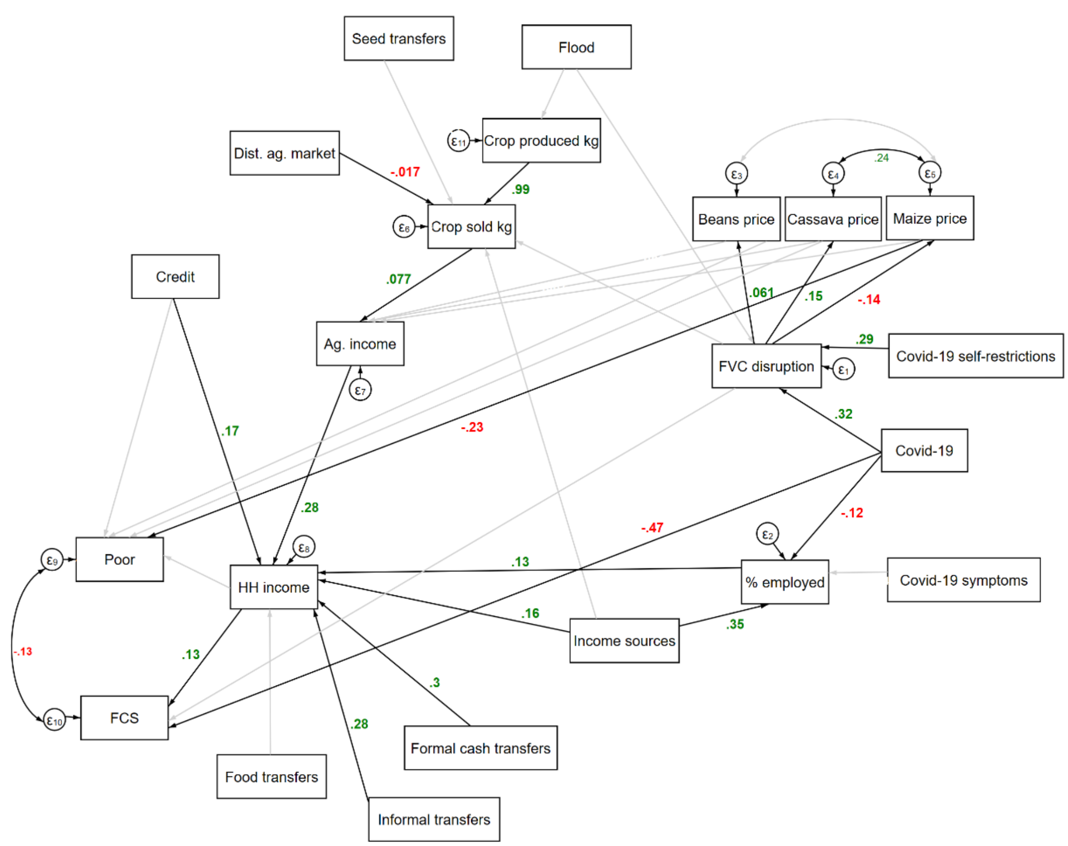
[25] RMSEA=0.048; CFI=0.936; TLI=0.900; SRMR=0.039

subsamples: hosts vs. refugees. 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.

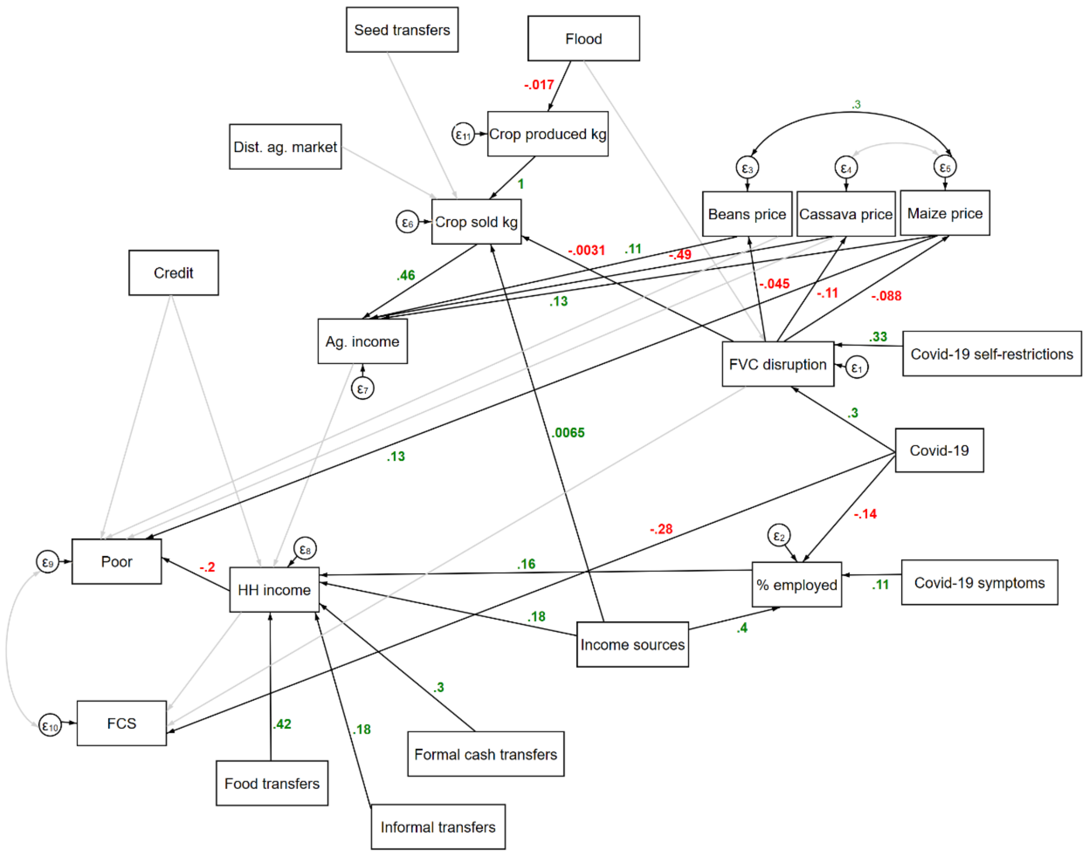
Figure 16 reports the estimates for the net-buyer category. We can see that COVID-19 significantly affects employment both for refugees and for hosts, though the effect is stronger among the former. Both groups experience a reduction in the price of maize due to the FVC disruption. However, for hosts, 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. Agricultural income is an important component of household income for hosts. Agricultural income has no significant effects on the total income of refugees, that largely depend 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 16. Standardized estimates of path analysis – Net-buyers, Hosts vs. Refugees

a) Net-buyer host households



b) Net-buyer refugee households



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

Regarding the goodness of fit, the model for hosts reports quite a good fit[26], while the model for refugees has a poor fit, therefore the results should be considered with caution.

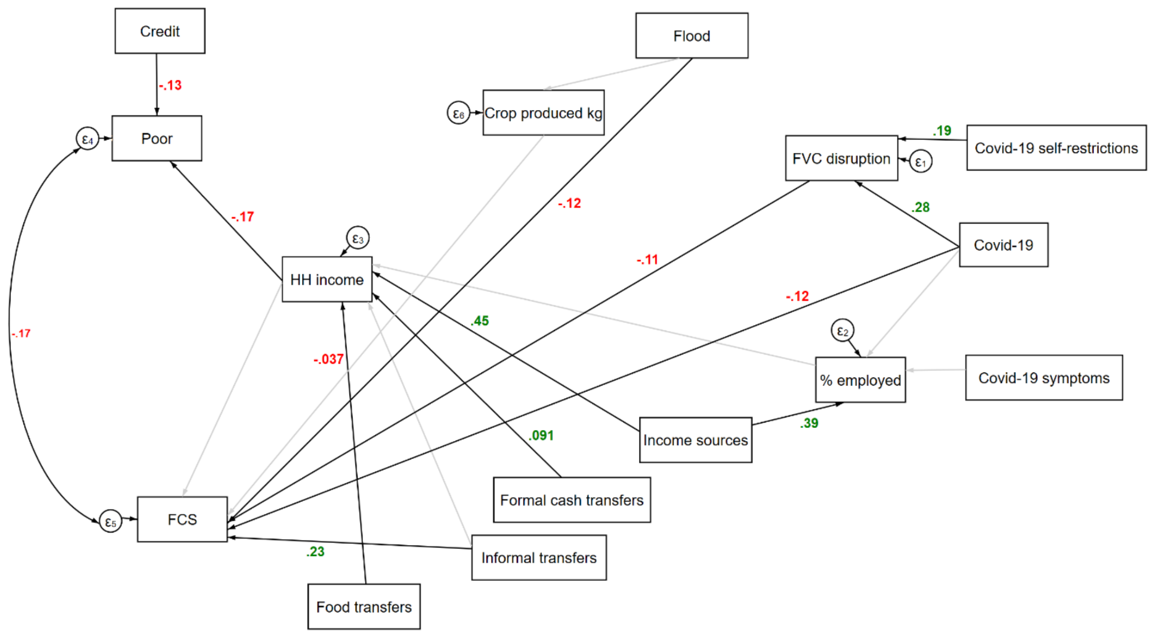
The comparison between refugees and hosts among self-sufficient households is reported in Figure 17. In this case, we can find some important differences between the two subgroups. First, for hosts, the negative impact on FCS is driven by FVC disruption and floods. Refugees confirm their dependency on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

[26] RMSEA=0.058; CFI=0.923; TLI=0.903; SRMR=0.056

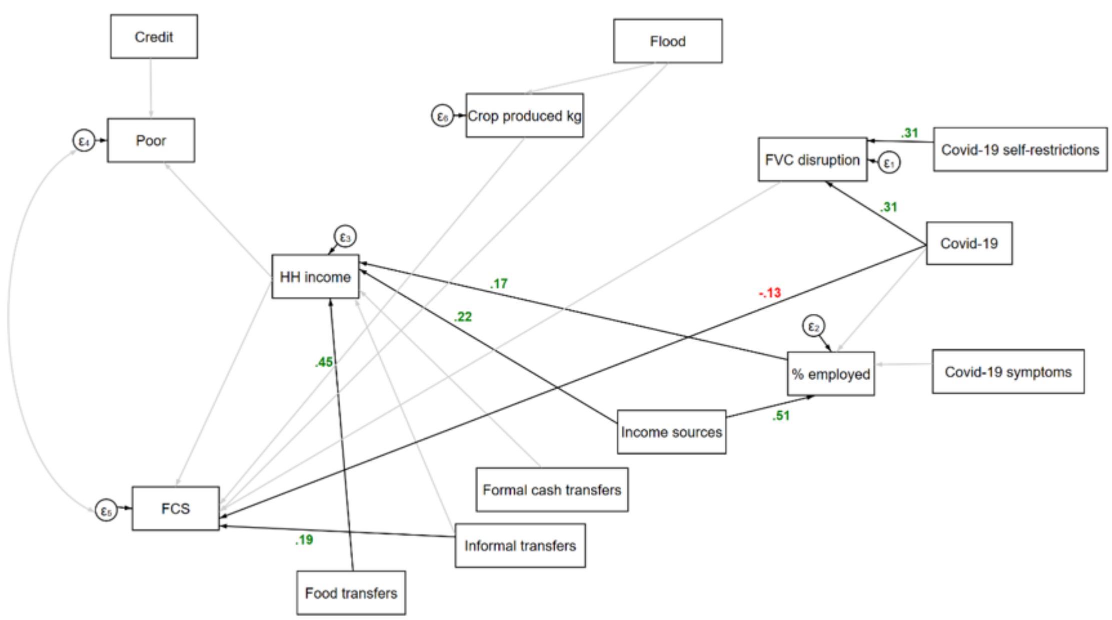
The model for refugees reports a good fit, instead, the model for hosts has a poor fit[27].

Figure 17. Standardized estimates of path analysis – Self-sufficient households, Hosts vs. Refugees

a) Host households



b) Refugee households



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

[27] For refugees: RMSEA=0.049; CFI=0.901; TLI=0.861; SRMR=0.047; for hosts: RMSEA=0.076; CFI=0.703; TLI=0.582; SRMR=0.056

.. Dealing with attrition

A high attrition rate could create problems of representativeness. This is because if the members who drop out from the baseline differ systematically from those who remain in the follow-up, then the dataset of continuing members is no longer representative of the original population (Baulch & Quisumbing, 2010). The dataset used in this analysis was designed to be representative at the baseline, while in the second and third rounds weights have not been adjusted to account for attrition. Given that the attrition rate is significant[28], it is important to check whether the estimates presented so far are biased due to low representativeness.

First, we need to check whether the attrition is random. If this is the case, we do not need to correct for it. The first test implemented 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 5 suggests that observable variables explain 8.75% of panel attrition; 12 out of 24 variables are significant predictors of attrition, since they are statistically different from zero at the 5% level. 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).

Table 5. Attrition probit

Probit regression	Number of obs.= 6227
	Wald chi2(24)=706.07
Log pseudolikelihood = -3911.9948	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

[28] Being equal to 25.48% between the first to the second round, and 27.65% between the second and the third round.

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

Another test to verify if the attrition is random is through pooling tests, in which the equality of coefficients from the baseline sample with and without attritors is tested (Becketti et al., 1988)[29]. 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 nonrandom, we proceed by using inverse probability weights.

Following Wooldridge (2002), we ran a probit regression to estimate the probability of being in the panel subsample over a set of variables at baseline. In addition to the usual variables on the household's demographic characteristics (age of household head, gender of household head, household size, number of male adults in the household, number of female adults, number of children below 5 years, average years of education of adults in the household, dependency ratio), we included other variables that may be correlated with attrition, which are having experienced a flood in the last year, having experienced a drought in the last year, refugee dummy, FCS, number

[29] 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. An 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 attrit from the panel (Baulch & Quisumbing, 2010).

of income sources, wealth index, land owned, and district dummies. The inverse of the estimated probability is the adjusted weight. This procedure gives more weight to observations that remained in the panel.

Table 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.

Table 6. 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	0.000	0.282	0.007	0.000
Flood	-0.016	0.011	0.154	-0.033	0.014	0.015
COVID-19 self-restrictions	0.311	0.013	0.000	0.287	0.014	0.000
Constant	0.013	0.019	0.467	-0.001	0.021	0.961
% employed						
COVID-19	-0.079	0.012	0.000	-0.065	0.014	0.000
COVID-19 symptoms	-0.002	0.013	0.867	0.002	0.014	0.913
Income sources	0.399	0.010	0.000	0.404	0.011	0.000
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	0.000	0.777	0.101	0.000
Cassava price						
FVC disruption	0.029	0.015	0.056	0.040	0.020	0.041
Constant	0.659	0.082	0.000	0.604	0.076	0.000
Maize price						
FVC disruption	0.036	0.021	0.084	0.029	0.019	0.135
Constant	0.321	0.056	0.000	0.341	0.067	0.000
Crop produced (Kg)						
Flood	-0.016	0.008	0.063	-0.014	0.007	0.053
Seed transfers	0.004	0.003	0.240	0.004	0.003	0.164
Constant	0.079	0.022	0.000	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	0.000	0.924	0.045	0.000
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	0.000	0.047	0.009	0.000
Maize price	-0.004	0.012	0.774	0.000	0.010	0.981
Income sources	0.117	0.013	0.000	0.112	0.013	0.000
Constant	0.195	0.040	0.000	0.259	0.037	0.000
Pc household income						
Ag. income	0.280	0.019	0.000	0.247	0.021	0.000
% employed	0.121	0.019	0.000	0.127	0.020	0.000
Income sources	0.214	0.016	0.000	0.198	0.018	0.000
Formal cash transfers	0.146	0.029	0.000	0.111	0.030	0.000
Informal transfers	0.130	0.014	0.000	0.147	0.019	0.000
Constant	0.350	0.042	0.000	0.345	0.045	0.000
FCS						
FVC disruption	-0.027	0.013	0.042	-0.012	0.015	0.410
Pc household income	0.130	0.012	0.000	0.134	0.014	0.000
COVID-19	-0.272	0.013	0.000	-0.259	0.014	0.000
Food transfers	0.026	0.008	0.002	0.036	0.008	0.000
Constant	4.539	0.051	0.000	4.534	0.054	0.000
Poor						
Pc household income	-0.121	0.011	0.000	-0.115	0.012	0.000
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	0.550	-0.011	0.009	0.241
Constant	1.142	0.025	0.000	1.135	0.027	0.000
Cov(FCS,Poor)	-0.130	0.012	0.000	-0.139	0.014	0.000
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	0.010

5. Conclusions

This paper 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 at the household level. However, experiencing direct COVID-19 symptoms does not have a significant impact on employment, while self-imposed restrictions (i.e., change in household member behavior because of the pandemic such as staying at home for the fear of being infected) contribute to exacerbating FVC disruption. This can affect food prices, which in turn affect agricultural revenues and total household income. As expected, the household members' employment is positively linked to household total income: therefore, its reduction negatively impacts household total income. Food prices can 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 sources 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, which is a proxy for diet quality, was impacted to a greater extent being highly dependent on the level of household income.

The comparison of refugee and host households shows that the former was more affected than the latter both directly and indirectly. Indeed, refugees reported a higher direct impact on FVC disruption and employment, resulting in a higher negative impact on poverty. The impact on food security is similar between the two groups. Host households benefit from the impact of COVID-19 on FVC disruption through higher food prices and increased agricultural income, while refugees were negatively affected through the impact on the labor market. Indeed, the loss of casual employment significantly reduced income opportunities for the refugee population, which affected access to food, health services, and other essential goods and services, 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. The price of cassava played a mixed role: while its increase is positively associated with the hosts' agricultural income, it negatively impacted the refugees' agricultural production.

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. On the production side, their agricultural revenue decreased because of the reduction of the price of maize; on the consumption side, they lost because of the increase in the price of beans. Vice versa, the impact on net-seller households was mixed. They were negatively impacted as consumers by the food price increase while they gained as agricultural producers because the increase in the price of beans determined the growth of agricultural revenues and total income.

Furthermore, agricultural net-buyer households, along with non-agricultural households, are the most affected group through the employment channel, showing serious COVID-19 negative impact on food security. These two groups of households heavily rely on off-farm incomes, thus being more sensitive to economic restrictions and the resulting decrease in labor market participation.

The refugee households, being mostly non-agricultural or net-buyer households, experiences similar impacts. Specifically, the effect of COVID-19 on employment and the importance of labor income in total household income qualifies the loss of job pathway as the most important mechanism affecting the welfare of these households. Instead, host households, being mainly net-sellers, took advantage of the food price increase that positively affected households' poverty and food security.

These findings suggest important 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. This eventually translates into higher poverty among the refugees than among hosts. Four main reasons explain why refugees are not able to profit from participating in agricultural market transactions:

a) the size of the land granted to refugee households is significantly smaller than the average land owned by hosts: operating such a small piece of land, the production is not enough to generate a marketed surplus;
b) the refugees' dependency on transfers, which are their most important income source, decreases their incentives to gain a livelihood through production efforts and/or market exchange;
c) refugees face more constraints than locals in accessing the market because of the loss of social and human capital after fleeing the home country, language and communication barriers, and physical isolation from the rest of the host country's economy;
d) a fast-increasing refugee population faces increasingly limited off-farm employment opportunities resulting in limited market participation.

These 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 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 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 (Hoddinott et al., 2014; Daidone et al., 2019), 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[30] that would prove helpful especially in a recovery phase.

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 such as the COVID-19 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 for doing similar jobs[31] (Beltramo et al., 2021; Loiacono & Vargas, 2019). As emphasized by Beltramo et al. (2021), 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 is not only a waste of resources but, as shown in this paper, it also increases the refugees' vulnerability to shocks, resulting in humanitarian assistance dependence and possibly poverty traps (Malevolti and Romano, 2022).

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 their own production such as non-agricultural and net-buyers households. This result suggests that food assistance should be better targeted to

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

[31] According to Loiacono & 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.

support those households that cannot rely on their own production as a coping strategy. This is particularly relevant for non-agricultural households. Indeed, for this group of households food transfers have the highest indirect effect on FCS than other types of transfers. However, they reported a reduction of 24% in the amount of food assistance received in 2020 compared to 2019.

Notwithstanding the relevance of the above findings, we acknowledge some limitations of our study, some of them related to the study design, and some others to the adopted methodology. First, it is important to emphasize that our results crucially depend on the time frame of data collection. The last round was administered nine months after the COVID-19 outbreak in the country: a longer reference period could lead to different results and different policy implications. Furthermore, our findings refer only to the refugee and host population that live in Uganda and cannot be extended to the rest of the population in the country or to other contexts. From the methodological viewpoint, we emphasize that the joint multivariate normality assumption for SEM does not hold. The existing literature suggests that non-normality does not affect parameter estimates, but standard errors appear to be underestimated relative to the empirical standard deviation of the estimates (Kaplan, 2001). An alternative estimation method that relaxes the normality assumption is the asymptotic distribution free estimator. Unfortunately, when using this estimator, our model does not converge. This calls for a certain degree of caution in interpreting our results.

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Annexes

Annex 1 - 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 refugee according to the respondent answer to question A9 asking the household type, i.e 1 = Refugee; or 2 = 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 as non-agricultural household.

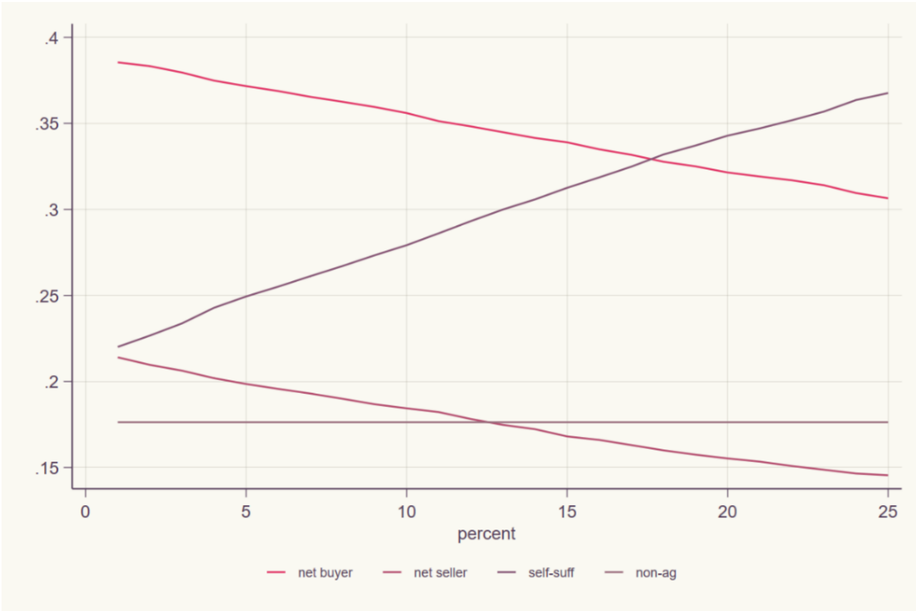
c) Agricultural household market position:

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 focus on staple food because it is relevant for expected food security, and especially for 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 A.1). Considering a reasonably low x and an acceptably 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 A.1 Change of household categories over different x



Annex 2 – Descriptive statistics (mean values)

Variables	Household types					
	Total	**Non-agr.**	**Agr.**	**Net-buyers**	**Net-sellers**	**Self-sufficient**
Age of household head (years)	44.11	43.10	44.60	43.94	46.59	43.02
Household size	6.41	5.13	6.59	6.73	6.53	6.60
Dependency ratio	0.50	0.51	0.50	0.47	0.52	0.50
Education of household head (years)	5.86	4.85	6.16	6.05	6.94	5.96
Employed household members (%)	0.15	0.18	0.15	0.17	0.11	0.16
Distance to ag. market (Km)	2.70	2.20	2.83	2.46	3.13	3.00
N. income sources	1.86	1.50	1.95	1.87	2.19	1.84
Crop produced (Kg)	2567	0	3274	700	10126	1323
Crop sold (Kg)	1423	0	1978	313	9313	86
Ag. revenues (USD $ in 2011 PPP)	126	0	162	57	536	71
Per capita household income (USD $ in 2011 PPP)	200	224	197	203	238	173
FCS	43.4	38.3	44.6	43.1	50.6	43.1
Poverty headcount	0.28	0.35	0.24	0.12	0.17	0.48
Household experienced flood	0.25	0.14	0.27	0.25	0.16	0.34
Household experienced drought	0.25	0.16	0.28	0.29	0.35	0.23
FVC disruption	0.10	0.13	0.09	0.11	0.04	0.09
COVID-19 symptoms	0.03	0.03	0.03	0.03	0.03	0.04
COVID-19 self-restrictions	0.02	0.02	0.02	0.02	0.02	0.01
Maize unit price (USD $ in 2011 PPP/kg)	0.59	0.42	0.64	0.46	0.52	1.03
Cassava unit price (USD $ in 2011 PPP/kg)	0.86	0.79	0.90	0.81	0.71	1.05
Beans unit price (USD $ in 2011 PPP/kg)	1.13	0.92	1.18	1.03	1.25	1.33
Per capita seeds transfer (USD $ in 2011 PPP)	0.52	0.05	0.59	0.52	0.44	0.37
Per capita food transfers (USD $ in 2011 PPP)	49.56	75.35	32.52	24.68	7.87	62.39
Per capita formal cash transfers (USD $ in 2011 PPP)	52.68	81.59	48.15	90.40	18.85	29.61
Per capita informal transfers (USD $ in 2011 PPP)	3.51	5.47	3.56	5.05	1.80	2.74
Per capita credit amount (USD $ in 2011 PPP)	16.98	7.39	19.69	19.83	46.73	10.78
Obs.	5938	396	4232	868	394	576

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

Annex 3 – Results of difference-in-difference

Refugee households

Outcome var.	**FCS**	**S. Err.**	**t**	**P>t**
Before				
Control	49.651			
Treated	40.156			
Diff (T-C)	-9.496	0.541	-17.55	0.000***
After				
Control	50.49			
Treated	42.145			
Diff (T-C)	-8.345	0.527	15.83	0.000***
Diff-in-Diff	1.151	0.755	1.52	0.128

R-square: 0.09
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1

Host households

Outcome var.	**FCS**	**S. Err.**	**t**	**P>t**
Before				
Control	40.214			
Treated	49.694			
Diff (T-C)	9.48	0.541	17.52	0.000***
After				
Control	42.163			
Treated	50.564			
Diff (T-C)	8.402	0.527	15.94	0.000***
Diff-in-Diff	-1.078	0.755	1.43	0.153

R-square: 0.09
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1

Net-buyer households

Outcome var.	FCS	S. Err.	t	P>t
Before				
Control	45.147			
Treated	43.133			
Diff (T-C)	-2.013	0.81	-2.49	0.013**
After				
Control	46.001			
Treated	47.21			
Diff (T-C)	1.208	0.78	1.55	0.121
Diff-in-Diff	3.222	1.124	2.87	0.004***

R-square: 0.00

* Means and Standard Errors are estimated by linear regression

**Inference: *** p<0.01; ** p<0.05; * p<0.1

Net-seller households

Outcome var.	FCS	S. Err.	t P>t	
Before				
Control	44.305			
Treated	52.26			
Diff (T-C)	7.955	1.104	7.2	0.000***
After				
Control	45.723			
Treated	52.584			
Diff (T-C)	6.861	1.099	6.24	0.000***
Diff-in-Diff	-1.094	1.558	0.7	0.483

R-square: 0.02

* Means and Standard Errors are estimated by linear regression

**Inference: *** p<0.01; ** p<0.05; * p<0.1

Self-sufficient households

Outcome var.	**FCS**	**S. Err.**	**t**	**P>t**
Before				
Control	44.945			
Treated	44.089			
Diff (T-C)	-0.856	0.945	-0.91	0.365
After				
Control	46.355			
Treated	44.526			
Diff (T-C)	-1.829	0.931	1.96	0.050**
Diff-in-Diff	-0.973	1.327	0.73	0.463

R-square: 0.00

* Means and Standard Errors are estimated by linear regression

**Inference: *** p<0.01; ** p<0.05; * p<0.1

Non-agricultural households

Outcome var.	**FCS**	**S. Err.**	**t**	**P>t**
Before				
Control	45.027			
Treated	42.5			
Diff (T-C)	-2.527	1.138	-2.22	0.026**
After				
Control	46.493			
Treated	41.765			
Diff (T-C)	-4.728	1.103	4.29	0.000***
Diff-in-Diff	-2.201	1.585	1.39	0.165

R-square: 0.01

* Means and Standard Errors are estimated by linear regression

**Inference: *** p<0.01; ** p<0.05; * p<0.1