WORKING PAPER

Changing profiles of child poverty: The case of Uganda during the COVID-19 pandemic

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Abstract

The COVID-19 pandemic worsened poverty risks for many people, including both poor and nonpoor households. Understanding the factors influencing poverty dynamics is crucial for targeted responses. This study examines the socioeconomic determinants of COVID-19-induced poverty among households with children in refugee-hosting districts of Uganda, comparing refugee and host households. It also investigates the role of social assistance in preventing poverty. Various econometric techniques, including multinomial logit models, are employed while addressing attrition bias. The findings reveal two distinct factors pushing the two groups into poverty: (i) family structure (number of children) for refugees populations; and (ii) occupation type (income from wage labor) for hosts populations. Social transfers were only partially effective in shielding households with children, suggesting insufficient levels of support.

It concludes that targeting interventions specifically towards children would have been more effective in reducing poverty rates. For refugee households with children, relying on income sources beyond transfers proved more successful in preventing poverty, emphasizing the need for interventions promoting refugee labor market participation.

This study contributes to the limited literature on the economic impact of COVID-19 in East Africa, focusing on households with children in a specific humanitarian context where post-COVID-19 data remains scarce.

Keywords: COVID-19; poverty; Uganda; refugees; hosts

JEL Codes: I30, O15, R20, J13

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1. Introduction

The global landscape is characterized by multiple, combined and increasingly harming shocks, the impact of which directly affect the lives of children. A number of reports by UNICEF (UNICEF ESA and UNICEF WCA, 2020; UNICEF and Save the Children, 2021) and the World Bank[1] (World Bank, 2022) highlighted how, iIn an increasingly interconnected world, covariate shocks like the COVID-19 pandemic are posing a risk to the livelihoods of millions of children, leaving no country and no context unaffected by its sweeping socio-economic drawbacks[2].

Although poor households are typically the most vulnerable to covariate shocks, these shocks often push individuals who were not previously considered poor into poverty, particularly when their coping capacities are overwhelmed. The COVID-19 pandemic has likely altered existing poverty profiles leading to the emergence of a new sociodemographic category of people, the new poor.

The new poor are individuals who, prior to a crisis, were not classified as near-poor or non-poor but fell into poverty due to the crisis. In the context of COVID-19 the new poor can be children who live in households reliant on heavily impacted occupations, with members engaged in unprotected contract work, like recent job starters and leavers, or who live in household types that have historically been little impacted by the shocks but not now, or who live in particular settings or areas. Globally, children living in households working in hard-hit sectors (low-skilled services, wholesale and retail trade, and construction) have been affected disproportionately compared to those relying more on high-skilled services as their main income source (ILO, 2021). As a result of restrictions on personal mobilities, which disrupted many economic activities, COVID-19 has significantly amplified existing inequalities (Dempster et al 2020; Josephson et al. 2020). Its impacts have not been evenly distributed among people, and children living in already disadvantaged and vulnerable households experiencing heightened deprivation. The result was that the most vulnerable communities were more at risk.

The economic impacts of COVID-19 have disproportionately affected marginalized groups, including refugee populations. Recent studies highlight that adults and children in vulnerable environments, such as humanitarian and forced displacement settings, have been more vulnerable compared to their peers in host communities (Dempster et al., 2020; Vintar et al., 2022). Refugees often have limited access to healthcare, restricted work rights due to their legal status, and are typically excluded from most government social protection programs, making them especially susceptible to the pandemic. The closure of public spaces, business restrictions, and the isolation of refugee camps eliminated many of the few economic opportunities available to refugees, leaving most households without income and reliant on aid in the initial months following the outbreak (Vintar et al., 2022).

This study contributes to the emerging literature investigating the socioeconomic impacts of the COVID-19 pandemic and the related impacts of Non-Pharmaceutical Interventions (NPIs) among households with children in Uganda. It has a special focus on understanding the characteristics of the

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[2] UNICEF ESA and UNICEF WCA, 2020; UNICEF and Save the Children, 2021; the World Bank[2] (World Bank, 2022) https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty

new poor in humanitarian settings, which remain under-investigated in the East-African context due to limited post-COVID-19 data availability[3].

Uganda is the country hosting the largest refugee population in Africa, with more than 1.5 million[4] of refugees coming from Burundi, Democratic Republic of Congo, Somalia, and South Sudan, mostly living in rural settlements (UNHCR, 2020). The country implemented strict measures to contain the pandemic: a total lockdown was instituted on April 1, 2020, with the closure of schools, public transport, and formal workplaces except those offering essential services. A temporary ban on the entry and exit of foreign nationals (including refugees and asylum seekers) was announced on March 22, 2020.

This study contributes to the emerging literature investigating the socioeconomic impacts of the COVID-19 pandemic and the related impacts of Non-Pharmaceutical Interventions (NPIs) among households with children, with a special focus on understanding the characteristics of the new poor in humanitarian settings, which remain under-investigated in the East-African context due to limited post-COVID-19 data availability.

The study aims to answering the following research questions:

1. What are the characteristics of those households, especially with children, that moved into poverty as a consequence of the COVID-19 crisis?
2. Is there any difference between host and refugee households?
3. How did social assistance respond to mitigate the negative effects of the crisis?

The study finds a differential effect of demographic composition and income sources on the probability of switching into poverty among hosts and refugees. The findings revealed that households with children, particularly refugee households, faced an increased risk of falling into poverty in 2020. The number of children is shown to affect refugees more than hosts, while on the other hand, the type of labor was a crucial determinant for host households mostly reliant on wage income.

The study highlights that transfers were only partially effective in shielding households with children from the likelihood of falling into poverty, suggesting that a larger focus on targeting the children would have been therefore more effective in reducing the incidence of the new poor.

Relying on other income sources than transfers, in particular wage income, shows to be effective in reducing the likelihood of moving into poverty for refugee households with 3 or more children. In this regard, the study highlights the need for interventions to increase the participation of refugees in the labor market.

The paper is organized as follows. Section 2 briefly reviews the key literature on the impact of NPIs on children and people's livelihoods, with a focus on humanitarian settings. Section 3 describes the situation of COVID-19 during 2020 in the country and the related measures and social protection interventions put in place by the government. Section 4 describes the data and the empirical models adopted for the analysis. Section 5 discusses the results of the main analysis and provides additional robustness checks. Section 6 concludes.

[3] Apart from Egger et al. (2021) who include refugee samples in their analyses, no studies, to our knowledge have empirically investigated poverty dynamics among refugee and host households with children in Uganda before and after the pandemic.

[4] As of January 2023.

2. Literature review

Several authors have highlighted the negative impacts of NPIs on children and people's livelihoods in different settings (Nuwematsiko et al., 2022). This study aims to synthesize two different strands of literature: the impact of COVID-19 and associated NPIs in humanitarian settings, and the effects of the COVID-19 crisis on households with children.

Some studies have analyzed transmission rates and the consequences of restrictions implemented in refugee and displacement camps in various countries. For example, Dempster et al. (2020) examined pre-COVID conditions for refugees in eight host countries, revealing that refugees were generally more at risk of employment loss compared to host populations. This was due to their higher likelihood of working in sectors heavily impacted by the crisis, such as accommodation and food services, manufacturing, and retail. The increased difficulty for refugees to access the labor market, coupled with pre-existing structural issues like economic recession and rising unemployment, exacerbated their exposure to poverty and economic exclusion.

Fouad et al. (2021) analyzed vulnerability factors driving transmission dynamics among Syrian refugees in Lebanon. Truelove et al. (2020) used a transmission model to project the potential COVID-19 burden, epidemic speed, and healthcare needs of people living in refugee camps in Bangladesh, while Gilman et al. (2020) evaluated the feasibility of NPIs in the Moria displacement camp in Lesbos, Greece, using a spatially explicit agent-based model of a COVID-19 outbreak in a refugee camp. Vintar et al. (2022) investigated the socioeconomic impacts of the COVID-19 pandemic, with a focus on labor-market impacts among refugee and urban national communities in Kenya, finding slower and often stagnant recovery in employment and income for refugees compared to nationals, confirming and exacerbating preexisting vulnerabilities.

In Uganda, the World Bank, in collaboration with the Uganda Bureau of Statistics and UNHCR, conducted phone surveys to track the socioeconomic impacts of COVID-19 among refugees and compared their conditions with those of the local population. The data showed a reduction in employment and off-farm business activities among refugees, leading to a decline in income and an increase in poverty. Refugees were substantially worse off than Ugandan citizens, with a slower recovery (Atamanov et al., 2021). Stein et al. (2022) examined the effect of cash transfers to offset the negative consequences of the COVID-19 crisis among South Sudanese refugees in the Kiryandongo settlement. They found that households receiving cash transfers were more food secure and had better mental health compared to control households, with those receiving transfers earlier being better off..

Regarding the impact of the COVID-19 shock on child poverty, many studies have focused on high-income countries, particularly in the EU and the US (Sinha et al., 2020; Fry-Bowers, 2020; Van Lancker and Parolin, 2020; Bessell, 2020; Holt and Murray, 2020; Abrams et al., 2022). In low and middle-income countries, there is no clear evidence yet on the effect of the pandemic on child poverty. Most studies conducted simulations on monetary and multidimensional child poverty based on various assumptions (Alkire et al., 2021; Cummins, 2021; UNICEF ESA and UNICEF WCA, 2020; UNICEF and Save the Children, 2021).

In Uganda, few studies have examined the impact of the COVID-19 shock on specific child outcomes and wellbeing dimensions or specific groups of children. Sserwanja et al. (2020) investigated the increase in child abuse during the pandemic, Atim et al. (2022) focused on maternal and child health outcomes, and Mbazzi et al. (2021) analyzed the effects on children with disabilities. Nuwematsiko et al. (2022)

found severe consequences for children, such as child labor and teenage pregnancies among slum dwellers in Kampala, Uganda.

However, it is important to provide evidence of how children and their families have been affected by the COVID-19 related crisis and the associated risk to fall into poverty. Previous economic crises have shown that children are more likely to fall into poverty and suffer its negative consequences more than any other age group (Sinha et al., 2020). None of the existing studies in Uganda has analyzed this in detail, and to the best of our knowledge, no study has empirically investigated the poverty dynamics of households with children in a humanitarian setting as a consequence of the COVID-19 crisis.

Egger et al. (2021) is the only study that includes both refugees and children in their analysis, but it does not combine the two groups. Based on data from 16 household surveys in nine countries in Africa, Asia, and Latin America, including three surveys in refugee camps (two in Bangladesh and one in Kenya), they did not find a clear pattern across refugee and non-refugee populations. For example, food insecurity was slightly lower among refugees than hosts in Bangladesh, while the opposite was observed in Kenya, possibly due to the presence of international humanitarian organizations in the Rohingya camp in Bangladesh buffering the economic shock. Mixed patterns were also found when considering children versus adults. In Kenya, more children (69%) than adults (38%) reported missing meals, while in Sierra Leone, the opposite was recorded (86% of adults and 68% of children).

3. Background

COVID-19 worsened child poverty and redefined its boundaries. Lockdowns, workplace and school closures, and other NPIs to combat the virus pushed many previously employed individuals below the poverty line. These top-down interventions had significant global repercussions on labor markets, economies, and the well-being of families and children. The crisis hit humanitarian and forced displacement contexts particularly hard due to existing vulnerabilities (Altare 2022).

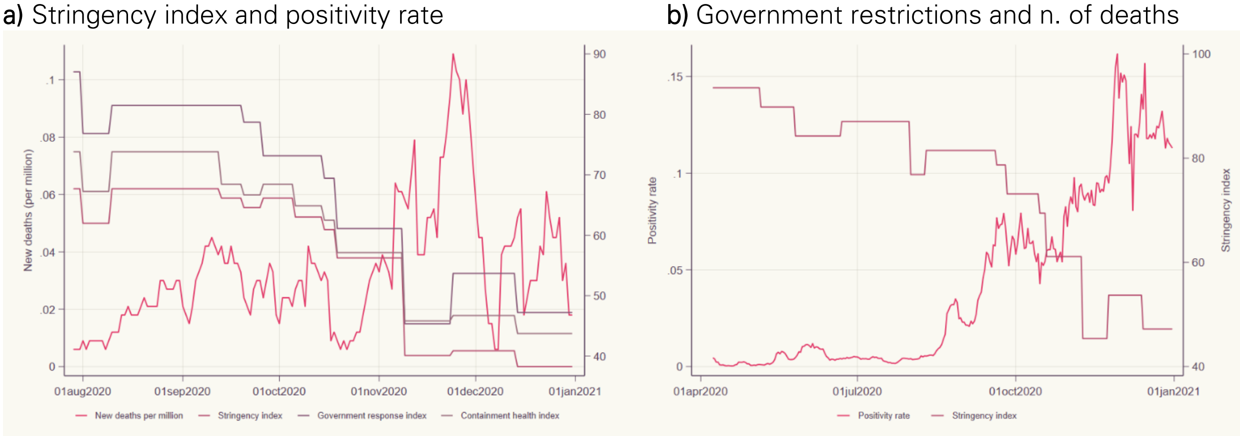
In Uganda, the government swiftly introduced lockdown restrictions a few days before registering the first case of COVID-19, on March 20. Measures included the closure of all schools, closure of the country's borders (except for the movement of cargo and goods), and suspension of public transport within the country (Agamile 2022), as well as night curfew and requirements to physically distance and wear masks. Entry and exit of foreign nationals, including refugees and asylum seekers, were also banned. The lockdown introduced in Uganda was one of the strictest in the world (Mahmud 2021), and it was effective in limiting the spread of the virus. Figure 1 panel a) clearly shows the opposite trend between the stringency index and the positivity rate. For deaths, the trend is not as clear as the number of cases, although deaths started to increase in mid-October, when government restrictions started to relax. Figures on deaths however also take into account the quality and preparedness of the health system.

Nationwide restrictions also applied to the refugee settlements, where specific measures like soap and hand sanitizer distribution were implemented. In addition, some measures were reinforced or reintroduced in specific settlements when the situation was worsening. For instance, while restrictions eased from June 2020 onwards, Kyangwali settlement re-entered lockdown by late August 2020 (Altare 2022). The first COVID-19 case among refugees was registered on May 22, 2020, in the Adjumani settlement. Refugee settlements experienced peaks in COVID-19 cases at various times, with West Nile reporting a peak around June and the South region reporting two peaks towards year-end (Altare 2022).

Although the Government of Uganda intervened to compensate businesses for the COVID-19 induced adverse effects, the COVID-19 related restrictions exacerbated existing fragilities. Poverty was increasing already before the pandemic, moving from 19.7% in 2012 to 21.4% of people below the national poverty line in 2016, and slightly decreasing to 20.3% in 2019. New influxes of refugees have steadily increased since 2018, reaching more than 1.5 million in 2023. Given the magnitude of the crisis and the pre-existing vulnerabilities in the refugee settlements, the government, in collaboration with international organizations, reinforced the social assistance response that was already in place, also introducing new interventions. Refugee households were already covered almost universally by different types of social assistance, mainly food and in-kind assistance, and cash transfers. The type of assistance differed across regions, for instance refugees in the West Nile region were more likely to report getting food and other in-kind assistance, while in the South West region cash transfers were more common (Atamanov et al., 2021a). However, due to resource constraints, general food assistance was reduced by 30% in all settlements from April 2020 (OPM and UNHCR, 2020). The decision was taken before the COVID-19 outbreak. To counterbalance this reduction, and to respond to the COVID-19 crisis, urban cash-based response was implemented to provide basic need assistance to urban refugees. Indeed, we can observe a reduction in food aid for all quintiles of the income distribution in 2020, especially for the second and third ones. At the same time, cash transfers increased for the poorest quintiles and decreased for the richest ones, suggesting a more equal distribution. On average, food assistance decreased by USD 12.17 in 2011 PPP per capita per year among refugee households, while cash transfers increased by only USD 2.78. Some interventions focused on women and children. In the West Nile for instance, the WFP, in partnership with UNICEF, provided one-off emergency cash transfers to women and children impacted by COVID-19, reaching 56,500 women, 59% of whom are refugees and 41% are Ugandan citizens. During the pandemic and the related lockdowns, digital cash transfers via agency banking have been introduced in some settlements, as for instance in Imvepi, Rwamwanja, and Kyangwali. Transfers however were not targeted to specific household characteristics, such as the sector and occupation of employment of household members, or the household composition. Additionally, it is worth highlighting the temporary nature of these interventions, which mainly aim to fix emergency situations over a relatively short time frame. Indeed, already in February/March 2021 the incidence of social assistance has been observed to decline, with twice as many households that did not receive any social assistance compared to the end of 2020 (Atamanov et al. 2021b).

Figure 1. Stringency measures and COVID-19 cases/deaths in 2020.

a) Stringency index and positivity rate   b) Government restrictions and n. of deaths



Source: authors' elaboration based on the Oxford COVID-19 Government Response Tracker (OxCGRT), Blavatnik School of Government, University of Oxford.

4. Data and methodology

4.1 Survey design

The dataset used in this study is the RIMA Uganda Refugee and Host Communities Panel Survey, a comprehensive longitudinal survey comprising four rounds representative of refugee and host communities in the country (d'Errico et al., 2021). Implemented by the Uganda Office of Prime Minister (OPM), the Uganda Bureau of Statistics (UBOS), the Food and Agriculture Organization of United Nations (FAO), the World Food Program (WFP) and the United Nations' Children Fund (UNICEF) this survey aims to monitor the execution of Refugee Response Plans and provide insights into the living conditions of both refugees and host communities across eleven refugee-hosting districts in Uganda. The host communities have been identified as the closest communities living in the same sub-county. This survey is unique in that it is one of the few in Uganda that covers both refugee and host communities and is the only one that tracks the same households in both communities over multiple time periods.

Data collection occurs annually in December from 2017 to 2021. The first round of data collection took place at three different points in time, spanning from 2017 to 2019. When possible, households were re-interviewed in 2019, 2020, and 2021. For subsequent rounds, data collection occurred within the same year.

The overall final sample consists of 20,079 observations, with 2,282 panel households tracked across all four rounds. However, due to high attrition rates (see Section 4.2) and our focus on the pre- and post-pandemic situation, we used the panel of households from 2019 and 2020 for the main analysis. This allows us to examine the situation nine months after the pandemic outbreak, corresponding to the period when lockdown restrictions were in place, during which we expect a greater effect. Other subsamples of households are used for additional analysis and robustness checks. The final balanced sample includes 2,963 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 (PSUs) and randomly selected households as the second sampling unit. The initial sample was designed in a way that the probability of selecting PSUs was proportional to the size of the settlement or sub-county, thus no sampling weights are applied. However, due to the high attrition rate from one wave to the other, some adjustments were necessary to ensure the representativeness of the initial sample. The sample covers 11 districts and 13 settlements and it is representative of approximately 80 percent of refugee and host populations living5 in the refugee-hosting districts in Uganda as of 2018.

4.2 Dealing with attrition

The attrition rate is significant, amounting to 26.3% between 2019 and 2020, and 54.9% when comparing the baseline to the panel of households in 2019 and 2020. This high attrition rate is primarily due to logistical challenges of data collection within the specific refugee context. Similar attrition rates

[5] Given that refugees are able to move across the country with no restrictions, some of them are located outside the refugee settlements. Since the survey was conducted only in refugee-hosting districts, they are not represented in the sample.

have been documented in other emergency contexts (Özler et al., 2020). Such attrition poses substantial representativeness issues, as the subsample of households in the 2019-2020 panel systematically differs from the original sample, as outlined in Table 1. The mean difference in most household-level variables between the two samples is significantly different from zero. If the attrition is not random and no corrective action is taken, the results would be biased (Wooldridge, 2010). Two tests confirm that the attrition is not random. Two tests confirm that the attrition is not random. The first test involves running an attrition probit with the attrition dummy as the dependent variable and a set of baseline explanatory variables that could affect the outcome variable and the probability of dropping out of the sample as regressors. The pseudo R-squared from the attrition probit indicates that observable variables explain 8.75% of panel attrition, with half of the variables being significant predictors of attrition. The second test is a Wald test of whether these variables are jointly equal to zero, confirming that they are significant predictors of attrition (Chi-square(24) = 706.07, Prob > Chi-square = 0.0000).

Table 1. Mean of household characteristics at baseline, subsample of panel for 2019/2020, and significance level of mean difference.

VARIABLE	BASELINE	SUBSAMPLE 2019-2020	MEAN DIFFERENCE
Age of HH head	41.00	42.72	***
Dep. Ratio	0.51	0.50	***
N. of male adults	1.48	1.52	***
N. of female adults	1.46	1.49	**
N. of infants	0.98	1.00	*
Average years of HH education	5.46	5.44	
HH head is female	0.35	0.33	***
Shock drought	0.54	0.53	
Shock flood	0.11	0.11	
Refugee HH	0.55	0.51	***
Wealth index	0.51	0.55	***
District=Adjumani	0.06	0.09	***
District=Arua	0.21	0.14	***
District=Isingiro	0.11	0.16	***
District=Kamwenge	0.06	0.06	
District=Kikuube	0.05	0.08	***
District=Kiryandongo	0.08	0.07	***
District=Kyegegwa	0.12	0.14	***
District=Lamwo	0.11	0.10	*
District=Moyo	0.12	0.07	***
District=Yumbe	0.08	0.09	
HH size	5.99	6.18	***
Land size	1.26	1.40	***
N. income sources	2.15	2.14	
FCS	44.18	44.86	***
N. observations	6,236	2,812	

Note: test for difference in means computed using a linear regression model. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. No weights applied. Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2017, 2018, 2019 and 2020.

To adjust for the attrition and ensure that the subsample remains representative of the original refugee and host population in the country, inverse probability weights are computed. Following Wooldridge (2010), a probit regression was run to estimate the probability of being in the panel subsample based on a set of baseline variables (see Appendix B). The inverse of the estimated probability yields the adjusted weight. As reported in Table 2, the new weights help reduce the bias, although statistically significant differences persist for some variables. Consequently, while we can rely on the analysis results from the studied household sample, we cannot assert the external validity of the findings to the entire refugee and host population.

Table 2. Balance test after adjusting with inverse probability weights.

DEPENDENT VARIABLE	NO WEIGHTS	WITH WEIGHTS
Age of HH head	3.14***	1.49***
	(0.36)	(0.37)
Dep. Ratio	-0.018***	-0.007
	(0.005)	(0.005)
N. of male adults	0.076***	0.055*
	(0.028)	(0.029)
N. of female adults	0.069**	0.027
	(0.027)	(0.028)
N. of infants	0.040*	0.020
	(0.024)	(0.024)
Average years of HH education	-0.041	0.029
	(0.088)	(0.092)
HH head is female	-0.045***	-0.024*
	(0.012)	(0.012)
HH experienced drought	-0.006	-0.017
	(0.012)	(0.013)
HH experienced flood	-0.007	0.002
	(0.008)	(0.008)
HH is refugee	-0.084***	-0.040***
	(0.012)	(0.013)
Wealth index	0.057***	0.031***
	(0.008)	(0.008)
HH size	0.349***	0.172**
	(0.077)	(0.080)
Land size	0.252***	0.126***
	(0.044)	(0.045)
N. income sources	-0.008	-0.030
	(0.026)	(0.027)
FCS	1.239***	0.380
	(0.366)	(0.372)
District=Adjumani	0.052***	0.024***
	(0.006)	(0.006)
District=Arua	-0.121***	-0.059***
	(0.010)	(0.011)
District=Isingiro	0.082***	0.038***
	(0.008)	(0.007)
District=Kamwenge	0.006	0.002
	(0.006)	(0.006)
District=Kikuube	0.056***	0.026***
	(0.005)	(0.005)
District=Kiryandongo	-0.023***	-0.009
	(0.007)	(0.007)
District=Kyegegwa	0.047***	0.021**
	(0.008)	(0.008)
District=Lamwo	-0.014*	-0.002
	(0.007)	(0.008)

District=Moyo	-0.091***	-0.045***
	(0.008)	(0.008)
District=Yumbe	0.003	0.004
	(0.007)	(0.007)

Note: independent variable=1 if HH is in the 2019/2020 subsample. Coefficients estimated through OLS. Weights computed as the inverse probability of a logit regression with clustered standard errors at the district level. Standard error in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2017, 2018, 2019 and 2020.

4.3 Variable definitions

To define the level of poverty, we use a poverty headcount at the household level based on daily per capita total household expenditure measured in USD 2011 PPP. This method aligns with official poverty estimates, which use expenditure rather than income (UBOS, 2019; MoFPED, 2023). We employ a relative poverty line set at half the median per capita daily expenditure in 2019, which is USD 0.13 in 2011 PPP. A relative poverty line is used instead of an absolute one because the consumption module does not include all the items required to estimate an expenditure measure comparable to official statistics. However, it ensures comparability across survey waves. Moreover, the relative poverty line used in this study is very close to the official national poverty line. The national annual poverty line was UGX 46,233.65 in 2016/2017 (UBOS, 2019), equivalent to a daily poverty line of USD 0.10 in 2011 PPP.

The latest official poverty data indicates that 20.3% of Uganda's population was below the national poverty line in 2019 (MoFPED, 2023). In our sample, however, the poverty headcount based on the relative poverty line was 29.9% in the same year. This difference is mainly due to the different poverty lines used and the focus on a specific subset of the population, which is historically poorer than the rest of the country (World Bank, 2019). Table 3 shows the percentage of households in the sample below the relative poverty line, divided between hosts and refugees and further categorized by whether they have children. It is important to note that most households have children, so statistics for households without children should be interpreted cautiously due to the small sample size.

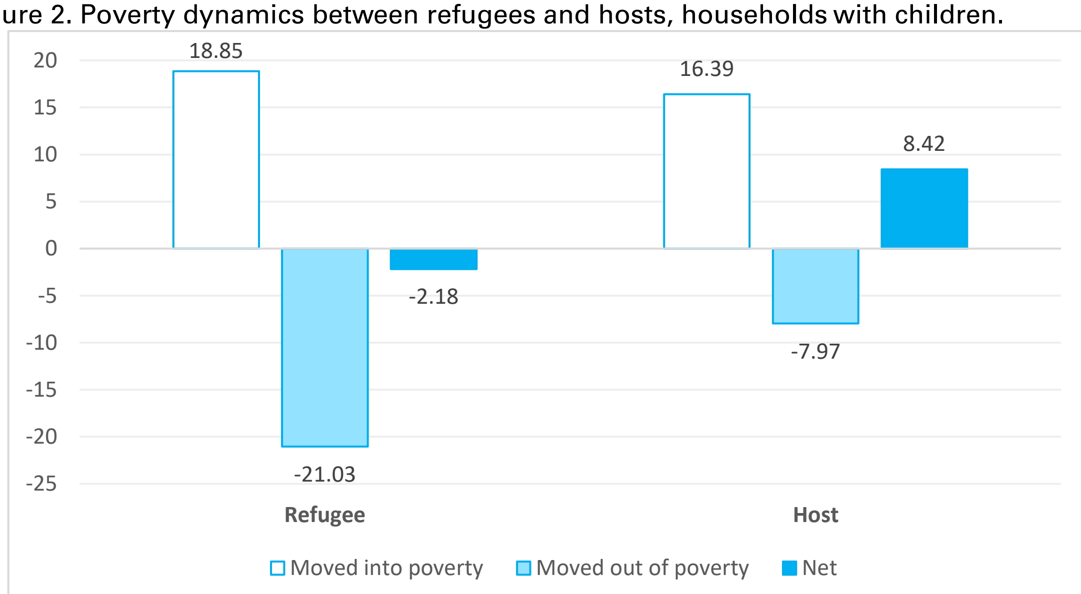
Table 3. Percentage and number of poor households in 2019 and 2020, by refugee status and with/without children

		HOST HHS		REFUGEE HHS	
		% POOR	OBS.	% POOR	OBS.
HH without children	2019	7.4%	95	24.1%	116
	2020	11.0%	91	22.2%	108
HH with children	2019	11.1%	1,330	41.6%	1,422
	2020	19.9%	1,334	39.3%	1,430

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2019 and 2020.
Note: no sampling weights applied. Percentage obtained considering the balanced sample of households in 2019 and 2020.

Regarding poverty dynamics, a larger percentage of refugee households with children fell into poverty in 2020 compared to host households with children (Figure 2). However, a greater proportion of refugee households also managed to lift themselves out of poverty, resulting in a net effect of-2.18%. This dynamic can be attributed to the significant role of transfers in determining the total income of refugees and the government's response to mitigate the crisis's negative effects on refugees. In response to the COVID-19 outbreak, urban cash-based response was implemented to provide basic need assistance to urban refugees. Conversely, among hosts, more households entered into poverty than moved out resulting in a net surplus of 8.4% of households with children flling into poverty. The movement of households in and out of poverty suggests higher volatility in poverty transitions among refugees compared to host. This volatility may indicate that many refugees are close to the poverty line. Host households, on average, are richer than refugees, but once they fall into poverty, they have fewer options to move out, suggesting a chronic condition of poverty. Evidence of a structural poverty trap among both refugee and host households is supported by a study by Malevolti and Romano (2024).

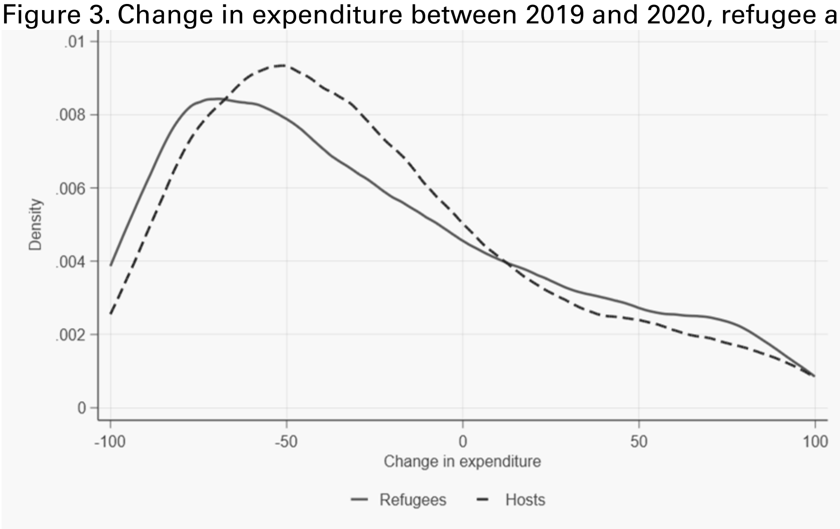
Figure 2. Poverty dynamics between refugees and hosts, households with children.



Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2019 and 2020.

Similar trends are observed when examining continuous variables of expenditure and income. Although both income and expenditure changed similarly between 2019 and 2020, the change in expenditure was more gradual, as expected (see Appendix A). When comparing refugees and hosts (Figure 3), a higher proportion of host households were likely to experience a reduction in expenditure, although this trend does not hold for significant expenditure reductions. This indicates that, on average, host households had to reduce their expenditure levels more than refugees in 2020. However, refugees were more vulnerable to experiencing very high reductions in expenditure.

Figure 3. Change in expenditure between 2019 and 2020, refugee and host households.

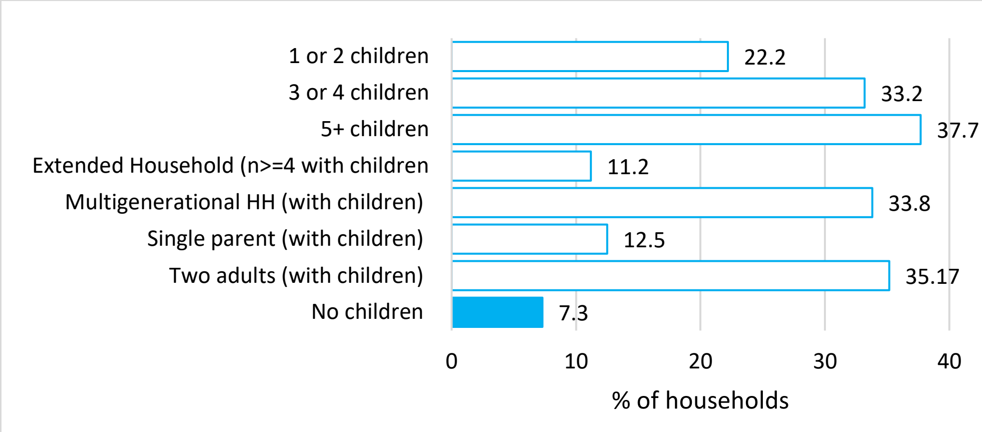


Note: kernel density function, no weights applied. Values>=100 excluded from the graph.

Household composition

The majority of families, both among refugees and hosts, include children. Indeed, only 7% of households in the sample do not have children. Examining household compositions (Figure 4), most of the families consist of either two adults or multiple generations with children, which together account for 69% of the sample. Nearly 38% of households have 5 or more children. On average refugee households are larger than host households, with 4.1 children per household among refugees compared to 3.7 among hosts.

Figure 4. Distribution of households across household types.



Note: Pooled sample of households (hosts and refugees) in 2019 and 2020.

Income composition

Significant differences exist in the income composition among refugee and host households. Refugees predominantly rely on transfers, with limited income coming from other sources (Figure 6). Transfers can be decomposed into formal cash transfers from the government; informal transfers from friends and family members (including remittances); and food in-kind assistance. However, informal transfers do not constitute a relevant part of income for refugees in Uganda, who primarily depend on formal assistance. As described in Section 3, in 2020 there was a decrease in the in-kind assistance, followed by efforts to rebalance the change with additional cash transfers. Although this attempt was quite effective for lowest income quintiles, households with more children experienced a decline. As reported in Figure 5, all households with up to 4 children experienced a reduction in food transfers in 2020, while only households without children and with a maximum of 2 children observed an increase in cash transfers. Households with 5 or more children instead faced a reduction of cash assistance and a slight increase in food assistance in 2020 compared to 2019.

Apart from transfers, the second main source of income for refugee households comes from employment-related activities. However, labor participation for refugees does not represent a stable and sustainable source of income. Indeed, refugees are mostly employed in casual jobs that systematically do not match their skills, and they are usually paid less than nationals (Beltramo et al., 2021; Loiacono and Vargas, 2019). The low market participation of refugees can be explained, among all, by high costs of compliance with local regulations and a lack of information about the legal status of refugees among others (Loiacono and Vargas, 2019).

Host households instead show a more diversified income composition, where agriculture, employment, and self-employed non-agricultural business represent the main sources. We do not see significant changes in the income composition of hosts between 2019 and 2020. For refugees, we can notice an increase in the share of income from transfers in 2020 compared to 2019. At the same time, income from employment reduced. This is in line with findings from other studies. The WB for instance estimated that in October/November 2020, about 13 percent of refugee respondents stopped working since March. Also in that study, authors found that the employment rate among refugees was significantly lower than the one among Ugandans, corresponding to 47 percentage points gap (WB URHFPS, first round).

Figure 5. Amount of per capita cash and food transfers received in 2019 and 2020, by number of children in the household.

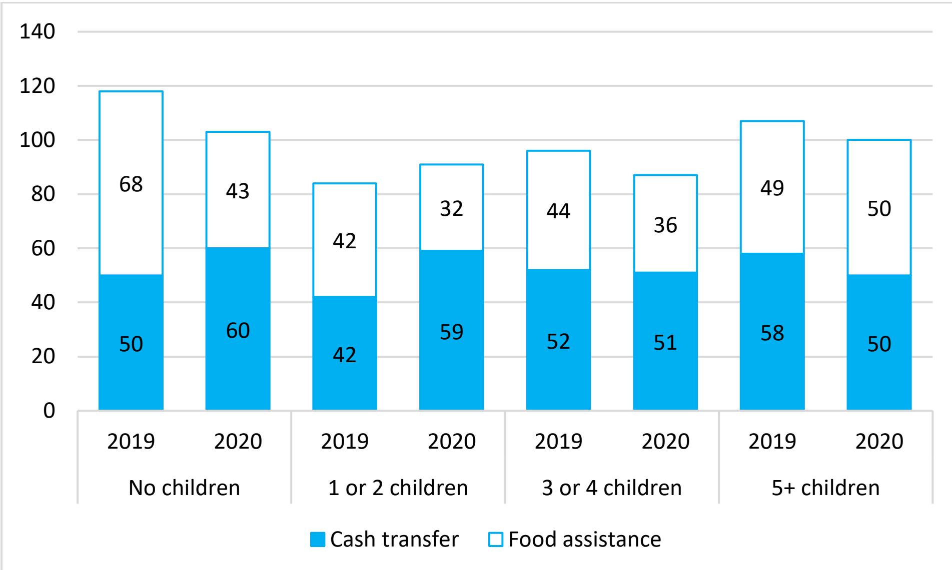
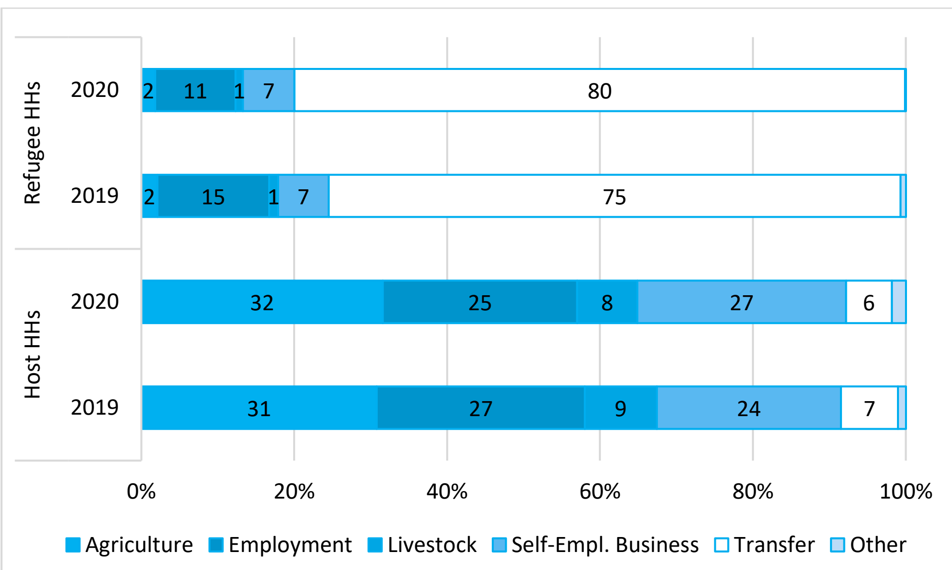


Figure 6. Income composition of refugee and host households, 2019 and 2020 (in percent).



4.4 Empirical model

To investigate the transition into poverty as a consequence of the COVID-19 pandemic, we first started to examine the change and the associated determinants of the continuous variable of expenditure. Taking advantage of the longitudinal nature of the data, we used different econometric models to control for different possible biases, and then we compared the results. Specifically, we conducted five models: pooled OLS, pooled OLS with district fixed effects, household fixed effects, random effects, and Mundlak estimation. Household fixed effects allow controlling for time-invariant unobserved characteristics that could create problems of omitted variable bias. However, if the time-invariant factors are not correlated with the regressors, the estimates when using the FE model are still unbiased but not efficient. For this reason, we also compute the analysis using the RE model, which instead is more efficient and it permits to include those variables that are constant over time. Following the RE model, the Mundlak model is an extension of the RE, where the assumption that the observed variables are uncorrelated with the unobserved ones is relaxed. This is done by adding to the RE model group-means of the independent variables which vary within groups.

The baseline model for the pooled OLS is the following:

$$y_{ht} = \beta_0 + \beta_1 x + \delta_t + \varepsilon_{ht} \qquad (1)$$

Where the subscripts h and t denote household and year, respectively; y_{ht} is the outcome variable, namely the household per capita daily expenditure in 2011 USD PPP; x is a vector of households characteristics that could affect the level of household expenditure; δ_t is the time fixed effect, capturing aggregate trends over time; and ε_{ht} is the error term. Regressors include the dummy of being a refugee household, demographic characteristics of the household, income composition, including the amount of per capita transfers received in a year, participation in the labor market, assets ownership (land and livestock), as well as other territorial-level variables, such as having experienced a flood and the distance to the main agricultural market. Given the importance of transfers in determining the level of income among refugees, we decided to use the continuous variable of the monetary amount received, in cash and in food assistance, to understand the implications of an additional dollar received by the government. Indeed, as almost all refugee households receive a type of assistance, a dichotomous variable equal to one for the recipients would not produce enough variability. The complete list of variables is reported in Table 4.

The dependent variable, as well as other continuous independent variables, have been transformed using the inverse hyperbolic sine transformation, to account for zero values. Regression results can be interpreted similarly to the log transformation (Johnson, 1949; Burbidge et al., 1988). Standard errors have been clustered at the household level to correct for possible heteroscedasticity and to adjust for spatial autocorrelation.

To specifically investigate the characteristics of those households that became poor as a consequence of the COVID-19 crisis, we used a different econometric model, looking at the poverty headcount each year. Moving from one year to another, we can have four possible outcomes: chronic poverty, namely households that are poor in both years; never poor, i.e. those households that were above the poverty line in both years; moved into poverty, which are those households that were not poor in 2019 and became poor in 2020; and moved out of poverty, namely households that were poor in 2019 and moved out of poverty in 2020. We are particularly interested in those households that moved into poverty, which represent the new poor after COVID-19.

We ran a multinomial logit model, with the switch in the poverty status from 2019 to 2020 as the dependent variable, and the variables at the household level included in equation (1) in 2019 among the regressors. We then computed the marginal effect when the predicted outcome is the switch from non-poor to poor. In this way, we are able to understand what are the characteristics in 2019 that are more likely to determine a switch into poverty in 2020.

The probability to switch the poverty status is given by

$$Prob(Switch = j) = x_h^T \beta + u_h \qquad (2)$$

Where h is the household, x is a column vector of observable household characteristics in 2019, and u_h is the error term. j takes 4 values: 1 (non-poor/non-poor), 2 (poor/poor), 3 (non-poor/poor), and 4 (poor/non-poor).

Given the short time span between the two rounds of data analyzed and the absence of other significant shocks over the period under analysis, we can assume that any changes that have occurred between 2019 and 2020 can be attributed to COVID-19. This approach presents limitations because it does not fully allow us to completely isolate the impact of the pandemic. The COVID-19 shock indeed, given its aggregate and simultaneous nature, cannot fit a typical treatment/control setting used for the usual impact assessment analyses. All individuals were affected by the crisis, although at a different magnitude and in different ways. Therefore, different, quasi-experimental models than randomized trials or diff-in-diff would be required.

Additionally, to control for any other possible shocks over the same period, we look for exogeneous shocks affecting the interviewed households. Among them, flood is the most frequently experienced shock, affecting 26.6% of households in the two years. Intense rainfalls triggered localized but significant flooding between September and November 2020 in the districts of Adjumani, Moyo, Lamwo, and Arua (FAO, 2020). Therefore, by including the variable for having experienced a flood within the model for each year, we are able to control for potential confounders that may bias the coefficients of the independent variables.

Table 4. Descriptive statistics of main variables used in the analysis, by refugee and host households, 2019 and 2020.

	HOST HHS			REFUGEE HHS		
	2019	2020	MEAN DIFF.	2019	2020	MEAN DIFF.
Outcome variables						
Per capita daily HH exp.	0.46	0.35	***	0.28	0.25	***
Poor HH	0.11	0.19	***	0.40	0.38	
Per capita daily income	0.46	0.49		0.62	0.61	
Independent variables						
Per capita cash transfers	5.24	4.10		95.59	98.37	
Per capita informal transfers	4.55	3.60		2.13	3.89	**
Per capita food assistance	0.74	0.43		90.74	78.51	*
% female in HH	0.50	0.51		0.52	0.53	
Age of HH head	46.87	47.69		40.63	41.77	**
Educ. of HH head	6.37	6.50		5.28	5.36	
Dep. Ratio	0.52	0.53		0.47	0.47	
HH size	6.43	6.60		6.17	6.46	**
Land size	3.58	3.77		0.41	0.51	***
% employed HH members	0.15	0.14		0.17	0.16	
Crop diversification	2.86	3.31	***	1.53	1.79	***
Training	0.30	0.17	***	0.31	0.16	***
Equitability index	0.18	0.17		0.13	0.16	***
Per capita credit	24.86	31.67		5.79	7.32	*
TLU	1.08	1.37	***	0.14	0.15	
HH experienced flood	0.32	0.32		0.16	0.18	
HH is in association	0.65	0.49	***	0.41	0.32	***
Distance to ag. market	3.25	2.91	***	2.44	2.26	**
Obs.	1,425			1,538		

Note: all monetary values are expressed in USD in 2011 PPP. The equitability index measures income diversification, ranging from 0 to 1, where 1 corresponds to no diversification. Mean difference computed through a linear regression. No weights applied. * p<0.05, ** p<0.01, *** p<0.001.

5. Results

5.1 Determinants of per capita expenditure

We first looked at the determinants of per capita expenditure by focusing on the full sample from 2019-2020 to understand the pre- and post-pandemic dynamics. Table 5 shows the results of the first set of regressions, which must be interpreted as the average between hosts and refugees. The estimates are consistent across the models, with some variations in magnitude and significance levels. As expected, the refugee status is associated with lower expenditure levels (β=[-0.19;-0.15], $p<0.01$).

Older household heads report lower expenditure levels, while higher educational attainment among household heads is linked to increased expenditure. Larger households tend to have lower per capita expenditure, and the expenditure further decreases as the number of children in the household rises. Compared to households without children (the reference category), all variables related to the number of children show negative coefficients, with the magnitude increasing as the number of children exceeds one or two. Cash transfers, both formal and informal, positively influence expenditure, whereas food transfers have the opposite effect. This can be attributed to households saving on food costs when receiving food aid. It is worth noting that since in this paper poverty is measured through expenditure, lower expenditure levels are thus associated with higher poverty. This in turn means that, in cases of in-kind transfers, increased poverty does not necessarily reflect a worsening of the household's welfare. A similar result is found for crop diversification. Higher crop diversification increases household self-sufficiency, thus reducing food expenditure. On the other hand, income diversification likely increases income and thereby expenditure. Instead, income diversification potentially increases income, and in turn expenditure. Among other variables, the type of occupation (share of wage laborers within the household) is not consistent across models, while the amount of credit received and membership in an association are both positively related to expenditure. Experiencing a flood and being distant from the agricultural market are negatively associated with expenditure. Lastly, all models show a negative coefficient for the year 2020, indicating that per capita expenditure decreased on average in 2020 compared to 2019.

Table 5. Different models over (ihs) per capita expenditure. Full sample.

	POOLED OLS	POOLED OLS WITH DISTRICT FE	FE	RE	MUNDLAK
Refugee	-0.187***	-0.173***		-0.164***	-0.150***
	[-13.14]	[-12.08]		[-12.22]	[-9.35]
% Females in hh	0.018	0.012	-0.037	0.023	-0.025
	[0.91]	[0.63]	[-0.86]	[1.20]	[-0.80]
Age of HH head (ihs)	-0.040***	-0.041***	-0.016	-0.030***	-0.029
	[-3.53]	[-3.72]	[-0.65]	[-2.81]	[-1.36]
Educ. of HH head (ihs)	0.011***	0.011***	0.002	0.010***	0.003
	[4.74]	[4.57]	[0.61]	[4.57]	[0.72]
Dep. ratio	0.005	0.002	0.020	0.011	0.048
	[0.25]	[0.10]	[0.51]	[0.58]	[1.40]
HH size	-0.017***	-0.018***	-0.020***	-0.018***	-0.020***
	[-8.69]	[-9.09]	[-5.46]	[-8.40]	[-7.91]
Cash transfers (ihs)	0.023***	0.017***	0.016***	0.023***	0.020***
	[12.02]	[8.49]	[6.55]	[12.49]	[8.38]
Food transfers (ihs)	-0.008***	-0.006***	-0.000	-0.006***	0.001
	[-3.82]	[-3.15]	[-0.18]	[-3.04]	[0.41]
Informal transfers (ihs)	0.012***	0.011***	0.012***	0.011***	0.008**
	[4.19]	[3.94]	[3.02]	[3.85]	[2.15]
Land (ihs)	-0.003	-0.000	-0.002	0.003	0.001
	[-0.48]	[-0.04]	[-0.28]	[0.58]	[0.12]
% wage labourers	-0.082***	-0.061***	-0.017	-0.069***	-0.017
	[-4.69]	[-3.51]	[-0.62]	[-3.94]	[-0.90]
N. crops produced	-0.013***	-0.012***	-0.010***	-0.012***	-0.010***
	[-5.71]	[-5.34]	[-3.09]	[-5.71]	[-3.06]
Training	0.009	0.003	0.012	0.010	0.015
	[1.24]	[0.34]	[1.17]	[1.44]	[1.58]
Shannon-equitability Index[6]	0.074***	0.068***	0.044	0.063***	0.039
	[3.46]	[3.23]	[1.46]	[3.19]	[1.45]
Credit (ihs)	0.014***	0.013***	0.008***	0.011***	0.006***
	[7.22]	[6.55]	[3.29]	[6.56]	[2.97]
TLU (ihs)	0.002	0.013**	0.002	0.007	0.009
	[0.41]	[2.33]	[0.29]	[1.43]	[1.13]
HH experienced flood	-0.006	-0.000	-0.010	-0.015**	-0.019*
	[-0.87]	[-0.04]	[-1.11]	[-2.52]	[-1.95]
HH in association	0.038***	0.039***	0.033***	0.039***	0.030***
	[5.34]	[5.64]	[3.38]	[6.02]	[3.48]
Dist. to ag. market (ihs)	-0.019***	-0.015***	-0.008*	-0.014***	-0.010*
	[-5.00]	[-3.94]	[-1.65]	[-4.07]	[-1.84]
Year=2020	-0.042***	-0.040***	-0.037***	-0.056***	-0.054***
	[-7.57]	[-7.21]	[-6.26]	[-10.54]	[-9.59]
1 or 2 children	-0.140***	-0.138***	-0.180***	-0.174***	-0.226***
	[-6.08]	[-6.12]	[-4.78]	[-7.60]	[-9.50]
3 or 4 children	-0.219***	-0.216***	-0.234***	-0.249***	-0.271***
	[-9.21]	[-9.28]	[-5.86]	[-10.29]	[-9.85]
5+ children	-0.225***	-0.224***	-0.229***	-0.257***	-0.268***
	[-8.46]	[-8.55]	[-5.05]	[-9.29]	[-8.14]
Constant	0.863***	0.881***	0.701***	0.842***	0.840***
	[14.38]	[14.79]	[5.79]	[14.88]	[14.89]
N	5614	5614	5614	5614	5614

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2019 and 2020. Note: Households in the panel sample for 2019 and 2020 are considered (2,963 households per year). Inverse probability weights applied. Standard errors clustered at household level. * p < 0.10, ** p < 0.05, *** p < 0.01t statistics in brackets. * p < 0.10, ** p < 0.05, *** p < 0.01

[6] The Shannon-equitability index measures the evenness of income sources. It ranges from 0 to 1 where 1 indicates complete evenness.

5.2 Determinants of the new poor households

In this section we aim to respond to the first research question, that is to understand first of all what are the factors associated with the likelihood of falling into poverty in 2020, and then to evaluate whether they are directly linked to the COVID-19 crisis and not to a general trend, which could have been observed also in normal conditions. This is achieved through a descriptive comparison of the determinants of being new poor in 2019 vis-à-vis 2020 using the full sample of households and lagged independent variables.

From the results reported in Table 6, we observe some differences between the two periods[7]. In 2020, households' occupation types became more relevant. Labor market participation emerged as a key factor during the pandemic, with employment being one of the main channels through which households were affected[8], alongside disruption of food value chains (Deconinck et al., 2020; Devereux et al., 2020; ILO, 2020; Squarcina and Romano, 2024). Our estimates show that households with a higher proportion of members in formal employment prior to the pandemic (t-1) had a lower probability of falling into poverty in 2020 (β=-0.15, $p<0.01$), a significant difference from the previous year where the effect was not statistically significant. When introducing a variable for job loss in 2020, we found that job loss significantly increased the probability of falling into poverty, unlike in 2019, indicating that reduced labor participation had a much greater impact in 2020.

During the pandemic, also sociodemographic characteristics of households became more significant compared to the pre-pandemic period. For instance, the education level of the household head and the number of women in the household became significant in 2020. This is likely linked to the types of occupations household members had, as high-skill jobs were less affected during the pandemic, particularly in sectors like services or IT (Reardon et al., 2021). Women in these districts were probably employed in more resilient sectors.

Looking specifically at income subsidies, we show that cash transfers did not affect the likelihood of becoming new poor, but receiving more food aid was associated with a higher probability of falling into poverty in both 2019 and 2020. This unexpected effect may be due to decreased expenditure levels when food or non-food products are directly transferred to households. The significance of owned land size diminished during COVID-19. The well documented disruptions in the agricultural value chain had a cascade effect also on households, reducing the protective role of land (Kansiime et al., 2021; Nchanj et al., 2021; Mekonnen et al., 2022). Delays in the delivery of production inputs such as seeds and fertilizers (BMAU, 2020), along with challenges farmers faced in reaching customers, could contribute to explain this outcome. Lastly, the significance of coefficients for households that experienced a flood or were members of an association disappeared in 2020.

[7] A formal comparison of the coefficients across the two models through different tests confirms that the coefficients are not equal.

[8] Uganda experienced a substantial rise in unemployment across both formal and informal sectors (Agamile 2022), with working time losses equivalent to 1.8 million full-time jobs in 2020 compared to 2019 (ILO, 2021).

Table 6. Determinants of moving into poverty, comparison over time. Full sample.

	PRE-COVID19 PROB (NEW POOR IN 2019)	POST-COVID19 PROB (NEW POOR IN 2020)
Refugee HH (t-1)	-0.047	-0.033
	(0.030)	(0.030)
% employed (t-1)	0.009	-0.150***
	(0.050)	(0.042)
Job loss in the HH (t-1)	0.007	0.079***
	(0.025)	(0.022)
% Female HH members (t-1)	0.018	-0.082**
	(0.048)	(0.038)
Age of HH head (ihs) (t-1)	-0.031	-0.029
	(0.026)	(0.025)
Educ. HH head (ihs) (t-1)	-0.003	-0.011*
	(0.006)	(0.006)
HH size (t-1)	-0.005	-0.003
	(0.044)	(0.003)
Dep. Ratio (t-1)	0.004	-0.103***
	(0.002)	(0.039)
Cash transfers (ihs) (t-1)	-0.002	0.007
	(0.006)	(0.005)
Food transfers (ihs) (t-1)	0.015***	0.011**
	(0.004)	(0.004)
Informal transfers (ihs) (t-1)	0.007	0.001
	(0.004)	(0.007)
Shannon-equitability index (t-1)	-0.063	0.087
	(0.073)	(0.055)
Land (ihs) (t-1)	-0.036**	0.004
	(0.018)	(0.015)
Crop diversification (t-1)	0.002	-0.003
	(0.004)	(0.006)
Training (t-1)	-0.014	0.028
	(0.019)	(0.019)
Credit (ihs) (t-1)	0.002	0.001
	(0.007)	(0.004)
TLU (ihs) (t-1)	0.020	0.010
	(0.020)	(0.016)
Flood (t-1)	0.054**	0.014
	(0.022)	(0.019)
Member of association (t-1)	0.051***	0.020
	(0.018)	(0.019)
Dist. Ag. market (ihs) (t-1)	-0.002	-0.006
	(0.007)	(0.010)
Observations	2,207	2,807

Note: Y= P(Switch to poverty=1). Ind. variables are in t-1. Coefficients are average marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level in parentheses. *** p <0.01, ** p<0.05, * p<0.1

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2017, 2018, and 2019 in the first column, 2019 and 2020 in the second column.

5.3. The role of children and different income sources

In this section, we focus on two types of determinants and their combined effects, i.e. the number of children in the household and the households' diversified sources of income. Families with a large number of dependents are expected to be at greater risk of falling into poverty if they experience an income reduction or employment loss, especially if the social assistance or insurance system is not specifically designed for them. To examine this, we augment the baseline model with the two sets of variables separately (Figure 7 and Figure 8), and then interact them to analyze the combined effect (Table 7). This analysis is conducted for the overall sample and repeated for the subsample of refugees and hosts.

Figure 7 shows the results of the model augmented with the coefficients related to the number of children. Estimates for the overall sample (green dot) do not exhibit any significant result in any of the years. When splitting the sample into refugees (orange dot) and hosts (blue dot), we find a differential effect. For host households, it is generally not significant in both years. In contrast, for refugees, having children is systematically linked with a higher probability of becoming poor in 2020, and this probability increases with the number of children. This result is the opposite of what was observed in 2019.

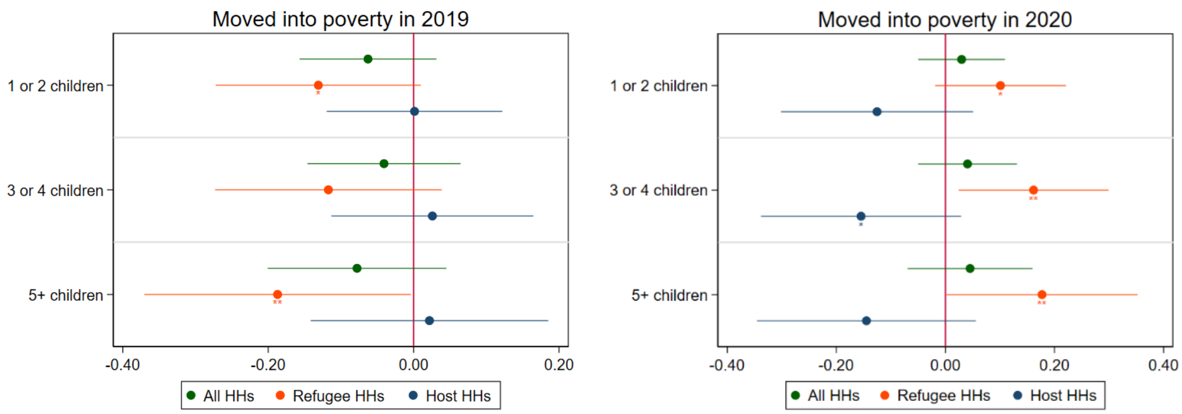
When examining the different income sources (Figure 8) as determinants of transitioning into poverty for the overall sample, interesting differences emerge between 2019 and 2020. While none of the income sources significantly influenced shifts into poverty in 2019, the pandemic brought notable changes. Dependence on agriculture and wage-employment became pivotal factors in determining whether households would fall into poverty. Contrary to expectations, the probability of becoming poor for households relying on non-agricultural businesses as their primary income source was minimal.

Splitting the sample reveals some interesting patterns between refugee and host households. Refugees show no relevant associations between income type and transitioning into poverty which can be attributed to their limited income diversification and primary dependence on transfers. In contrast, host households with a high share of income from agriculture and/or from wage employment were more likely to move into poverty compared to households relying on other income sources. This is due to the pandemic's disproportionate impact on these two income streams.

Given that wage income and agricultural income were the primary income sources significantly impacted by the crisis9 and also confirmed in our findings, we sought to investigate their effects on different household compositions based on the number of children. To achieve this, we examined the interactions between the proportions of income from agriculture and wage employment and the number of children, separately. Among refugees, wage labor during COVID-19 appears to be more effective in reducing the likelihood of falling into poverty for households with children. We observed a significant, although weak, effect ($p<0.1$) for households with 3 or more children. Conversely, among hosts, we did not observe any distributional effect of relying on wage income across households with children. On the other hand, agriculture income slightly counteracts the negative consequences of COVID-19 and the related movement into poverty for those households with few children, but only among hosts. The effect instead is not significant for the other types of households.

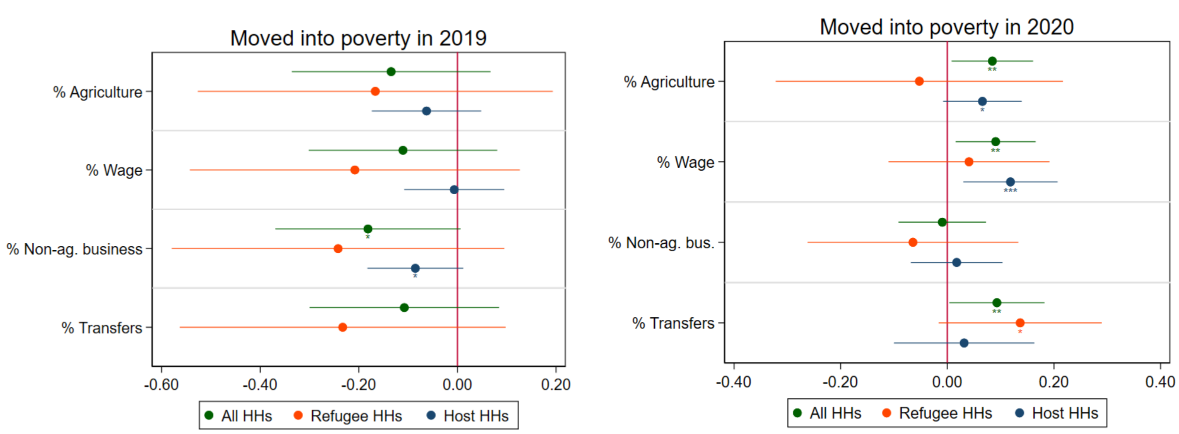
Figure 7. Number of children as determinants for moving into poverty, comparison over time. Full sample, host, and refugees.

[9] Due to job losses resulting from the closure of shops and businesses as a consequence of NPIs, and disruptions in the food supply chain, as documented by various authors (Demeke et al., 2020; Devereux et al., 2020; ILO, 2020; UN-HABITAT and WFP, 2020)



Note: Dep. Var.= P(Switch to poverty=1). Ind. variables are in time t-1. Dots are average marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level. Bars are 95% confidence intervals. The graph on the left includes the panel of households from baseline to 2019 (N=2,256), and the graph on the right b includes the panel of households between 2019 and 2020 (N=2,963).

Figure 8. Share of income as determinants for moving into poverty, comparison over time. Full sample, host, and refugees.



Note: Dep. Var.= P(Switch to poverty=1). Ind. variables are in time t-1. Dots are average marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level. Bars are 95% confidence intervals. The graph on the left includes the panel of households from baseline to 2019 (N=1,750), and the graph on the right includes the panel of households between 2019 and 2020 (N=2,963).

Table 7. Combined effect of income share from selected sources and number of children on the probability to move into poverty.

	WAGE INCOME			AGRICULTURAL INCOME		
	ALL HHS	REFUGEE HHS	HOST HHS	ALL HHS	REFUGEE HHS	HOST HHS
Ag. income share	0.050	-0.112	0.036	0.152	-0.527	0.114
	(0.057)	(0.311)	(0.037)	(0.111)	(0.696)	(0.119)
Wage share	0.206	0.287	0.062	0.052	-0.059	0.067
	(0.129)	(0.333)	(0.159)	(0.056)	(0.310)	(0.058)
Transfers share	0.064	0.047	0.008	0.058	0.035	-0.022
	(0.063)	(0.300)	(0.057)	(0.063)	(0.315)	(0.064)
1 or 2 children	0.048	0.145*	-0.122*	0.064	0.056	-0.020
	(0.050)	(0.077)	(0.063)	(0.051)	(0.065)	(0.076)
3 or 4 children	0.074	0.197**	-0.133**	0.078	0.119	-0.090
	(0.055)	(0.085)	(0.065)	(0.056)	(0.074)	(0.082)
5+ children	0.069	0.204**	-0.118	0.073	0.122	-0.076
	(0.067)	(0.104)	(0.076)	(0.069)	(0.095)	(0.093)
Wage share*1 or 2 children	-0.111	-0.285	0.099			
	(0.126)	(0.186)	(0.164)			
Wage share*3 or 4 children	-0.171	-0.334*	0.034			
	(0.121)	(0.176)	(0.156)			
Wage share*5+ children	-0.142	-0.340*	0.026			
	(0.123)	(0.193)	(0.156)			
Ag. income share*1 or 2 children				-0.192	0.518	-0.256*
				(0.123)	(0.622)	(0.138)
Ag. income share*3 or 4 children				-0.110	0.142	-0.071
				(0.114)	(0.662)	(0.126)
Ag. income share*5+ children				-0.0458	0.496	-0.084
				(0.112)	(0.638)	(0.125)
Socio-Demographic Controls	yes	yes	yes	yes	yes	yes
Observations	2,610	1,345	1,265	2,610	1,345	1,265

Note: Dep. Var.= P(Switch to poverty=1). Ind. variables are in time t-1. Coefficients are marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level. *** p <0.01, ** p<0.05, * p<0.1

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2019 and 2020.

5.4 The heterogenous effect of social assistance among refugee households

How did social assistance respond to mitigate the negative effects of the crisis? To answer our third research question we empirically investigate the role of transfers in mitigating the adverse effects of the COVID-19 crisis on the economic condition of refugee households with one or more children. We examined the coefficients of the interaction term between the number of children and the provision of social assistance, proxied by the variation in food and cash transfers from 2019 to 2020.

Given the minor role of transfers in the total income of host households, our analysis focuses only on the subsample of refugee households. Table 8 shows the marginal effects of the multinomial probit incorporating the interaction of the number of children with cash transfers alone, food transfers alone, and their combination.

Looking at the cash transfers, we observe that a one unit increase in cash transfers between 2019 and 2020 leads households with children to be less likely to fall into poverty compared to those without children. However, households with children still show a higher likelihood of experiencing poverty in 2020 compared to households without children, indicating that the effect is only partially effective in bridging the gap between households with and without children. Despite the additional cash transfers, households with children remain more likely to move into poverty in 2020.

Specifically, an additional unit of cash in 2020 compared to 2019 has a significant mitigating effect across households with a different number of children with respect to households without. However, the magnitude of the effect is the same regardless of whether the household has one child or five or more children. Although the effect is statistically significant, it is not enough to reduce the probability of falling into poverty. Households with more children are still more likely to move into poverty.

An increase in food assistance in 2020 compared to 2019 instead allows for reducing the probability to fall into poverty for households without children, while it increases it for those with children. The effect is marginal, although significant, therefore households with 5 or more children remain the ones more at risk to become poor. When combining cash and food transfers, we observe similar results. Transfers are associated with a lower probability to move into poverty among households without children compared to those with children, leaving households with children at a higher risk to fall into poverty.

These findings suggest that the additional cash assistance implemented was not effective in responding to the exposure of households to poverty based on the number of children. Overall, the intervention was not enough to reduce the likelihood of households with children becoming poor in 2020. These findings are in line with those from Mastrorillo et al. (2022), which show that transfers are unlikely to support refugees' self-reliance in the longer term, and better targeting is needed to make them more effective. A similar result was found in the study conducted by Staffieri et al. (forthcoming), where cash transfers were found to be less effective to build resilience during the COVID-19 pandemic than under normal circumstances.

Table 8. Effect of change in social assistance on the probability to move into poverty. Refugee households.

	CASH TRANSFERS ALONE	FOOD TRANSFERS ALONE	COMBINED EFFECT
Percapita cash transfer (his)	0.009	0.013**	0.006
	(0.006)	(0.005)	(0.006)
Percapita food transfer (his)	0.001	0.001	-0.006
	(0.005)	(0.006)	(0.006)
Change in food transfer		-0.001***	
		(0.000)	
Change in cash transfer	0.001**		
	(0.002)		
Change in total transfer			-0.001***
			(0.000)
1 or 2 children	0.120*	0.229***	0.126*
	(0.063)	(0.081)	(0.073)
3 or 4 children	0.190***	0.293***	0.198**
	(0.072)	(0.087)	(0.079)
5+ children	0.206**	0.306***	0.211**
	(0.091)	(0.104)	(0.096)
Change in cash transfer* 1 or 2 children	-0.001***		
	(0.000)		
Change in cash transfer* 3 or 4 children	-0.001**		
	(0.000)		
Change in cash transfer* 5+ children	-0.001**		
	(0.000)		
Change in food transfer* 1 or 2 children		0.001***	
		(0.000)	
Change in food transfer* 3 or 4 children		0.001***	
		(0.000)	
Change in food transfer* 5+ children		0.001***	
		(0.000)	
Change in total transfer* 1 or 2 children			0.000
			(0.000)
Change in total transfer* 3 or 4 children			0.001**
			(0.000)
Change in total transfer* 5+ children			0.001**
			(0.002)
Controls	yes	yes	yes
Observations	1,423	1,423	1,423

Note: Y= P(Switch to poverty=1). Ind. Variables are in t-1, except for the variables of change, which are in first difference. Coefficients are average marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level in parentheses. *** p <0.01, ** p<0.05, * p<0.1

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2019 and 2020.

5.5 Robustness checks

To validate previous findings, additional analyses and robustness checks have been computed. Specifically, we ran the same analysis reported in Section 5.2, but using a model based on a gaussian distribution function rather than a logistic one; we then ran a polynomial regression to check whether the findings of the relationship between the number of children and the probability to move into poverty emerging from the parametric regression are still valid when using a nonparametric technique; we replicated the estimates over the restricted panel of households tracked from the baseline to 2020; and we checked the bias occurring from the selection on unobservables caused by the high attrition rate.

Multinomial probit model

The advantage of using a logit model is that it is easier to maximize its likelihood compared to a probit model due to their closed form. For this reason, it is preferred when having multiple responses. Indeed, when using multinomial probit model, the computational effort required is too large and the model does not converge. However, the multinomial logit model requires the independence of irrelevant alternatives (IIA) assumption to be satisfied. This is typically relevant in discrete choice theory, where the decision of people to choose among a set of alternatives is assumed to not depend on whether some other alternatives are present. If the IIA property is not satisfied, the multinomial logit model is misspecified. Nested logit or probit models are possible alternatives, as they relax this assumption. In this case, there is no concern of violation of the IIA, as there are no other possible alternatives. Results of the Hausman-McFadden test (1984) and the Small-Hsiao test (1985) confirm that the IIA has not been violated (see Appendix C). As an additional check, we performed the same analysis using a multinomial probit model. The results, expressed in average marginal effects, are reported in Table 9. Comparing the estimates shown in Table 6, it can be seen that all the coefficients report similar values and with the same level of significance.

Table 9. Determinants of moving into poverty, comparison over time, based on a multinomial probit model.

	PRE-COVID	POST-COVID
	PROB(NEW POOR IN 2019)	PROB(NEW POOR IN 2020)
Refugee HH	-0.037	-0.025
	(0.029)	(0.030)
% employed	0.013	-0.147***
	(0.049)	(0.0417)
Job loss in the HH	0.006	0.0775***
	(0.024)	(0.0221)
% Female HH members	0.018	-0.0844**
	(0.046)	(0.0374)
Age of HH head (ihs)	-0.026	-0.0333
	(0.026)	(0.0247)
Educ. HH head (ihs)	-0.003	-0.0118*
	(0.006)	(0.00619)
HH size	0.003	-0.00269

	(0.002)	(0.00301)
Dep. Ratio	-0.005	-0.104***
	(0.043)	(0.0392)
Cash transfers (ihs)	-0.002	0.00628
	(0.005)	(0.00444)
Food transfers (ihs)	0.014***	0.00987**
	(0.004)	(0.00471)
Informal transfers (ihs)	0.006	0.00124
	(0.004)	(0.00730)
Shannon-equitability index	-0.060	0.0809
	(0.072)	(0.0557)
Land (ihs)	-0.042**	0.00392
	(0.017)	(0.0147)
Crop diversification	0.002	-0.00383
	(0.003)	(0.00634)
Training	-0.015	0.0302
	(0.019)	(0.0185)
Credit (ihs)	-0.001	-0.001
	(0.007)	(0.00432)
TLU (ihs)	0.019	0.010
	(0.018)	(0.016)
Flood	0.052**	0.013
	(0.022)	(0.018)
Member of association	0.049***	0.021
	(0.018)	(0.018)
Dist. Ag. market (ihs)	-0.003	-0.004
	(0.007)	(0.009)
Observations	2,207	2,807

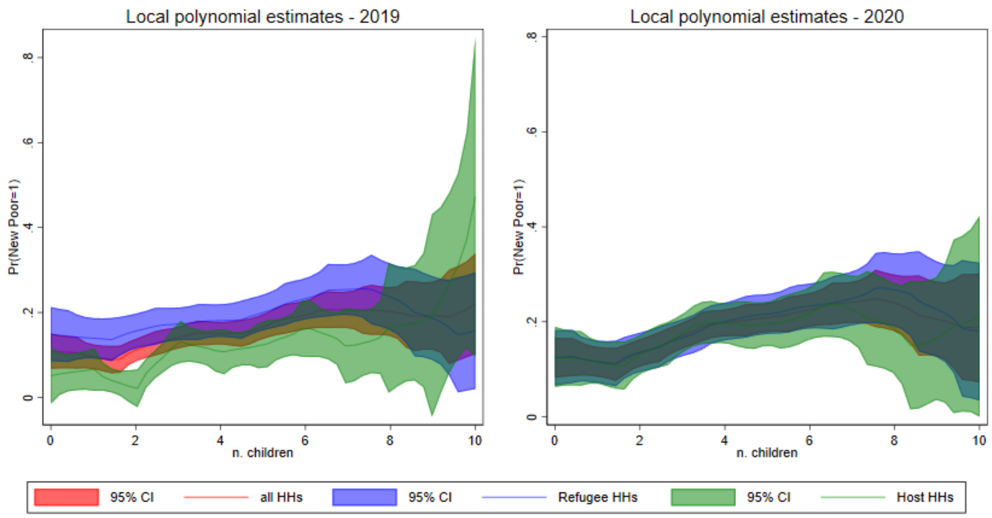
Note: Y= P(Switch to poverty=1). Ind. variables are in t-1. Coefficients are average marginal effects estimated from a multinomial probit model. Inverse probability weights applied. Standard errors clustered at the household level in parentheses. *** p <0.01, ** p<0.05, * p<0.1

Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2017, 2018, and 2019 in the first column, 2019 and 2020 in the second column.

Local polynomial regression

We estimated a kernel-weighted local mean-smoothing polynomial regression. Local polynomial regression is a nonparametric technique for smoothing scatter plots and modeling functions (Avery, 2010). This regression is more flexible than parametric techniques, but it only estimates a bivariate relation. For each point, x_0, a low-order weighted least squares regression is fit using data from some neighborhoods around x_0. Here, we look at the relationship between the number of children and the poverty switch variable to look at poverty dynamics. We find that an increase in the number of children is linked to an increase in the probability of being poor. We see that the gap between refugee and host households is reduced in 2020 compared to 2019. The two distributions indeed are closer, suggesting that the crisis has reduced the inequality between these two groups of households. Although the curves are quite flatted and not much different from 2019, the main result is that they overlap along almost the entire distribution.

Figure 9. Local polynomial regression results of the n. of children over the probability to move into poverty, 2019 and 2020.

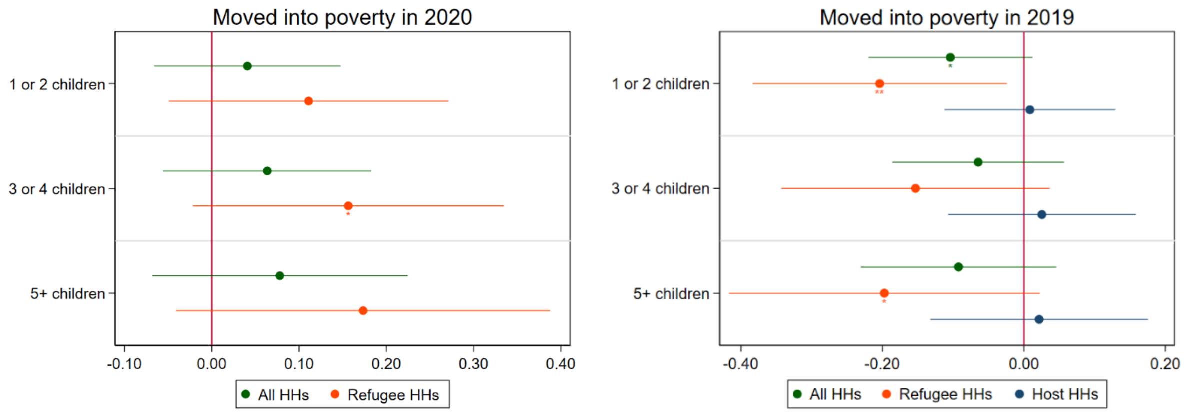


The poverty switch for the figure on the left refers to the change in poverty from the baseline to 2019, while the poverty switch for the figure on the right refers to the change from 2019 to 2020.

Estimates from the restricted panel of households

As a robustness check, we restricted the analysis to those households that were tracked from baseline up to 2020. The final sample size is 1,750 households. We find that results in general are consistent with previous estimates, although with few small differences. When looking at the number of children in the household as a determinant of falling into poverty in 2019 vis-à-vis 2020, we still find that the number of children increases the likelihood of moving into poverty for refugees in 2020, as compared to 2019, while for hosts it is not relevant in defining the poverty dynamic. However, the level of significance for refugees in 2020 is lower, probably due to the smaller sample size. When looking at the shares of income from different sources as determinants of moving into poverty, we find similar results. Even in this case, the value of the coefficient is similar to previous estimates, although the level of significance is lower. As above, this can be explained by the reduced variability in the sample.

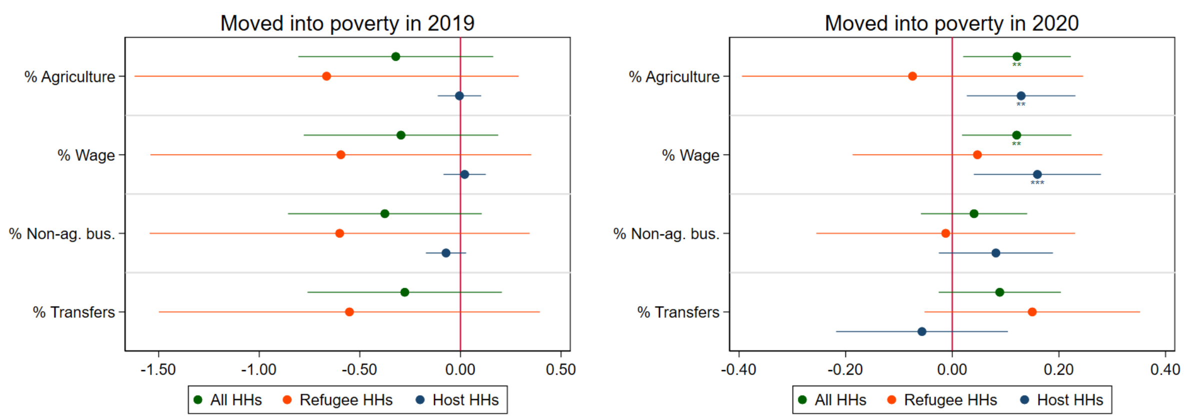
Figure 10. Effect of number of children over poverty dynamics, panel of HHs from baseline to 2020.



Note: Dep. Var.= P(Switch to poverty=1). Ind. Variables are in time t-1. Dots are average marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level. Bars are 95% confidence intervals.

The graphs consider the panel of households tracked from the baseline (in 2017/2018) up to 2020 (N=1,750). When looking at the shares of income from different sources as determinants of moving into poverty, we find similar results. Even in this case, the value of the coefficient is similar to previous estimates, although the level of significance is lower. As above, this can be explained by the reduced variability in the sample.

Figure 11. Effect of Income composition.over poverty dynamics, panel of HHs from baseline to 2020



Heckman selection

As described in Section 4.2, the data used for the analysis report a large attrition rate. To correct this, we produced inverse probability weights, where weights have been computed based on observable variables (selection on observables) to make the subsample more representative of the original one. There is however another method that allows correcting based on unobservables. This is the Heckman (1976) procedure, which uses a set of instrumental variables that correlate with attrition but not with the error term (selection on unobservables).

We implemented the Heckman selection model and compared the results with the original model, where no adjustments have been made, and with the model where weights have been applied. We used the same set of variables used to compute the IPW for the first-step selection model over the dummy variable equal to 1 if the household belongs to the subsample of the panel in 2019/2020, and then we computed the second-step estimation model.

Table 10 reports the results of the probit regression using the three different specifications. The dependent variable is the probability of being poor over the years 2019 and 2020. Overall, coefficients are quite similar from columns 1 to 3, both in terms of magnitude and significance level.

Table 10. Comparison of different models to correct for attrition.

	(1) NO WEIGHTS	(2) IPW	(3) HECKMAN
Dep. Ratio	-0.326***	-0.290***	-0.388***
	(0.080)	(0.095)	(0.086)
HH experienced flood	0.019	-0.044	-0.056
	(0.037)	(0.044)	(0.040)
HH size	0.099***	0.104***	0.089***
	(0.005)	(0.006)	(0.006)
% of female HH members	-0.157**	-0.163*	-0.191**
	(0.077)	(0.091)	(0.081)
Age of HH head (ihs)	-0.059	-0.089	0.022
	(0.050)	(0.058)	(0.053)
Educ. HH head (ihs)	-0.080***	-0.078***	-0.062***
	(0.013)	(0.015)	(0.013)
Per capita cash transfers (ihs)	-0.058***	-0.060***	-0.048***
	(0.008)	(0.009)	(0.008)
Per capita food transfers (ihs)	0.129***	0.133***	0.078***
	(0.007)	(0.008)	(0.008)
Per capita informal transfers (ihs)	-0.080***	-0.082***	-0.059***
	(0.016)	(0.018)	(0.016)
Land size (ihs)	-0.252***	-0.264***	-0.255***
	(0.032)	(0.037)	(0.034)
% employed HH members	0.325***	0.360***	0.313***
	(0.074)	(0.083)	(0.076)
Crop diversification	0.013	0.019	0.024*
	(0.013)	(0.014)	(0.013)
Training	-0.140***	-0.132***	-0.123***
	(0.043)	(0.049)	(0.043)
Income diversification	-0.566***	-0.692***	-0.521***
	(0.118)	(0.134)	(0.122)
Per capita credit (ihs)	-0.069***	-0.072***	-0.051***
	(0.010)	(0.011)	(0.010)
TLU (ihs)	-0.170***	-0.173***	-0.189***
	(0.033)	(0.036)	(0.035)
HH belongs to association	-0.194***	-0.148***	-0.152***
	(0.037)	(0.043)	(0.038)
Distance to ag. market (ihs)	0.091***	0.109***	0.090***
	(0.020)	(0.023)	(0.021)
Year=2020	0.101***	0.110***	0.114***
	(0.033)	(0.038)	(0.034)

Constant	-0.422*	-0.347	-0.972***
	(0.238)	(0.271)	(0.251)
Observations	8,207	8,207	8,207
Pseudo R2	0.172	0.180	
Rho			0.869
P value			0.000

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1-2 are estimated via OLS, column 3 with Heckman probit model. The dependent variable is a dummy equal to 1 if the household is below the poverty line, and 0 otherwise.

6. Conclusions

The objective of this study was to analyse the changing profiles of poverty as a result of COVID-19 for host and refugees housheholds. By comparing results from the pre-pandemic period, it aimed to understand whether the factors associated with poverty were the same over time, or if the pandemic reshaped the poverty determinants. The sample for the analysis has been drawn from the refugee-hosting districts of Uganda, the analysis has been conducted separately for refugee and host households and taking into account the number of children in each household. To better understand the underlying dynamics of poverty, and specifically of moving into poverty, other characteristics, in particular the share of income over different income sources, have been analyzed. Finally, the study evaluated the effectiveness of cash transfers and food aid as a means to mitigate the likelihood of falling into poverty.

The findings revealed that households with children, particularly refugee households, faced an increased risk of falling into poverty in 2020. This risk increased with an increasing number of children within the household. For host households, reliance on specific income sources significantly influenced the risk of poverty in 2020. In host households, the composition of income sources significantly influenced poverty risks in 2020. Those relying more on wage employment, and to a lesser extent on agriculture, were more susceptible to poverty due to the impact of job losses resulting from pandemic-induced closures. **Given that hosts rely more on labor participation than refugees, they experienced a greater impact.** Cash transfers were able to slightly reduce the probability of falling into poverty in 2020 for refugee households with children. However, the intervention was found to be not enough, so households with children were still more at risk to fall into poverty in 2020 compared to those without. In particular, **large households with many children are more exposed to becoming poor**.

The study suggests that improved targeting based on household composition would enhance the effectiveness of social assistance interventions. Moreover, given the transitory nature of this type of assistance and the existing reliance of refugee households on transfers, more impactful interventions are recommended. For example, long-term strategies addressing the specific needs and challenges faced by households with children, especially refugees, are essential not only for poverty reduction but also for resilience-building after shocks. Although children are recognized as the largest group with specific needs among refugees in Uganda (OPM and UNHCR, 2022), cash-based interventions specifically targeted to them, such as universal or age-specific child grants, should be promoted more effectively.

The results presented in this study confirm those of a previous simulation, which indicated the **importance of introducing a child-sensitive social protection grant to refugee households**[10]. This isespecially critical in the aftermath of shocks that affect the household capacity to guarantee adequate standards of living to children. At the same time, structural interventions in the labor market are needed to create more job opportunities among refugees, reducing their dependence on transfers and creating more stable economic conditions.

The study recommends a phased approach that combines social assistance in the immediate and short terms as an emergency response, and more structural interventions in the medium- and long-terms. Indeed, transfers represent an important emergency response in the immediate aftermath of systemic shocks, as found in several studies over different types of shocks (Daidone et al., 2019; Hoddinott et al., 2018), as well as when looking at the specific case of COVID-19 (Mastrorillo et al. 2022). However, in the long run, transfers are not able to support refugees' self-reliance (Mastrorillo et al. 2022) and are not enough effective in building the resilience capacity of households to offset negative shocks (Staffieri et al., forthcoming).

The emergency response should address both refugees and host individuals participating in the labor market. Indeed, host households relying more on wage earnings were found to be more at risk to fall into poverty in 2020 compared to the other households. This result instead does not emerge in the refugee sample because in this case there is a problem of accessibility to the labor market, therefore most of the households do not rely on employment activities for their livelihood. When they do it, having a higher share of income from wage shows to have a positive effect in reducing the likelihood of falling into poverty, especially for households with 3 or more children. This finding is significant, given that refugee households with many children were found to be most likely to fall into poverty.

Structural interventions are then needed to increase access to the labor market among refugees. Evidence shows that refugees in Uganda are usually employed in casual jobs that systematically do not match their skills, and they are usually paid less than nationals (Beltramo et al., 2021; Loiacono and Vargas, 2019). The interventions should tackle different social and economic aspects, including discrimination, skills mismatch, and asymmetric information. While in theory refugees can access any type of job across the country, in practice language issues can create problems in terms of access to information and opportunities, lowering the possibility to find a job in the country (Bohnet and Schmitz-Pranghe, 2019). This is in line with the policy recommendations provided by other scholars, as in Kansiime et al. (2022), which state that the government responses should focus on structural changes in social security able to mitigate the negative consequences among those households pushed into poverty while building financial institutions to support the recovery in the medium term.

[10] A micro-simulation exercise conducted by UNICEF in 2016 simulated the implementation of a child support grant over different age-thresholds for eligible children (below 2 or 8 years) and over 3 different targeting scenarios: universal programme, only poor households, and vulnerable households (namely those that fall below twice the poverty line). The analysis found that a child support grant as modest as UGX 23,500 (approximately USD$6.50) for families with children under the age of two (or alternatively, of 8) is effective in tackling childhood vulnerabilities associated with health and nutrition (UNICEF and Government of Uganda, 2017).

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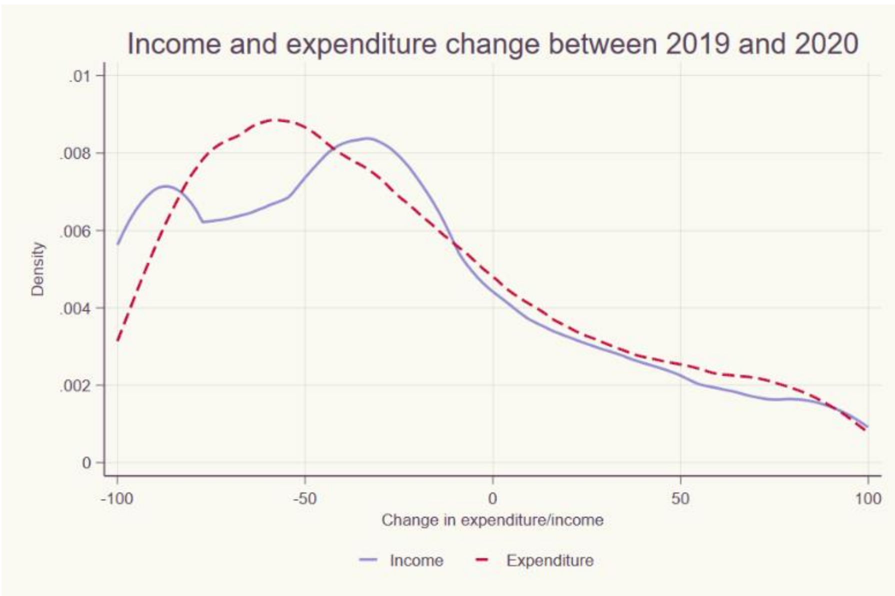
Appendix

Appendix A

Figure A1. Change in income and expenditure between 2019 and 2020.



Note: kernel density function, no weights applied. Values>=100 excluded from the graph.

Figure A2. Local polynomial regression results of the n. of children over per capita HH expenditure.

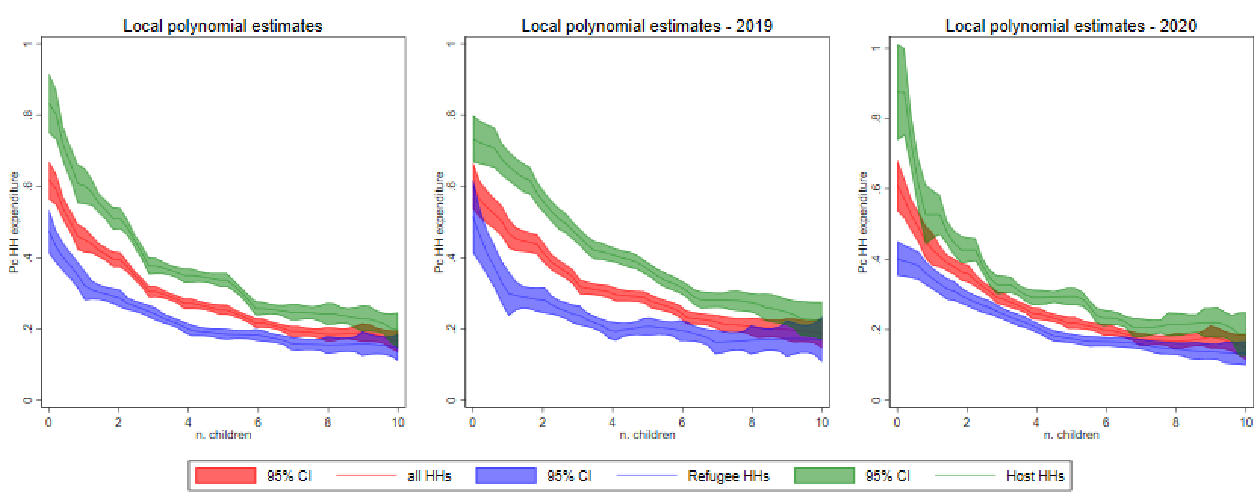


Figure A3. Local polynomial regression results of the n. of children over the probability of being poor, pooled sample, 2019 and 2020.

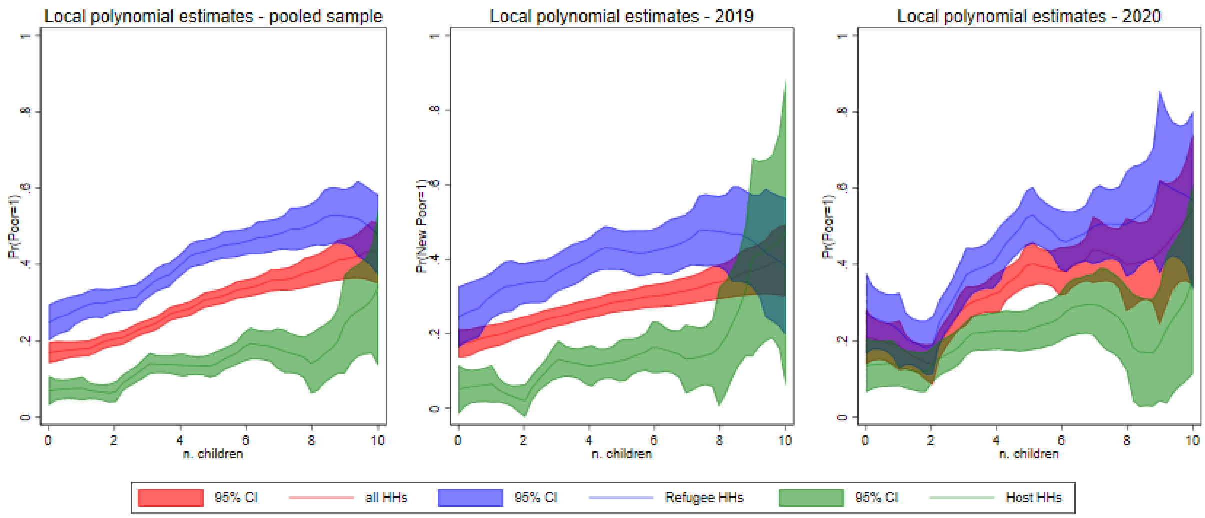


Table A1. Impacts of cash, food, and total transfers on poverty

	CASH TRANSFERS		FOOD TRANSFERS		TOTAL TRANSFERS		CASH AND FOOD TRANSFERS	
	All	Refugee	All	Refugee	All	Refugee	All	Refugee
Total transfers					-0.00511	0.0114		
					(0.0111)	(0.0266)		
Cash transfers	0.059***	0.0812***	0.00728	0.0149***			0.0562***	0.111**
	(0.0159)	(0.0214)	(0.00455)	(0.00539)			(0.0174)	(0.0481)
Food transfers	0.0107**	0.00346	0.00258	0.0268			0.00150	0.0340
	(0.00486)	(0.00553)	(0.0119)	(0.0202)			(0.0130)	(0.0457)
1 or 2 children	0.0245		0.0379	0.259**	0.0234	0.148	0.0310	0.284
	(0.0429)		(0.0480)	(0.116)	(0.0545)	(0.166)	(0.0543)	(0.282)
3 or 4 children	0.0386	0.0942**	0.0140	0.254**	-0.00569	0.233	0.00122	0.337
	(0.0476)	(0.0430)	(0.0525)	(0.121)	(0.0574)	(0.167)	(0.0574)	(0.284)
5+ children	0.0505	0.0943	0.0336	0.287**	0.0243	0.206	0.0316	0.330
	(0.0590)	(0.0615)	(0.0622)	(0.132)	(0.0651)	(0.174)	(0.0653)	(0.288)
Cash transfers*1 or 2 children	-0.0493***	-0.0584***					-0.0499***	-0.0966**
	(0.0167)	(0.0212)					(0.0184)	(0.0491)
Cash transfers* 3 or 4 children	-0.0513***	-0.0726***					-0.0456**	-0.104**
	(0.0163)	(0.0217)					(0.0180)	(0.0491)
Cash transfers*5+ children	-0.0550***	-0.0657***					-0.0517***	-0.0945*
	(0.0160)	(0.0216)					(0.0176)	(0.0489)
Food transfers*1 or 2 children			0.00111	-0.0354*			0.00200	-0.0389
			(0.0131)	(0.0211)			(0.0141)	(0.0465)
Food transfers*3 or 4 children			0.0157	-0.0191			0.0175	-0.0323
			(0.0124)	(0.0206)			(0.0135)	(0.0466)
Food transfers*5+children			0.00883	-0.0222			0.00900	-0.0289
			(0.0124)	(0.0205)			(0.0136)	(0.0466)
Total transfers*1 or 2 children					0.00448	-0.00928		
					(0.0122)	(0.0285)		
Total transfers*3 or 4 children					0.0136	-0.0148		
					(0.0116)	(0.0282)		
Total transfers*5+children					0.00569	-0.00663		
					(0.0116)	(0.0282)		
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,807	1,423	2,807	1,423	2,807	1,423	2,807	1,423

Note: Y= P(Switch to poverty=1). Ind. variables are in t-1. Coefficients are average marginal effects estimated from a multinomial logit model. Inverse probability weights applied. Standard errors clustered at the household level in parentheses. *** p <0.01, ** p<0.05, * p<0.1.

Appendix B

Attrition probit

Following (Wooldridge, 2010), we ran a probit regression to estimate the probability of being in the panel subsample over a set of variables at baseline. Results are reported in Table B1.

Table B1. Probit regression.

PROBIT REGRESSION						
					Number of obs = 6,227	
					Wald chi2(24) = 706.07	
Log pseudo likelihood	-3911.9948				Prob > chi2 = 0.0000	
					Pseudo R2 = 0.0875	
Dep. Variable= HH is in panel sample						
	Coefficient	Robust Std. Err.	z	P>z	[95% conf. interval]	
Age of HH head (year)	0.007***	0.001	5.420	0.0000	0.005	0.010
Dep. Ratio	-0.191	0.135	-1.410	0.1570	-0.455	0.074
N. of male adults	0.011	0.029	0.370	0.7080	-0.045	0.067
N. of female adults	-0.004	0.027	-0.150	0.8770	-0.057	0.049
N. of infants	0.016	0.023	0.710	0.4780	-0.028	0.061
Average years of education	-0.006	0.005	-1.180	0.2390	-0.017	0.004
HH head is female	-0.065**	0.038	-1.710	0.0870	-0.139	0.009
HH experienced drought	-0.018	0.036	-0.500	0.6190	-0.088	0.052
HH experienced flood	0.115**	0.057	2.040	0.0410	0.005	0.226
HH is refugee	-0.007	0.047	-0.140	0.8900	-0.099	0.086
Wealth index	0.294***	0.065	4.530	0.0000	0.167	0.421
Arua district	-0.956***	0.081	-11.740	0.0000	-1.115	-0.796
Isingiro district	0.008	0.090	0.090	0.9270	-0.169	0.185
Kamwenge district	-0.041	0.101	-0.410	0.6820	-0.240	0.157
Kikuube district	0.312***	0.109	2.860	0.0040	0.098	0.525
Kiryandongo district	-0.757***	0.092	-8.230	0.0000	-0.937	-0.577
Kyegegwa district	-0.461***	0.087	-5.320	0.0000	-0.631	-0.291
Lamwo district	-0.610***	0.087	-7.010	0.0000	-0.781	-0.440
Moyo district	-1.071***	0.090	-11.940	0.0000	-1.246	-0.895
Yumbe district	-0.675***	0.093	-7.260	0.0000	-0.857	-0.492
HH size	0.018	0.015	1.240	0.2140	-0.010	0.047
Land size	0.038***	0.013	2.950	0.0030	0.013	0.064
N. income sources	-0.062***	0.018	-3.540	0.0000	-0.097	-0.028
FCS	0.000	0.001	0.120	0.9040	-0.002	0.003
Constant	0.080	0.154	0.520	0.6020	-0.222	0.383

Note: Dependent variable is a dummy equal to 1 if household belongs to the subsample of panel. Model conducted over the baseline sample (2017 to 2018). Coefficients estimated from a probit regression with robust standard errors. No sampling weights applied.
Source: authors' elaboration based on RIMA Uganda Refugee and Host Communities Panel Survey, 2017, 2018, 2019, and 2020.

Appendix C

Tests of IIA assumption

Three different tests have been conducted to check the violation of the IIA assumption: the Hausman test, the Suest-based Hausman test, and the Small-Hsiao test. The tests have been conducted fore each year based on regressions reported in Table 7. Sampling weights and clustered standard errors have not been applied, as the tests do not allow for them. Results of the test for each year are reported in Figure C1. All the tests suggest the IIA assumption has not been violated.

Figure C1. Tests of IIA assumption

a) Prob(New poor in 2019)

Hausman tests of IIA assumption (N=2207)

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

	chi2	df	P>chi2
Non poor	-3.185	42	.
Poor/Poo	-0.472	42	.
Non poor	-61.314	42	.
Poor/Non	-15.715	41	.

Note: A significant test is evidence against Ho.
Note: If chi2<0, the estimated model does not meet asymptotic assumptions.

suest-based Hausman tests of IIA assumption (N=2207)

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

	chi2	df	P>chi2
Non poor	46.468	42	0.293
Poor/Poo	32.761	42	0.846
Non poor	46.154	42	0.305
Poor/Non	38.654	42	0.619

Note: A significant test is evidence against Ho.

Small-Hsiao tests of IIA assumption (N=2207)

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

				df	
Non poor/Non p~r	-399.959	-371.302	57.315	42	0.058
Poor/Poor	-683.622	-667.305	32.635	42	0.850
Non poor/Poor	-522.303	-496.758	51.089	42	0.159
Poor/Non poor	-607.381	-581.648	51.465	42	0.150

Note: A significant test is evidence against Ho.

a) Prob(New poor in 2020)

```
Hausman tests of IIA assumption (N=2963)

 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

                 |   chi2   df   P>chi2
-----------------+---------------------
        Non poor |  -4.239   41       .
        Poor/Poo |   4.793   42   1.000
        Non poor |  -8.964   42       .
        Poor/Non |  -8.822   41       .

 Note: A significant test is evidence against Ho.
 Note: If chi2<0, the estimated model does not meet asymptotic assumptions.

suest-based Hausman tests of IIA assumption (N=2963)

 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

                 |   chi2   df   P>chi2
-----------------+---------------------
        Non poor |  47.047   42   0.274
        Poor/Poo |  33.242   42   0.831
        Non poor |  30.395   42   0.908
        Poor/Non |  36.906   42   0.694

 Note: A significant test is evidence against Ho.

Small-Hsiao tests of IIA assumption (N=2963)

 Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives

                 |                              df
-----------------+----------------------------------------------
Non poor/Non p~r |  -621.749   -594.138    55.223   42    0.083
       Poor/Poor | -1044.440  -1024.092    40.696   42    0.528
   Non poor/Poor |  -797.129   -770.197    53.863   42    0.104
   Poor/Non poor |  -913.890   -893.482    40.816   42    0.523

 Note: A significant test is evidence against Ho.
```

Quantile analysis

The models presented in this study are able to provide estimates only related to the mean value. To shed light on the effect along the distribution, we can model the entire distribution of the data using conditional quantile regression. In quantile regression, Qq(y|x) is the conditional quantile point for the distribution y, given a set of covariates x. The coefficients estimated in this way quantify the expected change in the distribution of y for the quantile point q as the variable of interest increases by 1 unit net of the other covariates.

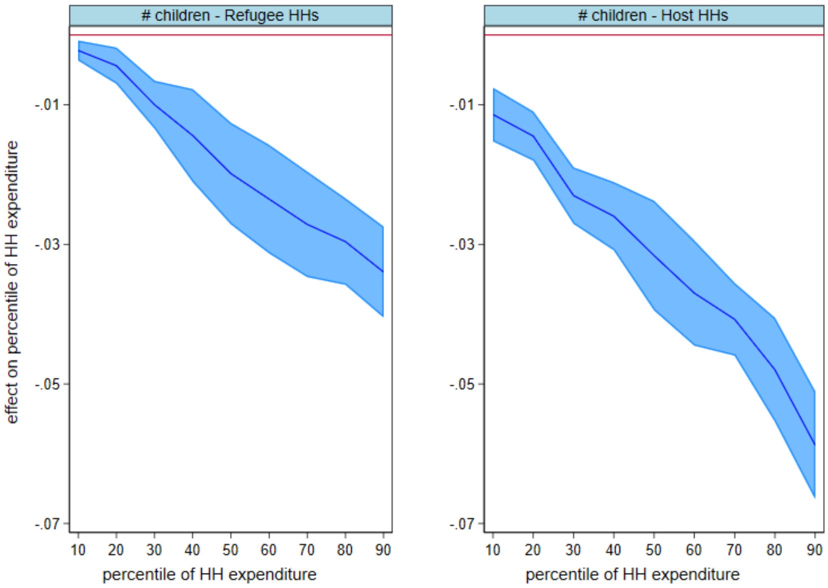
The corresponding equation is the following:

$$Qq(y|x) = x'\beta q \qquad (3)$$

where we consider the same set of covariates in (1), while y is the household per capita daily expenditure. In this way, we are able to understand if household characteristics have the same effect on expenditure for households with a higher expenditure level than households in the lowest percentiles of the expenditure distribution. We are particularly focused on those variables related to children, such as the number of children in the households.
We performed a quantile regression on the number of children over the expenditure distribution, splitting the sample across host and refugee households, divided by percentiles. The results show a

decreasing trend for both groups. This means that the negative effect increases in magnitude as the household is richer. This is expected, as wealthier households are more able to shrink expenditure than poorer households, so their expenditure elasticity relative to the number of children is higher. Host households seem to report a higher gap between the first and the last percentiles as compared to refugee households. The distribution instead does not differ much over time, reporting a similar shape in 2019 and 2020.

Figure C2. Quantile regression of the effect of n. of children on total household expenditure in 2020, by expenditure percentile.



a) Continuous variable of n. of children

Note: Dependent variable = Per capita HH expenditure (ihs). Inverse probability weights applied. Standard errors clustered at the household level. Bars are 95% confidence intervals. Percentiles separate for refugee and host households

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