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Poverty dynamics and poverty traps among refugee and host communities in Uganda

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Poverty dynamics and poverty traps among refugee and host communities in Uganda

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Abstract

This paper analyses poverty dynamics and checks for the existence of poverty traps among refugee and host communities living close to each other in Uganda. Although some non-linearities emerge in asset dynamics, there is convergence towards one stable equilibrium for the whole sample that suggests the existence of a structural poverty trap. However, households are quite heterogeneous: when analysing refugees and hosts separately, refugees converge to a lower own-group equilibrium than hosts. The household size, its location, the displacement reason as well as the household's head gender are correlates of lower equilibria. Panel attrition correction and robustness checks confirm these results. Interestingly, social cohesion positively impacts refugees' asset accumulation while it generally has a negative impact for hosts. From a policy perspective, structural poverty traps are bad news, because 'standard' asset transfers would not unlock the trap. More structural approaches aiming at promoting economic growth in the whole area where refugee and host communities live and targeting both communities are needed.

Keywords: refugees; hosts; asset accumulation; poverty traps; Uganda

JEL classification: D31, I32, O12, R23

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1. Introduction

There is compelling evidence that the integration of refugees in the host contexts is usually difficult (World Bank, 2017) while the impact on the local communities can be positive or negative depending on the skills of the refugees relative to the hosts and existing economic opportunities (Maystadt et al., 2019). An increasing literature examines the life conditions of refugees in developing countries, showing that poverty traps could develop because refugees have specific vulnerabilities that curtail their ability to exploit economic opportunities. For example, conflict and violence impoverish refugees directly by destroying, stealing, or making them leave behind their physical assets, and indirectly by disrupting their social capital ties (Jacobsen, 2012; World Bank, 2017). Often refugees lack documents that prevent them to be employed in formal jobs and to access credit institutions (Jacobsen, 2012). Additionally, psychological stress, trauma and insecurity lower their economic prospects (World Bank, 2017). All these compound with gender- (Stojetz & Brück, 2021) and child-specific vulnerabilities that significantly increase the risk of reproducing themselves across generations via costly coping strategies such as productive asset sale, child labour, early marriage or transactional sex (World Bank, 2017).

A parallel literature on the interaction between refugee and host communities has recently developed (Alix-Garcia et al., 2018; Alix-Garcia & Saah, 2010; Ayenew, 2021; d'Errico et al., 2022; Kadigo et al., 2022; Kreibaum, 2016; Zhu et al., 2023). The meta-analysis by Verme and Schuettler (2021) shows that the refugee impact on hosts' labour outcomes is negative, especially in the short term, while the impact on their wellbeing is generally positive. Maystadt et al. (2019) distinguish between short-term effects such as increased violence, environmental degradation and disease spread, and long-run effects with benefits for infrastructure, trade, and labour markets. However, the impact on hosts is unequal, leaving the worse-off hosts in poverty.

These two strains of literature suggest that there are heterogeneous effects and possibly trade-offs among social groups as well as over time, with potential benefits for some groups of the hosting communities. This suggests two main predictions: i) refugees, being very poor, may be all structurally in poverty; ii) hosts can either benefit or be penalized by the arrival of refugees, though generally they can aspire to higher steady states as compared to refugees. This paper builds on these insights by addressing two research questions and empirically testing them with reference to Uganda: Given the proximity and the interaction between refugees and hosts, how do these two groups' wealth dynamics differ? Does a poverty trap exist and, if so, for whom?

In order to address these questions, we adopt the poverty trap framework proposed by Carter and Barrett (2006). We focus on Uganda which, with 1.5 million refugees, is the largest hosting country in Africa (Atamanov et al., 2021; UNHCR, 2022). As compared to other contexts, refugees in Uganda can aspire to livelihoods beyond the humanitarian assistance thanks to the country's advanced refugee policy that aims at promoting refugees' self-reliance. However, environmental or economic shocks, especially if systemic, can worsen the refugee (and host) already fragile situation. For instance, in Uganda Covid-19 hit hard on refugees (Squarcina & Romano, 2022), limiting their recovery and reducing their chances of exiting from poverty (Atamanov et al., 2021). Understanding the dynamics of assets in face of such shocks can shed light on refugees and hosts' prospects and help designing effective policies to alleviate poverty.

The contribution of this work to the existing literature is threefold. First, we provide empirical evidence on poverty traps in a novel context[1] thanks to a panel dataset that surveys refugees and hosts between 2017 and 2021. This dataset includes information on the main challenges of the last years, namely increased refugee inflows, climate shocks, and the Covid-19 pandemic. Second, we disentangle the wealth dynamics of refugees and hosts focusing on group-specific vulnerabilities that are key for dynamic equilibria and accounting for the factors that may affect wealth accumulation such as assistance and major shocks. Third, we bring some insights to the relationship between asset growth and social cohesion between and within refugee and host communities. Indeed, refugee inflows impact social cohesion, exacerbating existing issues; at the same time, social cohesion is reported to be associated with safe and productive communities (World Bank, 2017), which may eventually favour asset growth and development outcomes.

We find evidence of a single low-level asset equilibrium, indicating a structural poverty trap. Hosts tend to a higher own-group equilibrium than refugees, but not sufficiently high to constitute a separate equilibrium. Further disaggregating the population across various dimensions highlights the importance of geography and selected household characteristics that drive the dynamics: asset growth enabling factors are the household size, education, and transfers, while asset reducing factors are environmental shocks and Covid-19. We also find a weak statistically significant association between social cohesion and asset accumulation that move in two opposite directions between the two communities. Specifically, when statistically significant, this association is positive for refugees, while it is negative for hosts.

The paper is organized as follows. Section 2 briefly reviews the key literature on poverty traps and refugees. Section 3 introduces the estimation methods. Section 4 describes the data. Section 5 discusses the results and deals with attrition. Section 6 provides additional robustness checks (i.e., a different dataset length, different asset index specifications and a different estimator). Section 7 concludes.

[1] The empirical literature on poverty traps has been fast-growing over the last years (Barrett et al., 2016; Barrett & Carter, 2013), but at the best of our knowledge there is no previous study assessing whether there is a poverty trap among refugees and hosting communities.

2. Poverty traps and refugees

Poverty traps are self-reinforcing mechanisms that reproduce poverty and make it persistent (Azariadis & Stachurski, 2005). They can be in the form of an S-shaped multiple-equilibria trap in which starting conditions matter for convergence and lead to threshold-separated regimes of accumulation. Another form is a structural poverty trap, which has a single low-level equilibrium that is stable and below the poverty line. Poverty traps arise when there are some exclusionary mechanisms at play that limit households' asset accumulation. In the case of refugees, there are basically four main mechanisms, namely: asset loss (physical or social), trauma and psychological stress, geography, and institutional factors.

The destruction, theft and abandonment of physical asset is the most common and evident mechanism (World Bank, 2017). However, conflicts and humanitarian emergencies can have serious detrimental effects also on human capital accumulation[2]. Conflicts may also increase poverty through the disruption of social capital links (Grant, 2010) and the reduction of off-farm opportunities (Mercier et al., 2020).

Trauma and psychological stress can induce loss of aspiration and general hopelessness, which are found to be detrimental to economic activities. Indeed, beliefs on socio-economic mobility play an important role in shaping future mobility. Depression and experience of violence among internally displaced persons is found to fuel pessimistic beliefs, increase the likelihood of being in poverty (Moya & Carter, 2019), raise the risk of a depression poverty trap (de Quidt & Haushofer, 2018; Haushofer, 2019).

Geography can be another poverty traps mechanism. Refugee settlements' location characteristics – entailing not only ago-ecological features and infrastructure, but also economic factors such as physical access to services, job opportunities and social relations (Grant, 2010) – can give rise to a spatial poverty trap.

Finally, institutional and legal barriers can affect the refugee status and hinder their integration prospects (Azariadis & Stachurski, 2005; Barrett & Carter, 2013; Carter & May, 2001; Sartorius et al., 2013; Zhang, 2017). Social institutions such as kinship systems, community organizations, and informal networks, greatly affect poverty outcomes. Discrimination on the basis of gender, ethnicity, race, religion, or social status can lead to social exclusion and lock people, and specifically refugees, in a poverty trap (Sartorius et al., 2013).

[2] Conflicts are found to decrease height (Grimard & Laszlo, 2014) and height-for-age in children, and lower school attendance, educational outcomes (Weldeegzie, 2017), and future earnings and labour productivity (Islam et al., 2016).

3. Methodology

To study asset dynamics of refugees and hosts, we use different complementary methods usually employed in the poverty traps literature, namely parametric, non-parametric and semi-parametric methods. Non-parametric regressions study the relationship between assets A at time t and assets at t-1, without imposing any pre-defined functional forms. They are very flexible, but they only estimate a bivariate relation (Adato et al., 2006; Barrett et al., 2006; Lybbert et al., 2004) as follows:

$$A_{it} = f(A_{it-1}) + \varepsilon_{it} , \tag{1}$$

where the error term ε_{it} is assumed to be normally and identically distributed with zero mean and constant variance. Equation (1) may be estimated with local polynomial regression, locally weighted scatterplot smoother (lowess), and different types of splines. This method assumes that the function to be estimated is smooth, covariates are uncorrelated with the error term, and all households are in the same accumulation regime. Some of these assumptions are heroic. Therefore, we rely on this method only for exploratory purposes and in combination with parametric regression.

Parametric regressions allow to study non-linearities in the relationship between lagged assets and asset growth while controlling for other factors (Giesbert & Schindler, 2012; McKay & Perge, 2013; Naschold, 2013). These can use OLS, fixed effects (FE) or random effects (RE) panel estimators:

$$\Delta A_i = \beta_0 + \sum_{k=1}^{4} \beta_k A_{it-1}^{k} + \beta_5 \mathbf{X}_{it-1} + \mu_{(i \times t)} + \varepsilon_{it} , \tag{2}$$

where asset change ΔA_i is a function of the fourth[3] polynomial expansion of assets at t-1 (Naschold, 2012, 2013), household's lagged characteristics, $\mathbf{X}_{it-1}$, and the interaction of district and year fixed effects $\mu_{(i \times t)}$. A negative β_1 means general convergence towards equilibrium, in the sense that those poorer in assets accumulate assets faster (Carter et al., 2007). The β_2, β_3 and β_4 coefficients, if significantly different from zero, indicate non-linearities in the asset accumulation process (Walelign et al., 2021). The household characteristics vector controls for socio-demographics (with some variables squared to account for possible non-linearities), location characteristics and shocks. Survey-related controls such as the different survey time of wave 1 (cf. Section 4.1) and the interactions between year and districts are included as well. The analysis is carried out for the whole population as well as separately for refugee and host subpopulations (Naschold, 2012).

The choice of the parametric regression estimator is not straightforward. Having more than two periods, it is possible both to look at the asset change of each subperiod with one-period lagged assets

[3] A fourth order is preferrable to a third order polynomial as it does not impose the stable equilibria to be in the tails of the distribution (Naschold, 2013). The polynomial expansion serve to capture non-linearities.

(RE or FE) and to look at the long difference between the last and the first wave, while controlling for initial assets (OLS).

The latter (OLS) does not exploit the panel structure of the data, but it is consistent with the idea of poverty traps that depend on initial conditions. A panel estimator (FE/RE) would capture the period-by-period relation of lagged assets with asset changes rather than general asset convergence. Since the length of the panel is rather short (2017-2021), we argue that it is convenient to exploit both the panel data structure for understanding the adjustments from the previous periods and the long difference consistently with the poverty traps literature[4]. In the OLS case, as we are using a long difference, standard errors are corrected for generic heteroskedasticity. In the panel case, as we are dealing with panel data, errors are not independent and identically distributed, therefore standard errors are clustered at the household level (see Appendix 2 for a discussion on clustering). This allows within-household error correlation, but assumes uncorrelated between-households errors (Baum et al., 2011).

To study the relationship of asset growth and social cohesion, we add to the FE regression a series of (lagged) dummy variables from the various dimensions of social cohesion: intra-group relationship, trust, sense of belonging, frequency of interaction.

Finally, we test the robustness of our main results with semi-parametric regressions, which combine the advantages of the previous two approaches: they are flexible and control for variables other than assets (Naschold, 2012, 2013):

$$A_{it} = \alpha + f(A_{it-1}) + \beta \mathbf{X}_{it-1} + \varepsilon_{it}. \quad (3)$$

The relation with current and lagged assets is estimated non-parametrically, while households' characteristics enter the equation parametrically.

4. Data

4.1. Survey description

We use data from the FAO-RIMA's Uganda Refugee and Host Communities Panel Survey (d'Errico et al., 2022). The sample spans over 11 districts and 13 settlements. During wave 1, interviews were conducted at three different points in time – 2017, 2018 and 2019 – covering different areas of the country (Figure 1). When possible, households were interviewed again in 2019, 2020 and 2021 (Table 1). The final sample consists of 20,079 observations (9,128 considering only the balanced panel). The attrition rate is quite high (Table 2), not surprisingly given the fragility of the situation (Özler et al., 2021).

[4] Most of the empirical works on poverty traps did not have the two options, as they only had two waves of panel.

Figure 1: Households' location by year of first interview.

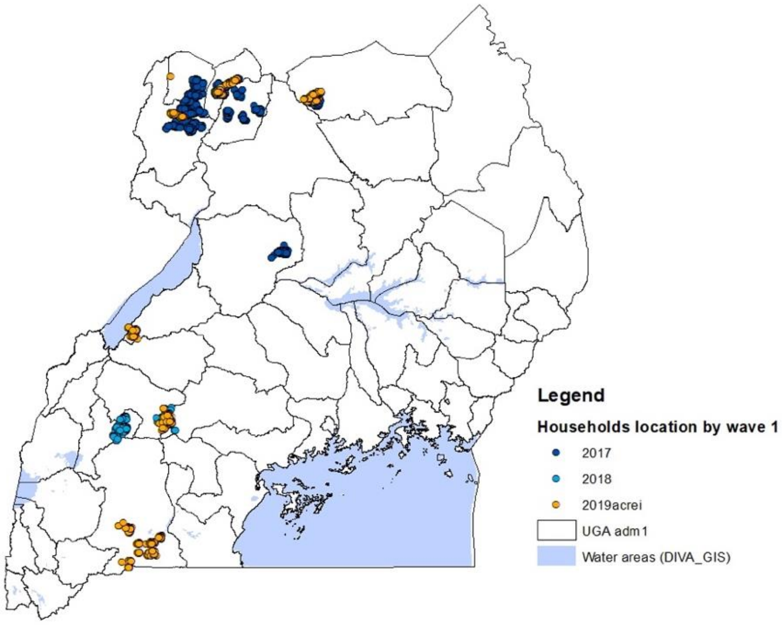


Table 1: Sample composition across waves and refugees and hosts subpopulations (row percentages)

Wave	Hosts (%)	Refugees (%)	Total (N)
1 (2017-2019)	44.60	55.40	6,236
2 (2019)	43.56	56.44	4,027
3 (2020)	49.88	50.12	4,180
4 (2021)	44.27	55.73	5,636
Total	45.35	54.65	20,079

Table 2: Pattern of observed data throughout the panel

Frequency	Percentage	Cumulative percentage	Pattern
2,282	29.51	29.51	1111
866	11.2	40.71	1_11
593	7.67	48.38	11_1
443	5.73	54.11	1_ _1
3,548	45.88	99.99	Other patterns
Total 7,732	100.00		

4.2. Data description

The survey collects information on a broad range of topics, at household as well as individual level, including: socio-demographics such as the refugee status, the age of household head, the average education of household members, the gender and marriage status of household head, the size of the household, the income generating activities as well as formal and informal transfers received, whether any of household member borrowed money, food consumption and coping strategies; location characteristics such as distances from the agricultural market, petty trading market and schools[5]; and shocks.

[5] Other location-related variables, such living in rural areas and the agroecological zone, have been constructed exploiting the georeferenced information on household location and combining it with other data

The information on shocks is self-reported by respondents. Specifically, the Covid-19-related shocks are household-specific indicators of own experience in 2020 and 2021, that are generally more severe among refugees (Table 3). Uganda experienced some floods over the period of analysis that only partially involved our sample's locations. Nonetheless we decided to control for local events such as abundant and scarce rainfalls, exploiting the georeferenced coordinates of each surveyed household and the availability of this information from third sources. we created two variables using the values of the SPEI index during the growing season[6], namely: scarce rainfalls if the SPEI index was below 1 standard deviation and abundant rainfalls if the SPEI was above 1 standard deviation from the long-term average[7].

Table 3: Percentages of households reporting a shock related to Covid-19 by refugee status.

		Households reporting a Covid-19-related shock (%)		
Year	**Subpopulations**	**Symptoms**	**Hard to access staple food**	**Experience an Income loss**
2020	Hosts	5.3	38.8	38.2
	Refugees	4.9	59.5	42.9
2021	Hosts	12.5	46.1	50.6
	Refugees	5.5	47.7	41.3

To represent household's wealth, we build a tradable asset index (Giesbert & Schindler, 2012) that includes a number of durables and tools (radio, tv, bicycle, solar panel, cooker, box, table, chair, bed, mattress, animals, hoe, axe, shovel, pickaxe, sickle, slasher) as well as land size[8]. Aggregation is done via principal components analysis[9] (Sahn & Stifel, 2000) and the index is normalized between 0 and 1. An asset index focusing on tradables is more suited for studying asset dynamics over short periods of time as it is the case of our panel. However, we compute also other asset indexes using different combinations of assets and alternative aggregation methods. The first includes both productive and non-productive assets (Giesbert & Schindler, 2012; Naschold, 2012, 2013; Walelign et al., 2021) (Table A.2 in the Appendix). The second is the livelihood index à la Adato et al. (2006) including all types of asset that predict household consumption. In principle, no approach is superior to the others (Naschold, 2013),

sources (e.g. http://geoportal.rcmrd.org/layers/servir%3Aafrica_agroecological_zoning and https://ghsl.jrc.ec.europa.eu/download.php?ds=smod).

[6] SPEI stands for Standardized precipitation evapotranspiration index (Beguería et al., 2014; Vicente-Serrano et al., 2010), downloaded from SPEI Global Drought Monitor (https://spei.csic.es/). We extract data for all years in August, in which the growing season is approaching its end for most of the country and for the most important crops, with reference period 6 months of the previous growing season (cf. Appendix 1 for details).

[7] The literature considers as flood and drought deviations that are ±1.5 (or 2) standard deviations. from the long-term average, respectively. This was not the case in the areas of analysis in the surveyed period, hence we talk of abundant and scarce rainfalls.

[8] Human capital and social capital are not included because of the imperfect transferability of such assets. However, we controlled for these capitals in the main specifications.

[9] The procedure also includes year dummies (cf. Table A.1 in the Appendix).

but in order to keep the analysis as clear as possible, we use the indexes other than the tradable index only as robustness check.

4.3. Descriptive statistics

Table 4 shows some descriptive statistics for refugee and host households by wave. On average, host households are larger in size and their heads are older and slightly more educated than refugee households'. The refugees' average land size is significantly smaller than hosts'. Per capita expenditure and income are very low for both groups[10], though on average hosts report higher values, and decreasing over time[11]. Formal transfers represent the largest source of gross income for refugees, while the main income sources for hosts are enterprise, wage and crop income (Figure 2). Refugees' average income is greater than hosts' in 2019, due to massive transfers[12]. In 2020, given this large support to refugee households, the income of each groups were almost the same. In 2021 there was a general worsening in both groups' conditions (less land, less livestock, less assets, less enterprise activities, less income per capita, less dietary diversity, higher coping strategy index), likely due to the protracted Covid-19 crisis.

Table 4: Mean comparisons over time, refugees and hosts

Mean values	Refugees				Hosts			
	Wave 1	Wave 2	Wave 3	Wave 4	Wave 1	Wave 2	Wave 3	Wave 4
Household head's age (years)	38.55	40.16	41.32	41.34	44.04	46.31	46.74	46.99
Average education (years)	4.80	5.76	5.84	5.97	5.96	6.67	6.81	6.95
Household head is a woman (yes/no)	0.46	0.49	0.50	0.53	0.22	0.23	0.23	0.27
Household size (N)	5.79	6.02	6.30	6.15	6.24	6.32	6.61	6.78
Household head is married (yes/no)	0.65	0.62	0.63	0.62	0.78	0.75	0.77	0.74
Dependency ratio	0.49	0.48	0.48	0.50	0.53	0.53	0.53	0.54
Food Consumption Score	40.35	41.87	37.16	36.77	48.94	50.20	44.43	43.06
Coping Strategy Index	29.90	22.99	23.99	26.36	16.34	15.14	15.08	16.00
Income source: crop (yes/no)	0.29	0.17	0.20	0.40	0.67	0.53	0.60	0.58
Income source: enterprise (yes/no)	0.19	0.26	0.25	0.16	0.45	0.40	0.41	0.30
Income source: wage (yes/no)	0.43	0.40	0.40	0.39	0.58	0.43	0.40	0.41
Annual income from formal transfers ($)	211.58	363.89	374.21	299.26	66.27	8.73	8.76	4.38
Annual income from informal transfers ($)	22.93	3.45	5.83	5.53	22.58	5.50	5.70	4.77
HH borrowed money (yes/no)	0.07	0.21	0.24	0.28	0.19	0.36	0.33	0.43
Tradable asset index	0.07	0.09	0.10	0.10	0.16	0.19	0.21	0.19
Livestock (TLU)	0.06	0.15	0.14	0.28	1.19	1.08	1.45	0.28
Land size (acres)	0.29	0.40	0.49	0.46	2.48	2.13	2.35	2.12
Income per capita per day (2020 US$)	0.49	0.86	0.56	0.52	0.77	0.52	0.58	0.40
Expenditure per capita per day (2020 US$)	0.09	0.10	0.11	0.11	0.22	0.18	0.15	0.16
Distance to agricultural market (km)	3.61	2.75	2.06	3.61	3.80	3.26	2.69	4.15
Distance to petty trading market (km)	1.25	1.22	1.03	1.28	1.43	1.57	1.39	1.74

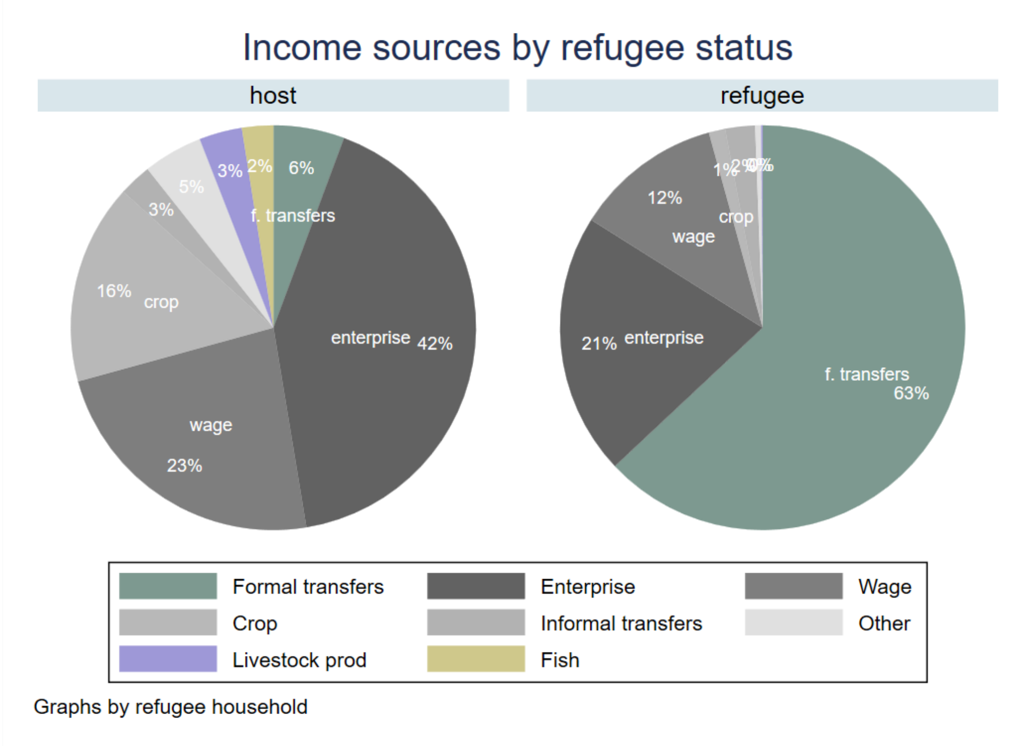
[10] This value is lower than national averages, but this can depend on the long recall period (12 months) that can lead to the recall decay bias (Beegle et al., 2012; Sawada et al., 2019). Nonetheless, the questions asked to refugees and hosts are the same, so a comparison between the two groups is possible.

[11] Again, this is partly due to how the questions are framed. The 2017 and 2018 questionnaires included many more expenditure items for both food and non-food categories. Generally, more detailed questions result in higher expenditures (Comerford et al., 2009; Jansen et al., 2013). Our approach identifies an expenditure lower bound by using only the categories included in all waves.

[12] In 2019, 80-95% of refugee households received transfers (food or cash), compared to less than 5 % of hosts.

Distance to primary school (km)	1.60	1.42	1.52	1.33	1.64	1.55	1.50	1.54
Scarce rainfalls (dummy SPEI < -1.5 s.d.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Abundant rainfalls (dummy SPEI > 1.5 s.d.)	0.09	0.01	0.02	0.00	0.16	0.01	0.01	0.01
Any Covid-19 shock (yes/no)	0.00	0.00	0.78	0.55	0.00	0.00	0.63	0.58
Rural (yes/no)	0.97	0.97	0.97	0.98	0.97	0.98	0.98	0.99

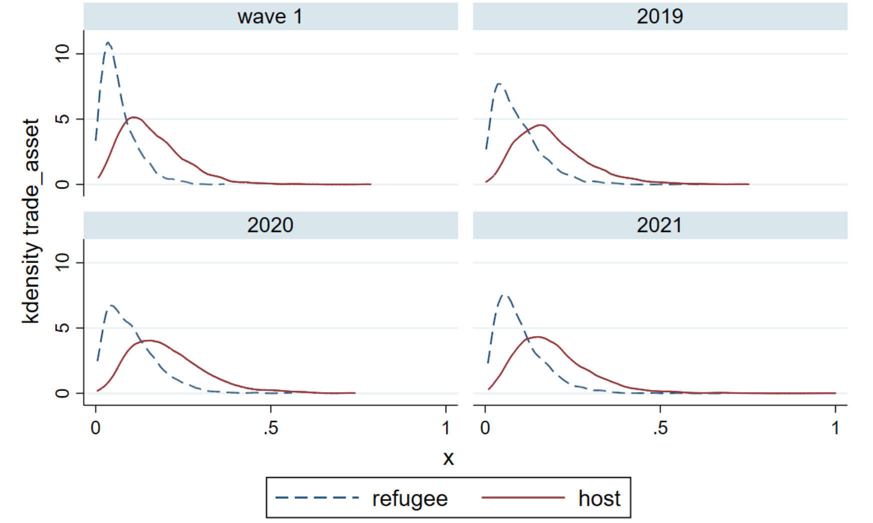
Figure 2: Income decomposition by refugee status, all years.



Kernel density functions of the tradable index show how refugees and hosts' wealth is distributed (Figure 3): refugees are more concentrated in the lower part of the distribution as they have lower levels of assets[13]. Over time, there a slight improvement in material conditions of the involved populations, though between wave 3 and 4 we observe a worsening of the household conditions, especially for refugees.

[13] The asset scores are not to be interpreted in absolute terms as they provide the relative position in the 0-1 wealth range (Walelign et al., 2021).

Figure 3: Kernel density of tradable asset index by wave by refugee status.



Asset dynamics can also be inferred from the transition matrix between quintiles from the first wave to the fourth wave (Table 5). There is a higher stability in the ranking of assets for higher quintiles among hosts (55% of those that started in the richest quintile ended in the richest quintile) and lower quintiles among refugees (57% of those that started in the poorest quintile ended in the poorest quintile). In general, a lot of households improved their position over the considered period, while the worsening of positions is more frequent among refugees.

Table 5: Transition matrix across asset quintiles from wave 1 and wave 4 of tradable asset index.

	Asset quintiles wave 4					
Asset quintiles wave 1	(poorest) 1	2	3	4	(richest)5	Total
Hosts						
(poorest) 1	31.67	28.33	16.67	18.33	5.00	100
2	9.44	26.67	23.89	22.78	17.22	100
3	7.02	16.29	24.56	29.07	23.06	100
4	4.15	11.13	25.08	32.72	26.91	100
(richest) 5	1.69	3.60	11.70	25.76	57.26	100
Total	4.88	10.75	19.06	27.89	37.42	100
Refugees						
(poorest) 1	45.97	26.95	16.28	7.49	3.31	100
2	30.73	29.03	19.52	15.28	5.43	100
3	17.18	23.63	27.45	19.81	11.93	100
4	10.19	20.75	23.77	29.06	16.23	100
(richest) 5	3.45	11.49	21.84	24.14	39.08	100
Total	29.31	25.41	20.69	15.73	8.86	100

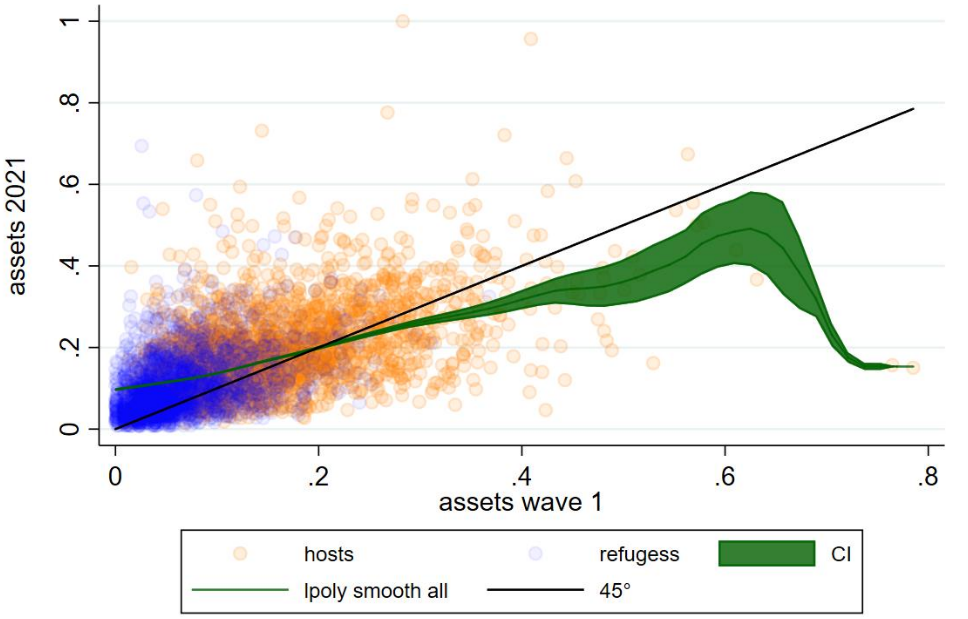
Row percentages. Those that improved their position are found above the main diagonal, and those that worsened in the ranking are found below the diagonal. In bold those that remained in the same quintile over time.

5. Results

5.1. Non-parametric regression

Local polynomial smooth recursion functions (cf. equation 1) show that there is only one stable equilibrium for the whole population at about 0.2 asset scores, although refugee observations are more concentrated around the lower left corner (Figure 4). This equilibrium divides the sample between 677 households (43 refugee and 634 host households) who have initial assets above the equilibrium and 3,507 household with assets below it (2,011 refugee households and 1,496 host households).

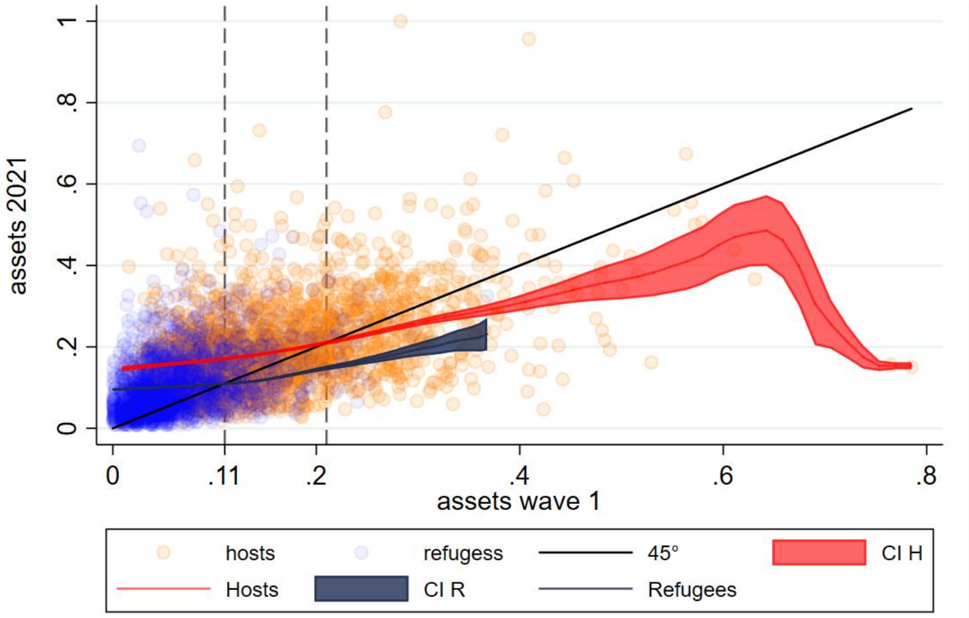
Figure 4: Local polynomial smooth, whole population



Relaxing the assumption that all households are in the same accumulation regime and running the local polynomial regression separately for refugees and hosts (Figure 5), we see that refugees converge to a lower equilibrium at around 0.11 asset scores while hosts to a higher equilibrium at 0.21 asset scores[14]. As these are own-group equilibria, a transition from one to another is unfeasible. We therefore exclude the existence of multiple equilibria in the whole population. Using other asset indexes confirms this result (cf. Section 6.2).

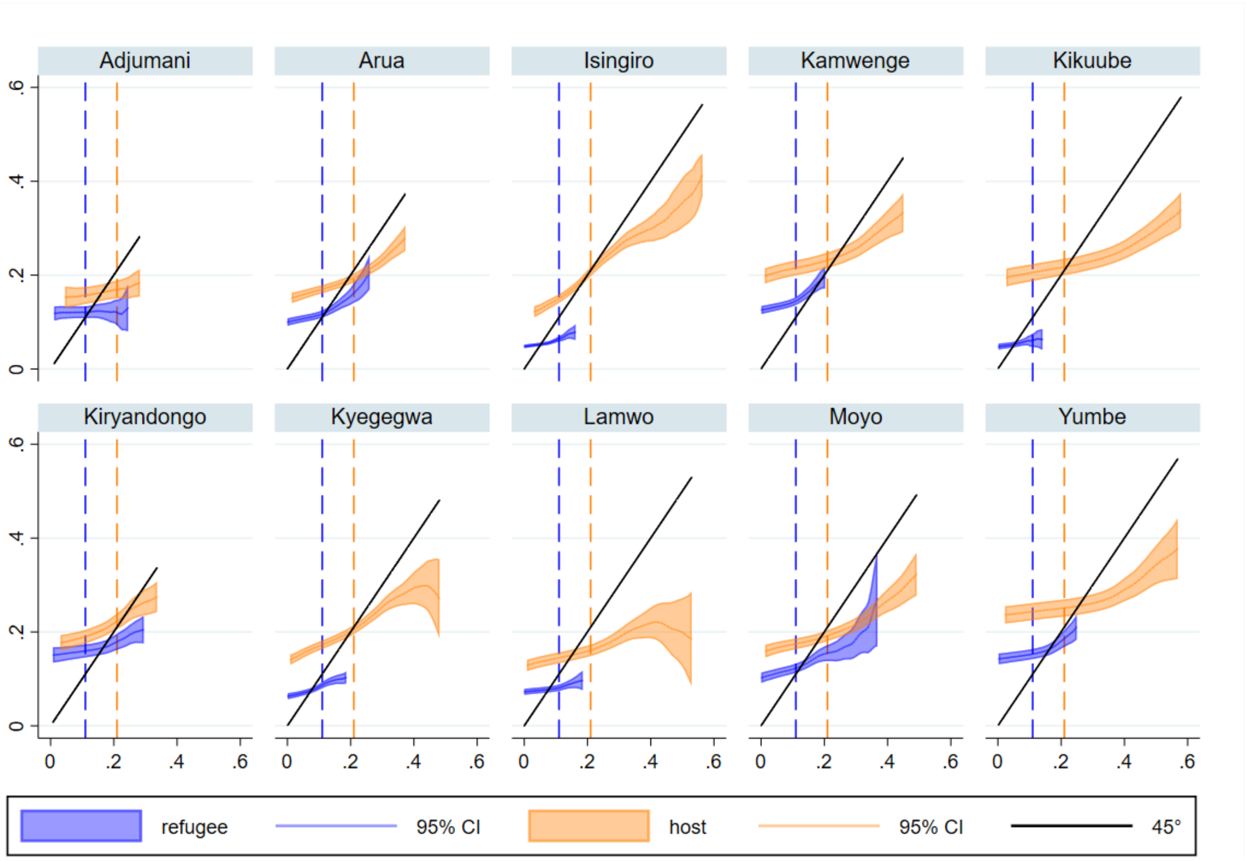
[14] Other functional forms confirm these results: only one equilibrium is identified per group, with refugees converging to a lower-level equilibrium (cf. Figure A.1 in the Appendix).

Figure 5: Local polynomial smooth, separately for refugees and hosts



However, when splitting the total sample by districts, some heterogeneity emerges (Figure 6). The equilibria are slightly different across districts, although the overall dynamics look similar. Some districts (Isingiro, in the south, and Kikuube in the west) show below-average asset level equilibria for refugees, while others (Adjumani and Lamwo, in the north) have below-average equilibria for hosts.

Figure 6: Local polynomial smooth by district for refugees and hosts.



Note: The dashed lines report the refugees' and hosts' average equilibria of 0.11 and 0.21, respectively.

To further explore the heterogeneity in the sample, we report the different equilibria of various refugee and host subgroups (Table 6) (Giesbert & Schindler, 2012; Walelign et al., 2021). Refugees that tend towards higher-than-average equilibria have high educated heads, larger households, receive no transfers, own an enterprise, came to Uganda because of persecution/human rights violation and originate from South Sudan. Refugees that converge to lower equilibria have smaller households, live in urban areas, were already displaced for more than 48 months at wave 1, moved because of famine and natural hazards, and originate from Burundi and DRC. Conversely, hosts show less heterogeneity and seem to converge to similar equilibria, except those with a small (large) household and female (male) heads who tend to a lower (higher) equilibrium.

Table 6: Non-parametric regression by groups, refugees and hosts.

Groups	Approximate location of the equilibrium					
	Refugees			Hosts		
	Equilibrium	95% CI		Equilibrium	95% CI	
Whole sample	*0.11*	*0.106*	*0.114*	*0.21*	*0.205*	*0.215*
Female headed at wave 1	0.105	0.098	0.11	0.17	0.16	0.18
Male headed at wave 1	0.12	0.112	0.125	0.21	0.204	0.22
Head age at wave 1	0.112	0.108	0.119	0.225	0.215	0.235
Head education > 10 years	0.14	0.131	0.15	0.23	0.215	0.24
Household size at wave 1 ≤ 6	0.095	0.09	0.1	0.17	0.165	0.175
Household size at wave 1 > 6	0.15	0.138	0.167	0.25	0.236	0.26
Married head at wave 1	0.12	0.116	0.128	0.21	0.205	0.22
Borrowed at wave 1	0.13	0.115	0.145	0.20	0.19	0.21
Urban	0.06	0.052	0.073	0.26	0.185	0.4
No transfers at wave 1	0.14	0.125	0.156	0.2	0.19	0.21
Formal transfers at wave 1	0.115	0.105	0.13	0.21	0.20	0.24
Informal transfers at wave 1	0.12	0.1	0.145	0.19	0.18	0.215
Informal and formal transfers at wave 1	0.13	0.11	0.14	0.21	0.175	0.26
Wage income at wave 1	0.11	0.105	0.115	0.205	0.195	0.22
Crop income at wave 1	0.12	0.11	0.125	0.21	0.195	0.215
Enterprise income at wave 1	0.135	0.125	0.15	0.20	0.19	0.21
Abundant rainfalls at wave 1 (dummy for SPEI>1.5)	0.08	0.065	0.12	0.20	0.19	0.22
Displaced because of famine/natural hazard	0.081	0.07	0.094	-	-	-
Displaced because of persecution/human rights violation	0.135	0.12	0.155	-	-	-
Displaced because of conflict	0.11	0.106	0.113	-	-	-
Experience of violence before displacement	0.10	0.096	0.106	-	-	-
Months in settlement at wave 1 > 48	0.095	0.09	0.104	-	-	-
Origin of head: DRC	0.092	0.085	0.10	-	-	-
Origin of head: South Sudan	0.125	0.12	0.13	-	-	-
Origin of head: Burundi	0.045	0.04	0.05	-	-	-
Subsample of wave 1: 2017	0.15	0.142	0.16	0.215	0.2	0.23
Subsample of wave 1: 2018	0.12	0.112	0.128	0.225	0.21	0.24
Subsample of wave 1: 2019	0.07	0.069	0.072	0.18	0.172	0.19

5.2. Parametric regression

We estimate the parametric regressions for the whole sample and separately for refugees and hosts (equation 2) first using OLS for the asset change between wave 4 and wave 1 (long difference) and then using FE panel estimator to model the one-lag asset dynamics.

We are interested in the non-linearities of the lagged assets and in their joint significance. Asset dynamics are convergent if it is possible to reject the hypothesis that all terms of the polynomial are equal to zero in favour of the alternative that β_1 is between -2 and 0 and $\beta_{2\text{-}4}$ coefficients are all equal to zero (Quisumbing and Baulch, 2013). In the OLS case, the null is rejected for the whole population and for hosts (Table 7, columns 1-3), indicating that non-linearities are relevant. Furthermore, β_1 is much larger for refugees. Interestingly, if we sum predicted asset change to lagged assets and plot it against lagged assets in a non-parametric regression (Giesbert and Schindler, 2012; Naschold, 2013), we obtain patterns very similar to the previous non-parametric ones (Figure 7). There is only one equilibrium for the whole population, but refugees converge to a lower stable equilibrium (0.125 asset scores) than hosts (0.23 asset scores). This signals that refugees have lower prospects for growth than hosts.

Table 7: Parametric regression, long difference w4-w1 (OLS) and asset growth from t-1 to t, pooled (FE).

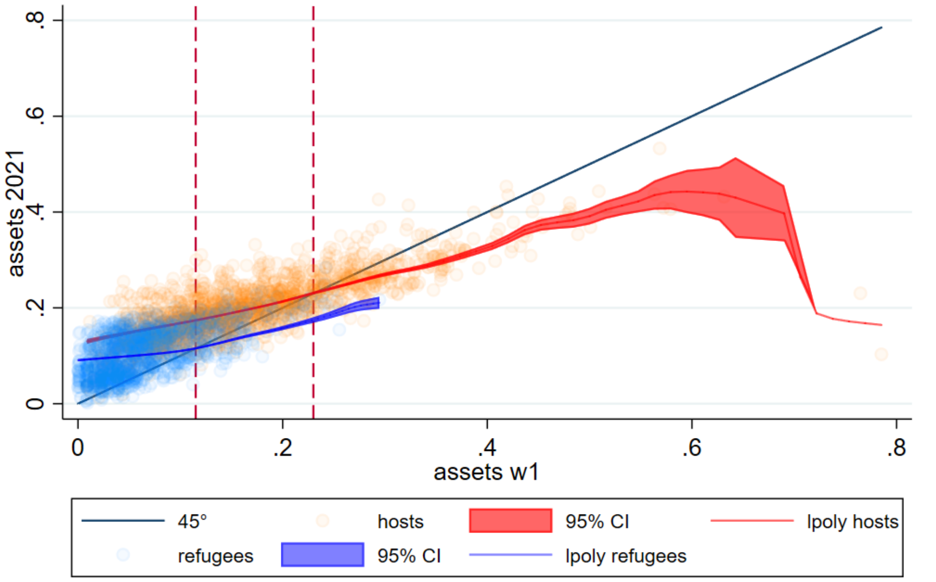
VARIABLES	(1) All OLS	(2) Refugees OLS	(3) Hosts OLS	VARIABLES	(4) All FE	(5) Refugees FE	(6) Hosts FE
L3. trade_asset^1	-0.653***	-0.807***	0.010	L. trade_asset	-1.433***	-1.249***	-1.537***
	(0.143)	(0.281)	(0.279)		(0.130)	(0.150)	(0.271)
L3.trade_asset^2	-0.341	-0.636	-4.030**	L.trade_asset^2	1.613	0.052	2.190
	(1.103)	(5.229)	(1.811)		(1.098)	(1.720)	(1.837)
L3.trade_asset^3	3.773	11.266	11.014**	L.trade_asset^3	-6.175*	-1.946	-7.166
	(2.983)	(33.689)	(4.317)		(3.341)	(6.731)	(4.793)
L3.trade_asset^4	-4.886**	-29.533	-9.450***	L.trade_asset^4	6.028*	1.503	6.610
	(2.347)	(67.210)	(3.178)		(3.171)	(7.638)	(4.122)
1.REF	-0.043***						
	(0.004)						
L3. age head of household	0.001**	0.000	0.002***	L. age head of household	0.001***	0.000	0.002***
	(0.001)	(0.001)	(0.001)		(0.001)	(0.000)	(0.001)
L3. age head of household^2	-0.000**	-0.000	-0.000**	L. age head of household^2	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. average years of education of adults	0.003***	0.003**	0.004*	L. average years of education of adults	-0.001	-0.002**	0.000
	(0.001)	(0.001)	(0.002)		(0.001)	(0.001)	(0.002)
L3. average years of education of adults^2	0.000	-0.000	-0.000	L. average years of education of adults^2	0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. female headed household	-0.002	-0.004	-0.004	L. female headed household	0.001	0.007**	-0.007

	(0.004)	(0.004)	(0.008)		(0.003)	(0.003)	(0.007)
L3. number of people in household	0.006***	0.005***	0.006***	L. number of people in household	0.001	0.002*	0.000
	(0.001)	(0.002)	(0.002)		(0.002)	(0.001)	(0.004)
L3. number of people in hh^2	-0.000	-0.000	-0.000	L. number of people in hh^2	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. head is married	0.009**	0.008	0.012	L. head is married	0.001	0.003	-0.004
	(0.004)	(0.005)	(0.008)		(0.003)	(0.003)	(0.006)
L3. income source: dummy 1 for selling crops	-0.000	-0.001	0.001	L. income source: dummy 1 for selling crops	-0.000	-0.004	0.002
	(0.003)	(0.004)	(0.006)		(0.002)	(0.003)	(0.003)
L3. income source: dummy 1 for enterprise	0.004	0.006	0.005	L. income source: dummy 1 for enterprise	0.000	0.003	-0.002
	(0.003)	(0.005)	(0.004)		(0.002)	(0.003)	(0.003)
L3. income source: dummy 1 for wage	-0.006**	-0.003	-0.002	L. income source: dummy 1 for wage	0.001	0.002	0.001
	(0.003)	(0.003)	(0.005)		(0.002)	(0.002)	(0.003)
L3. annual formal transfers, dol	-0.000***	-0.000**	-0.000*	L. annual formal transfers, dol	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. annual informal transfers, dol	-0.000	-0.000	-0.000	L. annual informal transfers, dol	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. borrowed money	0.000	-0.000	0.001	L. borrowed money	-0.000	0.003	-0.002
	(0.004)	(0.006)	(0.005)		(0.002)	(0.003)	(0.003)
Distance to agricultural market (km)	0.000**	0.000	0.001***	Distance to agricultural market (km)	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Distance to petty trading market (km)	-0.001	-0.000	-0.002	Distance to petty trading market (km)	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Distance to primary school (km)	-0.003**	-0.001	-0.004**	Distance to primary school (km)	-0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.002)		(0.001)	(0.001)	(0.002)
L. Covid	-0.006*	-0.001	-0.006	L. Covid	-0.000	0.000	-0.001
	(0.003)	(0.004)	(0.004)		(0.004)	(0.004)	(0.006)
				L. SPEIneg6	0.002	0.007	0.023*
					(0.004)	(0.005)	(0.013)
L.SPEIpos6	0.006	-0.010	0.004	L. SPEIpos6	-0.000	0.003	-0.015**
	(0.010)	(0.011)	(0.010)		(0.003)	(0.004)	(0.007)
Observations	3,095	1,410	1,685	Observations	9,478	4,766	4,712
Adjusted R-squared	0.276	0.295	0.284	R-squared	0.659	0.695	0.653
				Number of panel id	4,633	2,420	2,213
District#Year	Yes	Yes	Yes	District#Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
F-test all lags=0	0.000	0.000	0.000	F-test all lags=0	0.000	0.000	0.000
F-test lags 2-4=0	0.000	0.738	0.000	F-test lags 2-4=0	0.001	0.001	0.027
				R2 within	0.659	0.695	0.653

R2 between	0.096	0.008	0.141
R2 overall	0.142	0.048	0.207

Robust standard errors in parentheses (col. 1-3) and clustered at the household level (col. 4-6). *** p<0.01, ** p<0.05, * p<0.10. Columns 1-3 are estimated via OLS, columns 4-6 are estimated via FE. "L.variable" indicates the lagged variable. "L3.variable" indicates the lagged variable of three periods. The dependent variable is the asset difference between the last and the first wave (col. 1-3) and one-period asset growth (col 4-6). Controls are three-periods-lagged variables (col. 1-3) or one-period lagged variables: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, subsamples of wave 1, and the interaction between year and district.

Figure 7: Local polynomial smooth of OLS-predicted current assets and actual lagged assets, refugees and hosts



Next, we estimate equation 2 using the fixed effects (FE) panel estimator[15] with all covariates lagged one period (Table 7, columns 4-6). Asset growth in the pooled sample correlates positively and significantly with head age only. Running the FE model separately for refugees and hosts (columns 5 and 6) confirms the presence of group-specific strengths and vulnerabilities affecting period-by-period asset growth. For instance, refugees show a positive correlation with squared education and household size, but also with being female headed. This result, in contrast with expectations, might indicate an important role of assistance in the settlements[16]. Also, average education correlates negatively with asset growth, signalling perhaps a difficulty of adapting own skills to the new setting (up to a point). Hosts show a positive correlation with age of the household head and formal transfers, which are quite

[15] The FE estimator is preferred to a RE as the former considers the unobserved household-specific heterogeneity that is constant over time. RE coefficients (reported in Table A3 in the Appendix) support the FE results. Yet, the Hausman test suggests that the FE model is more suitable than the RE model. Therefore, we limit the use of RE models to attrition testing.

[16] In other words, being female-heading a proxy for targeting interventions and being the refugees mostly dependent on assistance, could explain this counterintuitive result vis-à-vis male-headed households.

in line with expectations and a negative correlation with wet weather, indicating the relevance of agriculture for hosts[17].

5.3. Social cohesion

We now focus on the relevance for asset growth of social cohesion within and between the refugee and host communities. Social cohesion has an important role for development: where it is strong, it is associated with safety and productivity, and consequently on asset accumulation; conversely, the lack of social cohesion is associated with crime and spatial segregation, resentment, social tensions, competition over resources (World Bank, 2017). At the same time, refugee inflows impact social cohesion, exacerbating existing issues. Indeed, the impact on social cohesion is linked to a number of factors, such as perceptions and prejudice, political discourses, cultural proximity, perceived justice about aid distribution and service delivery (World Bank, 2017) and the inclusivity of policies[18].

We exploit the richness of the survey which asks questions to both refugees and hosts about their intergroup relationship, the frequency and the ease of the interaction, the general level of trust and sense of belonging. We built on the model expressed in equation 2 with FE to include various social cohesion proxies[19] (Tables 8 and 9). The dependent variable is again one-period asset growth.

The two groups show opposite behaviours, with socio-economic interactions and trust generally having a positive effect on refugees' asset growth, while this effect, when statistically significant, is generally negative for hosts. For instance, in the case of refugees, improved relationships within own community, good and very good relations within own community, comfortable interactions, being involved in business and trusting others are positively associated with asset growth. Conversely, for hosts asset growth is negatively associated with frequent (social and business-motivated) interactions with other groups, trust and feeling comfortable (no matter how much) in interacting with others. This negative association could be due to the competition between hosts and refugees as their skills are quite similar and they produce and sell very similar goods (Betts et al., 2019).

[17] Note that most households live in tropic warm humid zones and no extreme weather event happened in the period and area of interest. The coefficient indicates that wetter seasons are negatively associated with asset growth. The coefficient for dry season (the variable is reversed, i.e. higher values mean drier conditions) is positive, which means that from normal to somewhat dry season, assets are accumulated. This result is confirmed if we replace it with a dummy variable or a self-reported measure for a dry season.

[18] A recent paper in Uganda finds positive spillovers of settlements to service provision (health, schools and roads), which contribute to social cohesion and reduce negative perceptions of refugees within host communities (Zhou et al., 2023).

[19] The proxy variables are the improvement over time of relationships with other groups in their community, the status of relationships within such community, the frequency of this interaction, feeling comfortable in interacting with these groups, the frequency of interaction with the other community's vendors and businesses (Ugandan nationals for refugees and refugees for Ugandan nationals), the level of trust with the other community and the sense of belonging to the community. All answer categories are rescaled to have higher values for situations characterized by higher interactions and trust.

Table 8: Social cohesion proxies and asset growth of refugees and hosts, fixed effects, first set.

VARIABLES	(1) REF	(2) HOST	(3) REF	(4) HOST	(5) REF	(6) HOST
L. trade_asset	-1.666***	-1.751***	-1.661***	-1.706***	-1.645***	-1.734***
	(0.225)	(0.508)	(0.225)	(0.511)	(0.223)	(0.509)
Relationship over time:						
L. relationship worsened	0.006	-0.054				
	(0.016)	(0.122)				
L. relationship stayed the same	0.014	-0.064				
	(0.010)	(0.121)				
L.improved a little	0.018*	-0.067				
	(0.011)	(0.121)				
L.improved a lot	0.018	-0.063				
	(0.011)	(0.121)				
Current relation:						
L. bad			0.023	-0.041		
			(0.024)	(0.087)		
L. nor good nor bad			0.033	-0.053		
			(0.020)	(0.084)		
L. good			0.039*	-0.064		
			(0.020)	(0.083)		
L very good			0.034*	-0.064		
			(0.020)	(0.084)		
Frequency of interaction:						
L. rare					0.010	-0.030
					(0.024)	(0.040)
L. occasional					0.005	-0.062
					(0.023)	(0.039)
L. frequent					0.013	-0.061
					(0.023)	(0.039)
L. very frequent					0.013	-0.064*
					(0.024)	(0.039)
Observations	2,736	3,026	2,746	3,031	2,755	3,035
Number of panel id	1,715	1,878	1,719	1,877	1,723	1,882
Adjusted R-squared	0.742	0.705	0.742	0.703	0.742	0.706
District#Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2 within	0.746	0.709	0.746	0.707	0.746	0.710
R2 between	0.138	0.171	0.141	0.173	0.137	0.170
R2 overall	0.200	0.229	0.203	0.230	0.198	0.226

Robust standard errors in parentheses clustered at the household level. *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: one-period asset growth, including assets_2021 - assets_2020, assets_2020 - assets_2019 and assets_2019 - assets_wave 1. "L.variable" indicates the lagged variable. Most controls are one periods lagged as described in Section 3. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, baseline, and the interaction between year and district.

Table 9: Social cohesion proxies and asset growth of refugees and hosts, fixed effects, second set.

VARIABLES	(1) REF	(2) HOST	(3) REF	(4) HOST	(5) REF	(6) HOST	(7) REF	(8) HOST
L. trade_asset	-1.712***	-1.723***	-1.699***	-1.770***	-1.697***	-1.738***	-1.698***	-1.797***
	(0.227)	(0.509)	(0.224)	(0.508)	(0.224)	(0.509)	(0.222)	(0.510)
Comfort in interaction:								
L. little	0.020	-0.090*						
	(0.015)	(0.049)						

L. moderate	0.017	-0.082*						
	(0.014)	(0.048)						
L. a lot	0.021	-0.087*						
	(0.014)	(0.048)						
L. extreme	0.024*	-0.094**						
	(0.015)	(0.048)						
Frequency of business interaction:								
L. rare			0.018	-0.028*				
			(0.019)	(0.015)				
L. occasional			0.025	-0.017				
			(0.018)	(0.014)				
L. frequent			0.031*	-0.017				
			(0.018)	(0.013)				
L. very frequent			0.030	-0.029**				
			(0.018)	(0.014)				
Trust								
L. not much					0.031***	-0.027*		
					(0.010)	(0.015)		
L. a little					0.026***	-0.034**		
					(0.009)	(0.015)		
L a lot					0.025***	-0.027*		
					(0.009)	(0.015)		
Belonging:								
L. not much							-0.018	0.015
							(0.014)	(0.050)
L a little							-0.011	0.002
							(0.012)	(0.051)
L. a lot							-0.009	-0.001
							(0.012)	(0.050)
Observations	2,754	3,036	2,758	3,027	2,755	3,033	2,772	3,041
Number of uhhidp	1,723	1,882	1,724	1,879	1,722	1,883	1,724	1,881
Adjusted R-squared	0.732	0.705	0.731	0.711	0.733	0.706	0.734	0.704
District#Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2 within	0.736	0.709	0.735	0.715	0.737	0.710	0.738	0.708
R2 between	0.137	0.172	0.136	0.180	0.142	0.173	0.139	0.172
R2 overall	0.197	0.229	0.197	0.236	0.202	0.230	0.201	0.229

Robust standard errors in parentheses clustered at the household level. *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: one-period asset growth, including assets_2021 - assets_2020, assets_2020 - assets_2019 and assets_2019 - assets_wave 1. "L.variable" indicates the lagged variable. Most controls are one periods lagged as described in Section 3. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, baseline, and the interaction between year and district.

5.4. Dealing with attrition

The attrition between wave 1 and wave 4, i.e., ignoring whether households appear in the intermediate waves or not, amounts to 33% for the whole population (23% for hosts and 41% for refugees) [20]. Should attrition be correlated with the variables of interest, our results would be biased (Wooldridge, 2010). For instance, we could expect that refugees that left after the first interview are

[20] Özler et al. (2021) found similar attrition rates in another panel of refugees. Nonetheless, overall absorbing attrition, i.e., the households at the first wave which do not enter the balanced panel, is rather high accounting for 63% of the whole sample, 68% for refugees and 57% for hosts.

richer or better connected[21]. This does not seem to be the case for Uganda refugees. T-tests at wave 1 show that attritor households are more often households with female, younger and less educated heads, generally smaller in size and with higher dependency ratios. Attritors are less engaged in crop and wage activities, receive larger amounts of formal assistance, borrow less, have fewer assets, and spend less. This seems to rule out the possibility that refugees do not achieve a higher equilibrium because better off households left the camps. Another strategy to test for attrition is to run the regression for the balanced as well as unbalanced samples and compare the coefficient estimates: these are very similar (cf. Table A.3 in the Appendix), signalling that attrition bias might be negligible (Prieto, 2021; Wooldridge, 2010). However, the coefficients of attrition-related auxiliary variables[22] indicate that attrition is somewhat relevant. Attrition probits show that the probability of attrition is not correlated to the asset index (except for hosts from wave 1 to wave 4, with a negative coefficient) and only marginally correlated with some other variables (Table A.4 in the Appendix).

Having ruled out that attrition is fully random, some corrections are needed. A first approach 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). As for any instrumental variable approach, it is difficult to find appropriate instruments[23] (Baulch & Quisumbing, 2011). Another approach is the inverse probability weights (IPW) correction which relies on auxiliary variables that are correlated with both attrition and the outcome variable (selection on observables[24]) (Robins et al., 1995; Wooldridge, 2002).

We implement both the IPW correction (Table 10, columns 2 and 5) and the Heckman model (column 3). Overall, coefficients on the lagged polynomial of assets are quite similar for the weighted and non-weighted sample. This is reassuring: the results we get using the balanced panel are valid for the overall sample as well.

Table 10: Parametric regression, correcting for attrition, all sample.

	w1 – w4 attrition				Absorbing attrition	
	(1) No correction	(2) IPW	(3) Heckman		(4) No correction	(5) IPW
L3. Trade_asset^1	-0.653***	-0.640***	-0.658***	L. trade_asset^1	-1.433***	-1.402***
	(0.143)	(0.143)	(0.142)		(0.130)	(0.129)
L3. Trade_asset^2	-0.341	-0.544	-0.328	L. trade_asset^2	1.613	1.461

[21] As emphasized by Jacobsen (2012), this may be the result of a location-selection strategy according to which households split with the better social and human capital endowed members leaving the camps and the others living on humanitarian assistance and remittances in the camps.

[22] Specifically, whether the household belongs to the balanced panel (cf. column 3 and 8 of Table A.3 for OLS and RE, respectively) and a count of the waves each household is included in the survey (cf. column 9 for the RE) (Nijman & Verbeek, 1992).

[23] We consider the distance to the closest border crossing point and the distance to the closest settlement, as well as the month of interview dummies and granular rural categories.

[24] Baulch & Quisumbing (2011) argue that a Pseudo R2 of 13% can be considered a relatively high explanatory power. We obtain values between 8% and 15%.

	(1.103)	(1.086)	(1.095)		(1.098)	(1.098)
L3. Trade_asset^3	3.773	4.303	3.753	L. trade_asset^3	-6.175*	-5.916*
	(2.983)	(2.933)	(2.962)		(3.341)	(3.375)
L3. Trade_asset^4	-4.886**	-5.258**	-4.862**	L. trade_asset^4	6.028*	5.928*
	(2.347)	(2.305)	(2.331)			
Observations	3,095	3,014	5,079	Observations	9,478	9,478
R2 adj	0.28	0.27		R-squared	0.659	0.657
Log likelihood			2,505.821	Number of uhhidp	4,633	4,633
Rho			-0.21	District#Year	Yes	Yes
Sigma			0.08	R2 within	0.659	0.657
Lambda			-0.02	R2 between	0.0958	0.00201
W test of indep			15.25	R2 overall	0.142	0.0155
P value			0.00			

Robust standard errors in parentheses (col 1-3) and clustered at the household level (col 4-5). *** p<0.01, ** p<0.05, * p<0.10. Columns 1-2 are estimated via OLS, columns 3 with Heckman two step model, 4-5 are estimated via FE. "L.variable" indicates the lagged variable. "L3.variable" indicates the lagged variable of three periods. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, baseline, and the interaction between year and district. The selection equation for column 3 includes: refugees, distance from the closest crossing point, distance to the closest settlement, self-reported flood and drought shocks, female headship, age of the head, average education, household size, number of infants, subsamples of wave 1, month of the interview, detail of rural areas (very low density rural grid cell, low density rural grid cell, rural cluster, suburban grid cell, urban cluster, urban centre).

6. Robustness checks

To further check the robustness of our results, we test for different specifications, namely excluding the first wave observations, using different asset index and running semi-parametric regressions.

6.1. Excluding wave 1 observations

To rule out that the different starting times of the first wave (cf. Section 4.1) are driving our results, we repeat the analysis by excluding the first wave (Table 11). In this case also, we reject the null hypothesis of convergence in all subsamples (marginally in the host sample). Predicted equilibria from the non-parametric regression are similar (graph available upon request).

Table 11: Parametric regression of asset change between wave 4 and wave 2 (OLS) by refugee status.

VARIABLES	(1) All	(2) Refugees	(3) Hosts
L2.trade_asset^1	-0.447**	-0.852***	-0.120
	(0.213)	(0.291)	(0.474)
L2.trade_asset^2	-1.723	1.668	-3.756
	(1.594)	(2.706)	(2.967)
L2.trade_asset^3	5.956	-5.206	10.313
	(4.299)	(9.205)	(7.070)
L2.trade_asset^4	-6.104*	4.232	-9.197*
	(3.502)	(9.382)	(5.356)
Observations	2,240	1,068	1,172
Adjusted R-squared	0.298	0.312	0.313
Controls	Yes	Yes	Yes
District#Year	Yes	Yes	Yes
F-test all lags=0	0.000	0.000	0.000

F-test lags 2-4=0	0.013	0.081	0.009

Robust standard errors in parentheses. OLS. The dependent variable is the asset difference between 2021 and the second wave. Most controls are two periods lagged and are described in Section 3. *** p<0.01, ** p<0.05, * p<0.10 "L2.variable" indicates the lagged variable of two periods. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, baseline, and the interaction between year and district.

6.2. Different asset indexes

Using a more comprehensive asset index, i.e., adding to the tradable asset index items such as the toilet type and the water source type dummies, the test cannot reject convergence for the two samples (Table 12, col 1-3). Hosts and refugees again have close but different equilibria (Figure A.2 in the Appendix). Another asset index, built by predicting household expenditure (divided by the poverty line[25]) with asset ownership and socio-demographic characteristics (Adato et al., 2006), indicates general convergence for all samples (Table 12, col. 4-6).

Table 12: Parametric regression (OLS) on the comprehensive and livelihood asset index

VARIABLES	(1) All	(2) Refugees	(3) Hosts		(4) All	(5) Refugees	(6) Hosts
L3.compr_asset^1	-0.572**	-0.670	0.301	L3.livel_index^1	-0.687***	-0.704***	-0.661***
	(0.285)	(0.461)	(0.899)		(0.059)	(0.091)	(0.103)
L3.compr_asset^2	-0.334	-0.463	-3.447	L3.livel_index^2	-0.033	0.041	-0.111
	(1.263)	(2.637)	(3.198)		(0.048)	(0.049)	(0.109)
L3.compr_asset^3	0.460	1.185	5.029	L3.livel_index^3	0.016	-0.045	0.058
	(2.220)	(5.941)	(4.751)		(0.026)	(0.035)	(0.051)
L3.compr_asset^4	-0.199	-1.132	-2.553	L3.livel_index^4	-0.001	0.010	-0.008
	(1.334)	(4.555)	(2.502)		(0.004)	(0.007)	(0.007)
Observations	3,095	1,410	1,685		2,386	1,062	1,324
Adjusted R-squared	0.416	0.401	0.405		0.476	0.505	0.466
Controls	Yes	Yes	Yes		Yes	Yes	Yes
District#Year	Yes	Yes	Yes		Yes	Yes	Yes
F-test all lags=0	0.000	0.000	0.000		0.000	0.000	0.000
F-test lags 2-4=0	0.969	0.908	0.737		0.114	0.376	0.338

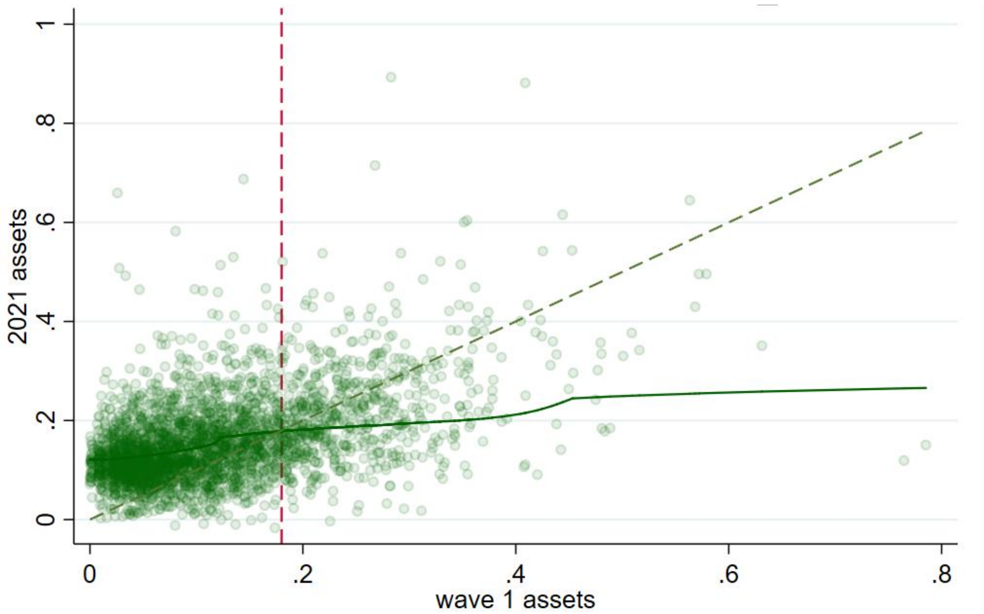
Robust standard errors in parentheses. OLS. The dependent variable is the asset difference between 2021 and the first wave, which in col. 1-3 is the comprehensive asset index and in col 4-6 is the livelihood asset index. Most controls are three-periods-lagged and are described in Section 3. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, baseline, and the interaction between year and district.

[25] Given the extremely low levels of expenditure and income (due to poverty but also to the types of questions included in the questionnaire), we used the expenditure median as poverty line (i.e., 0.10 dollars per day per capita).

6.3. Semi-parametric regression

Semi-parametric regressions (Figure 8) – confirm the existence of a single equilibrium for the whole population at 0.18 asset scores (slightly lower than parametric and nonparametric estimates). However, close but different equilibria emerge for refugees (0.11 again) and hosts (0.22). They also confirm the absence of non-linear dynamics. Resulting coefficients tell a story similar to the parametric case[26].

Figure 8: Semiparametric regression: lowess mean smooth, all sample.



Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, subsamples of wave 1.

7. Concluding remarks

In this paper, we analysed households' asset dynamics in Ugandan refugee camps and neighbouring villages. We find no evidence of multiple equilibria poverty traps. Rather, the whole population tends to a single low-level equilibrium, indicating a structural poverty trap. Looking at refugees and hosts separately, we find that the poverty trap is relatively more severe for refugees as their own-group equilibrium is lower. Further disaggregating the population across various dimensions highlights the importance of geography and specific household characteristics. The most important factors enabling asset growth are household size, education, and transfers, while those reducing it are environmental shocks such as heavy rains. There is evidence in the literature that the interaction with refugees may

[26] Available upon request.

bring positive effects to the native population[27] (at least in the medium-longer term). We find that social cohesion positively impacts the refugees' asset accumulation.

The different location of the equilibrium for refugees and hosts can be explained by refugees' lower physical asset endowments. This means that refugees, by owning fewer durables, fewer agricultural tools, fewer animals and smaller plots have lower production capacity, less buffer resources to cope with shocks, less collateral, hence less capacity to make investments, not only in assets but also in human capital[28]. This may affect the future prospects for the youngest household members, creating the basis for an intergenerational poverty trap[29].

Finding no evidence of multiple equilibria poverty traps could either mean a true absence of multiple equilibria poverty traps or that we are unable to capture it. The latter may be due to an inaccurate households' assets estimation or a too short time frame or significant attrition. Calculating the asset index together for refugees and hosts is fundamental for comparing them. Nonetheless, we could expect that refugees and hosts' asset bundles differ. For instance, refugees could accumulate relatively more tradable assets, while hosts could accumulate other types of capital (investments on dwelling or land) which are not well reflected in a tradable asset index. We tend to exclude that this might be a problem because our results are robust to different specifications of the wealth index. However, the short time frame of analysis could be a problem for the identification of a poverty trap. For this reason, we use the maximum stretch of the panel and show that the results hold even if this is shortened and we use also an asset index based only on tradables that captures faster accumulation/decumulation dynamics. However, we cannot completely rule this issue out. Vice versa, we are quite confident that households' mobility is not related to the main variable of interest: correcting for non-random attrition does not alter our findings.

The best explanation of the results is that all households in the study are in a structural poverty trap, more severe for refugees (Carter & May, 2001; McKay & Perge, 2013; Naschold, 2013). When there are

[27] Using nationally representative data from Uganda covering the period 2009-2012, i.e. before the huge inflow that started in 2014, Kadigo et al. (2022) found positive effects of refugee inflows on local population driven by subsistence farmers shifting towards commercial farming.

[28] Refugees in our sample have on average about one year less of schooling than hosts. 69% of refugees in Uganda between 18 and 25 years old completed only primary school education; 82% of working age refugees have no secondary education (WFP, 2020).

[29] Age at displacement can matter substantially for future outcomes (at least in high-income countries), giving the highest benefits to the youngest who, by relocating, can have the chance to increase their education and pursue more rewarding careers (Nakamura et al., 2019). Indeed, in the case of camps, humanitarian actors' provision of additional educational services can have positive effects on both refugee and host children (World Bank, 2017). For instance, hosts children living close to Congolese settlements in Uganda benefitted in terms of education (Kreibaum, 2016). For certain groups, such as displaced young women living in camps in Darfur, displacement provided a chance to catch up with their education (Stojetz & Brück, 2021). However, other studies in Uganda show no differences in hosts' education between refugee-hosting areas and non-hosting areas in 2012 (Kadigo et al., 2022), and more recently, education does not correlate with the distance to refugees location (d'Errico et al., 2022). Moreover, Ugandans who returned home after being internally displaced in 2002 still lag behind in terms of consumption, education and assets, especially the poorest at time of displacement (Fiala, 2015).

binding macro constraints, such as institutions, geography or technology, households are trapped in persistent poverty (Giesbert & Schindler, 2012; Naschold, 2012). The observed dynamics may be convex (as in the absence of poverty traps), but convergence leads to a dynamic equilibrium below the poverty line (Antman & McKenzie, 2007; Barrett et al., 2016), albeit with the possibility of stochastic movements in and out of poverty due to random fluctuations around the expected wellbeing dynamics.

From a policy point of view, a structural poverty trap means that the mere transfer of resources might not be effective in determining permanent changes[30]. Efforts should be directed at untying the knots that trap entire communities in poverty. In the case of refugees, this could involve tackling possible behavioural traps created by the psychological stress, trauma experienced and hopelessness (Dang et al., 2022; Moya & Carter, 2019) or, more broadly, reducing the impact of the mechanisms that decrease people's ability to sustain themselves and allow these households to effectively accumulate assets. Standard anti-poverty interventions such as cash and in-kind assistance are key in ensuring food security in the short run but to trigger a long term improvement in life conditions more extensive structural changes able to shift the equilibrium upwards are needed, such as interventions aiming to increase returns to assets currently available[31] or the opening of new livelihood opportunities (Naschold, 2012). Other interventions should be aimed at improving households' self-reliance promoting market creation and improving social cohesion.

A second policy implication of our findings is the need to address the needs of host and refugee communities together. We show that both populations are very poor and, despite tending towards two different dynamic asset equilibria, these equilibria are both below the poverty line. In such a context, standard interventions acting on education, skills, and the labour force have low returns because of the limited set of available economic opportunities for both hosts and refugees. For policies to become effective and a viable substitute to transfers, the set of economic opportunities available to refugees has to expand. As already emphasized in similar situations (Verme et al., 2016), the policy focus must shift beyond social protection for refugees to include economic growth in the whole areas hosting them, so that refugees and host communities can share in economic progress. This calls for a closer collaboration between humanitarian and development partners in order to transform a persistent humanitarian emergence into a development opportunity for all.

Finally, we show that a health emergency such as Covid-19 might risk overshadowing how poverty and extreme poverty impact the lives of people (Bryce et al., 2020). Vice versa, a specific attention should

[30] However, in the presence of a single equilibrium, a one-time livestock transfer coupled with training has proven effective to have positive effects on resilience and consumption 3.5 years after the intervention (Phadera et al., 2019). A different case is that of a bimodal asset distribution, indicating a multiple-equilibria poverty trap: a large asset transfer coupled with training is able to lift people out of the poverty trap (Balboni et al., 2021).

[31] For instance, investment in public infrastructure can be key in fostering higher asset returns via complementarities (Escobal & Torero, 2005).

be devoted to the most vulnerable groups. In the specific context of Uganda, those are primarily those suffering climatic shocks, those without access to land or those whose land base is reducing[32].

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[32] We do not show this as we incorporate land in the asset index. However, Betts et al. (2019) show that cultivating land improves food security for refugees in Uganda although farming remains at subsistence levels, unable to promote actual change.

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Appendix

Additional Tables and Figures

Table A.1: Tradable asset index components: means by asset quintiles and by refugee status

Mean values	Tradable asset index, quintiles 1	2	3	4	5	Hosts	Refugees
Nbr of mobiles owned by hh	1.11	1.27	1.25	1.43	1.71	1.57	1.17
Nbr of radio owned by hh	0.02	0.09	0.22	0.43	0.78	0.48	0.17
Nbr of tv owned by hh	0.00	0.01	0.01	0.02	0.15	0.07	0.02
Nbr of bicycle owned by hh	0.03	0.05	0.11	0.24	0.55	0.31	0.10
Nbr of solar_panel owned by hh	0.12	0.21	0.36	0.58	0.92	0.54	0.35
Nbr of cooker owned by hh	0.04	0.06	0.10	0.08	0.14	0.08	0.08
Nbr of box owned by hh	0.00	0.02	0.04	0.12	0.41	0.19	0.06
Nbr of tables owned by hh	0.07	0.32	0.65	1.01	1.64	1.03	0.49
Nbr of chairs owned by hh	0.83	1.77	2.56	3.20	4.40	3.13	2.07
Nbr of bed owned by hh	0.10	0.55	1.14	1.66	2.42	1.63	0.80
Nbr of mattress owned by hh	0.18	0.79	1.48	1.98	2.68	1.98	0.96
# cattle, cows owned by hh	0.01	0.07	0.22	0.45	2.54	1.40	0.04
# goats owned by hh	0.08	0.36	0.95	1.52	3.60	2.41	0.39
# sheep owned by hh	0.00	0.02	0.04	0.13	0.57	0.30	0.03
# pigs owned by hh	0.01	0.04	0.09	0.22	0.63	0.35	0.08
# chickens owned by hh	0.38	1.33	2.30	3.47	6.75	4.33	1.62
# donkey and horses owned by hh	0.00	0.00	0.01	0.01	0.01	0.00	0.01
# other animals owned by hh	0.04	0.06	0.06	0.11	0.27	0.14	0.09
Nbr of hoe owned	0.79	1.35	1.86	2.45	3.47	2.79	1.31
Nbr of axe owned	0.05	0.18	0.32	0.55	0.91	0.64	0.20
Nbr of shovel owned	0.02	0.04	0.07	0.15	0.34	0.17	0.08
Nbr of pickaxe owned	0.01	0.02	0.04	0.09	0.28	0.14	0.05
Nbr of sickle owned	0.14	0.21	0.29	0.38	0.65	0.42	0.26
Nbr of plough owned	0.00	0.01	0.03	0.03	0.09	0.05	0.01
Nbr of wheelbarrow owned	0.01	0.05	0.04	0.06	0.22	0.11	0.05
Nbr of slasher owned	0.44	0.66	0.85	1.12	1.57	1.14	0.75
Total arable land (acres)	0.34	0.70	1.11	1.60	2.51	2.28	0.40

The index is computed on the pooled sample (McKay & Perge, 2013; Naschold, 2012, 2013) and year is added (Waleign et al., 2021).

Table A.2: Comprehensive asset index: asset items added to the tradable asset index items.

Additional asset items	
Water source=Piped (dwelling)	Toilet: Covered pit latrine private
Water source=Piped public tap	Toilet: Covered pit latrine shared
Water source=Protected Shallow well	Toilet: VIP latrine private
Water source=Borehole	Toilet: VIP latrine shared
Water source=Protected spring	Toilet: Uncovered pit latrine
Water source=Roof rain water	Toilet: Flush toilet private
Water source=Unprotected spring	Toilet: Flush toilet shared
Water source=Tanker/Truck water	Toilet: Bush
Water source=River/stream	Toilet: Dig and Bury
Water source=Dam/pond/pan/lake	Toilet: Mobile/ portable toilets for settl.
Water source=Water vendor	Toilet: Other (specify)
Water source=Unprotected/open shallow well	Non-shared toilet
Water source=Other (specify)	

The index is computed on the pooled sample (McKay & Perge, 2013; Naschold, 2012, 2013) and year is added (Waleign et al., 2021).

Table A.3: Attrition check: Balanced and unbalanced panel, FE and RE

Variables	(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE	(6) RE	(7) RE	(8) RE	(9) RE

	Unbalanced	Balanced	Dummy for balanced	Unbalanced	Balanced	Unbalanced	Balanced	Dummy for balanced	Number of observations
L3.trade_asset^1	-0.653***	- 0.568***	-0.661***						
	(0.143)	(0.169)	(0.143)						
L3.trade_asset^2	-0.341	-0.944	-0.282						
	(1.103)	(1.323)	(1.100)						
L3.trade_asset^3	3.773	5.739	3.628						
	(2.983)	(3.664)	(2.975)						
L3.trade_asset^4	-4.886**	-6.657**	-4.773**						
	(2.347)	(2.955)	(2.343)						
1.balanced panel			0.007**					0.009***	
			(0.003)					(0.002)	
L.trade_asset				-1.433***	- 1.416***	-0.767***	- 0.656***	- 0.772***	-0.776***
				(0.130)	(0.141)	(0.107)	(0.129)	(0.107)	(0.107)
L.trade_asset^2				1.613	1.848	0.934	0.951	0.956	0.985
				(1.098)	(1.210)	(0.916)	(1.097)	(0.912)	(0.912)
L.trade_asset^3				-6.175*	-6.886*	-2.632	-1.830	-2.679	-2.739
				(3.341)	(3.708)	(2.719)	(3.261)	(2.706)	(2.705)
L.trade_asset^4				6.028*	6.741*	2.031	0.912	2.072	2.111
				(3.171)	(3.566)	(2.471)	(2.993)	(2.458)	(2.457)
3.obs in panel									0.011***
									(0.004)
4.obs in panel									0.018***
									(0.004)
Observations	3,095	2,240	3,095	9,478	6,629	9,478	6,629	9,478	9,478
District#Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test all lags=0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-test lags 2-4=0	0.000	0.000	0.000	0.001	0.001	0.450	0.217	0.463	0.451
Number of uhhidp				4,633	2,280	4,633	2,280	4,633	4,633
R2 within				0.659	0.639	0.581	0.496	0.581	0.579
R2 between				0.096	0.003	0.199	0.065	0.202	0.203
R2 overall				0.142	0.120	0.278	0.264	0.279	0.280
F-test balanc=0			0.024					0.000	0.000
R-squared			0.287	0.659	0.639				

Robust standard errors (col. 1-3) and clustered at household level (col. 4-9) in parentheses. Columns 1-3 OLS, col. 4-5 FE, col. 6-9: RE. The dependent variable is the asset difference between last and first wave in columns 1-2 and the asset difference wave-by-wave for columns 4-9. Same controls used in the main regressions, lagged of three periods if OLS, of one if panel model. They are described in Section 3. *** p<0.01, ** p<0.05, * p<0.10 "L.variable" indicates the lagged variable of one period, "L3.variable" indicates the lagged variable of three periods. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, baseline, and the interaction between year and district.

Table A.4: Attrition test: Probit model

	(1)	(2)	(3)	(4)	(5)	(6)
		Wave1 - wave4			Absorbing	
	All	Refugees	Hosts	All	Refugees	Hosts
1.Refugee	0.344***			0.083		
	(0.066)			(0.063)		
1.female head	-0.052	-0.070	0.004	-0.058	-0.075	0.160*
	(0.049)	(0.051)	(0.100)	(0.050)	(0.063)	(0.092)
1.marriedhead	-0.109**	-0.140**	-0.029	-0.142***	-0.174***	-0.012
	(0.053)	(0.056)	(0.104)	(0.053)	(0.066)	(0.094)
age head of hh	-0.007***	-0.009***	-0.004*	-0.007***	-0.008***	-0.010***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)

Average years of education of adults	0.007	-0.002	0.011	-0.002	-0.011	-0.000
	(0.006)	(0.010)	(0.011)	(0.006)	(0.008)	(0.010)
number of people in hh	-0.048***	-0.038	-0.082***	-0.040**	-0.014	-0.047
	(0.018)	(0.038)	(0.027)	(0.019)	(0.026)	(0.030)
number of people in hh ^2	0.002*	0.002	0.003*	0.001	-0.000	0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Number of infants (<5)	0.030	-0.014	0.064*	0.012	-0.019	0.013
	(0.023)	(0.029)	(0.036)	(0.022)	(0.032)	(0.033)
income source: selling crops	0.053	0.027	0.017	0.044	-0.045	-0.025
	(0.045)	(0.058)	(0.073)	(0.044)	(0.063)	(0.068)
income source: running enterprise	0.093**	0.088	0.100	-0.004	-0.028	-0.042
	(0.045)	(0.059)	(0.065)	(0.043)	(0.069)	(0.059)
income source: wage employment	-0.040	0.029	-0.066	0.020	0.048	-0.029
	(0.038)	(0.069)	(0.061)	(0.037)	(0.053)	(0.056)
1. borrowed money	-0.187***	-0.219	-0.158*	-0.271***	-0.237**	-0.270***
	(0.064)	(0.149)	(0.084)	(0.057)	(0.103)	(0.072)
Daily total income, ppp pc	-0.010	-0.005	-0.008	0.046**	0.130**	0.049**
	(0.020)	(0.029)	(0.023)	(0.022)	(0.051)	(0.024)
Annual food exp., dol	0.000	-0.000	0.000*	0.000	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tradable asset index	-0.454	0.408	-0.925**	-0.360	-0.322	-0.153
	(0.329)	(0.724)	(0.426)	(0.306)	(0.646)	(0.376)
1.improved_toilet	-0.105***	-0.144**	-0.079	0.033	0.049	0.094
	(0.041)	(0.072)	(0.069)	(0.041)	(0.056)	(0.065)
1.improved_water	-0.081*	-0.099	0.022	0.081*	0.160**	0.059
	(0.046)	(0.136)	(0.075)	(0.044)	(0.070)	(0.068)
Main livelihood: Agro-pastoralist	-0.210	-0.685***	0.514	-0.401	-0.263	-0.812**
	(0.233)	(0.235)	(0.498)	(0.282)	(0.375)	(0.359)
Main livelihood: Crop Farmer	-0.115	-0.683***	0.643	-0.387	-0.153	-0.787**
	(0.230)	(0.246)	(0.495)	(0.279)	(0.367)	(0.355)
Main livelihood: Fishing	0.279		1.035*	0.155	-0.051	-0.175
	(0.348)		(0.580)	(0.401)	(0.692)	(0.461)
Main livelihood: Petty trade/Formal empl.	0.062	-0.589**	0.874*	0.026	-0.013	-0.121
	(0.249)	(0.287)	(0.520)	(0.303)	(0.404)	(0.395)
Main livelihood: Other	-0.072	-0.531**	0.538	-0.272	-0.041	-0.674
	(0.238)	(0.239)	(0.548)	(0.286)	(0.373)	(0.411)
Training participation	-0.053	-0.059	-0.064	0.016	-0.039	0.075
	(0.045)	(0.073)	(0.071)	(0.043)	(0.064)	(0.064)
Participating in associations	-0.099**	-0.150***	-0.085	-0.131***	-0.109*	-0.154**
	(0.042)	(0.050)	(0.067)	(0.041)	(0.059)	(0.064)
Safety net: formal	-0.022	-0.069	0.074	0.058	0.052	-0.020
	(0.052)	(0.073)	(0.102)	(0.051)	(0.068)	(0.094)
Safety net: informal	-0.013	0.103	-0.023	0.121*	0.355**	0.016
	(0.075)	(0.133)	(0.094)	(0.071)	(0.139)	(0.087)
Safety net: both	-0.045	-0.058	-0.281	0.024	0.067	-0.210
	(0.079)	(0.128)	(0.187)	(0.081)	(0.104)	(0.160)
SPEI index>1sd (=1)	0.302*	0.236**	-3.902***	0.644***	0.818***	-0.269
	(0.172)	(0.096)	(0.537)	(0.155)	(0.199)	(1.046)
Shock on input prices	0.035	0.124	0.056	0.091	0.321**	-0.036
	(0.094)	(0.183)	(0.133)	(0.086)	(0.148)	(0.113)
Shock on food prices	-0.039	0.060	-0.161	-0.047	0.000	-0.055
	(0.074)	(0.122)	(0.116)	(0.067)	(0.098)	(0.096)
Reduced coping strategies index	-0.001	-0.001	-0.001	-0.001	-0.000	-0.003*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Harmonized food consumption score	0.001	0.004	-0.001	-0.002	0.003	-0.004**
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
km distance to primary school	0.010	0.029	-0.007	0.024	-0.001	0.039*
	(0.015)	(0.025)	(0.025)	(0.015)	(0.022)	(0.023)
km distance to petty trading market	-0.011	-0.007	-0.016	-0.021*	-0.007	-0.015
	(0.013)	(0.022)	(0.024)	(0.013)	(0.016)	(0.023)
Distance from crossing point (km)	0.011***	0.012	-0.001	0.005*	-0.002	-0.009**
	(0.003)	(0.008)	(0.004)	(0.003)	(0.005)	(0.004)

Distance from settlement (km)	-0.008	0.013	-0.011	-0.006	0.004	0.015
	(0.009)	(0.014)	(0.011)	(0.008)	(0.020)	(0.010)
Constant	0.095	0.828**	0.070	0.939***	0.694	2.138***
	(0.301)	(0.416)	(0.575)	(0.335)	(0.479)	(0.461)
Pseudo R2	0.09	0.11	0.08	0.11	0.15	0.13
Log likelihood	-3,193.97	-1,844.05	-1,249.17	-3,440.24	-1,715.84	-1,563.57
N	5,776	3,134	2,633	5,776	3,140	2,633

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 Probit. Robust standard errors in parenthesis. Controls not reported in the table: district, the subsamples of wave 1, months of interview, detail of rural areas (very low density rural grid cell, low density rural grid cell, rural cluster, suburban grid cell, urban cluster, urban centre).

Figure A.1: Tradable asset index: different functional forms, non-parametric regression.

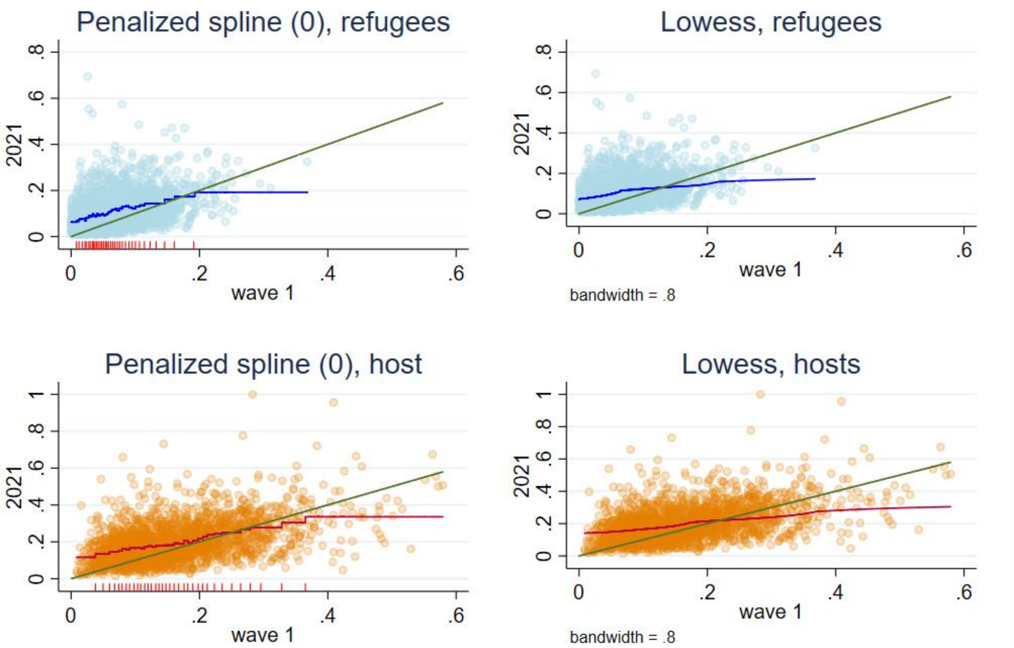
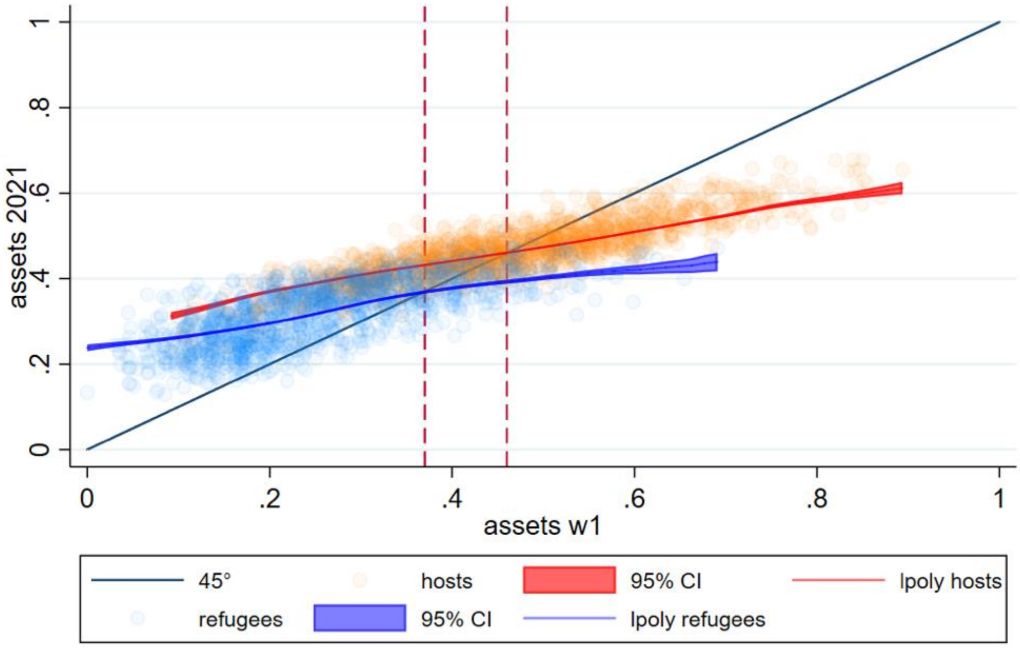


Figure A.2: Local polynomial smooth regression of comprehensive asset index, refugees and hosts



Appendix 1: Climatic variables and rainy seasons

There is not a consensus in the literature on which is the best indicator of a climatic shock, which reference period should be used and which product fits better the context of analysis. Uganda is subject to at least two rainy seasons patterns: a bimodal rain pattern in the south with March to May ('MAM') and September to November rains ('SON') (Majaliwa et al., 2015; Ocen et al., 2021), a long unimodal rainy season in the north-western region roughly from April to November (Ocen et al., 2021), and a unimodal rainy season in the north-east (Majaliwa et al., 2015) (not relevant for our geographical coverage). The bimodal area has two main farming systems, the Lake Albert Crescent and the Western Range Lands farming systems, whereas the long uninominal rainy season has the Northern farming system and the West Nile farming systems. Early harvest starts (for maize) in July (except for Western Range Lands). To keep into account the length of both the rainy seasons and the growing seasons and the timing of the interviews, we extract SPEI index in August and use as main reference period 6 months of the previous growing season. The year of reference for each wave is the same except for 2018 and 2019 parts of wave 1, for which the previous year's value applies.

Appendix 2: Clustering standard errors

Clustering standard errors is not straightforward. In this Appendix, we discuss on how to cluster standard errors in our sample, with specific reference to the OLS case. As mentioned in the Methodology section, standard errors in the OLS case are corrected for general heteroskedasticity, while in the FE case, they are clustered at the household level (in practice, in Stata, using robust or cluster over the panel id is the same). These OLS coefficients and t-statistics (in parenthesis) are reported in columns 1 in Tables A2.1 (all sample), A2.2 (refugees) and A2.3 (hosts). However, we might worry that the sample design suggests clustering standard errors on the district, as households are sampled with a two-stages cluster sampling (d'Errico et al., 2022). Even though we control for district fixed effects (interacted with year fixed effects), there is still the need to cluster standard errors (Abadie et al., 2022).

When there are more ways of clustering standard errors, if these are nested, the recommended approach is to use the more aggregate level only, but this makes sense only if there is a sufficient number of clusters (Baum et al., 2011; Cameron & Miller, 2015). The rule of thumb prescribes a minimum between 20 and 50 (Cameron & Miller, 2015), or each cluster being smaller than 5% of the total sample (Rogers, 1993). Unfortunately, we have a very small number of clusters (11 district or 13 settlements). Clustering on district (columns 2 in Tables A2.1, A2.2 and A2.3) would then be wrong, leading to residuals being suspiciously more close to zero than true error terms, biasing downward the cluster-robust variance matrix estimate (Cameron & Miller, 2015).

Two-way clustering of household id and cluster would not be a solution. Two-way clustering also needs a certain number of clusters in both dimensions of clustering (Baum et al., 2011). Indeed, ivreg2 and cgmreg offer two ways of estimating with two-way clustering (columns 3 and 4), however, clusters need to be non-nested.

One of the ways to correct finite cluster standard errors for inference, both for one-way and two-way clustering, is through wild cluster bootstrap (Cameron & Miller, 2015) using boottest (Roodman et al., 2019). Boottest uses a bootstrap procedure to test the null hypothesis that the coefficient is equal to zero under different assumptions about the level of clustering (columns 5 in Tables A2.1, A2.2 and A2.3 report the corrected t-statistics when clustering for district only, while columns 6 cluster both for household id and district). The difference between columns 5 and 6 is very marginal but it is there.

Note from Tables A2.1, A2.2 and A2.3 that column 5 corresponds to the correction of column 2: t-stats are the same, but p-values are adjusted for the finite clusters in column 5. Columns 6 correct for columns 3 and 4. Finally, note that as the Tables A2.1, A2.2 and A2.3 show, there is not much difference between columns 1 and 5 and 6.

We conclude that using heteroskedasticity-robust standard errors or standard errors clustered on district (with correction) makes little difference with respect to the statistical significance of our coefficients. Combining them (with correction) marginally reduces the statistical significance. However, the burdensome computation for correcting standard errors for finite clusters and the relative similarities between the two ways make us prefer the simplicity of robust standard errors.

Table A2 1: Coefficients and t-statistics with different clustering methods, all sample.

	(1) Heteroskedasticity- robust	(2) Cluster (district) - wrong	(3) Twoway cluster (hhid and district) with ivreg2 (for non-	(4) Multiway cluster (hhid and district) with cgmreg (for non-	(5) Wild cluster (district) – Few-clusters correction	(6) Wild cluster (hhid and district) – Few-clusters correction

			nested) - wrong	nested) - wrong		
L3.trade_asset^1	-0.614***	-0.614**	-0.614***	-0.614***	-0.614**	-0.614***
	(-4.416)	(-4.575)	(-4.853)	(-4.549)	(-4.575)	(-4.575)
L3.trade_asset^2	-0.534	-0.534	-0.534	-0.534	-0.534	-0.534
	(-0.487)	(-0.411)	(-0.436)	(-0.409)	(-0.411)	(-0.411)
L3.trade_asset^3	4.227	4.227	4.227	4.227	4.227	4.227
	(1.406)	(1.130)	(1.199)	(1.124)	(1.130)	(1.130)
L3.trade_asset^4	-5.246*	-5.246	-5.246	-5.246	-5.246*	-5.246
	(-2.207)	(-1.791)	(-1.900)	(-1.781)	(-1.791)	(-1.791)
N. of observations	3095	3095	3095	3095	3095	3095
Adj. R2	0.282	0.282	0.2	0.291	0.282	0.282

The dependent variable is the asset difference between the last and the first wave. Most controls are three-periods-lagged variables. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, subsamples of wave 1, and the interaction between year and district. "L3.variable" indicates the lagged variable of three periods. The heading over each column reports the type of clustering of standard errors that is applied. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A2 2: Coefficients and t-statistics with different clustering methods, refugees sample.

	(1)	(2)	(3)	(4)	(5)	(6)
	Heteroskedasticity- robust	Cluster (district) - wrong	Twoway cluster (hhid and district) with ivreg2 (for non-nested) - wrong	Multiway cluster (hhid and district) with cgmreg (for non-nested) - wrong	Wild cluster (district) – Few-clusters correction	Wild cluster (hhid and district) – Few-clusters correction
l3trade_asset	-0.828**	-0.828*	-0.828**	-0.828*	-0.828**	-0.828**
	(-2.923)	(-2.452)	(-2.619)	(-2.419)	(-2.452)	(-2.452)
l3trade_asset2	-0.433	-0.433	-0.433	-0.433	-0.433	-0.433
	(-0.083)	(-0.082)	(-0.088)	(-0.081)	(-0.082)	(-0.082)
l3trade_asset3	10.621	10.621	10.621	10.621	10.621	10.621
	(0.318)	(0.367)	(0.392)	(0.362)	(0.367)	(0.367)
l3trade_asset4	-30.42	-30.42	-30.42	-30.42	-30.420	-30.420
	(-0.457)	(-0.593)	(-0.634)	(-0.585)	(-0.593)	(-0.593)
Observations	1410	1410	1410	1410	1410	1410
Adjusted R-squared	0.314	0.314	0.197	0.333	0.314	0.314

The dependent variable is the asset difference between the last and the first wave. Most controls are three-periods-lagged variables. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, subsamples of wave 1, and the interaction between year and district. "L3.variable" indicates the lagged variable of three periods. The heading over each column reports the type of clustering of standard errors that is applied. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A2 3: Coefficients and t-statistics with different clustering methods, hosts sample.

	(1)	(2)	(3)	(4)	(5)	(6)
	Heteroskedasticity- robust	Cluster (district) - wrong	Twoway cluster (hhid and district) with ivreg2 (for non-nested) - wrong	Multiway cluster (hhid and district) with cgmreg (for non-nested) - wrong	Wild cluster (district) – Few-clusters correction	Wild cluster (hhid and district) – Few-clusters correction
l3trade_asset	0.104	0.104	0.104	0.104	0.104	0.104
	(-0.387)	(-0.642)	(-0.684)	(-0.635)	(0.642)	(0.642)

l3trade_asset2	-4.471**	-4.471***	-4.471***	-4.471***	-4.471***	-4.471**
	(-2.529)	(-3.410)	(-3.634)	(-3.371)	(-3.410)	(-3.410)
l3trade_asset3	11.978***	11.978**	11.978***	11.978***	11.978***	11.978**
	(-2.808)	(-3.235)	(-3.448)	(-3.199)	(3.235)	(3.235)
l3trade_asset4	-10.167***	-10.167***	-10.167***	-10.167***	-10.167***	-10.167**
	(-3.213)	(-3.478)	(-3.707)	(-3.438)	(-3.478)	(-3.478)
Observations	1685	1685	1685	1685	1685	1685
Adjusted R-squared	0.288	0.288	0.208	0.304	0.288	0.288

The dependent variable is the asset difference between the last and the first wave. Most controls are three-periods-lagged variables. Controls included are: refugee status, age of the head (and its square), average education level (and its square), female headship, household size (and its square), married head, crop income (dummy), enterprise income (dummy), wage income (dummy), annual formal transfers ($), annual informal transfers ($), borrowed money (dummy), distance from agricultural market, petty trading market, primary school, negative and positive SPEI values, agroecological zones, Covid-19-related shock in the household (any), rural, subsamples of wave 1, and the interaction between year and district. "L3.variable" indicates the lagged variable of three periods. The heading over each column reports the type of clustering of standard errors that is applied. T-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01