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Why do the poor stay poor?
Three essays on asset dynamics and poverty traps

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Abstract

World poverty is a persistent phenomenon despite international efforts and the improvements achieved in the last few decades. For many people it can be a chronic condition. This thesis aims at testing that the main reason some people are poor is due to a poverty trap, i.e., to some contextual mechanisms which limit their ability to escape poverty, reproducing it over time. To investigate this hypothesis, this thesis is guided by three different questions. First, does a poverty trap emerge in the aftermath of an extreme weather shock? Second, do communities in a humanitarian context have the same wealth dynamics? Third, what is the role of income diversification for agricultural households for asset accumulation, and does it depend on their wealth? The analysis focuses (a) on the case of Nigeria and a devastating flood, (b) on refugees and host communities in Uganda and (c) on agricultural households in Tanzania, respectively. Results show that Nigerian flooded households have poverty traps dynamics, condemning the poorest in a destitute state over time. Refugees and host communities in Uganda have similar wealth dynamics but both converge to a low-wealth equilibrium, suggesting a structural poverty trap that worse for refugees. Income diversification in Tanzania shows important nonlinearities according to households' wealth: it fosters the accumulation of durable assets for better-off households only, while helping the poorest to accumulate livestock. These findings shed light on the interaction of low-income conditions and contextual challenges and opportunities, suggesting policy actions able to lift poor people above a wealth threshold, improve their living conditions and favouring their profitability.

Keywords: poverty traps; asset accumulation; climatic shocks; refugees; income diversification

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Introduction

Global efforts in poverty alleviation decreased extreme poverty[1] from 37.1% of the world population in 1990 to 8.4% in 2019 (World Bank, 2023), but, in spite of this achievement, extreme poverty is still affecting 494 million people worldwide[2] (World Bank, 2023). Over the last 10-15 years the decreasing trend in world poverty has been slowing down with an annual poverty rate reduction of less than half a percentage point between 2015 and 2017 compared with one percentage point annually between 1990 and 2015. More recently, under the blows of the great recession, Covid-19 pandemic, the war in Ukraine and the rise in inflation, this trend reversed for the first time in a generation, with a headcount projection of 676.5-656.7 million people[3] in extreme poverty in 2022 (Lakner et al., 2022; Mahler et al., 2022; World Bank, 2023). Furthermore, the process is uneven across different regions, with Sub-Saharan Africa showing the most concerning increase in the number of people in absolute poverty[4] (Mahler et al., 2022; World Bank, 2023). Meanwhile, inequality is dramatically high, with the richest 10% owing 76% of world total wealth and the poorest 50% owning only 2% of total wealth[5] (Chancel et al., 2022). These figures show that poverty remains a stark reality for hundreds of million people and for a non-trivial share of them it is a persistent rather than a transient feature of their life[6]. Therefore, a key question for both policymakers and scholars is why poor people stay poor.

Chronic poverty emerges from a combination of poor endowments, low returns (therefore low ability to translate assets into income) and vulnerability to shocks (Baulch & Hoddinott, 2000). Researchers have emphasized the presence of both drivers (events responsible for pushing households into poverty) and maintainers of chronic poverty (institutions and processes which keep people in poverty) (Chronic Poverty Research Centre, 2005). From a complementary perspective, there are two broad views to explain why people stay poor, i.e., why they have consistently low-earning jobs (Balboni et al., 2021). One emphasizes differences in innate individual characteristics, such as ability, talent, or motivation. An alternative view emphasizes differences in opportunities that stem from access to wealth (Carter & Barrett, 2006). The poverty traps hypothesis embraces the latter explanation, meaning that there might be wealth thresholds below which people are locked in a poverty trap, while people above

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[1] People living below 1.90$ PPP per capita per day.

[2] The latest data available refers to 2019.

[3] These figures are projections based on 2019 data and scenarios about world poverty trends and inequality.

[4] From 271.49 million people (53%) in 1990 to 424.3 million people in 2019 (35%), to an estimated 463.6-460.4 million (according to the scenario) in 2022 (Mahler et al., 2022; World Bank, 2023).

[5] The latest estimates refer to 2021. Indeed, over the past two decades, within-country inequality has increased sharply in the majority of countries, while between-country inequality has decreased (Chancel et al., 2022).

[6] Using synthetic panels, it has been estimated that one third of the population in Africa is chronically poor (Dang & Dabalen, 2019).

the threshold have access to more rewarding opportunities. Indeed, there might be some self-reinforcing mechanisms which make poverty to persist (Azariadis & Stachurski, 2005).

This thesis aims at testing the poverty trap hypothesis in three African countries using household-level panel survey data. The current evidence on poverty traps is mixed and their existence could be limited to specific contexts or subsamples (Kraay & McKenzie, 2014; McKay & Perge, 2013). Nonetheless, there are economic (and noneconomic) reasons why it is worthwhile to improve our understanding of growth processes, poverty dynamics and how these interrelate with current development challenges. Furthermore, finding evidence of a poverty trap has enormous potential for poverty reduction, calling for 'big push' interventions, namely the transfer of resources to those below the threshold (Kraay & McKenzie, 2014). If the transfer is large enough (i.e., able to bring the poor above the threshold), people would be put on a growth path that makes them dynamically non-poor.

This thesis pursues three main objectives. The first one is to provide supporting evidence in different contexts that the causes of persistent poverty are not to be searched among individual traits of the poor but in contextual factors and unequal access to opportunities. If confirmed, this calls for more comprehensive interventions able to remove constraints in accessing different opportunities and fostering social mobility. Moreover, the poverty trap hypothesis, by focusing on asset ownership, provides a forward-looking approach to poverty, which can help in policy design. The second objective is to analyse different settings to test the validity of poverty trap theoretical models. The available evidence is limited and mixed and it is often related to contexts featuring homogeneous livelihoods (e.g., livestock rearing). This thesis aims at expanding this empirical literature by engaging with more complex settings in which wealth can be built through different livelihood pathways. The third objective is to understand the interplay of poverty persistence with exogenous shocks such as climate shocks and displacement and endogenous processes such as income diversification. The first two are some of the most important factors that can impact on individual wellbeing and represent, at the same time, some of the most concerning challenges of our times. Income diversification, on the other hand, has the potentiality of helping smallholder in managing agricultural risk, providing cash flows and eventually lifting people out of poverty but depends crucially on the local opportunities and skill endowments of the poor. Understanding how these processes interact with poverty could prove useful in designing more effective poverty reduction strategies in contexts featuring climate shocks, agricultural risks and/or population displacement.

A short review of the poverty trap literature

Poverty traps are self-reinforcing mechanisms that reproduce poverty and make it persistent (Azariadis and Stachurski, 2005). A poverty trap can be understood as "a critical minimum asset threshold, below which families are unable to successfully educate their children, build up their productive assets, and move ahead economically over time. Below the threshold lie those who are ruined, who can do no better than hang on and who are offered no viable prospects for economic advance over time. Those above the threshold can be expected to productively invest, accumulate, and advance" (Carter et al., 2007, p. 837).

The concept of poverty traps was very popular in development economics in the 1950s and 1960s, with the idea of a "big push" of aid that would give start to a rapid take-off. It recently gained renewed interest but with a different meaning (Easterly, 2006), based on the micro foundations of growth (Barrett et al., 2018). In particular, it entails the study of households' asset accumulation process of social, physical, natural, human, and financial capitals, yet the factors affecting such processes are less clear (Barrett et al., 2018).

A visual representation is given in Figure 0.1, where the x-axis shows the asset level in the starting period and the y-axis shows the asset level in the following period. The 45-degree line represents the case in which asset levels are constant across periods. The two other curves represent the case of convergence (the dotted line) and of the trap (the wiggly S-shaped line). The former portrays the canonical dynamics of wealth, associated to diminishing returns to assets: no matter the initial asset level, it is possible to start a process of accumulation of wealth that eventually pushes everyone along the same growth path (unconditional convergence). When convergence is not observed, in the second case, there can be club convergence or multiple equilibria. The latter is consistent with the concept of poverty traps and the existence of thresholds at which the return on assets is locally increasing (Carter & Barrett, 2006). The initial wealth stock is determinant for the type of dynamic. At the unstable equilibrium $\Lambda(\underline{A}_m)$, asset dynamics bifurcate (Adato et al., 2006): below the threshold, households converge to the low equilibrium poverty trap asset level $\Lambda(A^*_p)$, in which the process of saving little by little is doomed to bring little success. Above the threshold, households can exploit the ascending path and grow up to $\Lambda(A^*_c)$ (Carter & Barrett, 2006).

Figure 0.1: Asset dynamics with and without a poverty trap

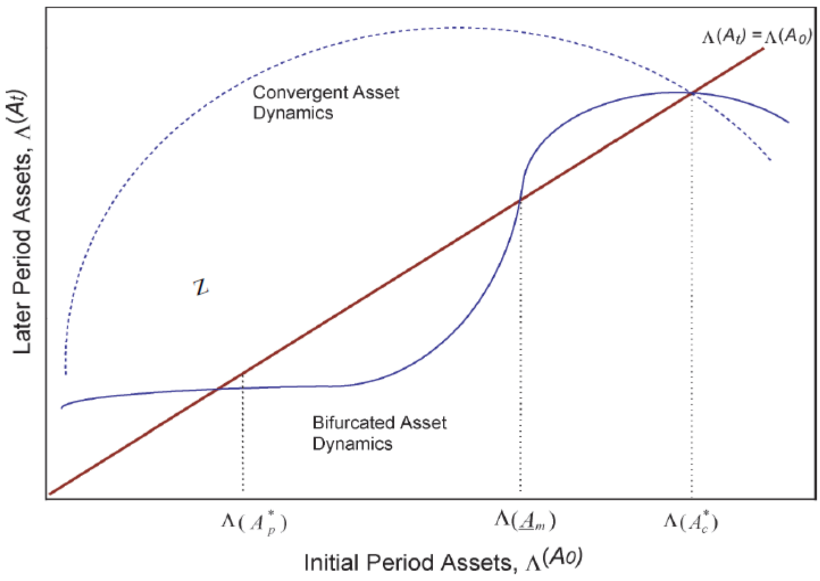

Figure 1. Hypothetical asset dynamics

Source*: Adato et al., 2006*

Poverty traps can emerge when income dynamics are nonlinear and create multiple equilibria (Barrett et al., 2018). This can happen because of some exclusionary mechanisms that trap households at the individual, community or regional levels (Barrett & Carter, 2013). At the individual level, such mechanisms include human capital, savings propensity, discount rates (Carter & Barrett, 2006), risk preferences (Barrett et al., 2018), mental health (Haushofer, 2019; Ridley et al., 2020), poor nutrition and health (Barrett et al., 2018). Other mechanisms relate to households' endowments: natural capital such as land size (Coomes et al., 2011) or poor land quality (Barbier & Hochard, 2019) can trap people in poverty. Community-level mechanisms include social networks, social capital (Chantarat & Barrett, 2013), and kinship sharing rules which reduce the incentives to save and accumulate assets, especially in the presence of locally covariant climatic shocks (di Falco & Bulte, 2011; Di Falco & Bulte, 2013; Hoff & Sen, 2006). Finally, there can be geographic factors (Carter & Barrett, 2006), but also market and institutional failures such as missing capital markets, lack of insurance, and fragile resource governance (Barrett et al., 2018), technological indivisibilities (in the case of complementary assets) and credit constraints (Balboni et al., 2021),

Poverty traps can be found in contexts with one single low-level equilibrium or in contexts where multiple equilibria exist, and in certain circumstances these two contexts can coexist. The first type of poverty trap can occur when there is a binding macro constraint, such as institutions, geography, or technology. This is referred to as structural poverty trap, having the single equilibrium laying below the poverty line (McKay & Perge, 2013; Naschold, 2013). The second type, multiple equilibria poverty trap, can occur when a nonpoor equilibrium coexist with a poor equilibrium; such trap is identifiable by searching for thresholds or tipping points that separate these basins of attraction (Barrett & Carter, 2013). Causes of these multiple-equilibria poverty traps are many. For example, in the presence of a fixed-cost technology, the lack of coordination among agents hinders such investment, even if at the local level social networks can help overcome this problem. At the individual level, multiple equilibria can arise when there is job rationing due to lack of caloric intake, the 'nutrition wage' (Dasgupta, 1997), when the non-tradability of a key input, such as land, disincentivizes investments (Stephens et al., 2012), when some behavioural anomalies exacerbated by poverty and shocks render time horizons shorter (Laajaj, 2017) and when fixed costs can create locally increasing returns to scale but farmers are credit constrained (Barrett & Carter, 2013).

Multiple financial market failures create a trap of this kind. This trap assumes inability to borrow, fixed intrinsic ability and two types of technology. Borrowing and insurance are not feasible, which implies that the endowments correspond to expected assets in the future, and that risk and shocks can have persistence effects. Multiple financial market failures have the behavioural consequence that instead of smoothing consumption, households smooth assets instead (Carter & Lybbert, 2012; Scott, 2019; Zimmerman & Carter, 2003). Additionally, risk taking by risk-averse agents is 'anomalous' when they are close to the threshold[7] (Lybbert et al., 2004).

Empirical studies in this context have found mixed evidence. Cases where poverty traps were found are linked to contexts where wealth can be represented by a livestock index, for example pastoralists in Ethiopia and Kenya. In more structured contexts, methods of aggregation of different assets have been proposed (Adato et al., 2006; Filmer & Pritchett, 2001). Nonetheless, identifying poverty traps is not easy from the methodological and empirical points of view[8]. Cases where poverty traps have not been identified are linked both to the absence of such traps and to data and methodological issues[9]. More recently, the study on poverty traps has coupled with the experimental settings: Balboni et al. (2021) study the impact of transferring livestock (and training) to poor women in Bangladesh while Banerjee et al. (2019) randomize the exposure to microfinance[10] to entrepreneurs in India. Others study randomized index livestock insurance (Cissé & Ikegami, 2016; Noritomo &

[7] They might take additional risk to avoid falling below the threshold (Lybbert et al., 2004).

[8] Poverty traps have been identified in Ethiopia (Carter et al., 2007; Lybbert et al., 2004; Lybbert & Barrett, 2007; Santos & Barrett, 2006), Northern Kenya (Barrett et al., 2006), South Africa (Adato et al., 2006; Carter & Ikegami, 2007; Carter & May, 2001; Woolard & Klasen, 2005), Bangladesh (Balboni et al., 2021), Burkina Faso (Carter & Lybbert, 2012), rural Mozambique (Laajaj, 2017), Honduras (Carter et al., 2007).

[9] Examples of works that do not find poverty traps are based in Pakistan (Naschold, 2013), India (Arunachalam & Shenoy, 2017; Naschold, 2012), rural Nepal (Walelign et al., 2021), rural Bangladesh (Quisumbing & Baulch, 2013), Hungary and Russia (Lokshin & Ravallion, 2001), rural China (Jalan & Ravallion, 2004), Mexico (Antman & McKenzie, 2007), Madagascar (Barrett et al., 2006), nor in a panel of eight countries (McKay & Perge, 2013).

[10] In general, evaluations of microfinance find at best modest impacts, i.e., not able to transform nor break a poverty trap (Banerjee, Karlan, et al., 2015; Meager, 2019). In some cases, it has increased the investments of already existing firms (Banerjee, Duflo, et al., 2015), which six years later persist, while providing an opportunity to talented low-wealth entrepreneurs to escape the poverty trap in India (Banerjee et al., 2019).

Takahashi, 2020), microinsurance (Janzen & Carter, 2019), cash transfer (Haushofer, 2019), and an incentive to migrate (Bryan et al., 2014) as indirect ways of testing for poverty traps.

Poverty traps call for specific policy action. Interventions such as safety nets can have large spillover and multiplier effects in such contexts (Barrett & Carter, 2013). Access to credit, insurance and savings can dissolve poverty traps (Janzen et al., 2021). When there are multiple equilibria, filling the gap to reach the threshold would suffice to propel households on the way out of poverty (big push). However, few studies document a sustained effectiveness of the interventions. Most of the lack of documented exits from 'poverty traps' from big push interventions or multi-scope interventions depend indeed on whether there is a poverty trap or not, on the targeting and the intervention type (multifaceted versus sole transfer)(Bouguen et al., 2019; Buera et al., 2018). For instance, multiple interventions in the spirit of the big push did not produce the expected results in Northern Ghana in the Millennium Village Project (Masset et al., 2020). Microfinance interventions, being more cost-effective, also produced high expectations. In their review on the impact of microfinance interventions, Buera et al. (2018) find no evidence of "large scale miracle escapes from poverty traps" (Buera et al., 2018, p. 190), also due to low takeup rates and heterogeneous responses. Small grants to entrepreneurs in general find increased capital and profits (see for instance de Mel et al., 2012, who find long lasting effects for men only in urban Sri Lanka), while targeting the ultrapoor leads to a shift in income generating activities (Buera et al., 2018), for instance in Banerjee et al., 2021; Haushofer & Shapiro, 2016. Although unconditional cash transfers and grants to entrepreneurs initially seem to have an effect on asset accumulation of the poor, over time the effect fades, with the exception of multiscope interventions[11] (such as Balboni et al., 2021; Bandiera et al., 2017; Banerjee et al., 2016) (Bouguen et al., 2019; Kondylis & Loeser, 2021). Nonetheless, the existence of longer-term evaluations is still scarce.

Overview of the three chapters

This thesis analyses poverty traps by looking at three different domains, namely: the role of an extreme weather event such as a flood that can create a poverty trap among Nigerian households (Chapter 1); the existence of different asset dynamics, and possibly of poverty traps, among host and refugee communities that live close to each other in Uganda (Chapter 2); and the existence of non-linearities in the relationship between income diversification and wealth accumulation among Tanzanian rural households (Chapter 3). The choice of such contexts and topics, while partially due to the availability of high quality and representative panel data, is also motivated by the relevance of these challenges for these countries, striving to ensure growth pathways and decent living conditions to their population.

[11] From the results of 17 RCTS it emerges that increasing the size of cash transfers has no effect on the persistence of the effects, while increasing the scopes of the transfer with complementary interventions can increase the magnitude of the effect and its persistence (Kondylis & Loeser, 2021).

Specifically, the first chapter, “Can weather shocks give rise to a poverty trap? Evidence from Nigeria”, aims at understanding the link between extreme weather events and poverty traps, i.e., whether extreme weather events induce poverty traps. Extreme events, which typically impact the poor disproportionately (Hallegatte et al., 2015), are becoming more frequent with climate change (IPCC, 2014). In particular, in 2012 a devastating flood hit Nigeria, affecting about 7 million people (CRED/UCLouvain, 2023). Once identified flooded and (neighbouring) non-flooded households through MODIS satellite data, it is possible to study their asset dynamics. Indeed, I find evidence of multiple equilibria for flooded households. The extended and prolonged shock affected both poor and non-poor households, but the poor were more severely impacted than the non-poor. On the one hand, a poverty trap emerges for those that before the flood had lower resources and creates the conditions that make poverty persistent. These results hold also after controlling for violent conflict events and other climatic shocks. On the other hand, non-poor flooded households are able to recover after the shock and converge to a higher equilibrium. Conversely, poor and non-poor non-flooded households living in proximity of the flooded households show convex dynamics and converge to only one high level equilibrium. Unfortunately, it was not possible to rule out that a poverty trap already existed among the households that suffered from the flood, as the survey collected only one wave before the shock. Moreover, to track their dynamics in the medium run, the sample size substantially reduces, and further subsample analyses with the available panel dataset are unfeasible. Nonetheless, it was possible to show that a poverty trap affects especially those that were flooded in 2012 living close to rivers that are the ones for whom the 2012 flood was most likely not their first flood. Vice versa, “first-time” hit households should be able to revert to their growth after the shock. This result sheds light on the location choices of households and might call for an immobility/geographical poverty trap (Jalan & Ravallion, 2002; Kraay & McKenzie, 2014; Nawrotzki & DeWaard, 2018).

The second chapter, “Poverty dynamics and poverty traps among refugee and host communities in Uganda”, co-authored with Prof. Romano, tests whether a poverty trap exists among poor host and refugee communities that live in proximity and can trade with each other. The research questions ask whether the wealth dynamics of refugees and hosts differ, and whether and for whom a poverty trap exists. The context of analysis is Uganda, which hosts 1.5 million refugees from neighbouring countries (Atamanov et al., 2021; UNHCR, 2022). They are hosted in settlements but to facilitate their self-reliance they are given land to farm and working rights (d’Errico et al., 2022). Refugees are at risk of falling into a poverty trap because of their specific vulnerabilities (asset loss, social capital disruption, psychological stress and trauma, forgone investments in human capital) (Jacobsen, 2012; Moya & Carter, 2019; World Bank, 2017). The massive influx of refugees and the setting up of large settlements constitute a shock on the (poor) local population and markets, presenting both challenges and opportunities (Maystadt et al., 2019; Verme & Schuettler, 2021). The analysis was possible given a unique panel dataset that surveys refugees living in settlements and hosts living close by. Results show evidence of widespread deprivation for both refugee and host communities. A worse picture emerges for refugees, who, despite international assistance supporting their basic needs, have poorer prospects. Asset dynamics show a convergent path with only one low-level equilibrium if refugees and hosts population are pooled together. However, if the two groups are analysed separately, each of them still converges to its own single low equilibrium that is lower for refugees than for hosts. This is consistent with the hypothesis of a structural poverty trap (Carter & May, 2001; McKay & Perge, 2013; Naschold, 2013). Heterogeneity is found in the initial conditions and in the factors affecting asset growth. Finally, the importance of social cohesion and social well-being for wealth accumulation is tested, finding contrasting results for the two communities. Given the fragility of the context, panel attrition is high. We test the correlations with the probability of attrition and provide two corrections for it showing that results remain valid. Despite the richness of the data and the relatively high sample size across the panel four waves, the main limitation of this chapter is its short time coverage spanning only from 2017-19 to 2021. Indeed, for poverty traps detection, a longer time coverage is desirable. In order to overcome this limitation, several robustness checks have been adopted, including employing an asset index that is more sensitive to changes in the short-medium run and testing different panel lengths. In both cases the results are very similar to the original results.

The third chapter, "Diversification across thresholds: Evidence from rural households in Tanzania", is co-authored with Prof. Romano, Dr. Scognamillo and Prof. Kraehnert. It focuses on the role of income diversification for the wealth accumulation of Tanzanian rural and agricultural households, explicitly modelling the presence of nonlinearities. Agricultural households diversify their sources of income mainly to reduce their exposure to agricultural risk and to escape poverty (Arslan et al., 2018; Gao & Mills, 2018; Tankari, 2020). However, the most rewarding activities to diversify are typically hardly accessible to the poorest, who might instead be forced to diversify with lower-quality non-farm activities (Bandiera et al., 2017; Barrett, Reardon, et al., 2001; Drall & Mandal, 2021; Niehof, 2004). This has implications for their asset investments and hence in their prospects. Indeed, the empirical evidence about the relationship between income diversification and wealth is mixed (Asfaw et al., 2019; Barrett, Bezuneh, et al., 2001; Ellis & Freeman, 2004; Reardon et al., 2006). We focus the analysis on Tanzania, where a fast structural transformation process is unfolding, and income diversification is widespread across the wealth distribution. The research questions of this chapter ask for whom income diversification is beneficial and how income diversification shapes households' ability to respond to shocks. A threshold model is used to identify structural breaks in the relationship between income diversification and asset growth (d'Errico et al., 2019; Hansen, 2000; Letta et al., 2018). We find that the role of income diversification is indeed heterogenous across the wealth distribution as well as across livelihoods. For richer households, more diversification is associated with higher durable assets growth, while for poorer households, diversification does not correlate with asset growth (Dercon & Krishnan, 1996; Dimova et al., 2021; Ellis & Mdoe, 2003). Conversely, for agricultural assets more diversification is associated with lower asset growth (especially livestock), while livestock-poor households accumulate more livestock the more they diversify (Ellis & Freeman, 2004; Hertz, 2009). These results hold also in the presence of climatic shocks, when income diversification partially offsets the negative impact of the shock. The main implication is that households diversify in a different way along the wealth distribution and, given the heterogeneity of these activities, this has consequences for their prospects. Although the paper does not aim at establishing a causal relationship, endogeneity is reduced by exploiting the lags of diversification and of asset thresholds. The remaining issue is the reduced size of the balanced long panel households (only 808 observations per wave because the panel was partially refreshed in wave 4 and only a subsample of the original panel can be tracked in wave 4 and wave 5). Yet by focusing only on the first three waves of the panel, the results are the same.

Concluding remarks

There are some difficulties in testing poverty traps empirically: first, long panel datasets are required, which usually imply a smaller sample. Second, to explore the entire distribution of wealth it is necessary to have a large enough sample, but it is likely that around the threshold, few observations are found, limiting the ability of the functions to properly describe wealth dynamics. Third, the state-of-the-art methods to test for poverty traps rely on a series of assumptions which need to hold but cannot be easily tested, such as that an asset index is able to represent household's wealth or that the cross-sectional variation can predict households' common path over time. Therefore, it is often required to use different methods in combination to overcome specific methods' drawbacks. Fourth, these methods cannot provide a causal interpretation of the drivers of poverty persistence but are aimed at describing the mechanisms at work that trap people in poverty. Fifth, as the analysis is carried out at the household level, inequalities among individuals, which can be substantial, risk being overlooked.

Another difficulty comes from the definition of the asset index(es). Asset indexes can proxy households' long term average income (Naveed et al., 2021) or a permanent income latent variable (Howe et al., 2008), but also cover the multiple dimensions of households' resources [12] (Adato et al., 2006; Sahn & Stifel, 2003). Asset indexes are more stable over time and reflect to a lesser extent small fluctuations in the income and the impact of shocks. To compute wealth indexes, we mainly rely on principal component analysis (PCA) and extract the first component following DHS wealth index procedure (Filmer & Pritchett, 2001; Rutstein, 2015). On the one hand, this approach lacks a monetary basis that makes its interpretation more difficult. On the other hand, it provides a measure of wellbeing in a relative way, and can also be used to measure inequality (McKenzie, 2005). Despite two decades of

[12] Aggregating assets in an index instead of focusing on single assets ownership is meaningful also because what matters for households' wellbeing is owning a set of assets in their variety (Vollmer & Alkire, 2022). Furthermore, asset indexes are used extensively in multidimensional poverty analysis also at the global level (Vollmer & Alkire, 2022).

discussion[13] over possible alternatives[14], PCA is still largely used for several reasons. In fact, it is computationally simple and works well with binary as well as continuous variables (while categorical variables need to be transformed into binary variables). Moreover, being an asset index, it does not pose as much measurement problems, such as seasonality, recall bias, measurement error, as monetary measures usually do (Cardozo Silva & Grosse, 2010).

Which assets might be more relevant for households' wellbeing and their accumulation process is not irrelevant and can influence the final result (Howe et al., 2008). In this thesis, the composition of the asset indexes varies across the three chapters according to the specific objectives: in the first chapter, it is centred on physical objects, tools, dwelling materials and livestock which can all be destroyed, lost, damaged and killed by a flood. In the second chapter, the core assets are only physical and tradable assets, in order to capture as many movements in assets as possible in a short window of time. In the third chapter, different types of asset indexes are created based on the possible different livelihoods. This serves to shed light on different scopes of income diversification and different combinations of households' resources.

These methodological challenges are addressed in this thesis, when possible. For instance, the focus is on countries for which at least four waves of panel data are available, covering 9, 5 and 12 years, respectively. Moreover, the availability of a large number of waves provides a control on the quality of data – reducing the risk of measurement errors and helping in running the analysis over different time intervals as a robustness check. Small sample size is the price paid, especially for the countries in which the panel is refreshed, but additional checks make sure that the results are consistent with the shorter and longer panel. This is particularly important for observing the whole range of the distribution of wealth.

This thesis finds evidence of contextual and geographical factors that can explain the persistence of poverty among heterogeneous households[15] (such as climatic shocks, displacement, lack of opportunities, inequality in starting conditions, etc.). Secondly, the thesis tests the theoretical models of poverty traps and extends the available empirical evidence to countries and contexts which had not been previously studied adopting this approach: Nigeria, Uganda and Tanzania. These countries, despite their fast-growing economy, have large shares of their population in poverty. The results find S-shaped dynamics among flooded households in Nigeria, a structural poverty trap among refugee and hosting

[13] For instance, PCA approach has been criticized for the weighting used especially with binary data (Naveed et al., 2021; Vyas & Kumaranayake, 2006), although this seems to be a minor concern (Howe et al., 2008).

[14] For instance, MCA, i.e., multiple correspondence analysis, exploratory factor analysis of the tetrachoric PCA (Naveed et al., 2021), factor analysis (Sahn & Stifel, 2003).

[15] This does not exclude that individual characteristics still play an important role. Individual traits might just make things worse in the case of adverse contextual factors and different opportunities. However, stressing the inequality in accessing the same opportunities provides the basis for a different kind of policies.

communities in Uganda and non-linear growth dynamics that are highly interrelated with income diversification and wealth in Tanzania.

Thirdly, this thesis provides evidence of poverty persistence in relationship with exogenous shocks and with more endogenous factors which shape their ability to escape poverty. In particular, it finds that extreme weather events can be linked with persistent states of destitution for the poorest and poverty traps can emerge. This is particularly important as climate extreme events are becoming more frequent with climate change. Secondly, analysing the wealth dynamics of refugees after their displacement and the dynamics of the hosting populations shows the importance of factors linked with faster asset accumulation. In particular, refugees, despite the aid support received, converge to lower asset levels than hosts, signalling that asset losses can have long-term consequences. Finally, analysing household wealth dynamics in relation to the income diversification strategy shows how the dynamics of different assets are shaped by income diversification and previous wealth. Income diversification is indeed a way in which households can accumulate assets faster, but only if their asset basis is larger than some thresholds. As agricultural households increasingly diversify away from farm activities in the Global South, understanding barriers to income diversification and to asset growth is crucial for smoothing this transition and favour exits from poverty.

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Chapter 1 - Can weather shocks give rise to a poverty trap? Evidence from Nigeria*

Giulia Malevolti

Abstract

As extreme weather events are becoming more frequent, the chronic poor, being overly exposed to these shocks, risk suffering the highest price. The 2012 flood in Nigeria was the worst in 40 years and hit more than 3 million people. Using nationally representative panel data, I study households' asset dynamics for the period 2010-2019. I find that households hit by the flood converge to multiple equilibria consistent with the poverty trap hypothesis. In particular, households whose assets fell below the threshold converge to a low-level equilibrium point, whereas better endowed households converge to a high steady state. This is consistent across several empirical methods, ranging from parametric to non-parametric methods, as well as panel threshold estimation. Robustness checks further examine the validity of the findings, testing different asset indexes and flood definitions, as well as controlling for conflict-related events and other climatic shocks. Identifying a poverty trap is crucially helpful for designing poverty alleviation policies and fostering a country's development.

Keywords: poverty traps; flood; climate shocks; asset poverty; Nigeria; poverty

JEL classification: D31, I32, O12, Q54

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1.1 Introduction

Currently, 494 million people live under the extreme poverty line of 1.90$ per capita per day[16]. Their situation is further aggravated by climate change which brings about slow alterations as well as more frequent extreme climate events (heat waves, droughts, floods, cyclones, and wildfires)[17]. The poor are typically more vulnerable to such events because as their buffer stocks and savings are insufficient for consumption smoothing[18]. The poor tend to be among the most hit groups by weather shocks[19]. Moreover, low-income countries are expected to bear most of the burden of climate change's negative impact, due to the greater reliance on natural processes – agriculture in the first place – and their constraints in adaptation and responsive capacity (Abeygunawardena et al., 2009). The poor in Africa are disproportionately exposed to both drought and flood (Winsemius et al., 2018). Not only do these shocks affect places unevenly, but also their impact is heterogeneous across regions, as the vulnerability of each place depends also on non-climatic factors, i.e. social, economic, cultural, political, and institutional factors[20] (IPCC, 2014).

As climate change is bringing about more frequent extreme weather events, too little is known about the relationship between climate shocks and poverty persistence. Can these shocks trap people in poverty? Can negative effects following large weather shocks be permanent if people have few assets? This issue is urgent also because as climatic shocks hit whole communities simultaneously, traditional and informal insurance mechanisms fail at protecting the poorest. The aim of this chapter is to study the relationship of climate shocks and poverty persistence within the framework of poverty traps.

The poverty traps approach has been used in many poor contexts yielding mixed results. However, the way poverty traps interact with climatic shocks is not well understood nor sufficiently explored. The available evidence on climate-induced poverty traps is mixed so far (Carter et al., 2007; Jakobsen, 2012; van den Berg, 2010). The main contribution on the link between poverty traps and weather shocks is from Carter et al. (2007), which find some evidence of poverty traps following a hurricane in Honduras and a drought in Ethiopia. Other papers studying the effects of the Hurricane

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[16] https://pip.worldbank.org/home [accessed on 9 January 2023]

[17] For Africa in particular, climate change projections warn that extreme events will become more frequent, desertification will advance due to changes in rainfall and land use intensification, grain yields will suffer, the sea level will rise, and there will be larger variations in river water availability (Abeygunawardena et al., 2009).

[18] Their higher vulnerability is also due to the fact that poor people live in places that generally are very vulnerable on the geographical, environmental, socioeconomic, institutional and political basis (Abeygunawardena et al., 2009). They generally know less about climate change and adaptation practices (Dercon et al., 2005), have access to less efficient early warning, infrastructure, technology, response systems and recovery assistance and can rely on scarcer economic resources and safety nets (McGuigan et al., 2002). Moreover, they live in fragile buildings (McGuigan et al., 2002), have all their assets in physical form (Winsemius et al., 2018) and gain large parts of their income from agricultural production, also vulnerable.

[19] For instance, in Viet Nam (De Laubier-Longuet Marx et al., 2019), in Zambia (Ngoma et al., 2019), in rural Nigeria (Amare et al., 2018), just to mention a few.

[20] Policies and interventions aimed at reducing vulnerability and improving adaptation capacity should include the poor as main target (Abeygunawardena et al., 2009). However, given the poor's limited weight on the state's national accounts, significant losses due to climate change risk being invisible (Hallegatte et al., 2018).

Mitch on poverty persistence, asset losses and livelihoods shift find mixed results (Carter et al., 2007; Jakobsen, 2012; van den Berg, 2010). Other important contributions to this literature have explored asset dynamics in relation to a drought and the coping strategies adopted (Giesbert and Schindler, 2012; Scott, 2019).

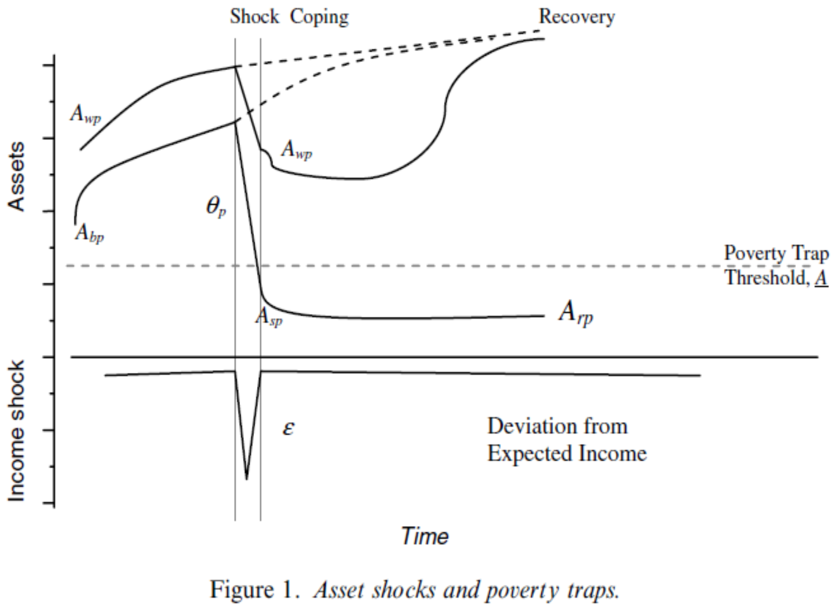
One representation of the consequences of an extreme weather shock for assets and poverty can be seen in Figure 1.1. Climate shocks such as floods directly destroy assets, kill livestock, ruin harvest, while indirectly, they exacerbate the impact of other hazards (IPCC, 2014), acting as a threat multiplier and making poverty eradication efforts harder (Hallegatte et al., 2015). Indirect effects include spikes in food prices, augmented food insecurity (IPCC, 2014), political instability and conflict[21] (Dercon et al., 2005). Climate shocks affect people's physical and mental health (Hallegatte et al., 2018), aspirations (Kosec and Mo, 2017), non-cognitive skills (Mehra et al., 2022) and risk behaviour[22]. Moreover, the poor, lacking social protection, have to deal with uninsured risk, which affects *ex-ante* the type of investments that are carried out, including human capital investment (Elbers et al., 2007; Hallegatte et al., 2018). Finally, extreme events can shift households into low-rewarding livelihoods, compromising their earning capacity (van den Berg, 2010).

In Figure 1.1, as the shock hits, the household with initial lower asset levels (A_{bp}) falls below the threshold and enters the poverty trap. Conversely, the better-off household which also suffers from the shock is able to avoid the same fate, even though recovery is a long process. The length of recovery can depend on the choice and availability of coping strategies. Indeed, certain coping strategies further limit the household's future responsive capacity and make poverty and the impact of negative shocks persistent (Jalan and Ravallion, 2004). For instance, diversification and risk-coping strategies are costly, as households cannot benefit from specialization gains (Elbers et al., 2007). Other strategies, such as withdrawing children from school, selling assets, reducing consumption, doing criminal activities (Barrett et al., 2007), and reducing health expenses can have permanent dramatic consequences (Hallegatte et al., 2020).

[21] For instance conflicts among farmers and herders, also in Nigeria (Eberle et al., 2020).

[22] Cyclone-affected households in Bangladesh are more risk-loving and more committed in risk-sharing mechanisms than non-affected households (Islam et al., 2020).

Figure 1.1 Asset shocks that can result in poverty traps.



Source: Carter et al., (2007, p. 837)

To enhance our understanding of poverty persistence in case of climate shocks, the research questions of this paper ask the following: Whether and to what extent do extreme weather events induce poverty traps? How does the coping strategy choice affect post-shock recovery?

In order to answer my research questions, I focus on the case of Nigeria. Nigeria is the most populous country in Africa as well as the largest economy in the continent. The country is the ideal context to study poverty dynamics and how they relate to weather shocks for two main reasons. First, the country's share of population living with less than 1.90$ per day was 53.5% in 2010 (World Bank, 2022), or 62.6% according to the national estimate (National Bureau of Statistics of Nigeria, 2020, 2012). About 12% of the population is chronically poor (Dang and Dabalen, 2019). Moreover, in recent years researchers have documented raising poverty, inequality[23] and polarization (Clementi et al., 2017, 2016; Eigbiremolen, 2018; Jaiyeola and Bayat, 2020; World Bank, 2016). Poverty rates have been very high despite sustained GDP growth[24]. To explain the paradox of strong economic growth and stable high poverty rates, factors blamed are jobless growth, wide inequalities (also gender disparities), poor governance and corruption, scarce social services expenditure, overconcentration on the oil sector and environmental degradation, conflicts and violence (Dauda, 2019, 2017). Referring to Niger Delta region,

[23] Others document a decrease in consumption inequality (led by expenditure in durable goods) and a sharp rise in poverty incidence and severity (Odozi and Oyelere, 2022).

[24] GDP growth rates ranged between 5% and 9% annually in the period 2004-2014, while more recently there has been a slowdown (World Bank, 2022).

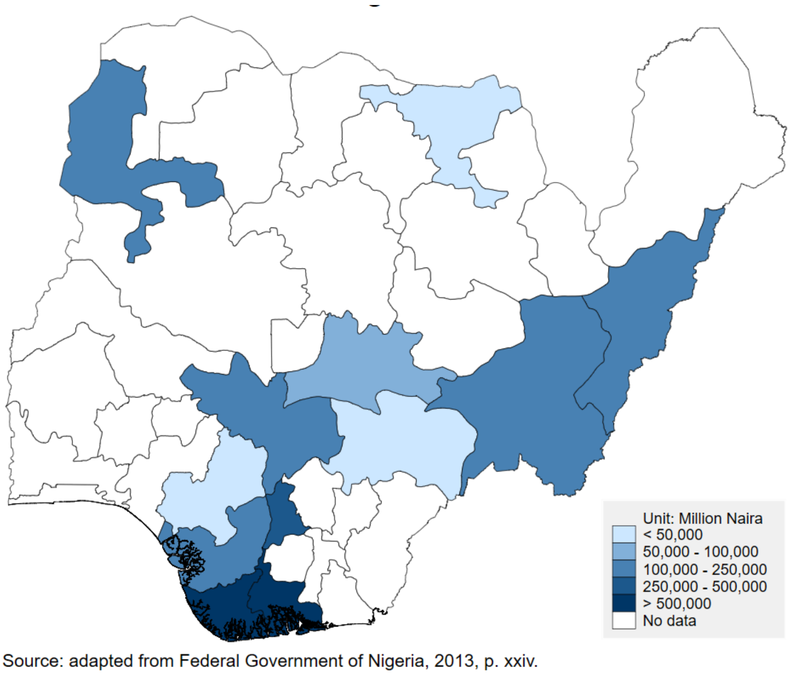
the existence of a poverty trap could be due to fast population growth and loss of capabilities, bad governance and corruption, bad transportation and oil extraction (Ibaba and Ebiede, 2010).

The second reason is that the country has the highest exposure to floods in sub-Saharan Africa (Najibi and Devineni, 2018). From 2000 to 2022, 57 events were registered among which 49 were floods, affecting (at median) 5000 people (CRED/UCLouvain, 2023). The most severe floods occurred in 2010 (affecting 1.5 million people), 2012 (affecting 7 million people), 2018 (affecting 1.9 million people) and 2022 (affecting 2.8 million people) (CRED/UCLouvain, 2023). Moreover, the vulnerability to climate shocks of the population comes from the large share of the population employed in agriculture, 41% in 2010 and 35% in 2019 (World Bank, 2022) and the high poverty rates. As agriculture is mainly rain-fed, the relationship between rainfall variability and food poverty becomes crucial. In Nigeria, there is a strong link between rainfall variability and food poverty (Olayide and Alabi, 2018). Rainfall shocks affect deeply agricultural productivity, increasing its variability and in turn decreasing household consumption significantly. This impacts also inequality (Amare et al., 2021).

In 2012, Nigeria experienced severe flooding which was defined the worst flood in 40 years. Heavy rains started in July made rivers overflow (Federal Government of Nigeria, 2013) and caused dams failure upstream Nigerian borders. The Benue and Niger Rivers, the main rivers of the country, flooded over their banks, destroying lives, crops, roads, and buildings. The flood killed 363 people, injuring 5,851 people and displacing 3.8 million people[25]. The estimated overall damage and losses of the flood in the 12 most affected states are estimated to total US$ 16.9 billion, a 1.4% impact on GDP (Federal Government of Nigeria, 2013). The floods hit low-laying areas rich in agricultural and natural resources, hence highly populated (Ojigi et al., 2013). The most affected sectors were housing, followed by agriculture, commerce, oil production, education, manufacture, environment, transport and health. The greatest damages and losses were concentrated in the states of Bayelsa, Rivers and Anambra (in the delta of the river) (see Figure 1.2).

[25] Despite the damages to dwellings, displacement was a temporary phenomenon (Federal Government of Nigeria, 2013). For panel attrition see Section 2.

Figure 1.2 Total damage and losses of the flood



Source: adapted from Federal Government of Nigeria, 2013, p. xxiv. Damage refers to the estimated replacement value of the physical assets that were destroyed, losses refer to the changes in the flows of goods and services in the economy such as production reductions and expenditure increases. These calculations refer to the 12 most affected states only.

Floods undermine transportation, drinking water and power supply, the availability of food and fuels and represent a direct income loss for daily labourers. Moreover, they bring about scarcer hygienic conditions, diseases as malaria, diarrhoea, viral fever (Hallegatte et al., 2020). Floods impact negatively household expenditure and food consumption, while pushing up extreme poverty rates (Azzarri and Signorelli, 2020) and slowing down growth, at least in the short term[26] (Hallegatte et al., 2020).

This paper contributes mainly to three strands of the literature: the empirical literature that tests for poverty traps, the literature on how climate shocks can have permanent effects on poverty and the literature on the migration-climate nexus. In the first case, it extends available empirical evidence on poverty traps to the case of Nigeria, so far neglected by this literature[27] despite its high and persistent poverty rates. Contrary to most of previous analysis on poverty traps based on pastoralist communities, the case of Nigeria is rather challenging. Asset endowments cannot simply be represented by livestock indexes but need to combine different assets' ownership to better represent wealth. For this reason, I compute a composite asset index combining information on a series of physical assets, among which durables, tools, livestock. Using a nationally representative panel dataset, I am able to follow households over a decade from 2010 top 2019. I identify flooded households and neighbouring non-flooded

[26] Floods, when not severe, are found to produce some positive effects on growth (Loayza et al., 2012) and on women's empowerment (Canessa and Giannelli, 2021).

[27] The only example (that I am aware of) of poverty traps analysis in Nigeria is by Janz et al. (2022). However, instead of asset-based measures, they use a consumption-based measure and focus their analysis on urban areas only. They find no evidence of poverty traps as the poor are able to improve their position over time.

households through satellite data and test the poverty traps hypothesis. As studying whether poverty traps exist is empirically demanding (McKay and Perge, 2013), I apply several methods following the literature: (i) non-parametric and parametric regressions, (ii) convergence and post-shock growth models, (iii) a panel threshold model. This study departs from a classical poverty trap analysis by pivoting on the aftermath of a severe climatic shock. The flood, being a one-time extreme asset loss event, is assumed to let affected households revert to their growth potential, absent any frictions. However, if a poverty trap exists, this could permanently affect the growth potential of these households, by trapping some of them into poverty. This would not necessarily shift the asset transition curve but would create an additional equilibrium.

Secondly, this paper expands the evidence of medium/long term effects of climate shocks for poor people. Some shocks are found to have long-lasting effect (for example in Ethiopia, Dercon et al., 2005), by bringing households below the poverty line, depleting their wealth stock and impeding the asset accumulation process (Carter et al., 2007). Indeed, climate shocks may worsen structural poverty (Ngoma et al., 2019), creating and worsening poverty traps. "Poverty traps may be created at a regional scale under circumstances where destruction of assets from extreme events and diversion of resources toward costly adaptation measures such as coastal defence structures permanently reduces economic output in affected regions" (Leichenko and Silva, 2014, p. 547). Theoretical works at the macro level show how after a disaster there can be a poverty trap if the intensity and the frequency of extreme events is above a certain threshold, also due to low reconstruction capacity (Hallegatte et al., 2007; Hallegatte and Dumas, 2009).

Indeed, this paper shows that poor flooded households are trapped in poverty. Non-parametric results show non-linear dynamics: while non-flooded households converge to one high equilibrium, flooded households converge to (at least) two equilibria, indicating a separation in the regimes of accumulation and indicating a poverty trap. Indeed, one of the two stable equilibria corresponds to very low levels of wealth. Parametric results confirm the existence of such non-linearities. I also find, in accordance with the previous results, that households that suffered the flood hazard differ in their growth dynamics depending on the initial asset holdings. All these findings provide empirical evidence of a poverty trap for poor flooded households.

Households' asset growth after the shock also depends on the choice and availability of coping strategies, both ex-ante and ex-post. I contribute to the literature on coping strategies by incorporating ex-ante and ex-post strategies in the regressions for flooded households. Receiving remittances after the shock is the only significant and positive correlate of asset growth. Moreover, flooded households with wage employment and remittances/migration do not enter the poverty trap.

Additionally, I control for a possible confounding effect of conflicts and other climatic shock, which also might affect asset accumulation: results hold. I check the sensitivity of the results to the definition of the flooded areas, by varying the distances from the coordinate points and increasing the time coverage. Results are stronger when the definition is stricter and weaker when the definition is loosened, signalling that the effect of the flood is mostly localized to the flooded areas.

Finally, by shedding light on a possible immobility/environmentally-induced poverty trap (Quiñones et al., 2021), I also contribute (marginally) to the fast-growing literature on climate shocks and migration, in particular to its absence: the case of immobility because of extreme poverty. For example, geographically disadvantaged areas in Zambia show little or no migration (Nawrotzki and DeWaard, 2018). While climatic shocks affect people's mobility, increasing forced migrations (Conigliani et al., 2021; Di Falco et al., 2022), climate shocks can also trap people that are too poor to migrate. Climate-related hazards can indeed prevent voluntary migration, trapping vulnerable communities in immobility, by reducing their liquidity (Letta et al., 2022; Marchetta et al., 2021). For instance, in Nigeria, at high temperatures and precipitations it is estimated that households reduce their migration and remain trapped (Cattaneo and Massetti, 2015). In this case, immobility is the consequence of an adaptation failure (Letta et al., 2022). Indeed, pre-shock density functions of the asset index presented two peaks, suggesting multiple equilibria before the flood (indications of possible poverty traps). Further investigating the intersection of those flooded in 2012 and those that live close to water (which most likely have suffered from flooded in the past) shows that they are the ones driving the poverty trap result, suggesting an immobility trap. Conversely, 'first-time' hit households show convergent dynamics. Unfortunately, it is not possible to inspect these subsamples as the size excessively reduces. Moreover, I cannot completely rule out the hypothesis that flooded households were already in a poverty trap, as the survey only has one pre-shock wave and to observe dynamics one needs two points in time.

This paper is structured as follows: the next Section 2 presents the dataset and discusses the approach used to measure the flood extent, Section 3 presents the methodological approaches used, Section 4 presents summary statistics, and Section 5 describes the results. Section 6 tests the validity of these results with robustness checks, while Section 7 extends the result with the threshold model and the coping strategies analysis. Finally, Section 8 concludes with some policy recommendations.

1.2 The data

This analysis is based on the General Household Survey (GHS) panel data, part of the Living Standard Measurement Survey - Integrated Survey on Agriculture (LSMS-ISA) project. Data was collected in four waves, 2010-11, 2012-13, 2015-16, 2018-19 and is representative at the national level and at the zonal level, for rural and urban areas. Enumerators visited households twice per wave (post-planting and post-harvest visits) and asked questions on a large range of topics, among which agricultural production, employment, food security, shocks, coping strategies, asset ownership, and so on. The sample was designed with a two-stage probability sample: 500 primary sampling units - the

Enumeration Areas (EAs) - were selected based on the probability proportional to the size of the EA. In each of these, 10 households were randomly chosen. Due to nonresponse, slightly less than 5,000 households (4,851 with 27,993 household members) were interviewed. During waves 2 and 3, households were interviewed again and tracked when possible. Households lost because of attrition were between 200 and 300 each wave, although some households that were not interviewed during wave 2 were found again in wave 3. Due to security reasons, households in the North-East zone were not visited. Overall attrition was around 8.3% mainly in North-East and South-West zones. During wave 4, the sample was partly refreshed: only a subsample of 1,490 households was maintained to be part of the long panel, keeping its representativeness. Of these, 1,425 were successfully interviewed in both visits. The new households added to the sample to refreshen it are dropped as they have no previous observation. Attrition totalled 10.4%. Nonetheless, attrition was not related to the flood of 2012[28].

1.2.1 Flood measurement

The peak of the flood occurred during the first visit of the second wave of the survey (Table 1.1). The flooding started from the early September and was 'visible' until the first days of November. It is therefore possible to study immediate and short run effects of the shock for the majority of households, while for a small subsample, also longer-term effects are observable (the panel component of wave 4).

Table 1.1 Timeline of panel waves and the shock

First wave	Flood	Second wave	Third wave	Fourth wave
Sep 2010 - mar 2011	Sep - Oct 2012	Sep 2012 - Mar 2013	Aug 2015 - Feb 2016	Jul 2018 - Jan 2019

Source: own elaboration.

Satellite data was downloaded for the period 11 September - 3 November from the NASA's MODIS NRT (near real time) Floodmap website[29], which provides elaborations of two or more days of observations (Figure A1). The instrument MODIS (Moderate Resolution Imaging Spectroradiometer), which operates on the satellites Terra and Aqua, captures medium-low (250m) resolution images of the terrain twice a day for the whole world (a snapshot of the flood on 13th of October is in Figure A2). The NRT products are elaborations which analyse colours from combined MODIS bands 1, 2, and 7 applying the Dartmouth Flood Observatory algorithm. This also contain a terrain shadow correction[30]. MODIS' released products for the period of interest are 2-days products. Compared to data from one single observation, these can give a first remedy to issues of cloud coverage[31], which during a flood is plausibly thick. Products of 3 or 14 days are more effective because they include observations for a longer period

[28] No household belonging to the flooded sample dropped from the panel in wave 2. Only using the largest possible definition (buffer of 10km) we have 12 households that could not be traced in 2012 but were followed afterwards. A probit on the probability of attrition found no significant correlation of flood (10km) nor assets. Looking at attrition from wave 1 to wave 3, attrition was 3.17% flooded and 8.66% for non-flooded (rural-urban definition), the attrition probit finds that flooded households are less likely to drop from the panel.

[29] https://floodmap.modaps.eosdis.nasa.gov/ [accessed before 2022; since then, the website has been revisited].

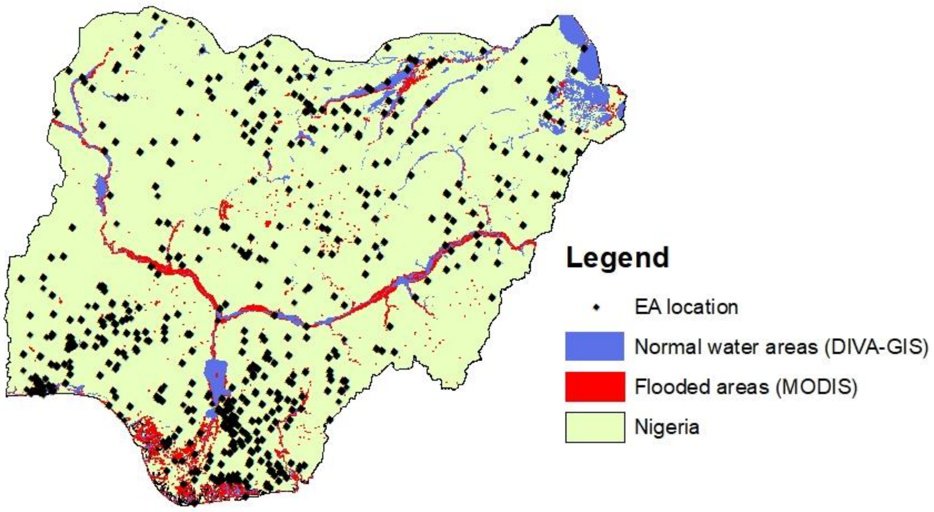
[30] More recent MODIS products also incorporate a cloud shadow masking (Nigro et al., 2014).

[31] SAR (synthetic aperture radar) images would overcome this issue but unfortunately there was no operational SAR mission in 2012.

and better able to capture the whole extensions of the flooded areas (Nigro et al., 2014). Given the location and period constraints, MODIS flood data is the best option available for studying flood extension[32]. Since for the period of interest only products of two days were available, a flooded area variable was created putting together the information of the entire period's 2-days products, mimicking what the longer-period products do. I then united those layers to show the maximum extension of flooded area.

Households' enumeration areas were plotted in the map, and a 2, 5 and 10 km buffer was constructed around them. I then build a rural-urban buffer, which has a radius of 2 km in urban areas and 5 km in rural areas[33]. The variable that was constructed takes the value of one if the area around the village intersects some inundated pixel, zero otherwise. Flooded households, according to this variable, are 793 (17.4%). Figure 1.3 represents Nigeria's map with the identified flooded areas in red and the usual water extent in blue. EAs' location is indicated by the diamonds. Flooded areas are predominantly rural.

Figure 1.3: Nigeria map with inundated areas in red and normal water in blue.



Source: own elaboration with MODIS NRT data and inland water of DIVA-GIS (*https://diva-gis.org/datadown*)

[32] Studies working on different periods and locations, hence enjoying different sources of satellite images, consider MODIS as a good approximation (Lin et al., 2019). For example, Ekeu-wei and Blackburn (2020) use this data to validate their hydrodynamic model in Nigeria, or Silas et al., (2019) to make useful comparisons. For a general overview see: Fayne et al. (2017); Notti et al. (2018); Revilla-Romero et al. (2015). Among the advantages of MODIS NRT are its free access, the frequency of observation, the extent of their coverage, and the ability to allow early notice (Revilla-Romero et al., 2015). Among the disadvantages, it is necessary to mention that they are produced with a seasonally static indication of reference water. Moreover, they do not perform at best in the identification of inundated vegetation, extreme terrain and volcanic material (overestimate). Their resolution appears – especially if compared to more recent satellites as Landsat/EO-1 – quite 'blocky' (Nigro et al., 2014).

[33] This is done to accommodate the fact that EA coordinates provided in the dataset are modified for confidentiality reasons by a random offset for urban areas in the range of 0-2 km and for rural areas in the range 0-5 km. As robustness check, I then evaluate different buffer sizes (see Section 6.1).

1.3. Methodology

Testing empirically for a poverty trap is no easy task[34]. In the literature, different methods have been used for identifying poverty traps. The most common way is to measure the development of wealth over time, modelling the relationship of current and past asset holdings. In order to have a poverty trap, the relationship between current and past assets has to be non-linear and non-convex. Given the non-linearities, non-parametric techniques are commonly used. These are very flexible and allow to identify complex dynamics. Nonetheless, their use is restricted to the bivariate relations, ignoring the heterogeneity of agents. To allow for covariates, complementary parametric approaches are needed, including polynomials to model non-linearities. Both approaches needs observations at all asset levels, which is hard to expect given the unstable nature of the threshold (Scott, 2019). Several authors have used both the parametric and non-parametric methods exploiting the advantages of each of them but keeping in mind each method's pitfalls (Giesbert and Schindler, 2012; Naschold, 2013, 2009). These methods are summarized hereafter.

Non-parametric approach

It is very flexible, as it does not impose any functional form, but can only estimate a bivariate relationship. It estimates the local curvature with nearby points, so that a local turn in the transition equation is not offset by the presence of more distant points which move the weight (Carter and Barrett, 2006). The relationship estimated can be seen in Equation 1:

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

where A_{it} are current asset holding of household i at time t, A_{it-1} are lagged asset holdings, the error term ε_{it} is assumed to be normally and identically distributed with zero mean and constant variance. The function f is a continuous function and can be estimated with local polynomial regressions[35]. The assumption underlying the use of such methods are that the function to be estimated is smooth and covariates are uncorrelated with the error term (Naschold, 2013). Also it is assumed that all households are in same accumulation regime, which can be quite a strong hypothesis (Carter and Barrett, 2006; Naschold, 2013). More generally, it is also assumed that assets are measured without error; such errors would create a regression-to-mean effect (Barrett et al., 2006; Giesbert and Schindler, 2012). Non-parametric approaches were applied originally to the study of asset dynamics by Adato et

[34] This is because of the presence of non-linearities, the unstable nature of some equilibrium points (therefore there should not be many observations around the threshold, reducing the ability to estimate it), the limited length of available panel data, the heterogeneity across households and potential measurement errors. Another difficulty is data availability: data might be missing for the S-shaped curve part, which would be invisible to tests, or the non-convex region might be small. Moreover, econometric techniques might be insufficient (McKay and Perge, 2013).

[35] Or with LOESS (locally estimated scatterplot smoothing), LOWESS (locally weighted scatterplot smoothing), different types of splines, or kernel-weighted local linear smoothers.

al. (2006), Barrett et al. (2006) and Lybbert et al. (2004). An important caveat of non-parametric models is that households' transition equations are estimated though the cross-sectional variation.

Parametric approach

The parametric approach allows to control for covariates at time t-s. It can be estimated via OLS with fixed effects or other panel models. In equation 2,

$$\Delta A_i = \beta_0 + \sum_{k=1}^{4} \beta_k A_{it-s}^k + \beta_5 \boldsymbol{X}_{it-s} + \beta_6 \boldsymbol{C}_{t-s} + \beta_7 R + \varepsilon_{it}, \tag{2}$$

asset growth of household *i* (ΔA_i) is a linear function of the fourth polynomial expansion of assets at the baseline, household's lagged characteristics ($\boldsymbol{X}_{it-s}$), community lagged characteristics ($\boldsymbol{C}_{t-s}$) and zone fixed effects ($\beta_7 R$). The polynomial expansion serves to capture the non-linearities are at the centre of distribution (Naschold, 2013, 2009). Controls include household characteristics (the age of the household head and its square, the average of years of education among household adults and its square, whether the head of the household is a woman, the size of the household and its square), proxies of household's earning capacity and social capital (having a wage job outside agriculture, receiving remittances, being part of some assistance programme, having borrowed money), whether the household is engaged in agricultural activities, and some community characteristics (availability of arable communal land, of agricultural jobs, the average agricultural wage, the presence of microfinance institutions, the distance from the closest market and town with more than 20,000 inhabitants, and a dummy for rural areas), as well as the dummy for flooded areas and its interactions with some of the variables mentioned above. Standard errors are clustered at the EA level[36].

Equation 2 can be complemented by a term $\beta_8 D_{i,t-s}$ representing a set of coping strategies (Carter et al., 2007; Giesbert and Schindler, 2012). This is an extension of the main results.

Convergence and post shock recovery

Other authors as Carter et al. (2007) estimate asset growth in two steps. In the first, asset growth is estimated as a function of initial asset level, income shocks, asset shocks and other control variables. To explicitly test for poverty traps, it is necessary a second step, which can establish whether a threshold exist with the method developed by Hansen (2000) and Wang (2015). Fixed effects panel threshold aims at finding structural breaks which split the sample. The advantage of this model is that it is not based on a pre-determined threshold but estimates directly a critical asset level that splits the sample (Carter et al., 2007; Carter and Lybbert, 2012). It can be tested whether below-threshold households have the same asset patters as above-threshold households, as follows:

[36] Possible candidates for clustering standard errors are EAs (enumeration area, about 400), LGAs (local government area, about 400), state (37) and zone (6). In the working flooded sample, there are 31 EAs, 44 LGAs, and 20 states. While state and zone have too few clusters, both EA and LGA should work better (Cameron & Miller, 2015). EA is a better candidate because it reflects the sampling structure.

$$g_i = \begin{cases} \beta_A^{\ell} A_{it-1} + \boldsymbol{\beta_X} \mathbf{X_{it}} + v_{it} & \text{if } A_{it-1} < \gamma \\ \beta_A^{u} A_{it-1} + \boldsymbol{\beta_X} \boldsymbol{X_{it}} + v_{it} & \text{otherwise,} \end{cases} \tag{3}$$

where g_i is the after-shock asset growth of household i, A_{it-1} the assets right after the shock, the superscripts indicate lower and upper equilibrium, γ is the asset threshold and $\mathbf{X_{it}}$ includes a set of control variables. A poverty trap is found if households in the lower regime tend to a lower equilibrium. This is seen by comparing the coefficients. This approach aims at extending the results of the main model.

1.3.1 Identification strategy

Establishing whether a disastrous flood changes the medium run dynamics of affected households requires a counterfactual, i.e., the dynamics of flooded households had not they been flooded. A second best to this counterfactual is to use as control group the households that live in proximity of the flooded households, which are supposedly more similar to the treated households than the rest of the country. To identify them, I draw a 10-km buffer around the flooded area (areas with vertical stripes in Figure 1.4). Households in this larger buffer that are not flooded (according to the definition given in Section 2.1) constitute the control households, in a sort of donut representation[37] (in Figure 1.4, the circles with dots inside and without red pixels of the flood are the donut enumeration areas). I provide comparisons of this donut households with the other non-flooded households (external households, depicted by circles without dots). Moreover, as the data allows only one pre-shock observation, I rely on different period pairs comparisons. I will show that it matters to consider as starting point pre- or post-shock assets.

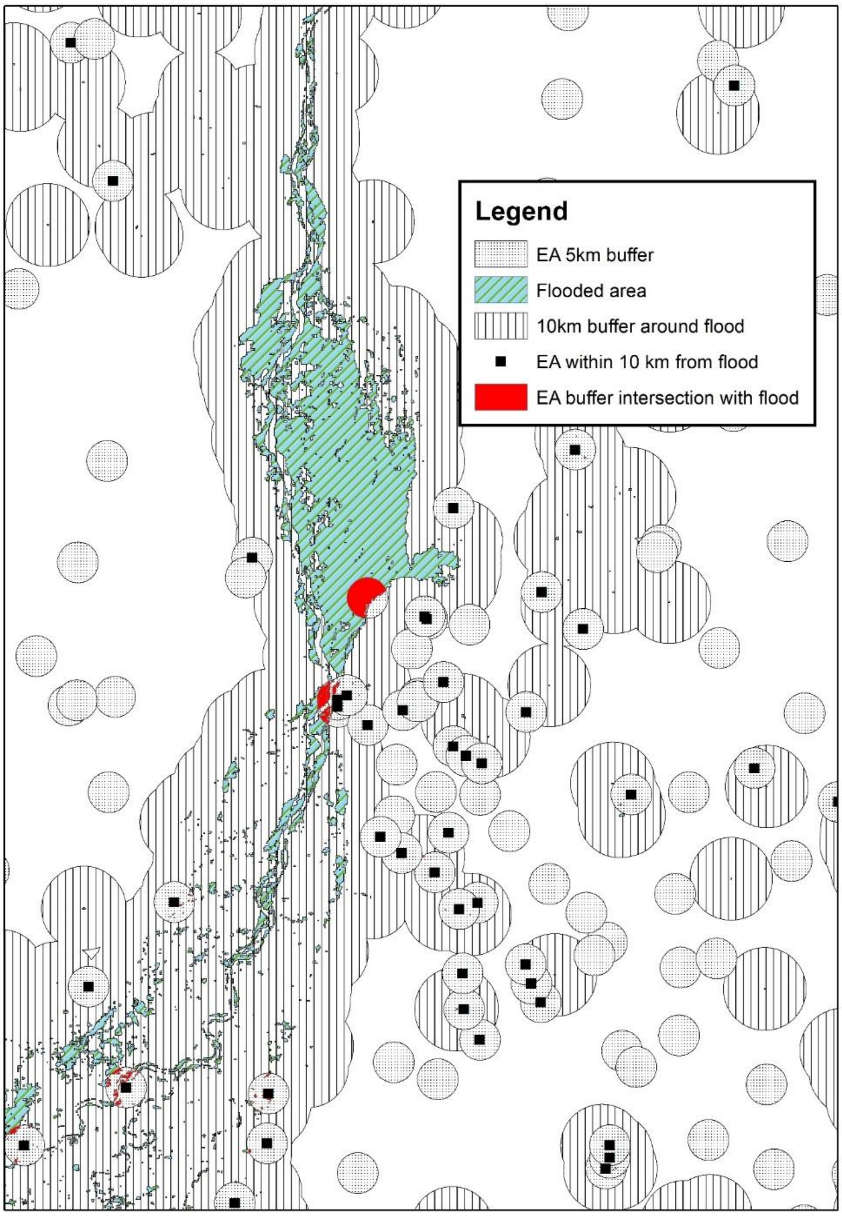
A second source of concern for the identification is the effect of the previous large flood of 2010[38]. Data collection of the first wave started in August but the majority of households were interviewed during the month of September. Indeed, flooding during the post-planting visit posed some difficulties in reaching households because some roads were flooded, so they had to resort to motorcycles (National Bureau of Statistics Federal and Republic of Nigeria, 2015). However, there is no available source of satellite data to identify which areas were flooded in 2010. We control for this flood using the community-administered module on shock experience (Cf. Section 1.6.4). Alternatively, we use as a

[37] The donut approach, or the rings method, relies on the physical proximity of treated and control units (relying on a "common neighbourhood trend"), however its validity relies on the correct radius of the inner circle identification (Butts, 2022). The underlying assumption is that flooded and non-flooded households are comparable, and unobservable factors which might affect their selection into the treatment are negligible.

[38] The 2010 flood was much shorter and less widespread than the 2012 flood, as it lasted from September 13th to September 30th 2010 and affected 'only' 1.5 million people (vs. 7 million of 2012) in the Jigawa, Sokoto, Kebbi, Niger, Katsina provinces (CRED/UCLouvain, 2023).

proxy for flooded areas the distance from the closest inland water during normal times[39] (cf. Section 1.6.2).

Figure 1.4: Visual representation of the donut approach to flooded areas



Source: own elaboration using Nigeria GHS panel data.

1.4 Descriptive statistics

Table 1.2 reports the T-test of some key variables for the pre-shock sample (wave 1) for flooded and non-flooded households: donut and external households[40]. Focusing on the first comparison (flooded versus donut households), some differences emerge: flooded households are more often headed by women, cultivate less, have higher asset index scores, receive more assistance and borrow on average more, they have more access to communal land and microfinance, live in communities with fewer job

[39] Retrieved from https://diva-gis.org/gdata
[40] The weights are not applied here.

opportunities and lower wages, live more distant from towns and recur more often to the withdrawal of children after a shock. On the other hand, they have similar land plots, livestock, expenditure, and diversification of income.

The second comparison is done between donut households and external households. The differences here are much more pronounced and concern almost all dimensions.

Table 1.2: T-test on sample between flood, donut and external samples at baseline

	Flood sample (n=793) mean	Donut sample (n=2005) mean	Mean difference between flood and donut	External sample (n=2531) mean	Donut sample (2005) mean	Mean difference between donut and external
Number of people in the hh	5.839	5.751	0.0870	5.938	5.751	0.187*
Female headed hh	0.182	0.152	0.029*	0.126	0.152	-0.026**
Age head of hh	49.18	50.21	-1.030	49.50	50.21	-0.704
Avg years of education among adults	7.261	7.006	0.255	5.408	7.006	-1.598***
HH dependency ratio	1.025	1.072	-0.0470	1.153	1.072	0.080***
Total livestock owned, tlu	0.687	1.809	-1.121	2.540	1.809	0.731
Land owned, hectares	0.0340	0.0280	0.00600	0.0510	0.0280	0.023***
HH cultivates crops/trees	0.483	0.575	-0.092***	0.796	0.575	0.222***
Asset index similar to DHS	0.153	0.126	0.0260	-0.400	0.126	-0.527***
Daily consumption per capita	3.911	3.632	0.279**	2.934	3.632	-0.698***
HH receives remittances	0.242	0.241	0.00100	0.192	0.241	-0.049***
HH received assistance	0.0350	0.0110	0.024***	0.0150	0.0110	0.00400
HH has borrowed	0.368	0.316	0.052***	0.410	0.316	0.094***
Food expenditure per capita per day	2.450	2.376	0.0740	2.056	2.376	-0.321***
Available arable communal land	0.349	0.287	0.062***	0.215	0.287	-0.073***
Community hires agric labourers	0.724	0.825	-0.101***	0.929	0.825	0.104***
Community's average agricultural wage	612.3	672.9	-60.559**	576.8	672.9	-96.111***
Microfinance in the community	0.228	0.198	0.030*	0.118	0.198	-0.080***
HH Distance in km to Nearest Market	59.04	60.60	-1.564	79.62	60.60	19.015***
HH Distance in km to Town >20k	20.05	15.86	4.190***	23.13	15.86	7.268***
HH withdraw a child from school	0.107	0.0770	0.030**	0.120	0.0770	0.042***
A hh member works for a wage	0.315	0.304	0.0120	0.203	0.304	-0.100***
A hh member is self employed	0.559	0.539	0.0190	0.394	0.539	-0.145***
A hh member migrated for work/land reason	0.0140	0.0190	-0.00600	0.0160	0.0190	-0.00400

Source: own elaboration using Nigeria GHS panel data

Looking at the frequencies of coping strategies by wave (Table 1.3), those that have the highest frequency at wave 2 are withdrawing children from school, receiving assistance, borrowing. The ex-ante strategies of non-farm employment and insurance show a less clear path. Remittances' frequency is the highest in the first and last wave. Panel B, concentrated on the flooded sample, tells a similar story.

Table 1.3: Coping strategies adoption – percentages by wave

	HH withdraw a child from school	A hh member works for a wage	A hh member is self employed	HH receives remittances	HH has insurance	HH has borrowed	A hh member migrated for work/la	A hh member migrated (internationally)	HH received assistance
					(a) Total sample				
1	9.9	26.7	48.6	22.2	2.7	36.2	1.7	.1	1.7
2	10.2	25.8	50.9	2.2	3	37.1	3.5	.3	3.1
3	2.3	25.7	57.7	4.9	3.1	17.7	11.1	.4	2
4	3.9	29.9	50.8	34.5	3.9	14.9	18.3	.7	8

(b) Flooded sample (rural-urban buffer)									
1	10.7	31.5	55.9	24.2	1.8	36.8	1.4	.3	3.5
2	9.2	32.7	60.9	1.9	3.4	36.8	3.4	.3	6.1
3	2.5	28.4	60.5	6.1	3.3	18.2	10	.4	1.1
4	3.6	32.4	57.2	32	3.6	20.5	14.7	1.4	9.4

Source: own elaboration using Nigeria GHS panel data

1.4.1 Creation of asset index

Asset-based approaches are more appropriate for the study of wealth dynamics, as they are free from the burden of prices and typically fluctuate less, are more easily collected in the questionnaires than monetary measures, and allow a forward-looking evaluation of poverty (Carter and Barrett, 2006). Moreover, they shed light on a minimum asset bundle with which households can find their own exit out of poverty (Carter and Barrett, 2006).

I followed DHS' methodology to create a comprehensive asset index[41] (Rutstein, 2015). The aggregation of all these dimensions is done via principal components extraction[42] (Sahn and Stifel, 2003, 2000) and the first component is extracted. Variables included are the material of walls, floor, roof, type of cooking stove fuel, the source of water during the rainy season, the type of toilet, a dummy for shared toilet, as well as typical durable assets like furniture, electronic items, the number of animals, a dummy for electricity, owning a bank account, the amount of land owned, and a dummy for domestic help. The asset index is calculated on the pooled sample (i.e., all time periods together) (McKay and Perge, 2013; Naschold, 2013, 2009).

Table A 1 in the Appendix reports the mean value of each component by quintile of the just created asset index. The table contains also the scoring coefficients of Factor 1 in the far-right column. They are the weights which are attributed to each variable used. The distribution of such asset index can be seen in Figure 1.5 for flooded households, those in their neighbourhood (donut households) and those outside these areas (external households). The flooded sample has a distribution with two peaks[43], giving a first clue about the presence of more equilibria. The other two samples present a very different distribution, quite normal for the donut households and left-skewed for the external households.

[41] I selected all the variables that were common and had common categories across waves. For each yes/no variable, missing values were replaced with 0. For each continuous variable, missing values were replaced with the variable mean at the enumeration area.

[42] As a robustness check, I also performed a polychoric principal component analysis, which suits categorical variables, discrete and continuous and most importantly ordinal data (for example, there's an ordering in the quality of the materials of the dwelling) (Moser and Felton, 2007). Polychoric PCA gives meaning to the ownership as well as non-ownership of durables (Kolenikov and Angeles, 2004; Moser and Felton, 2007). The asset index created in this way presents density and non-parametric estimations which give very similar results as those presented in the main analysis.

[43] Notice also that this is true in all waves. I will discuss this in the conclusions.

Figure 1.5: Kernel density of asset index for flooded households, donut households and external households, all waves.

Source: own elaboration using Nigeria GHS panel data

Moving to asset dynamics, a first idea of what happened across panel waves is given in Table 1.4. Panel A provides transition percentages for the donut sample across the entire period, while panel B focuses on flooded households from the shock onwards. In general, about half of the households remain positioned in the same quintile. Flooded household show very large stability for the lowest and highest quintile, and a large worsening percentage in the second initial quintile (60.9%).

Table 1.4: Transition matrices by asset quintiles, row percentages

Panel A: w1-w4 donut sample						
Quintiles of assets, w1	Quintiles of assets, w4					
	1	2	3	4	5	Total
1	62.50	28.75	7.50	1.25	0.00	100.00
2	22.46	37.89	34.04	5.61	0.00	100.00
3	2.19	21.72	49.45	21.53	5.11	100.00
4	1.64	4.91	24.34	50.31	18.81	100.00
5	0.00	1.99	5.79	24.01	68.21	100.00
Total	20.09	20.07	19.85	19.97	20.02	100.00

Panel B: w2-w4 flooded sample (rural-urban buffer)						
	Quintiles of assets, w4					
Quintiles of assets, w2	1	2	3	4	5	Total
1	71.15	21.15	3.85	3.85	0.00	100.00
2	60.98	24.39	14.63	0.00	0.00	100.00
3	2.70	18.92	37.84	40.54	0.00	100.00
4	0.00	2.56	28.21	43.59	25.64	100.00
5	0.00	0.00	1.83	22.94	75.23	100.00
Total	22.66	10.43	12.59	21.22	33.09	100.00

The cells on the diagonal (in yellow) represent households that did not move across quintiles from the starting period (on the rows) to the ending period (on the columns). Those below the diagonal (in red) are households that worsened their position, whereas those above the diagonal (in green) identify households that moved up in the distribution of assets. Source: own elaboration using Nigeria GHS panel data.

Alternatively, looking at the percentile changes from wave 1 to wave 4, we note that flooded households have significantly larger worsening of positions than non-flooded households in the neighbourhood (donut). Looking at the quintiles of wave 1, we see that this change is statistically significant but only for the households in the second poorest quintile.

Table 1.5: Mean changes of percentiles from wave 4 to wave 1

Asset quintiles at wave 1	flooded	non-flooded (donut)	Mean diff (flooded- non flooded)
1	5.877	7.338	-1.46
2	-3.025	4.319	-7.344**
3	2.367	1.329	1.038
4	0.091	-4.016	4.107
5	-7.514	-7.5	-0.014

Source: own elaboration using Nigeria GHS panel data

1.5. Results

1.5.1 Non-parametric regression

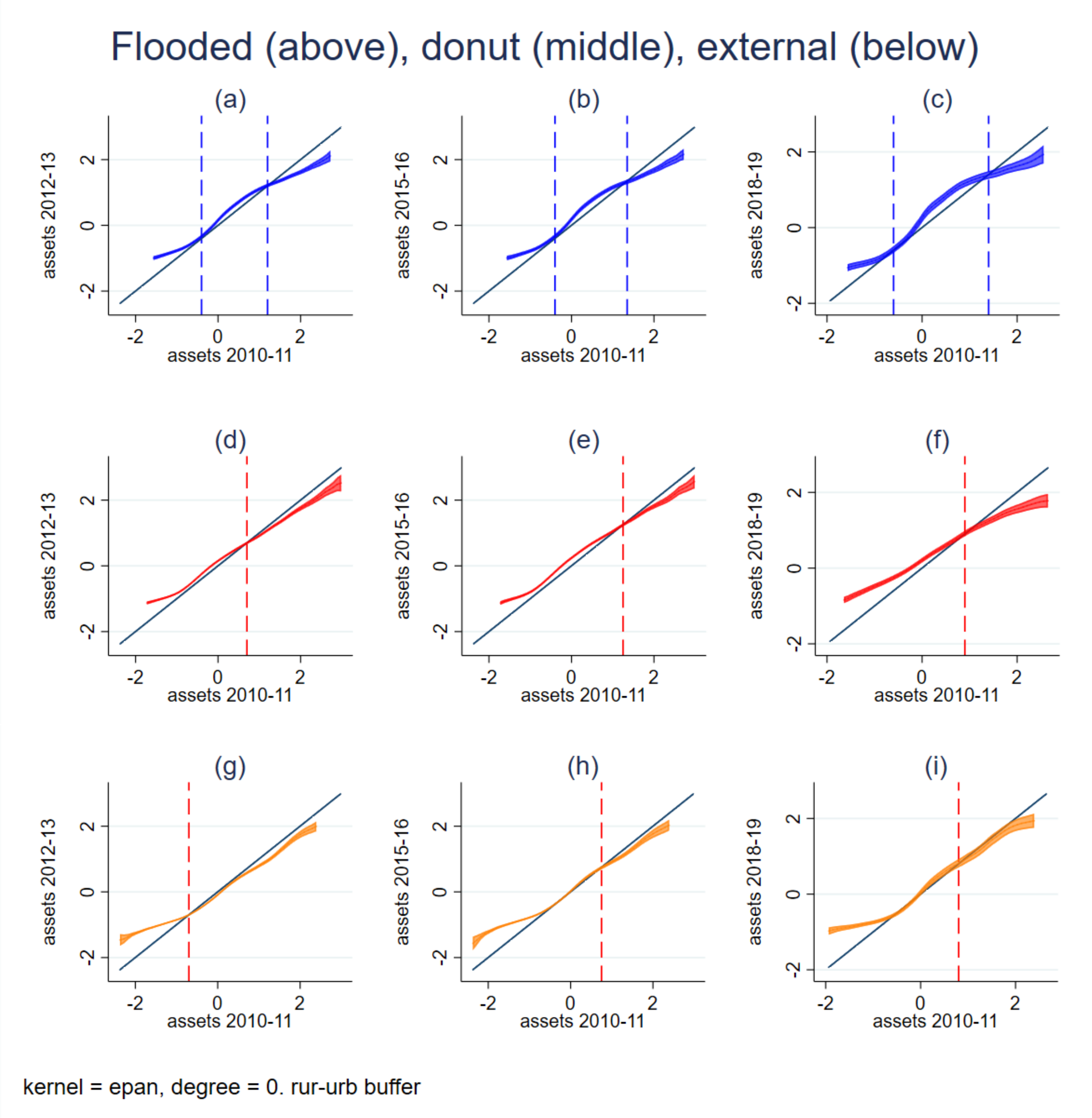
Using non-parametric regressions in an exploratory way[44] shows that households that were flooded in 2012 present dynamics shaped as an S with multiple equilibria, compatible with the poverty traps hypothesis, both if I start in wave 1 (indeed the impact of the shock is incorporated in the assets on the y-axis) (Figure 1.7, panels a, b and c) and if we start in wave 2 (Figure 1.7 panels a and d). Donut households, on the other hand, present flatter transition curves, with only one equilibrium located at the higher end of the distribution (Figure 1.6, panels d, e and f, and Figure 1.7, panels b and e). Similarly,

[44] Since these report only bivariate relationship, graphs are not reported but are available upon request.

external households are very flat and cross the diagonal only once (Figure 1.6 panels g, h, I and Figure 1.7 panels c and f).

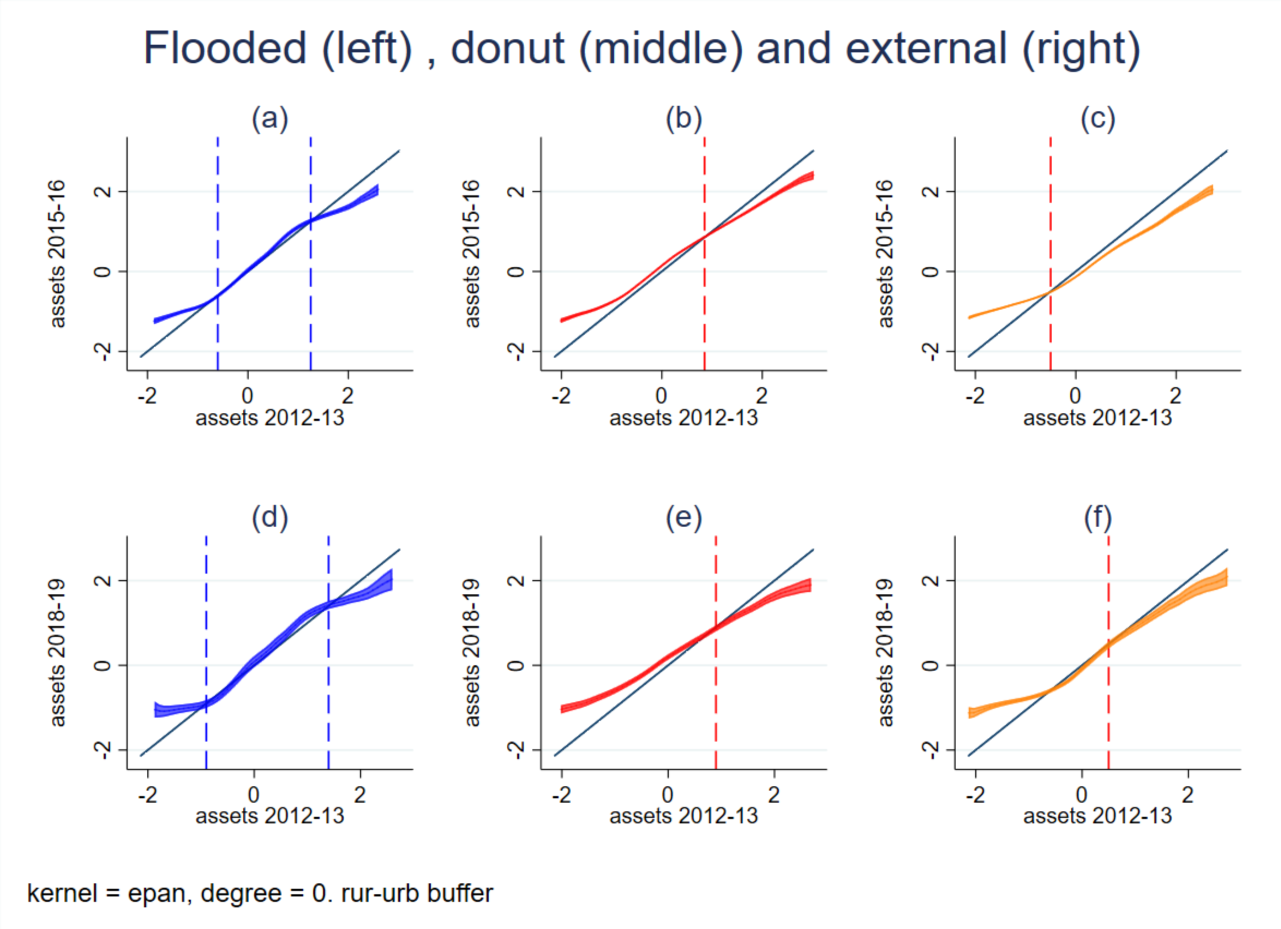
This can be a first clue that flooded households, following the climatic shock, converge to more than one equilibrium, while for non-affected households the path is less clear. Nonetheless, richer flooded households seem to be able to converge to higher equilibria than non-flooded households. The greater concavity of the curve of the flooded and the larger distance from the diagonal indicate faster dynamics (Naschold, 2013).

Figure 1.6: Local polynomial smooth, flooded and non-flooded (donut in the middle and external in the below panel), from wave 1



Source: own elaboration using Nigeria GHS panel data.

Figure 1.7: Local polynomial smooth, flooded and nonflooded (donut in the middle and external in the right panel), from wave 2



Source: own elaboration using Nigeria GHS panel data.

1.5.2. Parametric regression

Following Giesbert and Schindler (2012), parametric models are estimated for the growth of the asset index. I run a regression of the wealth change with the lagged wealth and lagged variables. The estimator is an OLS model. Lagged asset are modelled also with the squared, the third and the fourth degree terms[45] (Barrett et al., 2006; Giesbert and Schindler, 2012; McKay and Perge, 2013; Naschold, 2013, 2009). Table 1.6 reports the coefficients of the variables of interest. I run the regression on the three subsamples: the external non-flooded households, the donut non-flooded households and the flooded households. In columns 1-3 the dependent variable is the asset change from wave 4 to wave 1 (2018/19 – 2010/11), while in columns 4-6 it is from wave 4 to wave 2 (2018/19 –2012/13)[46].

[45] It is preferrable to a third order polynomial as it does not oblige the stable equilibria to be in the tails of the distribution (Naschold, 2013). Nonetheless, I check whether this is appropriate for the Nigerian case, following the approach used by Cissé and Barrett (2018). Criteria include R^2, AIC and BIC and a t-test which compares each specification's fitted values with those of the seventh polynomial. Results indicate that a third or fourth polynomial are the most appropriate. The t-test does not find relevant differences after the fourth polynomial among mean predicted values. After the fifth polynomial, no other coefficient is statistically significant.

[46] Hence, lagged variables are 2 periods lagged in the first case and 3 periods in the second.

Only the second difference (w2-w4) explicitly takes into account the occurrence of the flood shock by using as starting period wave 2. However, in both differences the assets in the final period are post-shock assets. The coefficient of the lagged assets is significant and negative, indicating that poorer households accumulate assets at a faster rate than wealthier households. This is in contrast with the expectation of poverty traps. Nonetheless, some non-linearities are found in the polynomial of lagged assets. Table 1.6 also reports the test of general convergence as described by Quisumbing and Baulch (2013). It indicates convergence if it possible to reject that all terms of the polynomial are all equal to zero in favour of the alternative that the β_1 is between -2 and 0 and all other β_{2-4} are all equal to zero. The null is rejected in all columns and indeed β_1 is found between -2 and 0, however $\beta_2=\beta_3=\beta_4=0$ is rejected only in the first column and in the third, indicating convergence in all samples but not in the external and the flooded sample (long difference).

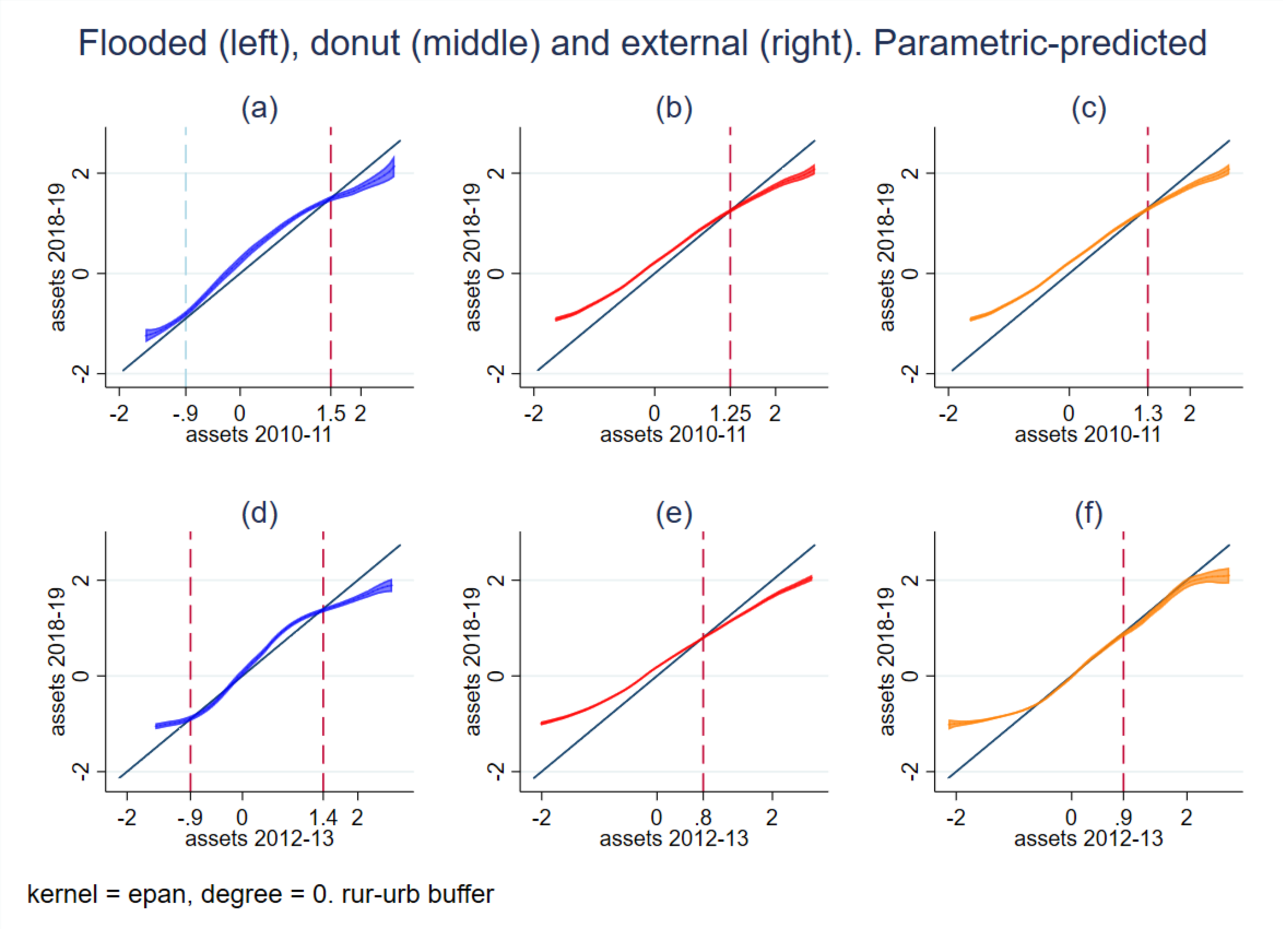
Table 1.6: Parametric regression, long differences until 2018-19 (extended panel), OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Growth w4 -w1			Growth w4 -w2		
VARIABLES	external	donut	flooded	external	donut	flooded
3-Lag assets	-0.381***	-0.357***	-0.296***			
	(0.091)	(0.111)	(0.089)			
3-Lag assets^2	0.096	-0.041	-0.102			
	(0.070)	(0.076)	(0.116)			
3-Lag assets^3	-0.061	-0.043	-0.083*			
	(0.037)	(0.042)	(0.042)			
3-Lag assets^4	-0.003	0.018	0.035			
	(0.018)	(0.023)	(0.030)			
2-Lag assets				-0.382***	-0.422***	-0.370***
				(0.100)	(0.083)	(0.111)
2-Lag assets^2				0.044	0.017	0.016
				(0.070)	(0.049)	(0.082)
2-Lag assets^3				-0.015	0.008	-0.044
				(0.028)	(0.024)	(0.059)
2-Lag assets^4				-0.009	-0.001	0.011
				(0.016)	(0.011)	(0.024)
Observations	610	545	270	610	524	270
Adjusted R-squared	0.244	0.179	0.218	0.206	0.160	0.216
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.054	0.787	0.036	0.485	0.841	0.891

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at EA level, panel weights. Flooded defined with a buffer defined according to the rural-urban definition.

These results can also be appreciated graphically with a non-parametric regression, by predicting fitted values of the growth variable, adding to it its lag and plotting it against the lag itself, as done by Giesbert and Schindler (2012) and Naschold (2013). Figure 1.8 provides the corresponding graph to the estimates of Table 1.6, therefore with 2018/19 final assets. Kernel-weighted local polynomial smoothing is used[47]. Asset dynamics of flooded households indeed differ substantially from non-flooded households', both donut and external ones. Indeed, they are markedly S-shaped, with multiple equilibria (especially in panel d, with both initial and final assets after the flood). When considering initial assets before the floods (panel a), the equilibrium[48] is only one, but when initial assets are those after the shock (panel d) a second equilibrium can be found at low levels of assets and the transition curve takes a more marked S shape. This indicates that new conditions created with the flood led to a bifurcation in which a poverty trap is found at -0.9 asset scores. In all other cases, there is one clear equilibrium or a very flat curve over an interval.

Figure 1.8: OLS-predicted asset change to wave 4, local polynomial smooth



Source: own elaboration using Nigeria GHS panel data.

We repeat the analysis in Table 1.7 using as final period the third wave but maintaining the same sample[49]. Now columns 1-3 report the asset change from wave 3 to wave 2 (2015/16 –2010/11), while

[47] Different functional forms provide the same result. For instance, penalized spline in Figure A4 and A5 in the Appendix.

[48] Since it crosses the line from above, this is a stable equilibrium.

[49] Table A 2 and Figure A 3 in the Appendix report results of this exercise without limiting the sample size to the extended panel. This increases the sample size to the full spatial extension of the panel. We find that the

in columns 4-6 it is from wave 3 to wave 1 (2015/16 – 2012/13). This restricts the time coverage of the effect . For most columns, the lagged asset is negative and significant. However, for the flooded sample it is not significant (column 3), while the polynomial is jointly significant. As for the previous table, we find non-linearities in the external and flooded sample for the longer difference (columns 1 and 3, referring to w3-w1) which reject convergence. In the shorter difference, as before there is still convergence.

Table 1.7: Parametric regression, long differences until 2015-16 (same sample as Table 1.6), OLS

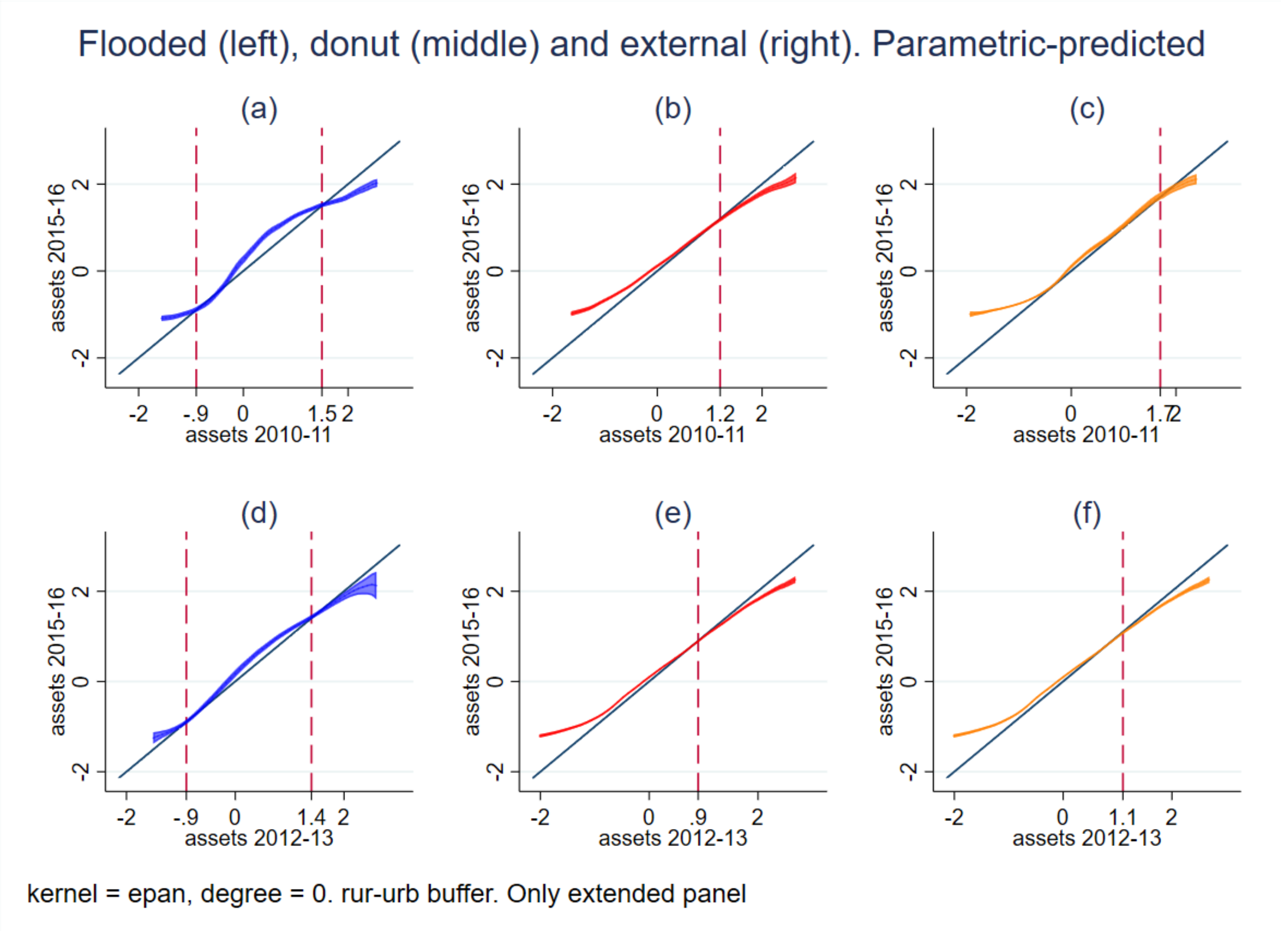
	(1)	(2)	(3)	(4)	(5)	(6)
		Growth w3 -w1			Growth w3 -w2	
VARIABLES	external	donut	flooded	external	donut	flooded
2-Lag assets	-0.311***	-0.340***	-0.199			
	(0.078)	(0.087)	(0.117)			
2-Lag assets^2	0.043	0.077	-0.086			
	(0.051)	(0.068)	(0.077)			
2-Lag assets^3	-0.062**	-0.022	-0.157***			
	(0.031)	(0.041)	(0.054)			
2-Lag assets^4	0.013	-0.005	0.056**			
	(0.014)	(0.021)	(0.025)			
1-Lag assets				-0.327***	-0.182***	-0.307***
				(0.106)	(0.067)	(0.109)
1-Lag assets^2				-0.001	0.052	-0.102
				(0.054)	(0.050)	(0.064)
1-Lag assets^3				-0.017	-0.023	-0.055
				(0.024)	(0.021)	(0.053)
1-Lag assets^4				0.001	-0.003	0.028
				(0.012)	(0.010)	(0.021)
Observations	610	545	270	610	524	270
Adjusted R-squared	0.221	0.272	0.290	0.160	0.128	0.302
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.020	0.351	0.029	0.624	0.315	0.267

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at EA level, panel weights. Flooded defined with a buffer defined according to the rural-urban definition.

Figure 1.9 shows local polynomial smooth functions from predicting asset growth in the parametric exercise of Table 1.7. The final period assets are those of 2015/16. Despite showing dynamics over a shorter period, Figure 1.9 confirms the results of Figure 1.8. The low-level equilibrium identified is the same as before (-0.9 asset scores).

Figure 1.9: OLS-predicted asset change to wave 3, local polynomial smooth

coefficient of the lagged assets is the lowest for flooded households, as in Table 1.6 and partly 1.7. Also, convergence now is rejected in the donut sample and more strongly in the flooded sample, both in the longer (w3-w1) and shorter differences (w3-w2). This is due to the increased sample size (765 households versus 270 households). Even though we are not able to track these additional 495 households until 2018/19 because of panel refreshment, these results confirm that non-linearities are an important component in the asset growth process of flooded households (necessary but not sufficient condition for a poverty trap).



Source: own elaboration using Nigeria GHS panel data.

1.6. Robustness checks

1.6.1 Flood measurement

Going beyond the dichotomic flood variable, a measure of flood intensity is created to count the maximum times the buffer's polygons are flooded[50] . The non-parametric regression graph shows again an S-shaped transition curve for flooded households, with three equilibria (Figure A6, left panel). Nonetheless, this restricts the flooded sample further, and the formal estimation of a threshold yields no significant results.

Changing the buffer radius helps understand how the results are sensitive to this choice[51]. The current buffer is either 2 or 5 km radius, according to the rural/urban zone. Three new buffer sizes are calculated for 2 (Figure A 6, right panel), 5 (Figure A 7, left panel) and 10 km (Figure A 7, right panel).

[50] A more intuitive approach could have been to create the average flooded days of the flooded polygons in the buffer. However, since the polygons may have different shapes, a maximum approach is preferrable. Moreover, it is important to remind the reader that such intensity variable constitutes a lower bound of the flooded period. Cloud coverage is thick during a flood. Hence, this measure emphasises those buffers that are *observed* to suffer from repeated flooding. Therefore, this intensity of flooding measure serves only as a robustness check. Note also that such count variable disregards the fact that days are consecutive or not. To make the measure more effective despite its pitfalls, only those villages with more than 2 flooded days (2 days are excluded) are considered.

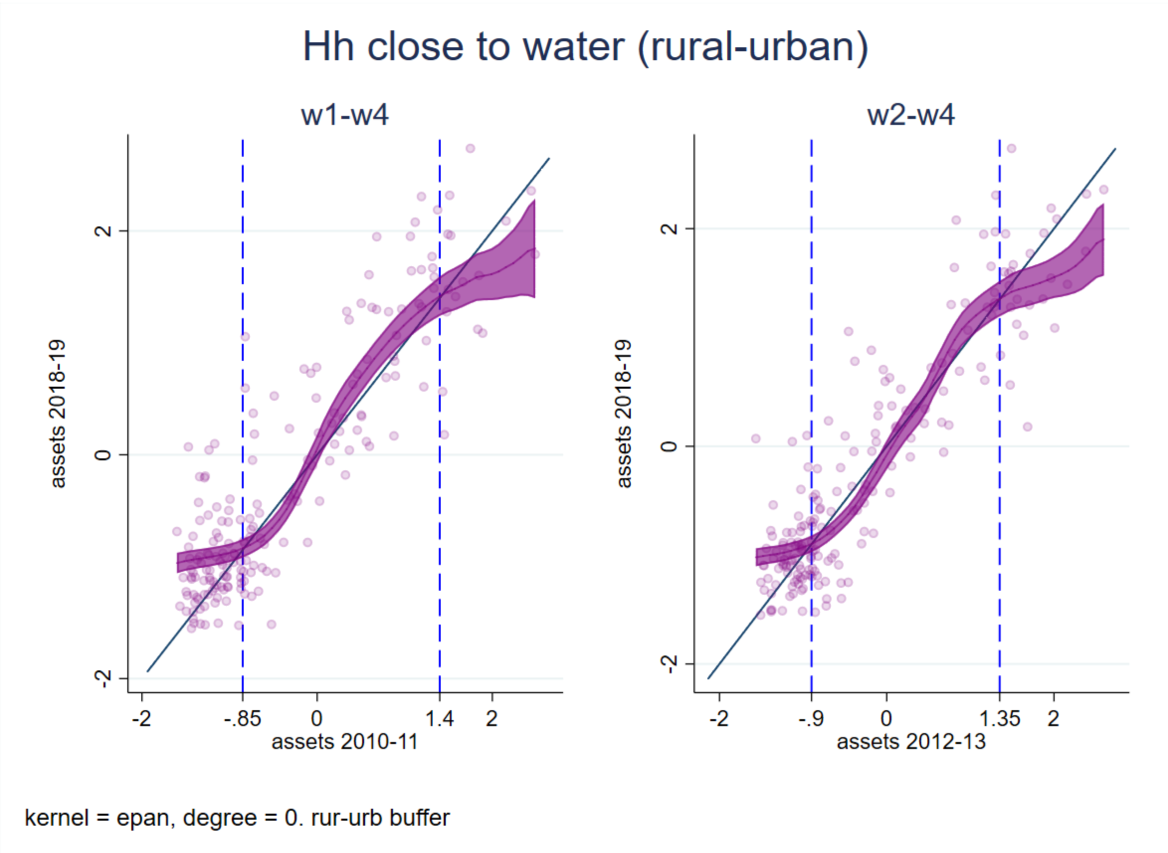
[51] See also Appendix 2 for a focus on sensitivity and convergence.

The 2 km buffer includes 522 households (11.4%), the 5 km buffer comprehends 1,067 households (23.4%), whereas the 10 km buffer affects 2,073 households (45.4%). Reducing the radius size shows a more defined S-shape transition curve; increasing the buffer to 5km maintains an S-shape dynamic with the same crossing points but less defined shape, while the 10 km buffer only crosses once at high asset levels (similar to non-flooded households). This means that with a buffer size within 2-5 km we are capturing more precisely the households hit by the flood, whereas increasing the buffer size dilutes the effect bringing in the buffer households which are less likely to have been hit directly by the flood.

1.6.2 Proximity to water

An alternative definition of flooded areas assumes as flooded those areas in proximity to water bodies. This has the advantage of overcoming the cloud coverage issue that typically is associated with satellite data. I define as flooded those households within a close distance from water (5 km for rural areas and 2 km for urban areas[52]). Non-parametric regressions show S-shaped dynamics with two stable equilibria, very similar to the results with the previous definition (Figure 1.10).

Figure 1.10: Local polynomial smooth, households close to water



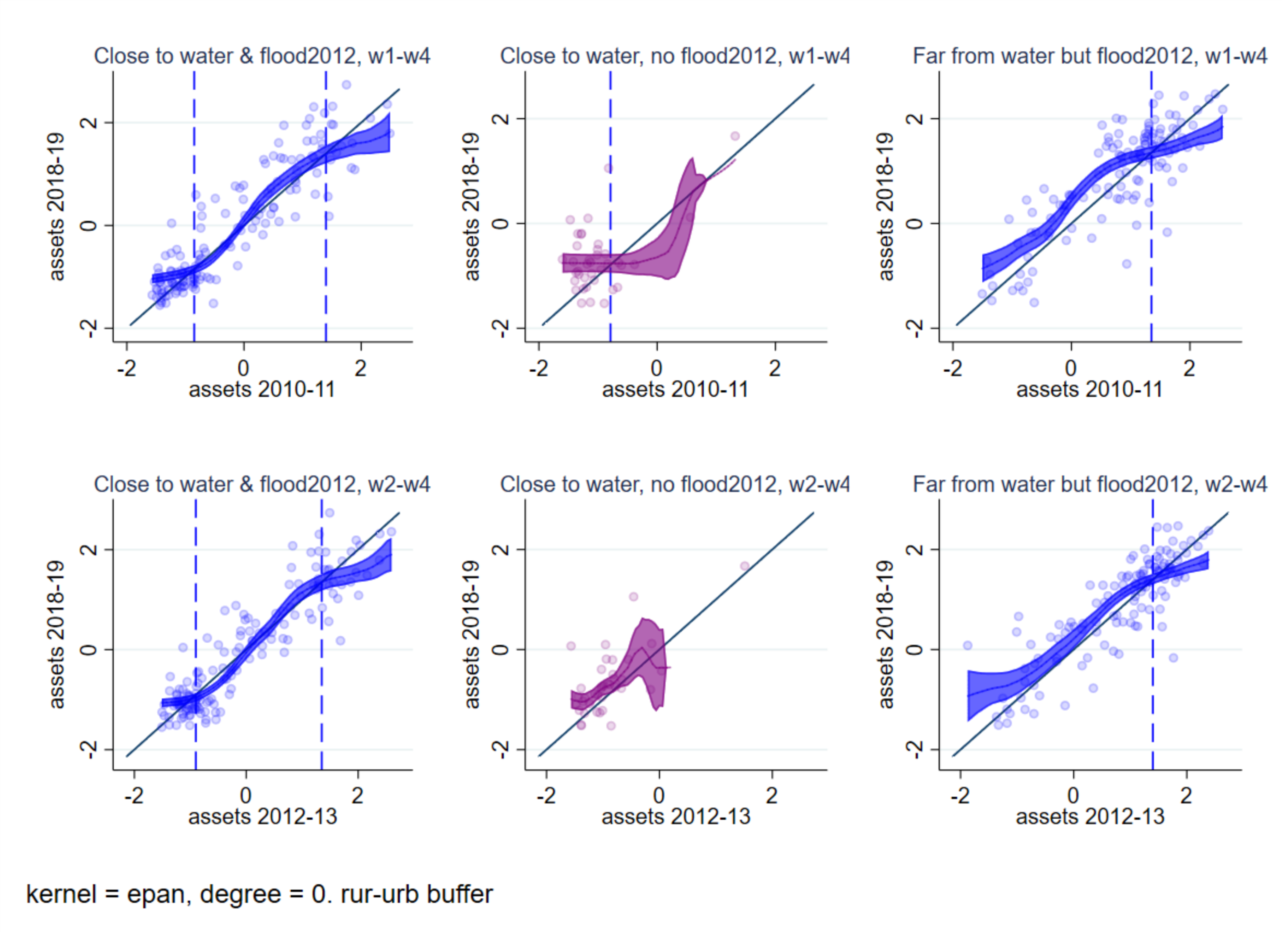
Source: own elaboration using Nigeria GHS panel data.

Cross tabulation of flooded areas and areas in proximity of water reveals that 67% of households close to water are also flooded, conversely, 51% of flooded households are found in proximity of water

[52] See also Appendix 2 for sensitivity tests of the distance to water and convergence.

(402 households). Further inspection reveals that the poverty trap pattern is due to this intersection of being close to water and suffering from the disastrous flood of 2012 (Figure 1.11, on the left), while those close to water that were not categorized as flooded in 2012 only have one low level equilibrium (very few households). Finally, those that were flooded in 2012 but were not living close to water, i.e., those that usually are not flooded but were exceptionally hit by the flood of 2012, show dynamics that are more compatible with the convergence hypothesis, as there is only one high equilibrium.

Figure 1.11: Intersections of households in proximity of water and flood of 2012



Source: own elaboration using Nigeria GHS panel data.

1.6.3 Different asset indexes

Using a different asset aggregation method (polychoric PCA) does not alter the main results parametrically (Table A 3) and non-parametrically. This time however, the coefficient on lagged assets is not consistently significantly negative and convergence is rejected only in the external sample in the short regression (column 4).

Another check on the asset index is exclude durables from the computation. Information on durables' ownership is collected during the first visit (September, i.e., post-planting) while information on other assets (agricultural tools, livestock, dwelling construction materials) is collected in the second visit (April, i.e., post-harvest). To exclude that the different period of the collection is driving the results, the analysis using an asset index computed on an asset index computed without durable dummies (Table A 4). Convergence is now rejected in the external and donut sample.

1.6.4 Conflicts and other climatic shocks

Since the period of analysis, Nigeria has suffered an escalation of violence and conflict events, especially in some zones (north-east primarily). Exposure to violence and conflicts increase poverty, and one the channels is the destruction of assets (Mercier et al., 2020). The uncertainties and the insecurity created likely affect the dependent variable to the point of 'confounding' the effect of the flood. Here it is explicitly taken into account by controlling for some measure of conflict. Geo-referenced data on conflict events is obtained from ACLED database (Armed Conflict Location & Event Data Project[53]) (Raleigh et al., 2010). I restrict the analysis to violent conflicts (battles, explosions/remote violence and violence against civilians). The first variable created is a dummy for the presence of a conflict in the 5-km buffer (Rotondi and Rocca, 2021) and it is modelled with 3 lags, to account for the evolution of conflict (Table A 5). Results are virtually unchanged. The conflict occurrence has both negative and positive correlation with asset growth. Predicting asset change and plotting it with local polynomial smoothing yields the same results as before (even if coefficients are different). Convergence is again rejected in the external sample and flooded sample in the long difference (col. 1 and 3).

A second variable created is the same dummy but restricted to those events in which there are fatalities. Results are unchanged[54] (Table A 6). Convergence is again rejected in the external sample and flooded sample in the long difference (col. 1 and 3).

Finally, I control for additional climatic shocks, floods and droughts, reported at the community level[55], so they should suffer less from the bias associated with self-reporting of the shocks (Table A 7). Quite reassuringly, the coefficients of the flood of 2010 (L3.flood in columns 1-3) are negative but not significant[56]. Nonetheless, I obtain the same results also on the non-parametric regression and convergence is rejected in the external sample and flooded sample in the long difference (col. 1 and 3).

1.7 Extension of results

1.7.1 Threshold estimation

Next, I check whether it is possible to estimate a threshold that signals a structural break with the model by Hansen (2000) and Wang (2015) (Carter et al., 2007). I start with a one-threshold model using one lag, up to 2015-16[57] (Table 1.8). The estimated thresholds are at 1.315 (significant) asset

[53] http://www.acleddata.com

[54] Yet again some conflict coefficients are positive. This is rather puzzling, but its interpretation goes beyond the scope of this paper.

[55] I use a threshold of 25% or more of households which were affected by that shock in the community.

[56] Nor is the one of the 2012 flood, namely L2.flood.

[57] The sample is otherwise too small.

scores for the flooded sample and 0.816 for the external sample. For flooded households, the effect of lagged assets above and below this interval is significantly negative and with a coefficient larger than 1 in absolute terms. The coefficients for lagged assets below and above the threshold are quite similar, signalling a somewhat different growth speed along the asset distribution. A second threshold is the found at 1.049 (not significant) asset scores[58]. The sample size is likely too small to be able to detect a structural break at the lower end of the distribution. Moreover, comparing the thresholds of the different samples, even if not significant, reveals that for flooded households the break in the relationship between asset growth and lagged assets happens at lower levels of assets.

Table 1.8: Fixed effects panel threshold regression, up to 2015

	(1)	(2)	(3)
VARIABLES	external	donut	flooded
Age head of hh	-0.002*	-0.002*	-0.002
	(0.001)	(0.001)	(0.002)
Head is female	-0.070*	-0.223***	-0.146**
	(0.042)	(0.054)	(0.058)
number of people in the hh	0.013	0.027***	-0.010
	(0.008)	(0.009)	(0.015)
A hh member works for a wage	0.047	0.063**	0.054
	(0.030)	(0.025)	(0.037)
A hh member is self employed	0.027	0.025	0.037
	(0.020)	(0.021)	(0.035)
HH receives remittances	0.022	0.092**	-0.033
	(0.055)	(0.043)	(0.072)
HH received assistance	-0.007	0.014	0.050
	(0.050)	(0.043)	(0.070)
HH has borrowed	0.032**	0.027*	0.005
	(0.016)	(0.015)	(0.024)
Available arable communal land	0.002	0.017	-0.095**
	(0.021)	(0.020)	(0.041)
Community hires agric labourers	-0.044	0.051	0.052
	(0.038)	(0.031)	(0.050)
Community's average agricultural wage	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Microfinance in the community	-0.044	-0.003	0.050
	(0.043)	(0.023)	(0.035)
HH Distance to Nearest Market	-0.006***	0.001	-0.000
	(0.002)	(0.002)	(0.001)
HH Distance to Nearest Town	-0.002**	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)
Rural dummy	-0.299**	-0.236**	0.064
	(0.120)	(0.120)	(0.088)
HH cultivates crops/trees	-0.123***	-0.022	-0.012
	(0.038)	(0.029)	(0.044)
Below threshold# lag_assets	-1.429***	-1.403***	-1.245***
	(0.029)	(0.034)	(0.048)
Above threshold # lag_assets	-1.271***	-1.343***	-1.343***
	(0.040)	(0.032)	(0.041)
Observations	3,580	3,966	1,586
Number of households	1,790	1,983	793
R2 within	0.690	0.700	0.693
R2 between	0.002	0.002	0.000
R2 overall	0.029	0.023	0.023
Th	0.816	0.829	1.315
Prob	0.000	0.507	0.060

[58] Table available upon request.

* p<0.1; ** p<0.05; *** p<0.01. Note: the dependent variable is the asset index growth, and the threshold variable and regime-dependent variable is the (one period) lagged asset index. Controls not shown: wave dummy variables. Flooded areas definition with the rural-urban buffer. Robust standard errors.

Now I can estimate what happens below and above this threshold. As Carter et al. (2007) did, I performed a short OLS regression of asset growth for the flooded households (Table 1.9). The coefficients on lagged assets are significant only below the threshold. The coefficient in the low growth regime is, as expected, 'sharply negative'. The one in the higher-growth regime is not different from zero (in Carter et al., it was close to zero). This is suggestive of different growth regimes for flooded households, although we cannot explore deeply further subsamples.

Table 1.9: Post-shock regression, flooded households only, pooled w2-w3-w4 (one lag).

	(1) Below 1.315	(2) Above 1.315
L. asset	-0.186***	-0.154
	(0.051)	(0.103)
Age head of hh	0.008*	0.023
	(0.004)	(0.025)
Squared age head of hh	-0.000**	-0.000
	(0.000)	(0.000)
Number of people in the hh	0.002	-0.007
	(0.006)	(0.010)
Head is female widow	-0.102**	-0.073
	(0.050)	(0.085)
HH Distance in km to Nearest Market	-0.000	0.002***
	(0.000)	(0.001)
HH Distance in km to Nearest town	-0.002*	0.001
	(0.001)	(0.002)
Available arable communal land	-0.116*	-0.124
	(0.058)	(0.118)
Rural dummy	-0.070	-0.127
	(0.100)	(0.100)
HH suffered income shock past 2yrs	-0.119***	-0.114*
	(0.045)	(0.064)
Shock: dwelling damaged past 2yrs	0.071	
	(0.141)	
Crop loss: climate, pest, violence	0.128**	-0.306**
	(0.061)	(0.151)
HH receives remittances	0.152**	0.016
	(0.066)	(0.148)
HH received assistance	-0.103*	0.509*
	(0.061)	(0.260)
HH has borrowed	0.054	0.053
	(0.048)	(0.072)
Community hires agric labourers	-0.119	-0.061
	(0.074)	(0.093)
Constant	0.165	-1.140
	(0.155)	(0.796)
Adj R-squared	0.11	0.08
N	797	244
Zone FE	yes	yes

* p<0.1; ** p<0.05; *** p<0.01. The dependent variable is the asset growth rate from one period to the next. OLS. Robust standard errors and panel weights. Flooded defined with the rural-urban buffer. Standard errors clustered at EA level.

1.7.2 Coping strategies among flooded households

Coping with a shock is highly dependent on which strategies the households can adopt. Following Giesbert and Schindler (2012), I extend the parametric regression on the flooded sample by simply adding binary variables representing the lag of common coping behaviours (Table 10). Some of these were already present in the main regression, here are added one by one. Indeed, the reported most common strategies put in place by households against the 2012 flood were the use of savings, the sale of assets and alternative work (Federal Government of Nigeria, 2013). I include all available variables from the survey with two lags (ex-post measures) and with three lags (ex-ante measures).

Most of the ex-ante variables have a positive sign even though not significant (non-farm wage, remittances, withdrawing children from school[59], and migration), while borrowing, assistance and self-employment and asset sale have negative signs. The ex-post variables have negative and nonsignificant signs with the exception of remittances (positive and significant) and borrowing (negative and significant). Remittances indeed have a valuable role in sustaining households' wellbeing in case of shocks, especially if they come from places which do not suffer from the same covariant shock. Post-shock borrowing, perhaps to sustain consumption, is associated with lower growth.

[59] Please remember that the asset index does not include human capital, which most likely suffers from such a choice.

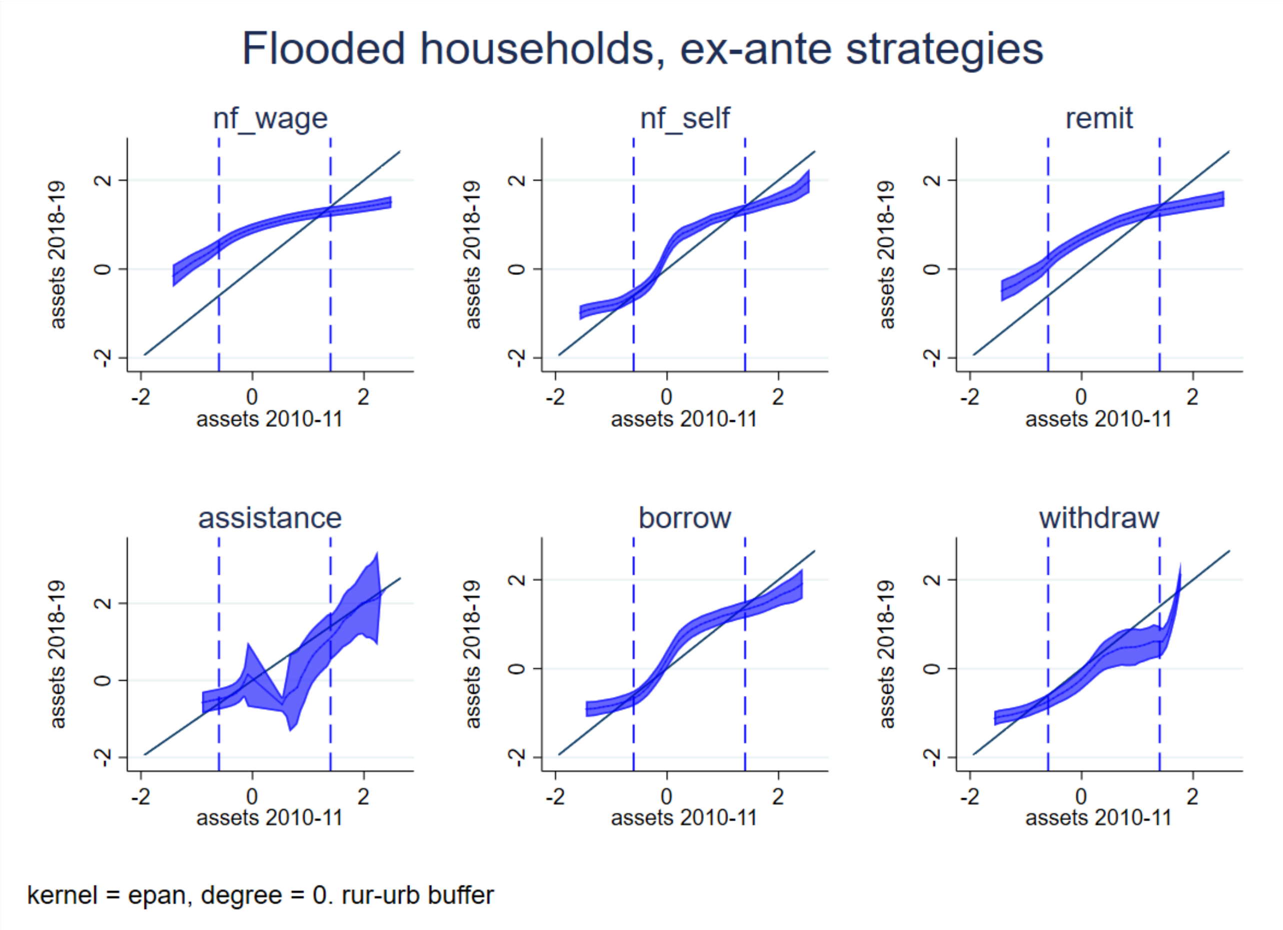
Table 1.10: Parametric regression for coping strategies OLS, flooded sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-Lag assets	-0.376***	-0.331***	-0.371***	-0.390***	-0.353***	-0.363***	-0.364***	-0.373***
	(0.111)	(0.113)	(0.115)	(0.113)	(0.111)	(0.116)	(0.117)	(0.113)
2-Lag assets^2	0.037	0.048	0.006	0.041	0.041	0.037	0.037	0.032
	(0.091)	(0.091)	(0.083)	(0.092)	(0.090)	(0.088)	(0.092)	(0.092)
2-Lag assets^3	-0.030	-0.035	-0.043	-0.021	-0.041	-0.038	-0.034	-0.028
	(0.060)	(0.063)	(0.058)	(0.060)	(0.058)	(0.060)	(0.061)	(0.060)
2-Lag assets^4	0.002	0.000	0.012	-0.001	0.004	0.005	0.003	0.003
	(0.028)	(0.028)	(0.023)	(0.028)	(0.026)	(0.026)	(0.028)	(0.028)
L2. Wage	-0.062							
	(0.070)							
L3. Wage	0.051							
	(0.070)							
L2. Self-empl.		-0.023						
		(0.059)						
L3. Self-empl.		-0.136						
		(0.093)						
L2. Remittances			0.741*					
			(0.415)					
L3. Remittances			0.042					
			(0.101)					
L2. Assistance				-0.228				
				(0.137)				
L3. Assistance				-0.031				
				(0.291)				
L2. Migration					-0.208			
					(0.202)			
L3. Migration					0.466			
					(0.314)			
L2. Borrow						-0.106*		
						(0.058)		
L3. Borrow						-0.001		
						(0.045)		
L2. Withdraw							0.036	
							(0.073)	
L3. Withdraw							0.052	
							(0.077)	
L2 Asset sale								-0.037
								(0.121)
L3. Asset sale								-0.192
								(0.183)
Observations	270	270	270	270	270	270	270	270
Adjusted R-squared	0.166	0.178	0.206	0.167	0.189	0.172	0.162	0.163
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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
F-test lags 2-4=0	0.912	0.841	0.907	0.936	0.812	0.871	0.894	0.929

* $p<0.1$; ** $p<0.05$; *** $p<0.01$. All regressions control for (lagged) socio-demographics, mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at EA level, panel weights. Flooded defined with a buffer defined according to the rural-urban definition. Coping strategies included: borrowing money from any source, receiving assistance from programmes, having a job outside agriculture, receiving remittances, withdrawing children from school, running a non-farm business, having some members of the household to migrate (all destinations), selling assets. I include all variables with two lags (ex-post measures) and with three lags (ex-ante measures).

Non-parametric regressions run for flooded households (w2-w4) subsamples according to the ex-ante strategies show that households with nonfarm wage employment and remittances converge only to the high equilibrium. Indeed, nonfarm wage and remittances are income diversification strategies which can be high-cost high-rewarding strategies. Households with self-employment, assistance or that borrowed show S-shaped dynamics, signalling that these strategies are common along the whole distribution of assets, and the outcome depends crucially on the type of business, type of moneylender and type of assistance and social safety nets. Finally, households who withdrew children from school ex-ante converge only to the poverty trap equilibrium (Figure 1.10). Ex-post strategies (Figure A 8) yield the same results as ex-ante strategies, moreover, instead of remittances it is possible to estimate that households with migration (ex-post) converge to the high equilibrium only.

Figure 1.12: Non-parametric regressions of subsamples of flooded households according to the coping strategies, w2-w4



Source: own elaboration using Nigeria GHS panel data. The dotted vertical lines are set at the equilibria identified in Figure 1.7.

1.8 Conclusions

As climate change entails more frequent extreme weather events, understanding the risk of falling into a poverty trap becomes policy relevant. The poor, being disproportionately exposed to these shocks, often lack adequate social protection and viable coping strategies to mediate the impact of these shocks. In this chapter, I have focused on Nigeria, which is affected by high rates of poverty and nontrivial exposure to floods. With satellite data, I identified households affected by the massive flooding that took place in 2012 and neighbouring non-flooded households.

In order to determine whether the 2012 disastrous flooding created a poverty trap, this analysis used a combination of methods. First, the simple bivariate relationship between current and lagged assets showed that non-flooded households converged to one high equilibrium, while flooded households converged to (at least) two equilibria (Adato et al., 2006; Zimmerman and Carter, 2003). Second, parametric regressions confirmed the absence of convergence for flooded households. Predicting the asset change and using it in non-parametric regressions (Giesbert and Schindler, 2012; Naschold, 2013), shows how a poverty trap is identified around -1 asset scores, and the transition curves identifies three equilibria. This is compatible with the multiple equilibria poverty trap story, in which the two extreme equilibria are stable and the middle one is of unstable nature. Third, panel threshold estimations provides significant evidence in favour of the presence of a threshold splitting the sample for flooded households around the high equilibrium, signalling different speed of growth according to the asset level (Carter et al., 2007). This identification provided the basis for an analysis of the different growth patterns according to the initial asset holdings, whether they were below or above the thresholds. The post-shock recovery of flooded households depends on their resources but also on their coping strategies (Giesbert and Schindler, 2012; Scott, 2019). Checking both ex-ante and ex-post strategies, I find only a significant effect of remittances fostering asset growth. High-rewarding strategies (non-farm wage, remittances and migration) are associated with convergence to the high equilibrium, while withdrawing children from school shows convergence to the poverty trap only. Other strategies (self-employment, borrowing and social assistance), both ex-ante and ex-post are common across the distribution of assets and are associated with S-shaped dynamics.

Robustness checks confirmed the general findings, while highlighting the limitations of the sample size. In particular, the asset transition functions of flooded households show more pronounced S-shaped dynamics as the buffer size is reduced, while showing a less and less identifiable shape as the buffer size increases. This is reassuring that the buffer size chosen is the most correct one (and captures a number of households large enough to conduct the analysis). The results are stable using different functional forms in the non-parametric regression, varying the asset bundle composition and aggregation method. Finally, to exclude that other confounding factors might drive the accumulation of assets, I control for violent conflict event dummies and other climatic shocks, which reassure about the validity of my results.

I cannot however exclude that the poverty trap was already present before the 2012 flood, as highlighted by the two peaks in the asset distribution also at wave 1[60]. Plausibly, some households living in proximity of water have very low levels of assets and periodically suffer from (minor) inundations. This is consistent with geographical/immobility poverty traps (Jalan and Ravallion, 2002; Nawrotzki

[60] Indeed, the country suffered from a significant but shorter and smaller flood in 2010 but MODIS NRT products are available only from 2011.

and DeWaard, 2018). On the other hand, there are other households living close to water which tend to a high-level equilibrium and are able to carry on despite the flood. This seems to be also the case of the households that do not live in proximity of water but were hit by the 2012 extreme flood: they converge to a high-level equilibrium. The poverty trap dynamics are indeed driven by the subsample of households suffering from the 2012 flood and living close to water. Unfortunately, it is not possible to inspect further subsamples as the sample size becomes too small.

Plausibly, it is recurrent climatic shocks among vulnerable populations that trap people in poverty[61], while a one-time devastating shock among more resilient households can be manageable, temporarily driving them away from their steady state but without compromising their asset capacity[62]. To further confirm this, further research will be needed to shed light on disentangling the effects of one large extreme event and recurrent climatic shocks and its effect on poverty persistence by resilience levels.

Previous studies on poverty traps have concentrated on more homogeneous settings in which wealth could be easily proxied by a representative asset – livestock. Nigeria is a more complex and heterogeneous case, which requires nontrivial asset aggregation. Testing empirically for a poverty trap is not easy. Different methods have been applied to overcome this issue. Another major difficulty has been the limited duration of the large panel and the partial refreshment which further reduced the sample size. Nevertheless, the availability of data from before and following the shock offers a valuable opportunity to study the impact of the shock on households with different starting conditions. In spite of the complexity of the setting and of the goal, being able to identify a poverty trap is meaningful and useful from a policy perspective.

This paper provides empirical evidence of a poverty trap in Nigeria in relation to a major flood. By definition, absent any other (positive) shock, these households are still in poverty, in a low-level stable equilibrium. They may still be in need of recovery assistance programmes, which were probably insufficient. Moreover, their situation is likely to have been exacerbated by the current Covid-19 crisis. Adequate social protection programmes, credit availability and insurance programmes are among the most important measures that need to be implemented.

[61] Indeed, pastoralists' likelihood of being trapped in poverty is correlated with *recurrent* exposure to climatic shocks through the deterioration of social capital in Ethiopia (Berhanu, 2011). On the impact of repeated droughts on migration see Di Falco et al. (2022).

[62] A study on the impact of Hurricane Mitch in Nicaragua finds that households do not lose productive assets but manage to cope with the large shock by depleting non-productive assets (Jakobsen, 2012).

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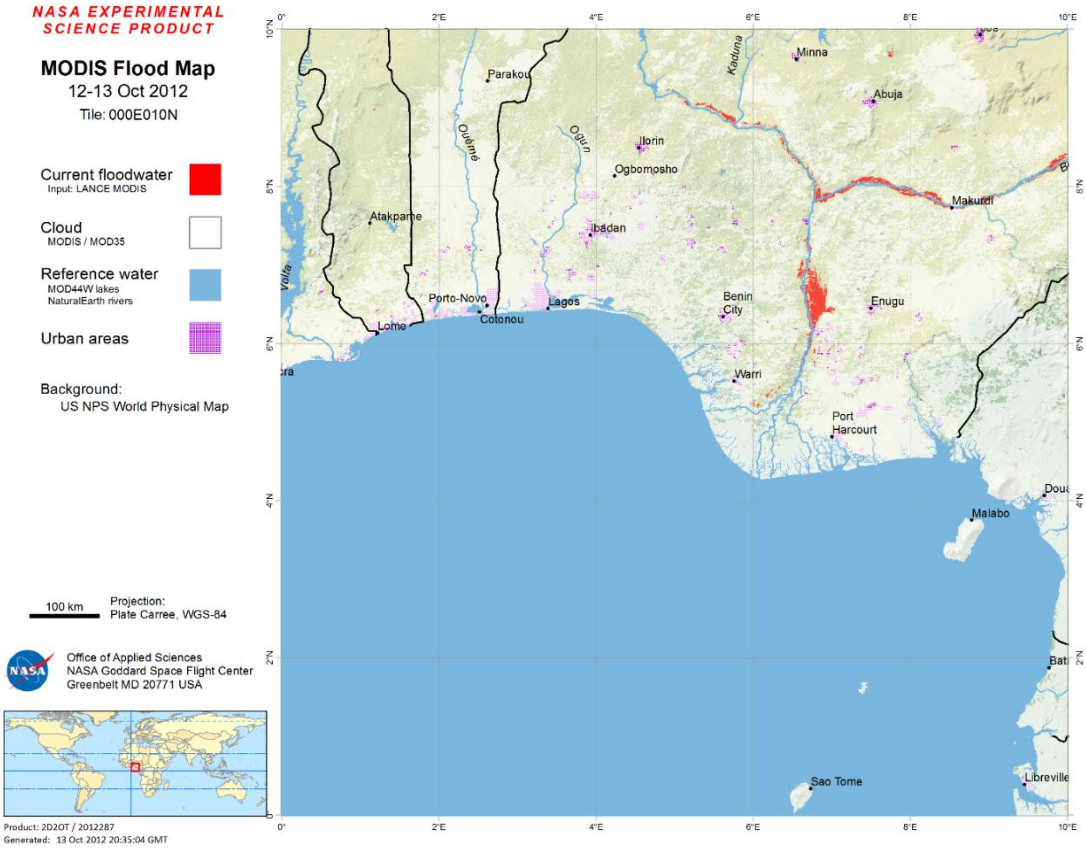
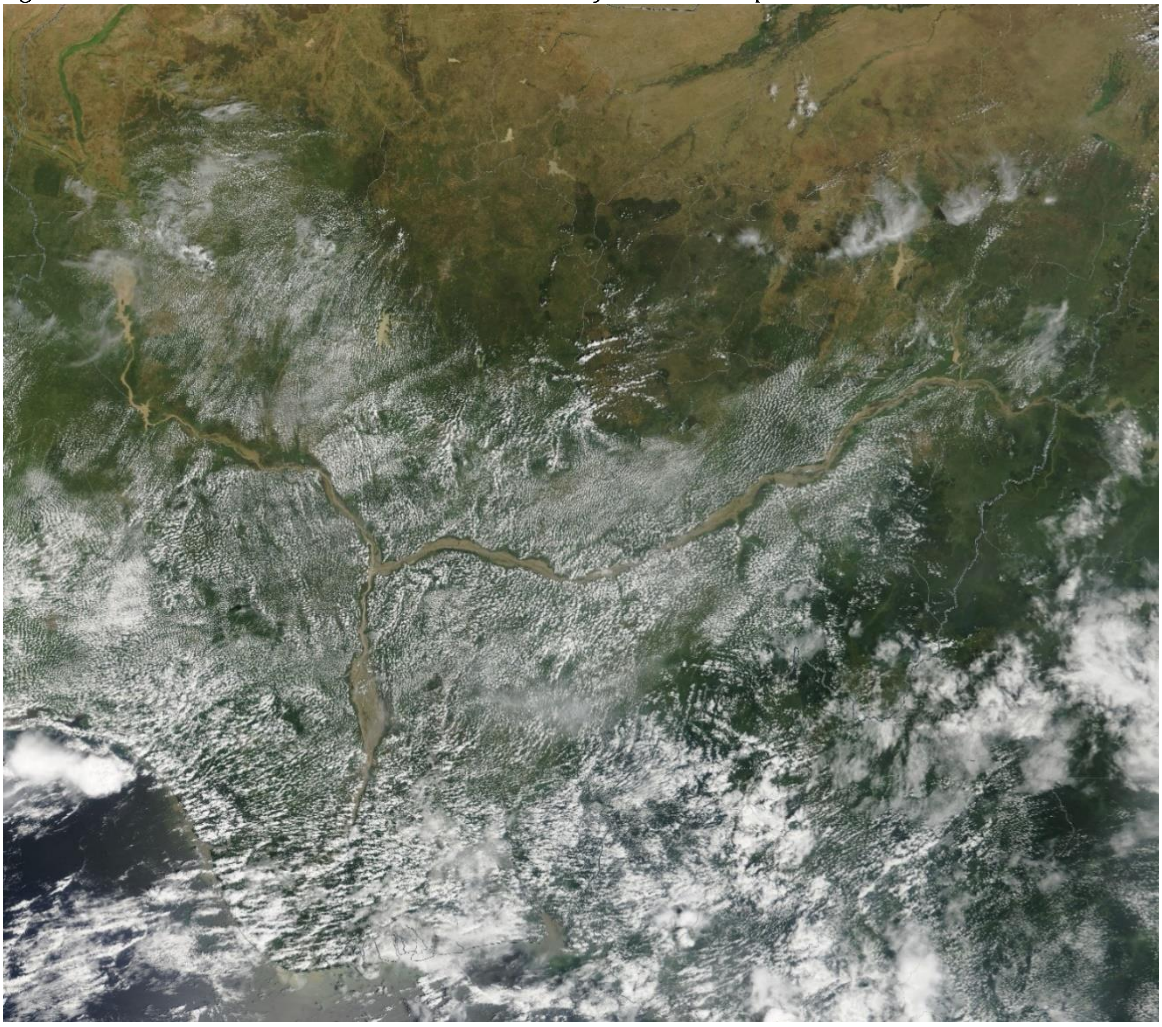
Appendix 1

Figure A 1: MODIS Flood map for one of the four tiles used for the construction of the flood variable



Accessible from https://floodmap.modaps.eosdis.nasa.gov/Africa.php (one tile of four)

Figure A 2: Terra MODIS True Color Corrected Reflectance snapshot 13 October 2012



Accessed from Earthdata.nasa.gov

Table A 1. DHS asset components, their mean by asset quintiles and scoring coefficients

Components	DHS assets, quintiles 1	2	3	4	5	Total	
	mean	mean	mean	mean	mean	mean	Factor1
wall==mud/compacted earth	0.79	0.74	0.28	0.09	0.01	0.38	-0.076
wall==mud brick (unfired)	0.05	0.10	0.07	0.04	0.01	0.05	-0.012
wall==burnt bricks	0.01	0.01	0.02	0.02	0.02	0.01	0.003
wall==concrete	0.00	0.08	0.60	0.83	0.95	0.49	0.090
wall==wood	0.00	0.01	0.01	0.01	0.00	0.01	-0.001
wall==iron sheets	0.00	0.00	0.01	0.01	0.00	0.01	0.002
wall==other (specify)	0.15	0.04	0.01	0.00	0.00	0.04	-0.028
roof==grass	0.58	0.09	0.02	0.01	0.01	0.14	-0.088
roof==iron sheets	0.33	0.82	0.90	0.90	0.80	0.75	0.000
roof==clay tiles	0.03	0.02	0.00	0.00	0.00	0.01	-0.020
roof==concrete	0.00	0.01	0.01	0.02	0.02	0.01	-0.003
roof==plastic sheeting	0.00	0.00	0.01	0.01	0.01	0.01	-0.002
roof==abestos sheet	0.00	0.02	0.03	0.05	0.13	0.05	0.008
roof==other (specify)	0.04	0.04	0.02	0.01	0.03	0.03	-0.018
floor==sand/dirt/straw/mud	0.93	0.41	0.10	0.03	0.01	0.30	-0.138
floor==smooth cement	0.07	0.57	0.88	0.94	0.84	0.66	0.000
floor==wood	0.00	0.02	0.01	0.01	0.00	0.01	-0.014
floor==tile	0.00	0.00	0.01	0.02	0.14	0.03	0.015
floor==other (specify)	0.00	0.00	0.00	0.00	0.00	0.00	-0.006
cookfuel==firewood	0.99	0.96	0.87	0.61	0.17	0.72	-0.082
cookfuel==coal	0.00	0.00	0.01	0.03	0.03	0.01	0.012

Table A 2. (continued). DHS asset components, their mean by asset quintiles and scoring coefficients

	DHS assets, quintiles						
	1	2	3	4	5	Total	Factor1
	mean	mean	mean	mean	mean	mean	
cookfuel==grass	0.00	0.00	0.01	0.01	0.01	0.01	0.006
cookfuel==kerosene	0.00	0.02	0.10	0.32	0.64	0.22	0.067
cookfuel==electricity	0.00	0.00	0.00	0.01	0.02	0.01	0.012
cookfuel==gas	0.00	0.00	0.00	0.01	0.13	0.03	0.038
cookfuel==other	0.00	0.01	0.01	0.01	0.00	0.01	-0.001
water, wet s.==pipe borne water	0.02	0.06	0.09	0.11	0.17	0.09	0.022
water, wet s.==bore hole/hand pump	0.12	0.21	0.31	0.42	0.49	0.31	0.035
water, wet s.==well/spring protected	0.14	0.16	0.12	0.12	0.08	0.13	-0.009
water, wet s.==well/spring unprotected	0.32	0.19	0.07	0.03	0.01	0.13	-0.040
water, wet s.==surface water: pond, river, lake	0.22	0.14	0.07	0.03	0.01	0.09	-0.031
water, wet s.==rain water	0.17	0.22	0.30	0.22	0.10	0.20	-0.009
water, wet s.==tanker/truck/vendor	0.00	0.01	0.02	0.03	0.03	0.02	0.010
water, wet s.==other	0.00	0.01	0.01	0.03	0.12	0.03	0.029
toilet==none	0.48	0.32	0.27	0.17	0.04	0.26	-0.042
toilet==toilet on water	0.01	0.02	0.02	0.04	0.05	0.03	0.011
toilet==flush to sewage	0.00	0.00	0.02	0.06	0.21	0.06	0.039
toilet==flush to septic tank	0.00	0.00	0.03	0.12	0.49	0.13	0.064
toilet==pail/bucket	0.01	0.01	0.01	0.01	0.00	0.01	-0.002
toilet==covered pit latrine	0.21	0.38	0.45	0.47	0.18	0.34	-0.004
toilet==uncovered pit latrine	0.19	0.18	0.12	0.08	0.02	0.12	-0.024
toilet==v.i.p latrine	0.01	0.02	0.02	0.03	0.01	0.02	0.000
HH does not share its toilet facility	0.38	0.50	0.43	0.43	0.61	0.47	0.018
HH owns a mobile phone	0.38	0.60	0.76	0.90	0.98	0.72	0.057
HH uses electricity	0.03	0.19	0.52	0.81	0.95	0.50	0.085
HH mem has a bank account	0.02	0.08	0.22	0.49	0.88	0.34	0.082
# cattle, cows owned by hh	4.63	0.99	0.39	0.20	0.06	1.25	-0.020
# oxen owned by hh	0.23	0.12	0.03	0.01	0.00	0.08	-0.016
# donkey/horse owned by hh	0.89	0.04	0.01	0.01	0.01	0.19	-0.001
# goats owned by hh	7.88	2.82	1.41	5.02	0.40	3.51	-0.002
# sheep owned by hh	2.54	1.30	0.52	0.29	0.11	0.95	-0.029
# pigs owned by hh	0.11	0.08	0.08	0.14	0.40	0.16	0.005
# chickens owned by hh	8.47	6.50	3.83	3.34	18.23	8.07	0.004
# other poultry owned by hh	1.38	0.68	0.18	0.09	0.45	0.56	-0.007
# other livestock owned by hh	0.03	0.04	0.01	0.09	0.01	0.04	0.000
HH owns radio	0.49	0.56	0.54	0.64	0.67	0.58	0.016
HH owns tv	0.00	0.06	0.26	0.73	0.96	0.40	0.093
HH owns fridge	0.00	0.00	0.02	0.17	0.59	0.16	0.074
HH owns satdish	0.00	0.00	0.01	0.04	0.28	0.07	0.054
HH owns generator	0.01	0.06	0.14	0.32	0.67	0.24	0.071
HH owns aircond	0.00	0.00	0.00	0.00	0.09	0.02	0.036
HH owns computer	0.00	0.00	0.00	0.02	0.19	0.04	0.047
HH owns iron	0.05	0.13	0.20	0.53	0.89	0.36	0.080
HH owns fan	0.00	0.04	0.23	0.75	0.96	0.40	0.095
HH owns bike	0.22	0.26	0.21	0.18	0.10	0.19	-0.014
HH owns motorbike	0.23	0.34	0.35	0.39	0.24	0.31	0.000
HH owns trailer	0.01	0.01	0.00	0.00	0.00	0.01	-0.007
HH owns car	0.01	0.02	0.02	0.07	0.35	0.09	0.056
HH owns boat	0.01	0.00	0.00	0.00	0.00	0.00	-0.003
HH owns canoe	0.01	0.01	0.00	0.01	0.00	0.01	-0.003
Land owned, hectacres	0.07	0.04	0.02	0.02	0.01	0.03	-0.011
HH uses domestic help	0.00	0.00	0.01	0.02	0.06	0.02	0.022
HH owns land	0.07	0.07	0.04	0.03	0.02	0.04	-0.012

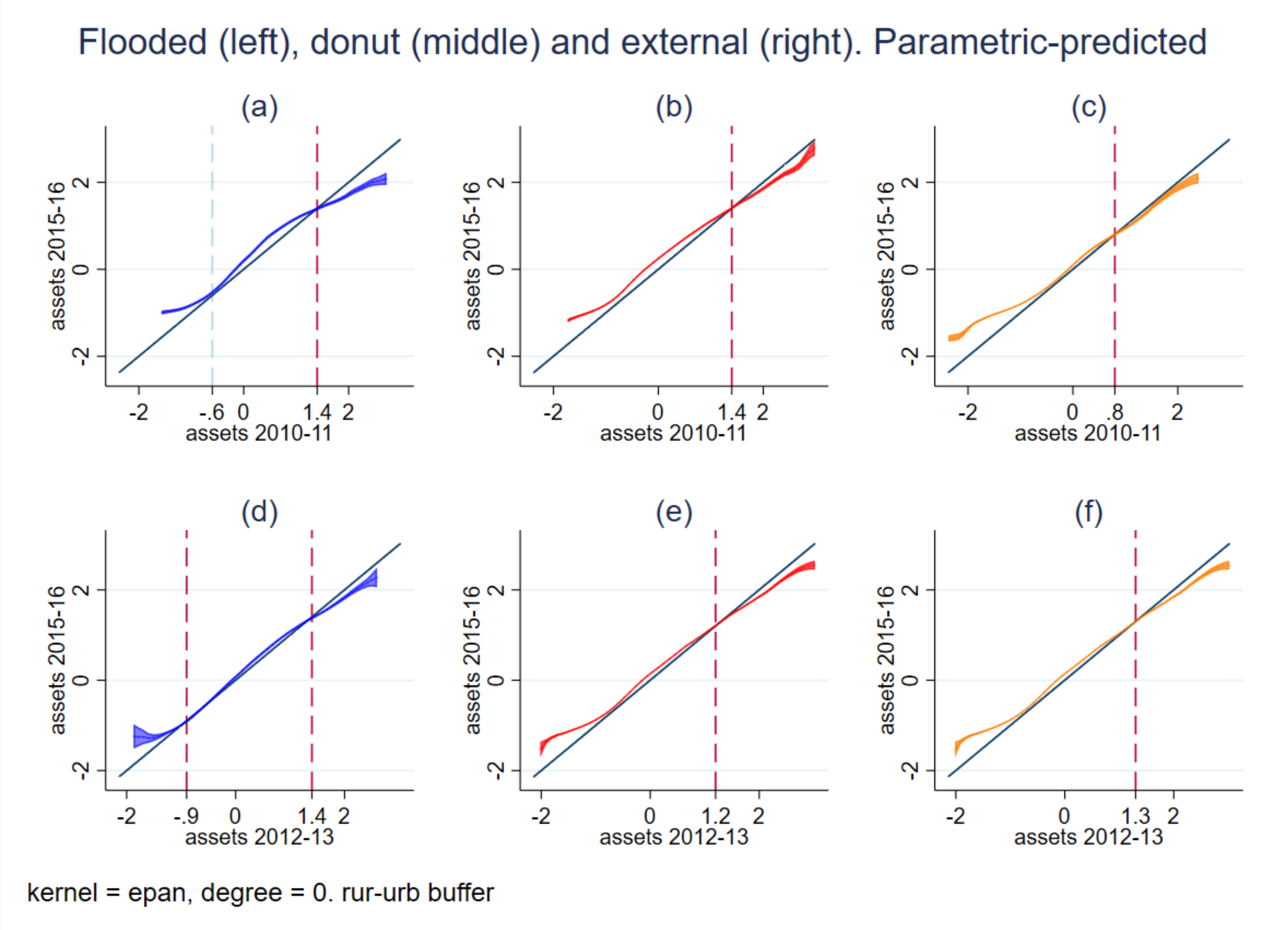
Source: own elaboration using Nigeria GHS panel data

Table A 3. Parametric regression, long differences until 2015-16 (shorter large panel), OLS

	(1)	(2)	(3)	(4)	(5)	(6)
		Growth w3 -w1			Growth w3 -w2	
VARIABLES	external	donut	flooded	external	donut	flooded
2-Lag assets	-0.364***	-0.296***	-0.131*			
	(0.072)	(0.073)	(0.071)			
2-Lag assets^2	-0.041	-0.075**	-0.091*			
	(0.041)	(0.030)	(0.046)			
2-Lag assets^3	-0.004	-0.040	-0.156***			
	(0.020)	(0.028)	(0.043)			
2-Lag assets^4	0.009	0.021**	0.057***			
	(0.009)	(0.010)	(0.016)			
1-Lag assets				-0.319***	-0.174***	-0.153***
				(0.059)	(0.050)	(0.056)
1-Lag assets^2				0.019	-0.024	-0.081**
				(0.032)	(0.023)	(0.037)
1-Lag assets^3				0.009	-0.026	-0.083***
				(0.020)	(0.020)	(0.026)
1-Lag assets^4				-0.008	0.007	0.036***
				(0.010)	(0.008)	(0.012)
Observations	1,751	1,891	765	1,751	1,891	765
Adjusted R-squared	0.184	0.190	0.241	0.156	0.117	0.169
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.754	0.060	0.000	0.880	0.051	0.007

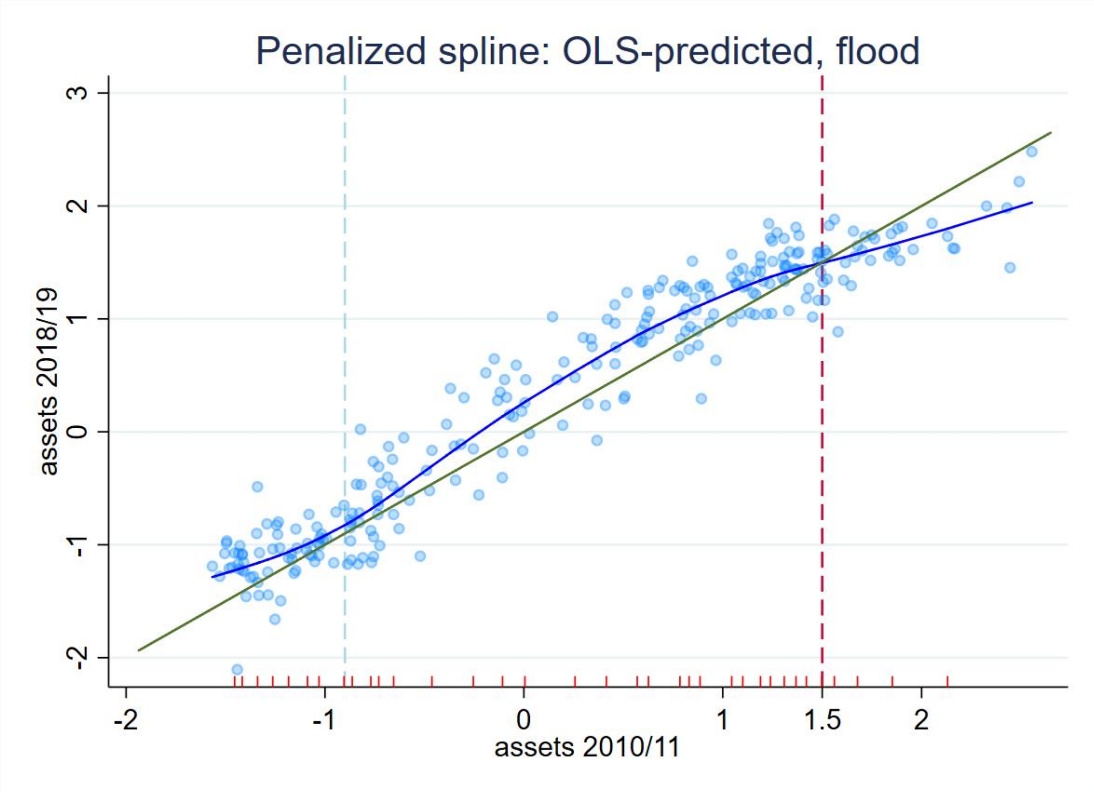
p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at EA level, panel weights. Flooded defined with a buffer defined according to the rural-urban definition.

Figure A 3: OLS-predicted asset change to wave 3, local polynomial smooth



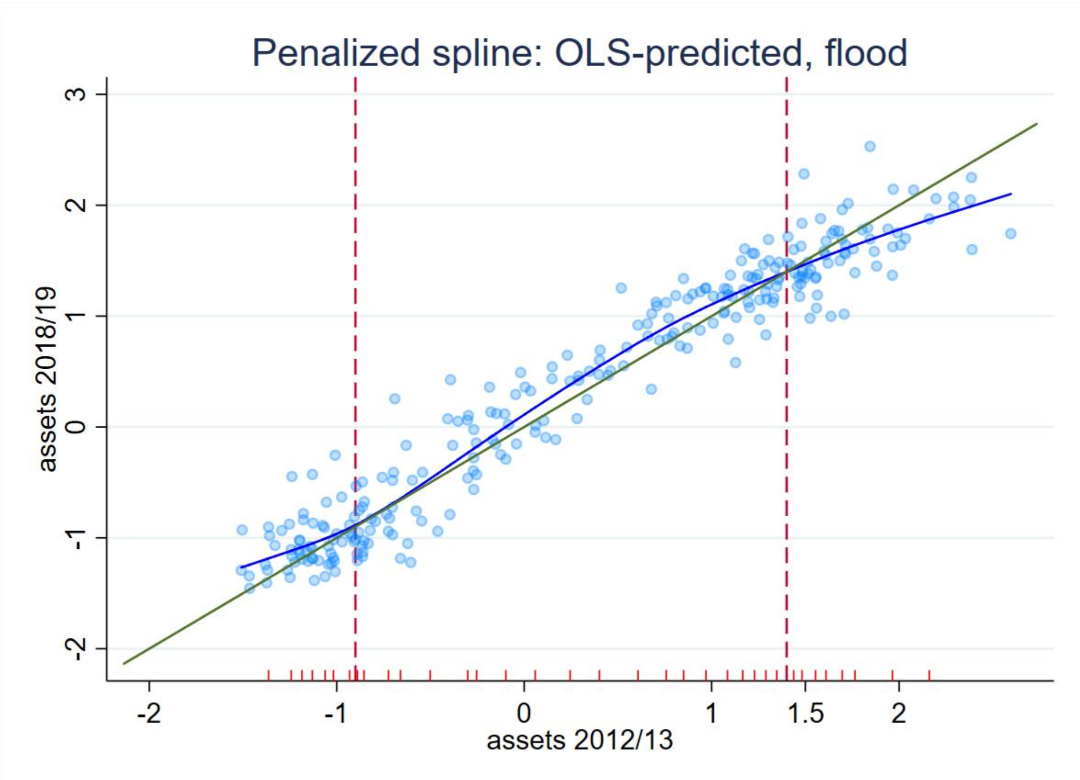
Source: own elaboration using Nigeria GHS panel data. Large panel up to w3.

Figure A 4: OLS-predicted asset change w1-w4. Penalized spline, flooded



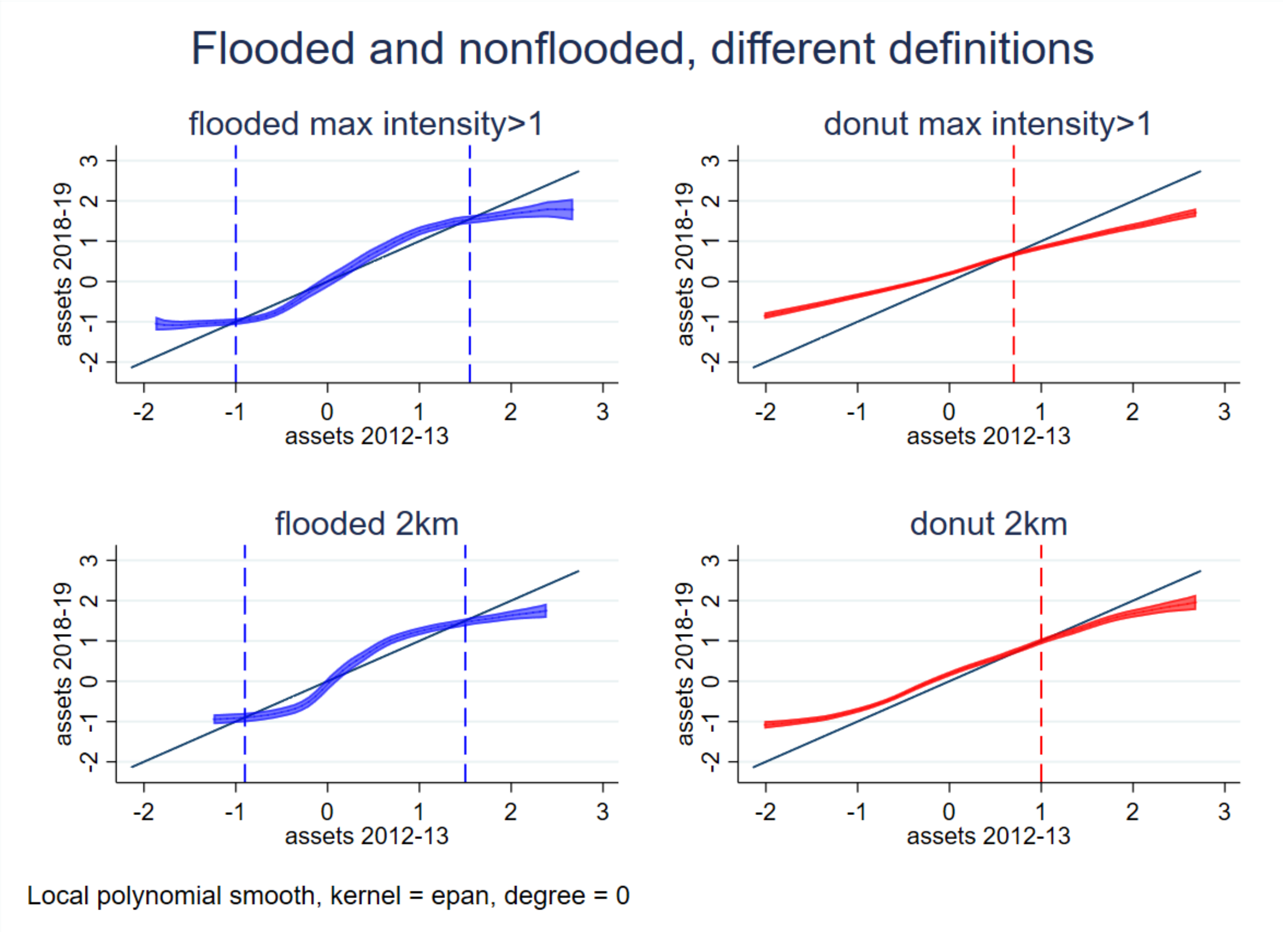
Source: own elaboration using Nigeria GHS panel data

Figure A 5: OLS-predicted asset change w2-w4. Penalized spline, flooded



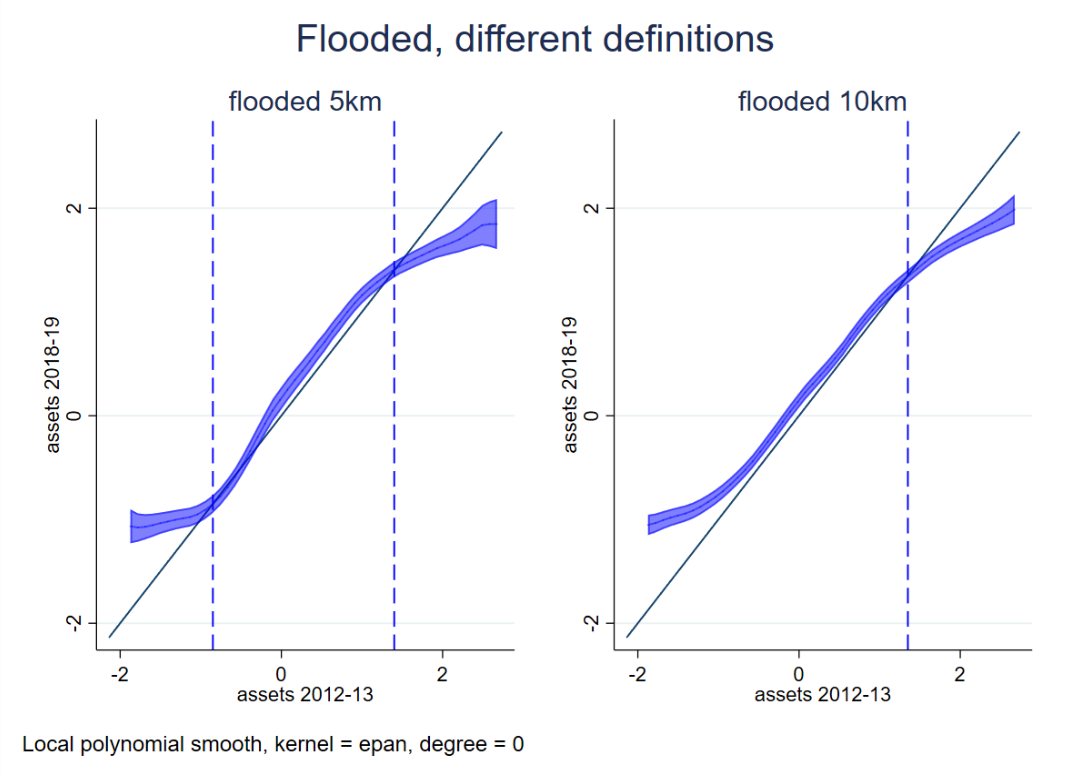
Source: own elaboration using Nigeria GHS panel data

Figure A 6: Non-parametric asset change from wave 2 - wave 4, different definitions



Source: own elaboration using Nigeria GHS panel data.

Figure A 7: Non-parametric asset change from wave 2 - wave 4, larger buffer size



Source: own elaboration using Nigeria GHS panel data.

Table A 4: Parametric regression, long differences until 2018-19 (small extended panel), OLS with polychoric PCA asset index.

	(1)	(2)	(3)	(4)	(5)	(6)
		Growth w4 -w1			Growth w4 -w2	
VARIABLES	external	donut	flooded	external	donut	flooded
3-Lag assets	-1.286*	-0.545	-1.696			
	(0.667)	(0.626)	(1.053)			
3-Lag assets^2	0.711	0.049	1.507			
	(0.988)	(1.023)	(1.559)			
3-Lag assets^3	-0.201	0.014	-0.721			
	(0.583)	(0.592)	(0.830)			
3-Lag assets^4	0.005	-0.015	0.113			
	(0.116)	(0.111)	(0.145)			
2-Lag assets				-0.610	-1.378**	-0.290
				(0.622)	(0.576)	(0.903)
2-Lag assets^2				-0.048	1.443	-0.371
				(0.948)	(0.898)	(1.270)
2-Lag assets^3				0.195	-0.825	0.238
				(0.523)	(0.516)	(0.669)
2-Lag assets^4				-0.065	0.158	-0.046
				(0.096)	(0.098)	(0.118)
Observations	610	545	270	610	524	270
Adjusted R-squared	0.292	0.278	0.315	0.227	0.160	0.243
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.236	0.187	0.320	0.033	0.300	0.958

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at EA level, panel weights. Flooded defined with a buffer defined according to the rural-urban definition.

Table A 5: Parametric regression, long differences until 2018-19 (small extended panel), OLS with an asset index that exclude durables.

	(1)	(2)	(3)	(4)	(5)	(6)
		Growth w4 -w1			Growth w4 -w2	
VARIABLES	external	donut	flooded	external	donut	flooded
3-Lag assets	-0.401***	-0.498***	-0.484***			
	(0.117)	(0.086)	(0.098)			
3-Lag assets^2	0.113*	-0.178**	-0.148			
	(0.064)	(0.086)	(0.160)			
3-Lag assets^3	-0.109**	-0.024	-0.055**			
	(0.044)	(0.030)	(0.024)			
3-Lag assets^4	-0.035	0.038	0.038			
	(0.021)	(0.026)	(0.046)			
2-Lag assets				-0.311***	-0.435***	-0.394***
				(0.083)	(0.090)	(0.102)
2-Lag assets^2				0.054	-0.017	0.054
				(0.065)	(0.057)	(0.142)
2-Lag assets^3				-0.067**	0.011	-0.047
				(0.031)	(0.031)	(0.038)
2-Lag assets^4				-0.019	0.009	-0.029
				(0.018)	(0.014)	(0.039)
Observations	603	533	267	600	516	268
Adjusted R-squared	0.332	0.301	0.340	0.259	0.185	0.255
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.014	0.052	0.143	0.102	0.604	0.186

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at EA level, panel weights. Flooded defined with a buffer defined according to the rural-urban definition.

Table A 6: Parametric regression, long differences, OLS. Conflict as dummy for events>0

	(1)	(2)	(3)	(4)	(5)	(6)
		Growth w4 -w1			Growth w4 -w2	
VARIABLES	external	donut	flooded	external	donut	flooded
3-Lag assets	-0.259***	-0.247*	-0.233**			
	(0.090)	(0.124)	(0.092)			
3-Lag assets^2	0.055	-0.053	-0.127			
	(0.075)	(0.082)	(0.109)			
3-Lag assets^3	-0.085**	-0.056	-0.102**			
	(0.037)	(0.051)	(0.047)			
3-Lag assets^4	0.015	0.023	0.043			
	(0.019)	(0.026)	(0.032)			
Conflict =1	0.087	-0.017	0.009	0.111	0.127	0.130
	(0.125)	(0.069)	(0.105)	(0.116)	(0.080)	(0.139)
L. Conflict =1	0.008	0.195*	-0.129	-0.116*	0.231**	0.090
	(0.102)	(0.109)	(0.163)	(0.066)	(0.095)	(0.136)
L2. Conflict =1	0.354	-0.091	0.050	0.143	-0.238**	-0.180
	(0.213)	(0.125)	(0.137)	(0.121)	(0.095)	(0.144)
2-Lag assets				-0.248**	-0.358***	-0.084
				(0.095)	(0.090)	(0.126)
2-Lag assets^2				0.007	-0.012	-0.028
				(0.064)	(0.047)	(0.085)
2-Lag assets^3				-0.047	0.000	-0.106
				(0.029)	(0.026)	(0.068)
2-Lag assets^4				0.008	0.004	0.030
				(0.014)	(0.011)	(0.024)
Observations	610	524	270	610	524	270
Adjusted R-squared	0.188	0.167	0.225	0.160	0.158	0.121
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.020	0.725	0.017	0.390	0.899	0.241

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at the EA level, panel weights. Flooded defined with rural-urban buffer. Conflict is a dummy that equals 1 if in the 5km buffer there was at least a violent conflict in the months between the second interview and 12 months prior the first interview. Source of data for conflicts from ACLED (www.acleddata.com).

Table A 7: Parametric regression, long differences, OLS. Conflict as dummy for fatalities>0

	(1)	(2)	(3)	(4)	(5)	(6)
	Growth w4 -w1			Growth w4 -w2		
VARIABLES	external	donut	flooded	external	donut	flooded
3-Lag assets	-0.287***	-0.262**	-0.239**			
	(0.088)	(0.119)	(0.094)			
3-Lag assets^2	0.040	-0.045	-0.102			
	(0.076)	(0.084)	(0.104)			
3-Lag assets^3	-0.085**	-0.048	-0.118***			
	(0.036)	(0.050)	(0.037)			
3-Lag assets^4	0.021	0.022	0.046			
	(0.020)	(0.027)	(0.028)			
Conflict with fatalities =1	0.226	0.069	0.269	0.381**	0.120	0.087
	(0.267)	(0.090)	(0.236)	(0.165)	(0.082)	(0.160)
L. Conflict with fatalities =1	-0.370***	0.036	0.200	0.066	-0.044	0.022
	(0.108)	(0.096)	(0.161)	(0.149)	(0.080)	(0.140)
L2. Conflict with fatalities =1	-0.747**		0.139	-0.334*		0.257***
	(0.307)		(0.119)	(0.194)		(0.062)
2-Lag assets				-0.270***	-0.340***	-0.016
				(0.101)	(0.093)	(0.137)
2-Lag assets^2				-0.005	-0.028	-0.018
				(0.066)	(0.044)	(0.090)
2-Lag assets^3				-0.040	-0.002	-0.115
				(0.028)	(0.026)	(0.074)
2-Lag assets^4				0.013	0.008	0.030
				(0.015)	(0.011)	(0.025)
Observations	610	524	270	610	524	270
Adjusted R-squared	0.209	0.162	0.240	0.170	0.141	0.116
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.011	0.816	0.003	0.414	0.670	0.189

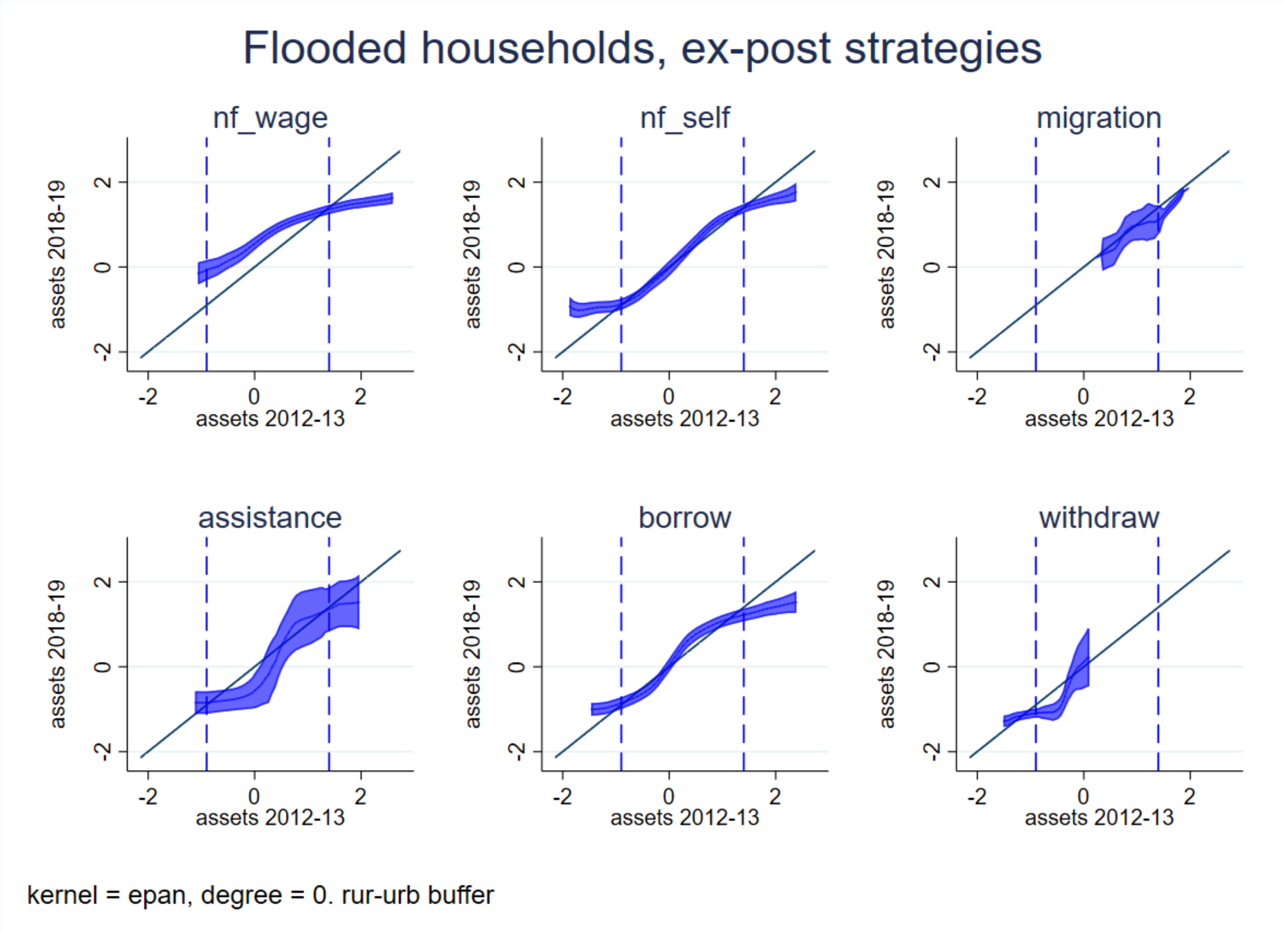
p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at the EA level, panel weights. Flooded defined with 2 km buffer. Conflict is a dummy that equals 1 if in the 5km buffer there was at least a fatality related to violent conflict in the months between the second interview and 12 months prior the first interview. Source of data for conflicts from ACLED (www.acleddata.com).

Table A 8: Parametric regression, long differences, OLS. Community climatic shocks

	(1)	(2)	(3)	(4)	(5)	(6)
		Growth w4 -w1			Growth w4 -w2	
VARIABLES	external	donut	flooded	external	donut	flooded
3-Lag assets	-0.227***	-0.289**	-0.267**			
	(0.085)	(0.126)	(0.098)			
3-Lag assets^2	0.059	-0.073	-0.102			
	(0.076)	(0.085)	(0.102)			
3-Lag assets^3	-0.090**	-0.056	-0.084*			
	(0.036)	(0.048)	(0.045)			
3-Lag assets^4	0.016	0.031	0.034			
	(0.020)	(0.026)	(0.030)			
L. drought (community)	-0.154	0.159	-0.074	-0.022	0.106	-0.270
	(0.159)	(0.104)	(0.224)	(0.088)	(0.084)	(0.186)
L2. drought (community)	0.138	-0.104	0.103	0.168	-0.118*	0.001
	(0.126)	(0.134)	(0.120)	(0.112)	(0.066)	(0.123)
L3. drought (community)	-0.146	0.288***	-0.087			
	(0.120)	(0.099)	(0.113)			
L. flood (community)	0.179	0.243**	-0.024	0.138*	0.119	-0.056
	(0.115)	(0.094)	(0.088)	(0.078)	(0.075)	(0.082)
L2. flood (community)	0.019	-0.052	0.014	0.049	-0.052	-0.055
	(0.078)	(0.088)	(0.081)	(0.078)	(0.067)	(0.071)
L3. flood (community)	-0.048	0.028	-0.107			
	(0.088)	(0.062)	(0.079)			
2-Lag assets				-0.245***	-0.349***	-0.039
				(0.091)	(0.099)	(0.127)
2-Lag assets^2				-0.000	-0.035	0.008
				(0.063)	(0.048)	(0.087)
2-Lag assets^3				-0.049*	-0.002	-0.123*
				(0.026)	(0.028)	(0.072)
2-Lag assets^4				0.013	0.008	0.030
				(0.015)	(0.012)	(0.025)
Observations	610	524	270	610	524	270
Adjusted R-squared	0.194	0.188	0.223	0.163	0.146	0.118
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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	0.009	0.626	0.046	0.252	0.641	0.146

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at the EA level, panel weights. Flooded defined with rural-urban buffer.

Figure A 8: Non-parametric regressions of subsamples of flooded households according to the coping strategies, w2-w4



Source: own elaboration using Nigeria GHS panel data.

Appendix 2: sensitivity tests on convergence

The first sensitivity test reports the parametric regression for the different buffer sizes, the one used throughout the analysis (rural-urban buffer) and those used in the robustness checks section (Table A2 1). Convergence is rejected in the long difference only when the buffer size is 2-5 km (rural-urban definition) and 5 km; in the short difference it is rejected when it is 2 km only. In either case, in the 10 km buffer convergence cannot be rejected. Indeed, a 10 km buffer which intersects at least a flooded pixel is not a believable identification of the flooded areas, contrary to 5 km buffers and smaller buffer sizes, which have higher chance of capturing really hit households. It is reported in the analysis to show that the effect is localized and can be captured with smaller buffers. This is confirmed in the nonparametric cases, too (cf. Section 1.6.1).

As for what concerns the smaller buffers, indeed there is some somewhat disturbing sensitivity to the buffer definition at least in the parametric regression. For the non-parametric regressions, results look more coherent.

Table A2 1: Sensitivity test: distance from water and different buffer sizes. Parametric regression, w4-w1 and w4-w2, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Growth w4 -w1				Growth w4 -w2		
VARIABLES	Flood 2km	flood 2-5km	flood 5km	flood 10km	Flood 2km	Flood 2-5km	Flood 5km	Flood 10km
3-Lag assets	-0.722***	-0.296***	-0.325***	-0.419***				
	(0.206)	(0.089)	(0.085)	(0.105)				
3-Lag assets^2	0.098	-0.102	-0.171*	-0.023				
	(0.134)	(0.116)	(0.097)	(0.079)				
3-Lag assets^3	-0.010	-0.083*	-0.058	-0.021				
	(0.120)	(0.042)	(0.047)	(0.042)				
3-Lag assets^4	-0.008	0.035	0.035	0.006				
	(0.046)	(0.030)	(0.029)	(0.025)				
2-Lag assets					-0.268*	-0.370***	-0.355***	-0.424***
					(0.154)	(0.111)	(0.112)	(0.104)
2-Lag assets^2					0.289**	0.016	0.010	0.036
					(0.115)	(0.082)	(0.074)	(0.053)
2-Lag assets^3					-0.257*	-0.044	-0.043	0.008
					(0.126)	(0.059)	(0.054)	(0.044)
2-Lag assets^4					0.045	0.011	0.009	-0.010
					(0.033)	(0.024)	(0.022)	(0.017)
Observations	158	270	357	621	156	270	346	610
Adjusted R-squared	0.253	0.218	0.230	0.194	0.257	0.216	0.219	0.178
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone FE	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
F-test lags 2-4=0	0.783	0.036	0.007	0.690	0.002	0.891	0.742	0.823

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at the EA level, panel weights. Flooded defined according to the header of each column.

Instead of using the satellite-identified flood measure, the sensitivity check in Table A2 2 plays with the distance from inland water. In the long difference (w1-w4), convergence is rejected for households within 12 km from the water, while in the short difference (post-shock) convergence is rejected until 13 km. This indicates clearly that non-linearities (a pre-requisite for poverty traps) are significant and strongest for households closest to water, no matter the time frame considered. This is reassuring that no matter the definition of distance from water, within a range (0-12km) we have consistent results.

Table A2 2. P-value from the F-test for joint significance of lags 2-4 of asset index which changing the distance from inland water.

Distance (km)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
w1_w4	0.000	0.013	0.030	0.043	0.058	0.042	0.022	0.032	0.047	0.084	0.084	0.084	0.138	0.196	0.142
N	99	128	166	190	239	248	269	315	332	342	342	342	351	376	413
w2_w4	0.000	0.021	0.029	0.015	0.006	0.004	0.013	0.008	0.044	0.078	0.078	0.078	0.080	0.144	0.254
N	99	128	165	189	228	237	250	295	312	322	322	322	331	356	393

p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), distances from the market and nearest population centre, as well as some interactions with flood, zone dummies, rural. Standard errors clustered at the EA level, panel weights. Flooded defined according to the header of each column.

Chapter 2 - Poverty dynamics and poverty traps among refugee and host communities in Uganda *

Giulia Malevolti and Donato Romano [a]

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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2.1 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[63] 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.

[63] 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.

2.2 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[64]. 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).

[64] 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).

2.3 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:

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

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:

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

where asset change ΔA_i is a function of the fourth[65] 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 2.4.1) 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

[65] 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[66]. 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.

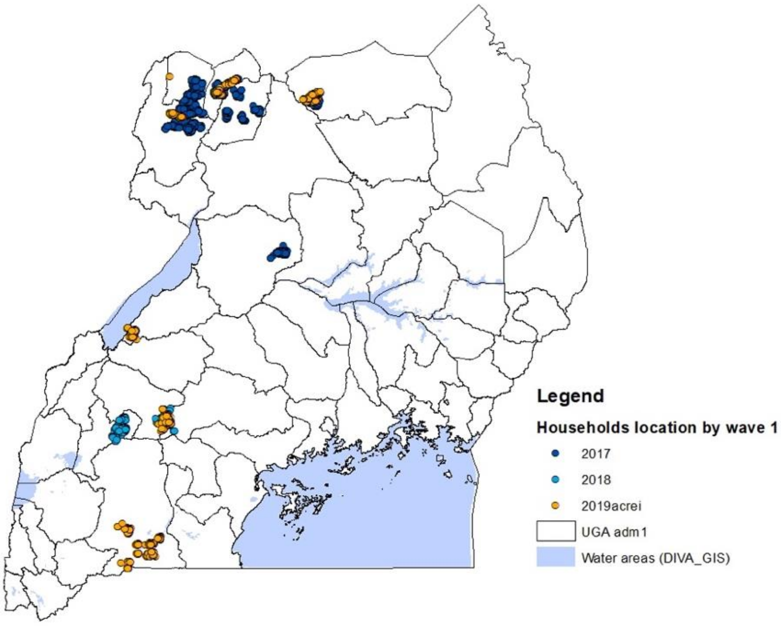
2.4 Data

2.4.1 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 2.1). When possible, households were interviewed again in 2019, 2020 and 2021 (Table 2.1). The final sample consists of 20,079 observations (9,128 considering only the balanced panel). The attrition rate is quite high (Table 2.2), not surprisingly given the fragility of the situation (Özler et al., 2021).

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

Figure 2.1: Households' location by year of first interview.



Source: own elaboration.

Table 2.1: 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

Source: own elaboration.

Table 2.2: 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		

Source: own elaboration.

2.4.2 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[67]; and shocks.

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 2.3). 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[68], 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[69].

Table 2.3: 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

Source: own elaboration.

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[70]. Aggregation is done via principal components analysis[71] (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

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

[68] 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).

[69] 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.

[70] 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.

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

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

2.4.3 Descriptive statistics

Table 2.4 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[72], though on average hosts report higher values, and decreasing over time[73]. 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 2.2). Refugees' average income is greater than hosts' in 2019, due to massive transfers[74]. 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.

[72] 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.

[73] 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.

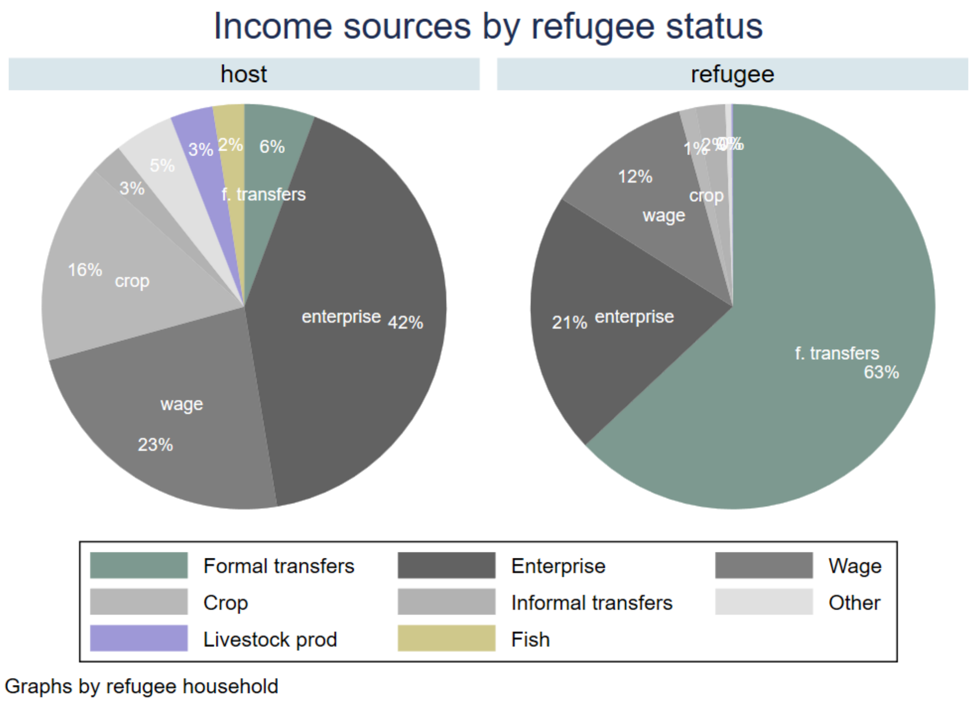
[74] In 2019, 80-95% of refugee households received transfers (food or cash), compared to less than 5 % of hosts.

Table 2.4: 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
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

Source: own elaboration.

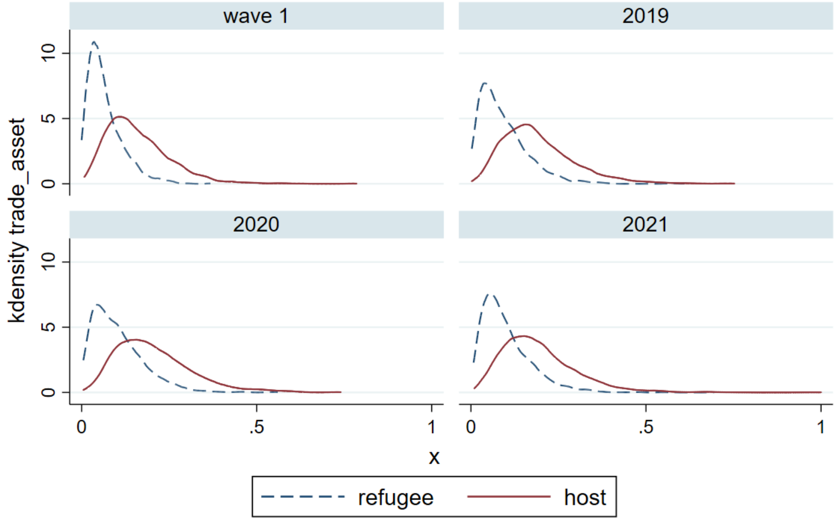
Figure 2.2: Income decomposition by refugee status, all years.



Source: own elaboration.

Kernel density functions of the tradable index show how refugees and hosts' wealth is distributed (Figure 2.3): refugees are more concentrated in the lower part of the distribution as they have lower levels of assets[75]. 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.

Figure 2.3: Kernel density of tradable asset index by wave by refugee status.



Source: own elaboration.

Asset dynamics can also be inferred from the transition matrix between quintiles from the first wave to the fourth wave (Table 2.5). 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.

[75] 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).

Table 2.5: 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

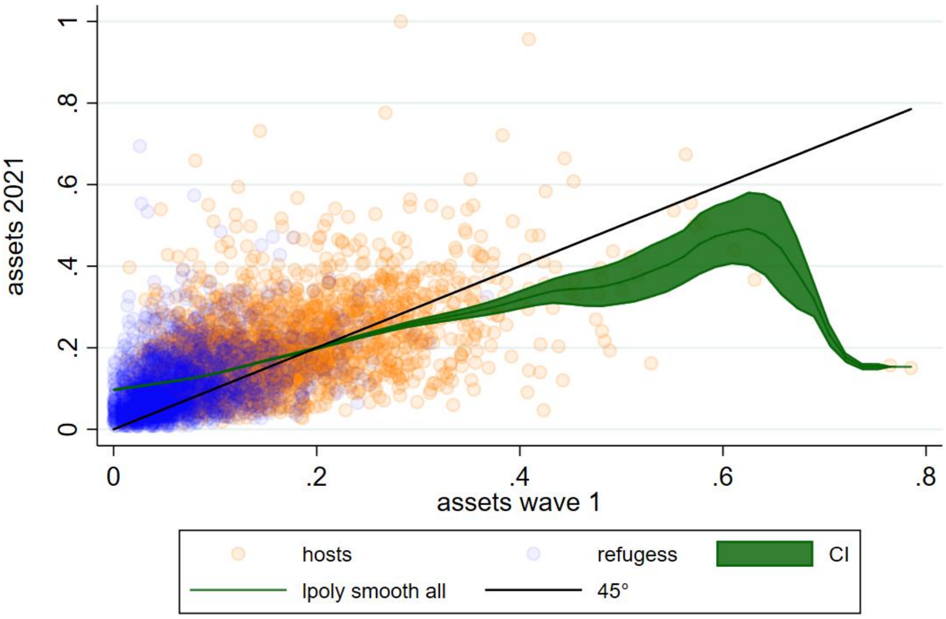
Row percentages. Those that improved their position are found above the main diagonal, and those that worsened in the ranking are found below the diagonal. In bold those that remained in the same quintile over time.

2.5 Results

2.5.1 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 2.4). 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).

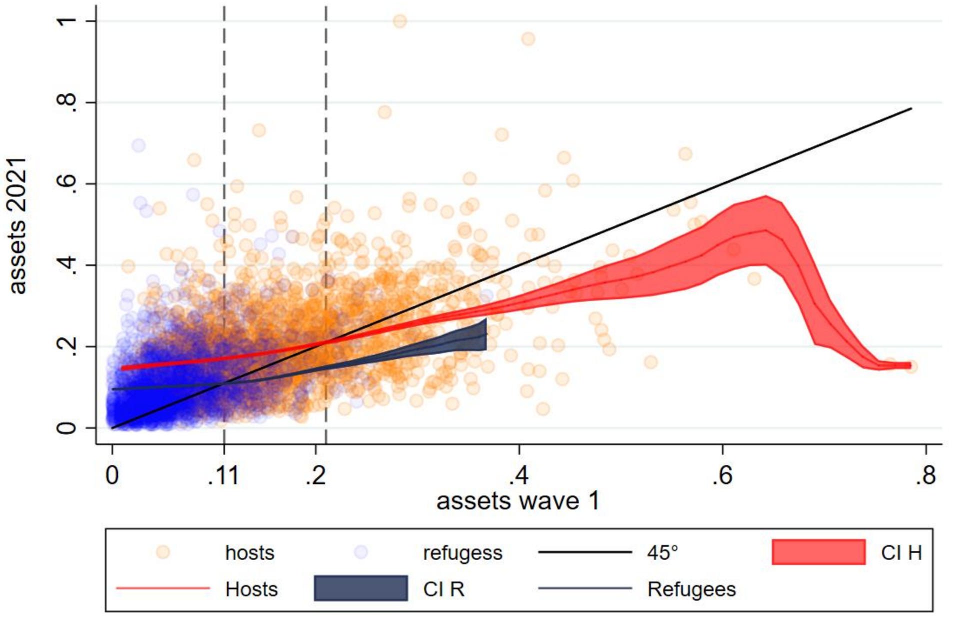
Figure 2.4: Local polynomial smooth, whole population



Source: own elaboration.

Relaxing the assumption that all households are in the same accumulation regime and running the local polynomial regression separately for refugees and hosts (Figure 2.5), 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[76]. 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 2.6.2).

Figure 2.5: Local polynomial smooth, separately for refugees and hosts.

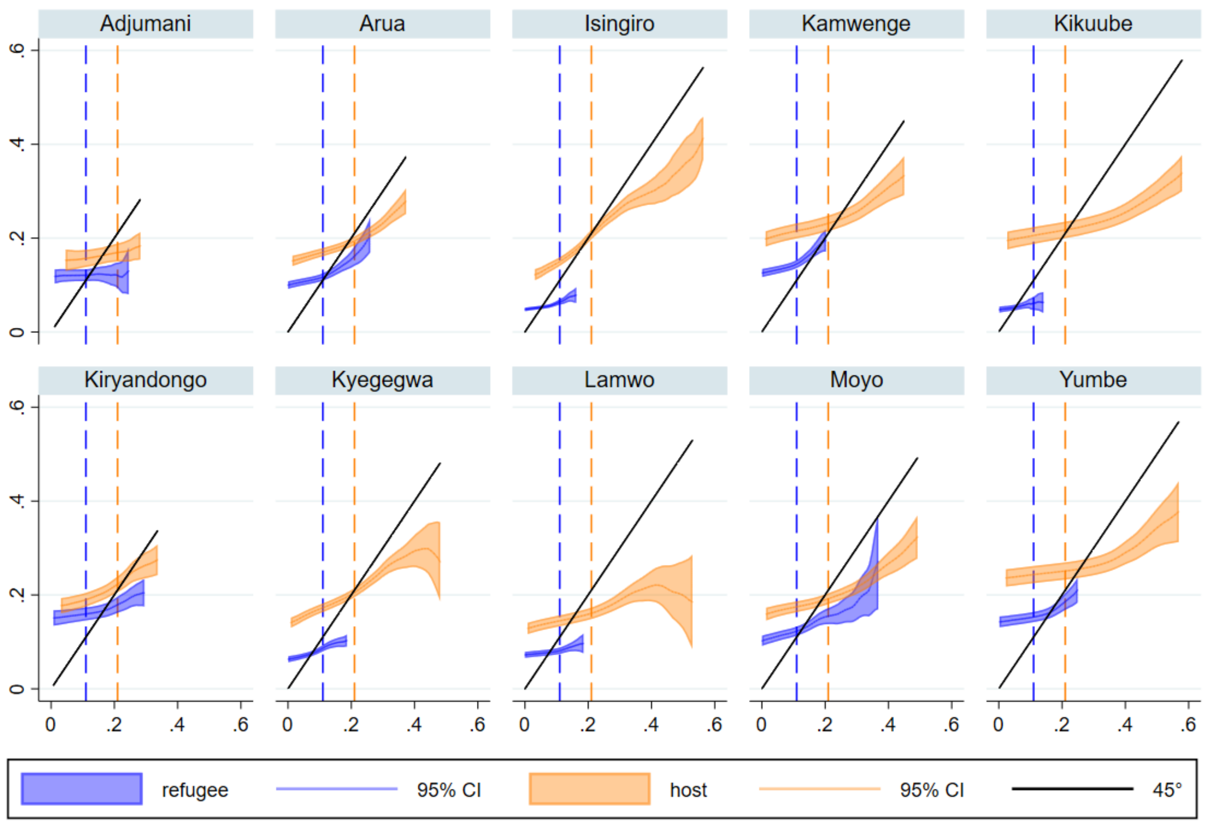


Source: own elaboration.

However, when splitting the total sample by districts, some heterogeneity emerges (Figure 2.6). 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.

[76] 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 2.6: Local polynomial smooth by district for refugees and hosts.



Source: own elaboration. 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 2.6) (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 2.6: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

Source: own elaboration.

2.5.2 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.

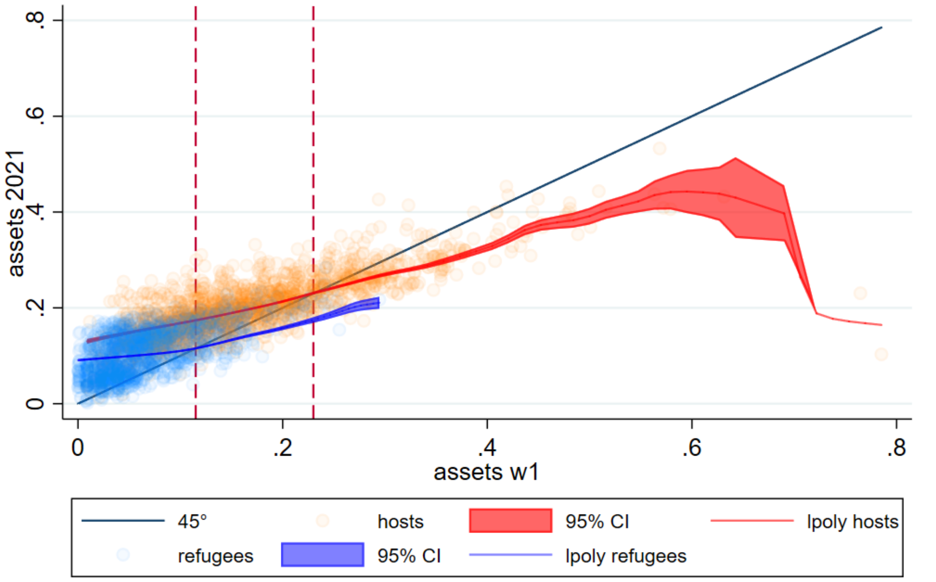
We are interested in the non-linearities of the lagged assets and in their joint significance. Asset dynamics are convergent if it is possible to reject the hypothesis that all terms of the polynomial are equal to zero in favour of the alternative that β_1 is between -2 and 0 and $\beta_{2\text{-}4}$ 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 2.7, 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 2.7). 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 2.7: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 hh.^2	-0.000**	-0.000	-0.000**	L. age head of hh.^2	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. avg education of adults	0.003***	0.003**	0.004*	L. avg education of adults	-0.001	-0.002**	0.000
	(0.001)	(0.001)	(0.002)		(0.001)	(0.001)	(0.002)
L3. avg. education of adults^2	0.000	-0.000	-0.000	L. avg. 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 hh.	-0.002	-0.004	-0.004	L. female headed hh.	0.001	0.007**	-0.007
	(0.004)	(0.004)	(0.008)		(0.003)	(0.003)	(0.007)
L3. N. of people in hhhh.	0.006***	0.005***	0.006***	L. n. of people in hh.	0.001	0.002*	0.000
	(0.001)	(0.002)	(0.002)		(0.002)	(0.001)	(0.004)
L3. N.r of people in hh^2	-0.000	-0.000	-0.000	L. n.r 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: selling crops	-0.000	-0.001	0.001	L. income: selling crops	-0.000	-0.004	0.002
	(0.003)	(0.004)	(0.006)		(0.002)	(0.003)	(0.003)
L3. income: enterprise	0.004	0.006	0.005	L. income: enterprise	0.000	0.003	-0.002
	(0.003)	(0.005)	(0.004)		(0.002)	(0.003)	(0.003)
L3. income: wage	-0.006**	-0.003	-0.002	L. income: wage	0.001	0.002	0.001
	(0.003)	(0.003)	(0.005)		(0.002)	(0.002)	(0.003)
L3. formal transfers, $	-0.000***	-0.000**	-0.000*	L. formal transfers, $	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
L3. informal transfers, $	-0.000	-0.000	-0.000	L. informal transfers, $	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 agr. market	0.000**	0.000	0.001***	Distance to agr. market	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Dist. to petty trading market	-0.001	-0.000	-0.002	Dist. to petty trading market	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Distance to school	-0.003**	-0.001	-0.004**	Distance to school	-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
				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
Adjusted R-squared	0.276	0.295	0.284	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 2.7: Local polynomial smooth of OLS-predicted current assets and actual lagged assets, refugees and hosts



Source: own elaboration.

Next, we estimate equation 2 using the fixed effects (FE) panel estimator[77] with all covariates lagged one period (Table 2.7, 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[78]. 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 in line with expectations and a negative correlation with wet weather, indicating the relevance of agriculture for hosts[79].

[77] 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.

[78] 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.

[79] 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

2.5.3 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[80].

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[81] (Tables 2.8 and 2.9). 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).

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.

[80] 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).

[81] 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 2.8: 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 2.9: 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.*

2.5.4 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)[82]. 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 richer or better connected[83]. 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[84] 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[85] (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[86]) (Robins et al., 1995; Wooldridge, 2002).

We implement both the IPW correction (Table 2.10, 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.

[82] 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.

[83] 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.

[84] 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).

[85] 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.

[86] 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%.

Table 2.10: 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
	(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).*

2.6 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.

2.6.1 Excluding wave 1 observations

To rule out that the different starting times of the first wave (cf. Section 2.4.1) are driving our results, we repeat the analysis by excluding the first wave (Table 2.11). 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 2.11: 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.*

2.6.2 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 2.12, 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[87]) with asset ownership and socio-demographic characteristics (Adato et al., 2006), indicates general convergence for all samples (Table 2.12, col. 4-6).

Table 2.12: 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

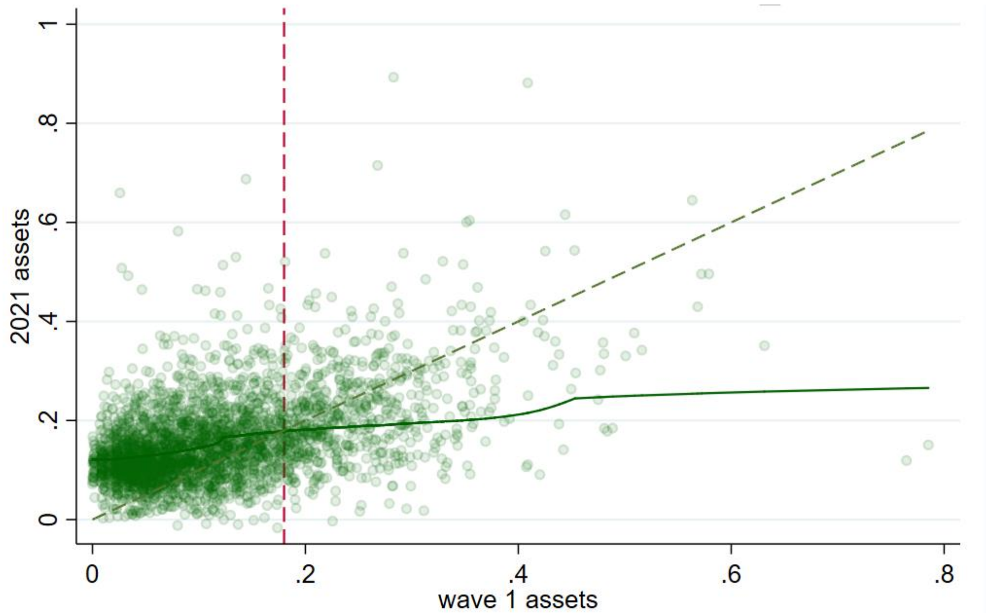
[87] Given the extremely low levels of expenditure and income (due to poverty but also to the types of questions included in the questionnaire), we used the expenditure median as poverty line (i.e., 0.10 dollars per day per capita).

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.

2.6.3 Semi-parametric regression

Semi-parametric regressions (Figure 2.8) – 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[88].

Figure 2.8: 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.

2.7 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

[88] Available upon request.

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 bring positive effects to the native population[89] (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[90]. This may affect the future prospects for the youngest household members, creating the basis for an intergenerational poverty trap[91].

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,

[89] 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.

[90] 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).

[91] 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).

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 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[92]. 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[93] 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

[92] 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).

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

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 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[94].

[94] 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.9: 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.10: 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.11: Attrition check: Balanced and unbalanced panel, FE and RE

Variables	(1) OLS Unbalanced	(2) OLS Balanced	(3) OLS Dummy for balanced	(4) FE Unbalanced	(5) FE Balanced	(6) RE Unbalanced	(7) RE Balanced	(8) RE Dummy for balanced	(9) RE 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.12: Attrition test: Probit model

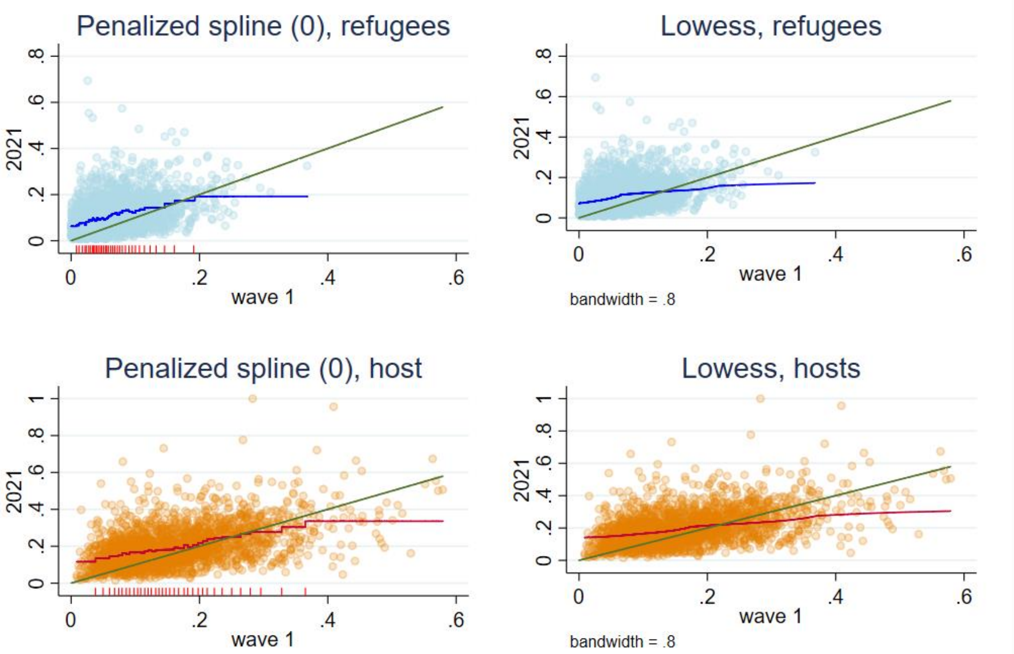
	(1)	(2)	(3)	(4)	(5)	(6)
		Wave1 - wave4			Absorbing	
	All	Refugees	Hosts	All	Refugees	Hosts
1.Refugee	0.344***			0.083		
	(0.066)			(0.063)		
1.female head	-0.052	-0.070	0.004	-0.058	-0.075	0.160*
	(0.049)	(0.051)	(0.100)	(0.050)	(0.063)	(0.092)
1.marriedhead	-0.109**	-0.140**	-0.029	-0.142***	-0.174***	-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)

Table A.13 (continued): Attrition test: Probit model

	(1)	(2)	(3)	(4)	(5)	(6)
		Wave1 - wave4			Absorbing	
	All	Refugees	Hosts	All	Refugees	Hosts
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

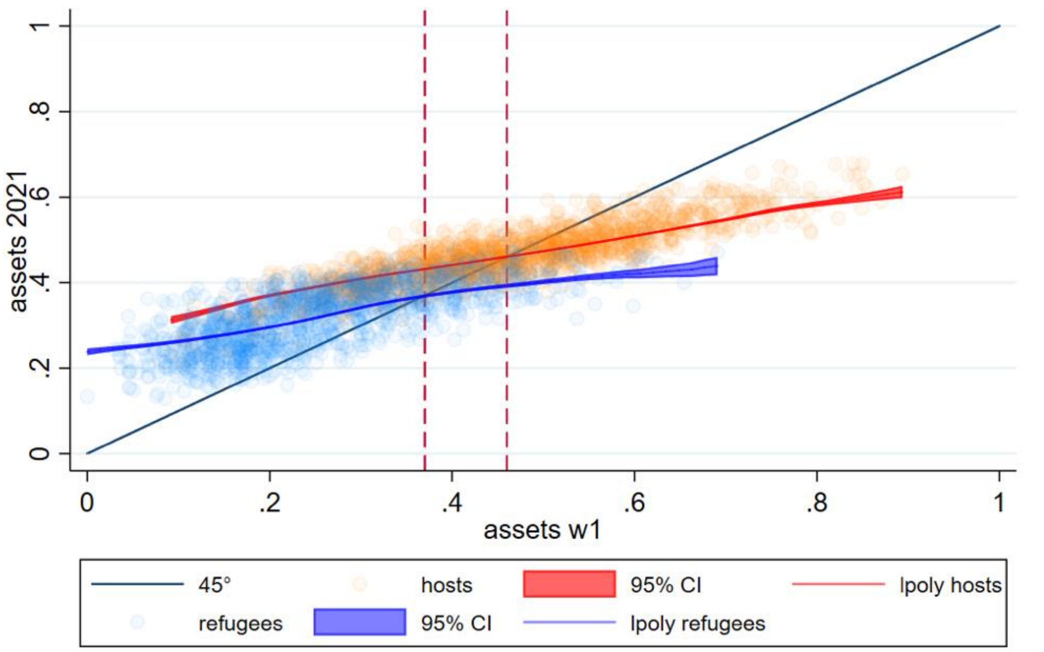
** p<0.1; ** p<0.05; *** p<0.01 Probit. Robust standard errors in parenthesis. Controls not reported in the table: district, the subsamples of wave 1, months of interview, detail of rural areas (very low density rural grid cell, low density rural grid cell, rural cluster, suburban grid cell, urban cluster,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

Figure A.9: Tradable asset index: different functional forms, non-parametric regression.



Source: own elaboration.

Figure A.10: Local polynomial smooth regression of comprehensive asset index, refugees and hosts



Source: own elaboration.

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 3: Coefficients and t-statistics with different clustering methods, all 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
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 4: 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 5: 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*

Chapter 3 - Diversification across thresholds: Evidence from rural households in Tanzania *

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Abstract:

Diversifying into non-farm or off-farm activities is considered an effective risk management strategy and a way out of poverty for many rural households, especially for smallholder farmers with limited access to credit and insurance. However, previous studies suggest that households' income diversification is neither equally feasible nor equally rewarding for all. For instance, those who begin poor in land and capital may face difficulties in participating in more attractive non-farm activities and may be kept in less-profitable unskilled off-farm labours, whether in agriculture or not, which are not capable to lift them out from poverty. Farmers' heterogeneity may be mirrored by the presence of non-linearities in household diversification strategies, welfare outcomes and vulnerability to shocks. By unbundling the complexity and the heterogeneity underlying rural households' income diversification strategies and outcomes, this study aims to shed light on the presence of bottlenecks and trade-offs in the rural transformation process ongoing in many Sub-Saharan African countries. This study explicitly models non-linearities to identify different income diversification regimes around specific asset thresholds in rural Tanzania analysing a decade-long panel (LSMS-ISA) dataset collected between 2008 and 2020. We compare the livelihood dynamic pathways of households adopting different diversification strategies and their ability to cope with weather shocks. We show that off-farm diversification serves wealthier households' accumulation of durable assets, while decreasing the accumulation of agricultural assets (in particular, livestock). Conversely, for poorer households the effect of diversification on durables accumulation is not significant, while livestock-poor households benefit from diversification accumulating more livestock. We also show that income diversification can partially offset the negative impact of climatic shocks such as droughts. These results shed light on the heterogeneous role of income diversification and can contribute to better design welfare-enhancing interventions and policies based on rural non-farm activities diversification.

Keywords: income diversification; threshold; shocks; rural non-farm activities; Tanzania.

JEL Codes: J21, J43, O12, Q12

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3.1 Introduction

The diversification of the rural economy is one of the most striking evidence of the 'rural transformation' (de Janvry & Sadoulet, 2020; World Bank, 2007) and there is already a robust evidence that the number of rural households diversifying their sources of income is increasing all over the world (Davis et al., 2010; FAO, 2017; IFAD, 2016). Diversifying into non-farm or off-farm activities is considered an effective risk management strategy and a way out of poverty for many rural households, especially for smallholder farmers with limited access to credit and insurance (Arslan et al., 2018; Gao & Mills, 2018; Tankari, 2020). However, previous studies suggest that households' income diversification is neither equally feasible nor equally rewarding for all (Barrett, Reardon, et al., 2001; Niehof, 2004). Diversification is indeed associated with both livelihood survival and distress under deteriorating conditions (reported in the literature as 'push factors', 'survival-led diversification' or 'diversification by necessity', cf. Ellis 2000; Lay *et al.* 2008; Reardon *et al.* 2006) as well as by livelihood strategies that improve the household's welfare ('pull factors', 'opportunity-led diversification' or 'diversification by choice'). In order to let livelihood diversification secure better living standards, rural households must be able to generate cash, build assets and diversify across farm and non-farm activities (Ellis & Freeman, 2004). However, those who begin poor in land, capital and skills, or live far from urban areas or in areas with unfavourable agroecology, poor market access, underdeveloped infrastructure, or have limited access to credit and insurance (Balboni et al., 2021; Bandiera et al., 2017; Drall & Mandal, 2021; Losch et al., 2012; Reardon, 1997; Winters et al., 2009) may face difficulties in participating in more attractive non-farm activities and may be kept in less-profitable unskilled off-farm jobs, whether in agriculture or not, which may not help in lifting them out from poverty (Delacote, 2009).

The empirical evidence on the relationship between income diversification, income level, and wealth is mixed (Dedehouanou & McPeak, 2020). For instance, Schwarze & Zeller (2005) found that rural income diversification is higher among poorer households compared to richer households in Indonesia. The opposite has been observed in Mali and Ethiopia (Abdulai & CroleRees, 2001; Block & Webb, 2001) and Nigeria (Dedehouanou & McPeak, 2020). How households respond to push and pull factors and what the welfare impact of livelihood diversification is ultimately depend on the households' characteristics and on the range of options available to them (Barrett, Reardon, et al., 2001; Barrett, Bezuneh, et al., 2001; Ellis & Freeman, 2004; Reardon et al., 2006). Farmers' heterogeneity may be mirrored into the presence non-linearities in household diversification strategies, welfare outcomes and vulnerability to shocks (Asfaw et al., 2019). Disentangling this heterogeneity and gauging a clear understanding of household diversification patterns, determinants, and impacts proves useful to design better policies aiming at providing job opportunities and fostering income diversification and, ultimately, to fully leverage on livelihood diversification potential.

The process of household income diversification initially unfolded in South Asia and Latina America (Haggblade et al., 2007) and more recently has spread also to Sub-Saharan Africa (SSA) (Alobo

Loison, 2015; Asfaw et al., 2019; Davis et al., 2017; Nagler & Naudé, 2014; Pesche et al., 2016). In this region it has been welcomed as a process that can improve the livelihood of agricultural households in a context that is still largely dominated by subsistence farming (FAO, 2017; IFAD, 2016) and contribute to a smoother rural transformation in a context where the demographic transition has not completed yet[95] (Losch et al., 2012, 2013). However, there is still a considerable debate on whether household diversification into non-farm activities contributes to improve standards of living in SSA. In fact, while some authors argue about the evidence of a positive relationship between diversification in non-farm activities and household welfare measured in terms of income, wealth, consumption and nutrition (Alobo Loison, 2015; Ellis, 1998; FAO, 1998; McPeak & Barrett, 2001; Reardon, 1997), others show that the impact of both crop and income diversification on household welfare is generally higher for the poorest households while it decreases, and in some cases turns to be negative, moving toward the upper end of the income distribution in three SSA countries (Asfaw et al., 2018, 2019; Tran & Vu, 2020).

This paper presents new evidence with reference to Tanzania, which is a very interesting case study in the SSA context (World Bank, 2017). In fact, this country is undergoing a structural transformation where agriculture is declining in favour of services, while manufacture remains marginal. Growth in rural non-farm employment has contributed to 90% of net job creation in the period 2002-2012 (Diao et al., 2018). Previous studies in Tanzania have emphasized that income diversification is common among rural households at all levels of income (De Weerdt, 2010; Dercon & Krishnan, 1996; Dimova et al., 2021; Ellis & Mdoe, 2003) and is an important driver of poverty reduction (De Weerdt, 2010). However, Dercon & Krishnan (1996) found that households engaged in off-farm activities with high entry barriers to trade or business had higher levels of assets, income and consumption. This is confirmed by Ellis & Mdoe (2003) who found that in Tanzania richer households tended to diversify into high-return non-farm activities and had higher agricultural productivity compared to poor households.

The overall objective of this paper is to provide new evidence on the degree of livelihood diversification among Tanzanian rural households with a focus on the relationship between diversification, wealth and the household ability to manage/cope with risks. Specifically, the paper aims at answering the following research questions: Are there non-linearities in the relationship between household income diversification and wellbeing? If so, for whom is income diversification beneficial and for whom is it not? How does income diversification shape households' ability to respond to shocks? Our assumption, consistently with the literature on non-linear asset dynamics (Balboni et al., 2021;

[95] In SSA a huge youth bulge of 375 million young people is expected to reach working age by 2030 (Losch, 2016). As a result, policymakers are urgently looking for solutions to create jobs. Rural economic activities diversification can help in making this process smoother, though the question remains whether rural non-farm activities could absorb most of these young people in a context where the agricultural sector is still dominated by subsistence farming, and the industrial sector remains weak and limited (Barrett et al., 2017; FAO, 2017).

Barrett, Reardon, et al., 2001), is that answering to these questions crucially depends on the relative wealth of households and on the composition of assets they are endowed with.

From the theoretical viewpoint, the paper builds on two different strands of literature – i.e., households' determinants of income diversification and non-linear livelihood dynamics – linking them into a common framework. Specifically, the paper contributes to the former, moving beyond the conceptual dichotomy of 'push' and 'pull' factors by explicitly modelling the presence and relevance of thresholds to identify heterogeneous diversification choices (Barrett, Reardon, et al., 2001; Barrett, Bezuneh, et al., 2001; Bezu & Barrett, 2012; Block & Webb, 2001; Dedehouanou & McPeak, 2020; Drall & Mandal, 2021). Moreover, it creates an explicit link between the households' diversification strategies and the literature on non-linear livelihood dynamics pathways (Cissé & Barrett, 2018; Santos & Barrett, 2011) as well as with the recent literature on welfare thresholds and weather shocks (d'Errico et al., 2019; Letta et al., 2018).

In terms of empirical strategy, the paper explicitly models non-linearities to identify different income diversification regimes around specific asset thresholds. In fact, exogenously assuming a given threshold level would entail a certain amount of arbitrariness. We instead rely on a method that is data-driven and the model itself determines the level of the threshold at which there is a structural break in the relationship between income diversification and asset accumulation. To this end, we use a panel fixed effects threshold model (Hansen 1999) that allows the relationship between income diversification and asset accumulation to vary according to the level of lagged assets, while controlling for household-specific time invariant heterogeneity. By exploiting the panel structure of the data and the lags we are also able reduce the risk of endogeneity. In carrying out the analysis, we adopt several household wealth indicators as outcome variables, namely the growth of total assets, durables and agricultural assets. Beside the specific interest in the dynamics of each of these indicators, they provide some insights on different asset smoothing mechanisms.

We find indeed a non-linear relationship between income diversification and asset growth, confirming the results of previous studies (Alobo Loison, 2015; Barrett, Reardon, et al., 2001; Barrett, Bezuneh, et al., 2001; Ellis & Freeman, 2004; Haggblade et al., 2005; Lay et al., 2008; Losch et al., 2012) that showed that the poor are generally confined to low-income, labour-intensive non-farm activities that tend to leave them trapped in structural poverty, while richer households tend to specialise in high-return farm or non-farm activities. Specifically, we show that off-farm diversification fosters asset accumulation of durable goods for better-endowed households only. For poorer households, the effect is not significant. Looking at agricultural assets, as better-endowed households diversify more, their decumulate agricultural assets, in particular livestock, while for households below the threshold, more diversification fosters livestock accumulation. Furthermore, we find that income source diversification can partially offset the negative impact of climatic shocks on the accumulation of agricultural assets.

This qualifies income diversification as a key strategy especially for the ones who do not have access to alternative means for risk management (Barrett, Bezuneh, et al., 2001; Barrett, Reardon, et al., 2001).

The paper is organized as follows. Section 2 describes the datasets we used, i.e., the Tanzania National Panel Survey (LSMS-ISA) for socio-economic data and the SPEI Global Drought Monitor for climatic data, and illustrates the elaboration we made to compute the wealth index and income diversification measures. Section 3 describes the livelihood diversification patterns and dynamics over the last decade in Tanzania. Section 4 summarizes our empirical strategy explaining the econometric models we adopted to assess the existence of non-linearities in income diversification across households and to identify asset thresholds. Section 5 presents the main results discussing them with specific reference to diversification and its effects on household income and asset dynamics and on be ability of household to cope with weather shocks. Section 6 presents some robustness tests. Section 7 concludes discussing the main policy implications.

3.2 Data

3.2.1 Socio-economic data

This study uses the Tanzania NPS (National Panel Survey), a LSMS-ISA dataset collected by the World Bank in Tanzania that includes five rounds of geo-referenced panel data spanning over twelve years from 2008 to 2020 (Table 3.1). The first three rounds constitute a large panel representative at the national, urban/rural, and major agroecological zones. The sample was partially refreshed on the fourth round. However, a nationally representative part of the panel was continued and re-interviewed at round four and five, so there is a subsample of the original households which has five rounds of observations, while the majority of households have only three observations. For convenience reason, we start from the Uniform Panel (UP) dataset that was recently released as it harmonizes the first four rounds. To add the fifth wave to the UP, a new panel identifier was created. The final balanced sample is made of 808 households per wave (4,040 total observations). Attrition during the first three waves was around 4%, while in the extended sample it was 8% and 9%, respectively. The working sample further reduces as we drop those households for which we have no information on income, which leaves us with 778 households (3,890 total observations over the five rounds).

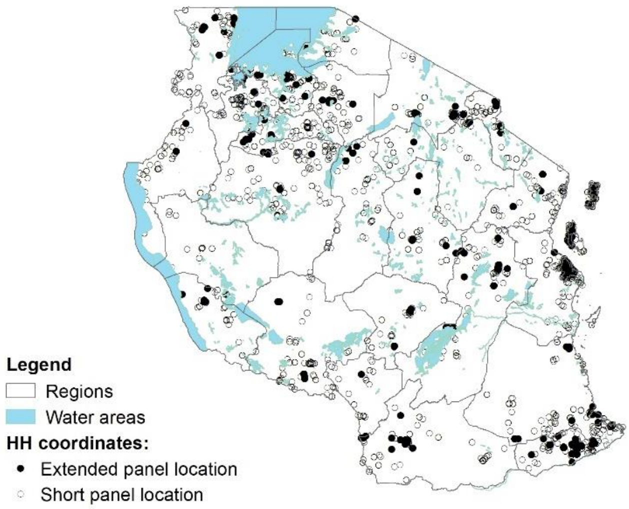
Table 3.1: Sample size by round

Rounds	N (UP)	N final (UP+R5)	N bal.
(1) 2008/09	6,128	6,243	808
(2) 2010/11	6,128	8,293	808
(3) 2012/13	9,998	10,139	808
(4) 2014/15	4,961	1,860*	808
(5) 2019/20	1,184	1,212	808

*Refreshed panel households are dropped (only observed once). Source: own elaboration.

In order to geo-locate the households considered for this study a geographic representation of the pooled LSMS-ISA sample is provided in Figure 3.1.

Figure 3.1: Map of Tanzania with the location of households



Source: own elaboration.

Table 3.2 shows the breakdown of the pooled sample across household location (i.e., rural vs. urban) and household economic activity by production sector (i.e., agriculture vs. non-agricultural[96]). Given the objective of this study, we restricted the sample of interest to rural households and households have been practicing agriculture in all 5 waves (507 households).[97]

Table 3.2: Sample size by rural/urban and agricultural/non-agricultural characterization

		HH cultivates plot in all 5 rounds		
		0	1	Total
Rural areas	0	1,355	195	1,550
	1	875	1,465	2,340
	Total	2,230	1,660	3,890

Source: own elaboration.

3.2.2 Wealth index

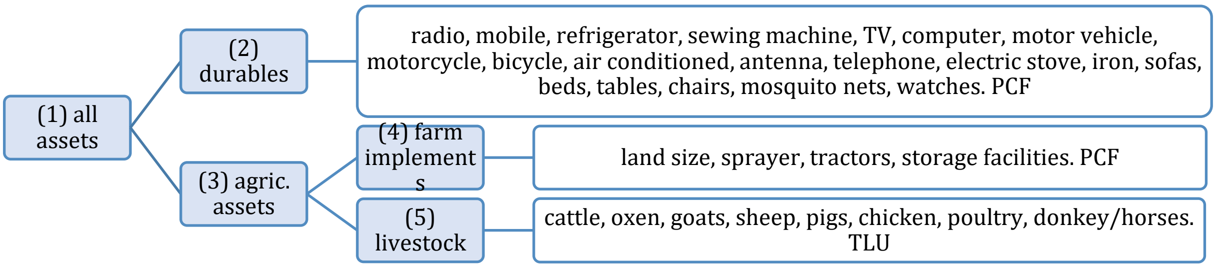
We use five asset indexes (Figure 3.3). The first is an overall asset index (1), comprising durables (2) and agricultural assets (3). The agricultural assets include both farm implements and land (4) and livestock (5). According to the previous literature, all asset indexes but livestock are computed using principal components analysis to extract the first component as a proxy of the household wealth (Rutstein, 2015; Sahn & Stifel, 2000).[98]

[96] A household is defined as agricultural if in all waves the household cultivates any crop or trees in at least one of the two rainy seasons.

[97] More details on the data cleaning process are reported in Appendix 1.

[98] See Appendix 2 for details on how the asset indexes have been built.

Figure 3.2: Asset indexes composition



The numbered boxes are the asset indexes' names. The boxes on the right indicate the composition of the indexes. Source: own elaboration.

The various asset indexes shed light on different accumulation process that might differ across households, according to their livelihood and their income diversification process. The all-assets index serves to capture household overall wealth, no matter the household livelihood, and includes all assets that enter the other indexes. The durables index includes potentially tradable assets that are common in urban as well as rural areas. The agricultural asset index focuses on farm activities, both crop cultivation (represented with land size and farm implements) and livestock rearing. The two might coexist but not necessarily. Therefore, we further disaggregate between farm implements and land (physical non-living capital) and livestock (in tropical livestock units, TLU)[99]. Table 3.3 summarizes the mean and standard deviation of the asset indexes over the rounds.

Table 3.3: Descriptive statistics of the asset indexes over time, rural and agricultural sample

	All asset		**Durables**		**Agricultural asset**		**Farm implements**		**Livestock**	
round	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
1	0.184	0.145	0.164	0.152	0.175	0.150	0.093	0.086	2.500	5.806
2	0.191	0.134	0.170	0.138	0.163	0.168	0.100	0.138	2.715	6.827
3	0.175	0.131	0.157	0.136	0.148	0.162	0.082	0.119	2.640	4.905
4	0.174	0.136	0.157	0.141	0.132	0.167	0.070	0.128	3.062	7.475
5	0.178	0.128	0.169	0.143	0.114	0.144	0.049	0.098	2.288	5.109

Source: own elaboration.

3.2.3 Climate data

Climate shock data use the Standard precipitation and Evapotranspiration Index (SPEI) obtained from the Global Drought Monitor[100] which provides ready-to-use and updated SPEI index for the world for intervals of 1 to 48 months (Beguería et al., 2014). The information at a granular resolution 0.5 degree (about 50 km) has been downloaded for the month of May of each round considering an accumulation period of seven months to cover the two agricultural seasons characterizing the Tanzanian crop calendar[101]. Table 3.4 shows that 21% of the households in the relevant sample in the

[99] All indexes are calculated on the pooled panel sample to allow for over-time comparisons and include an indication of the round and panel weights. All the indexes but livestock, which is measured in tropical livestock units (TLU) are normalized.

[100] SPEI data have been downloaded at https://spei.csic.es/map/maps.html#months=1#month=3#year=2022.

[101] It is crucial to understand which is the relevant agricultural season, otherwise misspecified temporal aggregation can lead to measurement errors (Li & Ortiz-Bobea, 2022). Tanzania's main rainy season goes from March to May. A period of accumulation at the month of May should capture both the main rainy season and the

second wave suffered from extreme dry conditions, while extreme precipitation seem less of an issue in the analysed period except the fifth round when 12% of respondents was affected by floods.[102] Therefore, we concentrate on droughts.

Table 3.4: Prevalence of shocks in the sample by round

round	SPEI7 drought	SPEI7 flood
1	0.00	0.00
2	20.71	0.00
3	6.11	0.00
4	11.05	0.00
5	0.00	12.43

Source: own elaboration. The droughts episodes have been identified when the index is below the critical threshold of -1.5. Since the index is more suited for droughts detection, we raise the threshold to 2 in the case of heavy rains.

3.2.4 Income diversification

A diversity index is a quantitative measure that reflects how the different modalities of a given construct (e.g., in our case, income sources) are distributed in a given observation unit (e.g., households) defining some relationship of modalities distribution (richness, evenness, heterogeneity) among observations. The literature proposes different indexes (Shannon, Simpson, Gini-Simpson, Berger Parker) which are all related although, by construction, they may emphasize different aspects. For the purpose of this study, we choose the Gini-Simpson index which gives relatively more weight to common (or dominant) types. In this way, we expect to represent better the income source structure of the households in our sample which tend to obtain a greater share of income from a specific activity. In particular, the Gini-Simpson index is equal to one minus the sum of the squared share of income from each source:

$$D_i = 1 - \sum_{j=1}^{J} {s_{ij}}^2, \quad (1)$$

where $j = 1, 2, \ldots, J$ are the various on-farm and off-farm income categories. The greater the index, the more diverse the income portfolio of the household (i.e., the more equal the shares from all sources). Income generating activities were assembled combining a sectoral classification – agriculture and non-agriculture – and a functional classification – wage and self-employment. Specifically, we consider seven income sources, three on-farm (i.e., crop, trees, and livestock incomes), and four off-farm (i.e., off-farm agricultural wage, non-farm wage, self-employment, and transfers). The household total income is simply the sum of all these incomes, irrespective of the household members' specific earning pattern and of the hours spent on each activity. Since our analysis focuses primarily on the income and asset dynamics in relation to household off-farm income diversification, following the literature on this topic

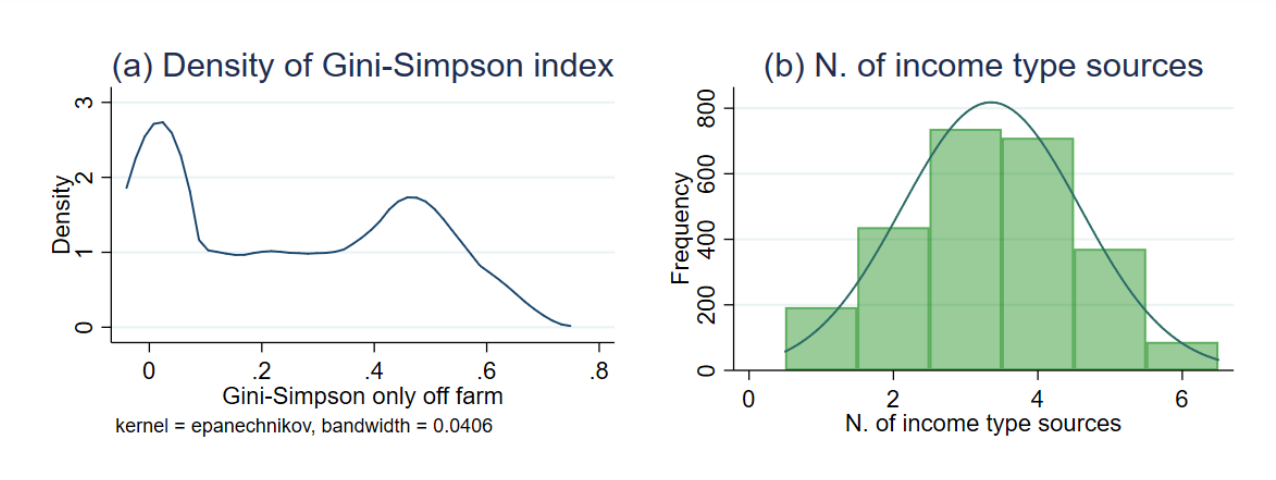
short rainy season (if any), and the unimodal rainy season for the places where it applies. The month of May corresponds roughly to the end of the growing season for the most important crops.

[102] To merge the climatic information with household coordinates, we match the coordinates with a discrete grid without smoothing the values at the grid borders for simplicity reasons. The spatial offsetting of LSMS coordinates for confidentiality issues (between 0-2 km in urban areas, between 0-5 km in rural areas) should not matter for the merging with climatic data (Michler et al., 2022).

(e.g. Barrett *et al.* 2005), we collapsed the three on-farm income shares into a single on-farm share,[103] thus considering in our analysis only five income sources, i.e. one on-farm and four off-farm. It is worth nothing that, in any case, the classification of income sources in a number of categories is subject to a certain degree of arbitrariness.

The density distributions of the income diversification Gini-Simpson index (off-farm) shows the highest concentration at the lower end of the distribution (i.e., only one income source), though there is a not trivial mass of combination of different income generating activities across all rounds. The density distribution of the number income categories is bell-shaped with a mode of three categories (Figure 3.3).

Figure 3.3: Distribution of income diversification index (Gini-Simpson) and the number of income categories (all)



Source: own elaboration.

3.3 Patterns and dynamics of livelihood diversification

Most households in the sample derive their income from combining agricultural and non-agricultural activities. Irrespective of the survey round, farming is the most important source of income in rural areas, although structural transformation is shifting people away from farming towards self-employment and wage income outside agriculture, with on farm sources of income decreasing from roughly 65% in 2008-09 to 46% of total household income in 2019-20 (Table 3.5). This pattern shows that households are intensively involved in farming activities such as crop growing and livestock rearing, complemented mostly with off-farm activities such as self-employment and non-agricultural wage employment[104]. Agricultural wage labour and especially transfers represent a much lower share in total household income.

[103] This does not mean, however, that on-farm agricultural diversification is not important as a risk management tool (Asfaw et al., 2019).

[104] Non-agricultural wage employment is further broken down into skilled and unskilled waged labor roughly based on the sector of employment. Specifically, skilled wage includes the sectors of professional, scientific, technological, financial, insurance, real estate, administrative, public, education and health service, arts

Table 3.5: Mean shares of income from the sources, by round

Mean shares of income from (%):	On-farm			Off-farm				
Round	Crop	Tree	Livestock	Agr. wage	Self-employment	Transfers	Wage (non agr.) skilled	Wage (non agr.) unskilled
1	34.4	5.3	25.1	3.5	16.5	5.5	3.9	5.8
2	29.8	5.0	23.2	5.9	20.1	5.6	5.8	4.6
3	32.4	5.5	19.8	7.3	17.2	4.5	4.6	8.7
4	22.0	3.3	21.3	10.2	21.9	5.9	5.3	10.1
5	22.9	5.0	18.3	6.8	22.3	9.3	4.9	10.4

Source: own elaboration. Absolute percentages.

The maximum number of income categories per household was six. Around 64% of households in the sample had exactly 3 or 4 sources of income in wave 1, while this decreases to 58% in wave 5. Table 3.6 shows the transitions from wave 1 to wave 5 across the number of income sources categories. For all categories, the share of households that increased the number of income sources is larger than the share of those decreasing it.

Table 3.6: Transition probabilities in income sources for rural households and farming households (row %)

	Number of income sources - Wave 5 (2019-20)				
Number of income sources Wave 1 (2008-09)	1 income source	2 income sources	3 income sources	More than 3 income sources	Total (%)
1 income source	19.2	38.5	26.9	15.4	100
2 income sources	15.7	22.9	44.6	16.9	100
3 income sources	10.3	17.3	35.9	36.5	100
More than 3 income sources	13.2	19.8	26.5	40.5	100
Total (%)	13.0	20.5	32.4	34.1	100

Source: own elaboration.

The considered income-generating activities are unevenly distributed across the income deciles. For instance, at round one all on-farm income shares decrease moving from the poorer to richer deciles. Similarly, all off-farm sources of income but transfers monotonically increase with income (Table 3.7).

Table 3.7: Total shares of income from the sources, by income deciles at round 1, rural areas (%)

Shares of income from	**On-farm**			**Off-farm**				
Income deciles at round 1	Crop	Tree	Livestock	Agr. wage	Self-employment	Transfers	Wage (non-agr.) skill	Wage (non-agr.) unskill
1	54.5	8.0	9.5	5.4	6.0	16.6	0.0	0.0
2	51.4	11.8	17.2	4.5	4.3	10.8	0.0	0.0
3	46.6	7.3	31.0	7.7	4.0	3.4	0.0	0.0
4	43.0	5.7	36.2	4.1	2.6	8.5	0.0	0.0
5	47.1	4.3	27.6	3.4	7.1	3.9	0.0	6.7
6	28.7	4.4	32.3	3.6	19.9	5.7	3.2	2.2

recreation activities, as well as other services, household employers, extra organizations. Unskilled wage includes all remaining wage employment.

7	31.0	3.8	32.4	1.9	17.7	2.4	1.5	9.4
8	19.1	4.8	25.4	3.0	25.8	2.2	10.6	9.1
9	13.0	2.4	23.5	0.2	41.3	1.3	6.4	12.0
10	5.7	1.0	10.8	0.2	43.2	1.2	18.7	19.2

Absolute percentages.

A slightly different picture emerges considering asset deciles at round one (Table 3.8), reflecting an ambiguous relationship between income and assets. For instance, while it is confirmed that the share from self-employment share increases and the transfers share decreases moving from the lower to the upper tail of the asset distribution, the shares of on-farm income, non-agricultural wage and agricultural wage exhibit a non-linear relationship across the wealth distribution.

Table 3.8: Total shares of income from the sources, by deciles of asset index at round 1, rural areas (%)

Shares of income from	On-farm			Off-farm				
Wealth quintiles at round 1	Crop	Tree	Livestock	Agr. wage	Self-employment	Transfers	Wage (non-agr.) skill	Wage (non-agr.) unskill
1	53.9	8.8	11.3	9.0	1.5	15.5	0.0	0.0
2	26.3	5.4	13.7	1.8	19.7	1.4	0.0	31.7
3	20.0	2.6	8.9	2.5	21.9	0.7	0.0	43.3
4	34.5	5.2	20.7	3.8	21.3	2.8	0.0	11.9
5	19.2	2.8	15.0	2.2	47.9	3.7	0.0	9.2
6	18.1	2.7	31.4	1.8	32.8	1.9	2.9	8.3
7	15.5	1.3	23.1	1.4	38.5	1.1	18.7	0.3
8	13.8	2.2	33.7	0.2	40.7	1.3	3.9	4.2
9	15.1	4.6	29.7	0.2	28.1	3.7	4.5	14.1
10	5.3	0.8	8.6	0.1	39.6	1.8	31.2	12.6

Absolute percentages.

Several authors found that initial asset holdings are important factors for transition into high-return rural non-farm employment (cf. among others, Barrett *et al.* 2001a, 2001b; Bezu & Barrett 2012). It is therefore interesting to look at the transition probabilities of asset distribution among households between the first wave and the last wave. Table 3.9 shows that there is a dynamic especially around the middle quintiles of the asset distribution, while the probability of remaining in the same starting quintiles is much higher at the two extremes of the distribution.

Table 3.9. Transition matrix of assets between first and fifth round

	Wealth quintiles at round 5						
	rounds	1	2	3	4	5	Total
Assets quintiles at round 1	1	42.2	27.5	13.7	10.8	5.9	100
	2	26.7	20.8	25.7	18.8	7.9	100
	3	15.4	25.0	26.0	24.0	9.6	100
	4	8.0	17.0	22.0	33.0	20.0	100
	5	8.0	9.0	13.0	13.0	57.0	100
	Total	20.1	19.9	20.1	19.9	19.9	100

Row percentages. Source: own elaboration.

The income diversification dynamics is qualitatively similar, although the proportion of households increasing or decreasing their own level of income diversification between the first and the last wave is significantly larger than in the case of assets as shown by the row sum of off-diagonal figures in Table 3.10. However, in this case also it is confirmed that the higher level of immobility is concentrated at the extreme of the distribution, especially at the lower end with almost 33% of households that had very low levels of income diversification in 2008-09 that still show very low levels in 2019-20.

Table 3.10: Transition matrix of Gini-Simpson index of diversification off-farm

		Gini-Simpson index at round 5					
		1	2	3	4	5	Total
Gini-Simpson index at round 1	1	32.9	15.0	15.0	17.9	19.3	100
	2	11.1	12.7	25.4	28.6	22.2	100
	3	29.1	9.7	22.3	20.4	18.5	100
	4	32.7	8.9	22.8	18.8	16.8	100
	5	25.0	14.0	19.0	18.0	24.0	100
	Total	27.8	12.2	20.1	19.9	19.9	100

Row percentages. Source: own elaboration.

One of the key hypotheses of this paper is that income source diversification can play a role in determining the asset accumulation dynamics as well as income and consumption dynamics. Therefore, it is interesting to contrast the asset dynamics – that is, households that accumulated, decreased or stayed at the same level of assets between the first wave and the last wave – with income diversification broad levels at the beginning of the period under scrutiny (Table 3.11). Overall, there was a lot of movement on an asset dynamics with no clear relationship with the household diversification level. However, the fact that in aggregate we cannot observe a clear relationship is not evidence of absence of relationship. It could only reflect the fact that, for instance, the ones included in the bottom diversification group may be not only the highly specialized households (i.e., households that are happy with gaining their own livelihood from only one source of income), but also households that are unable to diversify.

Table 3.11: Row percentages of household between income diversification quintiles and all-asset growth categories

		All-asset growth rate (4 lags)			
		decreased	Stable*	increased	Total
Levels of diversification at wave 1	No diversification	44.03	12.69	43.28	100
	Moderate diversification**	37.76	17.86	44.39	100
	High diversification	47.37	12.87	39.77	100
	Total	42.71	14.77	42.51	100

Source: own elaboration. Row percentages. * The benchmark for the categories is +/- 10%. ** below than 0.4 but different from 0 (corresponding roughly to terciles of income diversification).

By and large, over the period of analysis we identify three different rural household livelihood strategies as per the transition of the income diversification index between the first and the last survey waves. The first group of households are those that stayed at the same level of the income diversification index. The second group consists of those who moved to a lower level of the income diversification index over time. The third group moved to a higher level of the income diversification index in the last wave as compared to their level in the first wave. Table 3.12 presents some descriptive statistics for these three groups of households according to their initial diversification level and compare them making a t-test of difference of the means at wave 1, using the group of households that maintained the same level of the income diversification index as reference group. Table 3.12 shows that few differences emerge in land and livestock.

Table 3.12: Summary statistics at wave 1 by income diversification transition between the first wave and the fifth wave

	Income diversification transition from wave 1 to wave 5									
	Total sample		Stay in the same diversification group		Move to a lower diversification group			Move to a higher diversification group		
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.	Signif.	Mean	S.D.	Signif.
Household size	6.517	3.525	5.915	3.006	6.462	2.772		6.627	4.051	
Age of HH head	48.829	14.794	46.106	14.451	49.339	13.758		48.749	15.572	
Female-headed HH	0.269	0.444	0.255	0.441	0.272	0.446		0.267	0.443	
Years of education of the HH head	5.478	3.777	5.66	3.178	5.339	3.873		5.564	3.771	
Farm size (ha)	1.073	1.527	1.373	1.53	0.914	1.092	**	1.161	1.78	
Per-capita landholdings (ha)	0.189	0.316	0.354	0.689	0.167	0.211	***	0.186	0.313	***
All-asset index	0.233	0.177	0.222	0.155	0.237	0.173		0.232	0.182	
Durables	0.229	0.201	0.217	0.173	0.232	0.192		0.228	0.21	
Agricultural index	0.132	0.141	0.123	0.099	0.125	0.122		0.138	0.157	
Farm implements	0.074	0.078	0.08	0.068	0.072	0.069		0.075	0.084	
Livestock (TLU)	2.248	5.418	1.096	2.9	1.709	4.589		2.887	6.244	*
Droughts	0	0	0	0	0	0		0	0	
Floods	0.004	0.062	0	0	0	0		0.007	0.085	

Source: own elaboration. * The benchmark for the categories is +/-10%

3.4 Empirical strategy

In order to model and test potential non-linearities characterizing the association between income diversification and the households' welfare outcome dynamics (proxied by asset growth) this study uses the fixed-effect panel threshold model firstly proposed by Hansen (1999). Threshold models have been used to study the relationship between self-employment with respect to credit and labour constraints for microenterprises (Lahiri & Daramola, 2022). Other studies focus on the nonlinear relationship between working hours and life satisfaction (Zheng et al., 2023), financial development and growth (Botev et al., 2019; Samargandi et al., 2015), technology spillovers and TFP (Huang et al., 2019), growth and natural resource dependence (Dramani et al., 2022), and the relationship between short-run growth, temperature shocks and poverty thresholds (Letta et al., 2018). We analyse the empirical relationship between income diversification and household welfare outcomes using the following empirical specification:

$$Y_{it} = \begin{cases} a_i + W_{i,t-1}\beta_0 + \boldsymbol{X}_{it}\beta_1 + S_{it}\beta_2 + D_{it-1}\beta_{3_L} + \epsilon_{it} & if\ W_{i,t-1} < \lambda \\ a_i + W_{i,t-1}\beta_0 + \boldsymbol{X}_{it}\beta_1 + S_{it}\beta_2 + D_{it-1}\beta_{3_U} + \epsilon_{it} & if\ W_{i,t-1} > \lambda \end{cases} \quad (2)$$

where Y_{it} is a variable representing the growth of each asset index; D_{it-1} is the diversification index which measures the heterogeneity of the off-farm income sources; $W_{i,t-1}$ is a lagged normalized assets index which controls for convergence processes and difference in the levels of consumption and food security due to the previous wealth status of the households; $\mathbf{X}_{it}$ is a vector of sociodemographic characteristics including the household head's gender, age and educational level, the number of household members, and lagged income terciles; S_{it} identify locally covariant climate shocks (specifically droughts); a_i is the household specific fixed effect which captures the time invariant unobserved heterogeneity; and ϵ_{it} is the i.i.d. disturbance term.

The coefficient of interest is represented by β_3 that estimates the empirical relationship between the outcome variables and the diversification index, D_{it-1}, assumed to vary across two discrete regimes, below (β_{3_L}) and above (β_{3_U}) the threshold parameter λ. When λ is unknown, the nuisance parameter problem[105] makes the distribution of the estimator $\hat{\lambda}$ nonstandard in a fixed effect model. Hansen (1999) proposed a model to consistently estimate the threshold and developed a non-standard asymptotic distribution theory for confidence intervals and hypothesis testing. The threshold is estimated through least squares: the estimator is the value that minimizes the residual sum of squares. To ease the computation, the search for this number is done over quantiles (Hansen, 1999). Confidence intervals are calculated using the "no-rejection region" method with a likelihood ratio (LR) statistic. In order to test the hypothesis that the estimated threshold is significantly different from zero, the author proposed a bootstrap method[106].

Such a threshold model is expected to test and capture the potential structural breaks characterizing the relationship between the off-farm income diversification strategies put in place by the Tanzanian households and their welfare outcomes over a longer time horizon (i.e., assets growth). It is worth noting that, although the empirical approach does not allow to estimate the causal impact of the diversification on the household welfare, it controls for the unobserved time invariant heterogeneity which may confound the estimated empirical associations. We do acknowledge that other unobserved time varying heterogeneity may give rise to reverse causality between the dependent outcomes and the diversification index. To minimize this risk, we lagged all possibly endogenous variables of one period. Another potential empirical issue may be related to the endogeneity of the thresholding variable (Gørgens & Würtz, 2019; Kourtellos et al., 2016; Yu & Phillips, 2018). However, in our empirical framework this concern is relaxed by the fact that also the threshold parameter is estimated with respect to the lagged assets variable.

In order to investigate the existence of regime switches in the relationship between households' off-farm diversification and welfare outcomes in case of localized covariant climate shocks, equation (2)

[105] This problem arises when any parameter is unspecified but is essential for inference and hypothesis testing of the parameters of interest.

[106] We use the Stata command xthreg developed by Wang (2015) that allows for hypothesis testing, confidence intervals estimation, and the estimation of multiple thresholds. However, the strong assumption of this estimator is that the covariates need to be strongly exogenous (Seo et al., 2019) and time-varying.

model has been expanded including climate variables. This has been done including an interaction term between the diversification index and a dummy variable identifying a climate shock (specifically, a drought) as follows:

$$Y_{it} = \begin{cases} a_i + W_{i,\mathrm{t}-1}\beta_0 + X_{it}\beta_1 + S_{it}\beta_2 + D_{i,t-1}\,\beta_3 + D_{it-1} * S_{it}\beta_{4_L} + \epsilon_{it} & if\ W_{i,\mathrm{t}-1} < \lambda \\ a_i + \ W_{i,\mathrm{t}-1}\beta_0 + X_{it}\beta_1 + S_{it}\beta_2 + D_{i,t-1}\,\beta_3 + D_{it-1} * S_{it}\beta_{4_U} + \epsilon_{it} & if\ W_{i,\mathrm{t}-1} > \lambda \end{cases} \quad (3)$$

In this specification, the estimated coefficients of the interaction term, β_{4_L} and β_{4_U}, refer to the association between diversification and welfare outcomes in case of shocks and are interpreted as marginal difference relatively to the same association in "normal" periods.

3.5 Results and discussion

We now present the results of the threshold model. We start by estimating equation 2 (Table 3.13), characterizing the relationship between income diversification and asset growth as varying on the asset level. We comment on the model estimated, the identified threshold and on the mean characteristics of households that are located above the threshold. Then we take a closer look at the interaction with climatic shocks by estimating equation 3 (Table 3.14).

3.5.1 Income diversification, income and asset dynamics

A nonlinear relationship

Equation 2 is estimated for each of the five outcomes (i.e., the growth of each asset indexes), identifying a threshold on the lagged level of the same outcome variable[107] (Table 3.13). The first result is that a threshold can be identified for each asset indexes (Table 3.13 columns 1-3 and 5) but farm implements (column 4). The threshold indicates a switch in the regime of the relationship between income diversification and asset growth, rejecting the linear model. The second result is that all-asset and durables behave differently from all agricultural asset indexes. Above the threshold, there is a positive relationship between diversification and asset growth in the case of all-assets and durables, while for agricultural assets this relationship is negative. Below the threshold, the only significant association is for livestock growth (column 5) that shows a positive coefficient.

A nonlinear relationship between all-assets and durables growth and income is estimated, with the households located in the upper income tercile being significantly associated with high asset growth. The climatic shock dummy is negatively related to (any) asset growth, though it is significant only for all-asset durables and farm implements (columns 1, 2 and 4). This could suggest that in case of droughts

[107] We call this a 'relative' threshold. We also do the same exercise on an 'absolute' threshold, meaning that for all asset outcomes we use the same asset threshold, i.e., the all-assets index. This produces very similar results and allows a comparison of the threshold level across regressions (see Table A2 in the Appendix 4 for details).

households might reduce investments or even sell their durables and farm implements to smooth consumption.

All the above results hold if we control for self-reported shocks (climatic, agricultural, income, price, health and conflict) (Annex 4, Table A6) and if we use a different estimator such as the Generalized Method of Moments (GMM)[108] (Appendix 4, Table A5).

Differences between households in the two regimes

Table 3.13 estimates show that for households in the high regime more diversification is associated with higher all-assets growth and durables growth. This indicates that income diversification can foster asset accumulation for better-endowed households, while for households below the threshold higher diversification does not have significant effects. Furthermore, the thresholds are located at the higher end of the asset variable, with the high regime being less populated than the lower regime[109].

Who are those above the (all-assets and) durables thresholds?[110] A simple t-test (Table A1 in Appendix 4, columns 1 and 2) shows that they have higher yields, higher education, higher income level but similar diversification level, they earn higher shares in non-farm wage and self-employment and lower agricultural wage, crop and livestock income. They own smaller plots of land, their dwelling is provided with electricity and running water, and have a better diet (i.e., they eat more and have a more diversified diet). Finally, they have similar livestock holdings and similar agricultural assets. By unpacking the industry from which non-farm wage income is earned, we observe that those above the threshold earn significantly higher shares from manufacturing activities and less from agriculture.

In the case of households above the agricultural asset index threshold, more diversification is associated with lower growth in the same asset (Table 3.13, column 3). This indicates that specialization might be more meaningful for better endowed households. Households above the agricultural asset threshold (Table A1, column 3) have statistically higher asset indexes, farm implements, livestock, but also higher productivity, employ more household and hired labour, have fewer income sources, are less educated, earn higher shares from livestock and lower shares from self-employment, wage, tree, transfers (indeed they have a lower diversification index) but have larger land plots and more animals (especially cattle, oxen, goats and sheep). They are more likely to live in 'low quality' dwelling (in terms

[108] The GMM model developed by Seo & Shin (2016) and implemented on Stata by Seo *et al.* (2019) explicitly sets the lag of diversification as endogenous with a first-differenced GMM estimator that allows both threshold variable and regressors to be endogenous. However, the model treats all covariates as regime-dependent, not allowing to distinguish between the regime-dependent and regime-independent variables (we have no reason to believe that all regressors show a break in the relationship between asset growth according to lagged assets). Therefore, we only use it as a robustness check.

[109] For instance, in the all-asset model (column 1), only 5.1% of households have assets above the threshold. We discuss whether the low number of households in the high regime is an issue by running some sensitivity tests in Appendix 3.

[110] The households above the all-assets index largely overlap those above the durables' threshold. We comment the results of the durables index as it is more specific.

of floor material, running water, toilet), have higher food consumption score but less caloric diets. They earn lower shares of wage income from primary sectors than those below the threshold (the other sectors showing non statistically significant differences).

The coefficients estimated for farm implements regimes are not statistically significant[111] (Table 3.13, column 4). Vice versa, in the case of livestock growth (Table 3.13, column 5), more diversification for those below the threshold is associated with higher growth. Those above the livestock threshold show significantly higher agricultural asset scores (both farm implements and livestock) and higher productivity (Table A1, column 5). They employ more days of household labour (but similar hired labour), have fewer income sources and lower diversification index, lower education, lower shares of non-farm wage and higher share from livestock, and manage a larger land area. Their dwelling feature lower quality characteristics, and their diet is less caloric. A confounding matrix confirms only a minimal overlap of the households above the livestock threshold and the agricultural asset threshold (and the all-asset index).

Table 3.13: Panel threshold fixed effect regression

	(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
(Lower regime) lag diversification	-0.003	-0.001	-0.002	-0.011	0.011**
	(0.008)	(0.009)	(0.009)	(0.008)	(0.005)
(Higher regime) lag diversification	0.233***	0.347***	-0.265**	0.090	-0.247***
	(0.065)	(0.108)	(0.122)	(0.073)	(0.067)
Lag all assets	-1.059***				
	(0.028)				
Lag durables		-1.030***			
		(0.033)			
Lag agricultural assets			-1.023***		
			(0.035)		
Lag farm implements				-1.283***	
				(0.040)	
Lag livestock (TLU)					-0.933***
					(0.068)
Lag income (tercile n.2)	0.036	0.047	0.503	0.787	-0.458
	(0.422)	(0.418)	(0.542)	(0.487)	(0.298)
Lag income (tercile n.3)	1.272**	1.711**	-0.327	0.468	-0.606
	(0.600)	(0.666)	(0.703)	(0.697)	(0.393)
Drought SPEI 7	-1.324**	-1.363*	-0.785	-1.169*	-0.801
	(0.651)	(0.713)	(0.676)	(0.619)	(0.607)
Observations	2,028	2,028	2,028	2,028	1,020
R-squared	0.587	0.530	0.600	0.663	0.568
Number of households	507	507	507	507	255
R2 within	0.587	0.530	0.600	0.663	0.568
R2 between	0.105	0.059	0.036	0.009	0.092
R2 overall	0.224	0.162	0.190	0.259	0.240
Threshold (lag asset index)	48.710	61.816	59.949	29.251	20.200
Prob	0.000	0.000	0.000	0.220	0.000
Trim	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	103	45	62	100	29
% Obs above the thr.	5.1%	2.2%	3.1%	4.9%	2.8%

[111] Descriptive statistics show that over time farm implements' ownership shares decrease as well as the average land size (Annex 4, Table A5).

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

3.5.2 Diversification and climate shocks

To assess the relationship between diversification, climatic shocks and asset growth, we estimate a model including an interaction between the lagged diversification index and the drought dummy (equation 3). Results show that the coefficient of the shock is negative in all cases but significant only in the case of the three agricultural asset indexes (Table 3.14, columns 3, 4 and 5), as expected. Moreover, the coefficients of the diversification terms are not significant for all-assets and durables index, while being positive and significant for the agricultural asset indexes. In particular, coefficients are positive and significant for the agricultural asset index (for both households below and above the threshold but larger for the latter), for the farm implements index (only for households above the threshold), and for livestock (for households below the threshold only). This indicates a partially mitigating effect of diversification on the impact of drought, although it is not able to fully offset the negative impact of the shock (see the bottom rows of Table 3.14 for the aggregate drought + diversification computation).

Households indeed diversify mainly[112] for risk management (ex-ante) and risk coping (ex-post) (Barrett, Reardon, et al., 2001). Ex-ante, poorer households, being more risk averse, have higher incentives to diversify. Similarly, the poor have also higher incentives to cope with shocks through diversification, but their ability to do it effectively might be insufficient (Barrett, Reardon, et al., 2001). In practice, it is hard to disentangle whether households diversify for ex-ante or ex-post motives. Here we are only able to say that when a shock occurs (ex-post), poorer households increasing their diversification have a partial mitigation of the impact of the shock. On the other hand, better-off households seem to be able to offset the impact of the shock on agricultural assets, with or without diversification (having access to effective ex-ante mechanisms?).

[112] Other reasons are diminishing or time-varying returns to labour or land, market failures, frictions, (Barrett, Reardon, et al., 2001) and economies of scope (Chavas & Di Falco, 2012).

Table 3.14: Panel threshold fixed effect regression, interaction with climatic shocks

	(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
(Lower regime) lag diversification # drought	-0.022	-0.039	0.062**	0.008	0.031*
	(0.025)	(0.027)	(0.026)	(0.024)	(0.016)
(Higher regime) lag diversification # drought	0.117	0.110	1.736***	0.290***	0.288
	(0.082)	(0.100)	(0.315)	(0.031)	(0.289)
Lag all assets	-1.028***				
	(0.032)				
Lag durables		-0.999***			
		(0.038)			
Lag agricultural assets			-1.067***		
			(0.035)		
Lag farm implements				-1.255***	
				(0.038)	
Lag livestock (TLU)					-1.021***
					(0.062)
Drought SPEI 7	-0.951	-0.461	-2.672***	-1.640*	-1.901**
	(0.787)	(0.840)	(0.994)	(0.990)	(0.800)
Lag diversification	0.007	0.008	-0.013	-0.011	0.003
	(0.010)	(0.010)	(0.010)	(0.009)	(0.006)
Observations	2,028	2,028	2,028	2,028	1,020
R-squared	0.578	0.517	0.604	0.664	0.544
Number of households	507	507	507	507	255
R2 within	0.578	0.517	0.604	0.664	0.544
R2 between	0.111	0.073	0.033	0.008	0.075
R2 overall	0.211	0.158	0.187	0.260	0.215
Threshold (lag asset index)	48.710	47.391	50.495	14.446	5.850
Prob	0.077	0.073	0.003	0.020	0.177
Trim	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	103	101	99	282	132
% Obs above the thr.	5.1%	5.0%	4.9%	13.9%	12.9%
Drought + (low regime) lag diversif. # drought	-0.973	-0.500	-2.611	-1.632	-1.869
P-value	0.208	0.678	0.008	0.093	0.018
Drought + (high regime) lag diversif. # drought	-0.834	-0.351	-0.936	-1.351	-1.613
P-value	0.291	0.543	0.355	0.166	0.064

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

We test the sensitivity of these results by extending the accumulation period of the SPEI index (Table A6 in the Appendix). The results are largely consistent with those obtained using the 7 months SPEI, with a few more significant results for all-assets and durables, showing that diversification below the threshold could strengthen the negative impact of shock when the shock is extreme (though the linear combination of the climatic shock coefficient and the coefficient of the interaction term is not significant).

3.6. Robustness and heterogeneity test

We now test the validity of our results by using a larger panel, comprising the first three waves of the Tanzania NPS panel (Table 3.15). Next, we show some heterogeneity within our model from diversification levels (Tables 3.16 and 3.17).

3.6.1 Robustness test

To rule out that our main results are driven by the small size of our sample, we replicate the same analysis using the panel including only the three waves before the refreshment (Table 3.15). In doing this, we lose in time length and lags but gain substantially in sample size and geographical coverage. Results are in line with those from the extended panel. This is reassuring. The larger sample size allows to identify three new significant relationships: for durable assets (column 2) also households below the threshold have a positive relation between diversification and their growth, though the magnitude of the estimated coefficient is less than for the above threshold regime. Moreover, farm implements (column 4) now also have a significant threshold and show that households below the threshold as they diversify more, they accumulate slower farm implements and land, while the inverse is true for households above the threshold. Finally, for the all-assets index (column 1), the threshold is located in the lower end of the distribution, where the negative coefficient becomes significant, indicating that for the poorest households increasing diversification is associated with asset depletion or lower growth, most likely due to the dynamics of farm implements/land, which is important for poorer households that gain their own livelihood mostly from farming.

Table 3.15: Panel threshold fixed effect regression, short panel

	(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
(Lower regime) lag diversification	-0.060**	0.009*	0.000	-0.015***	0.004
	(0.026)	(0.005)	(0.006)	(0.005)	(0.006)
(Higher regime) lag diversification	0.013**	0.118**	-0.215***	0.014**	-0.226*
	(0.006)	(0.048)	(0.058)	(0.007)	(0.126)
Lag all assets	-1.281***				
	(0.022)				
Lag durables	-1.281***	-1.304***			
		(0.028)			
Lag agricultural assets			-1.306***		
			(0.024)		
Lag farm implements				-1.448***	
				(0.034)	
Lag livestock (TLU)					-1.438***
					(0.237)
Lag income (tercile n.2)	0.016	-0.045	0.312	0.112	0.370
	(0.246)	(0.216)	(0.311)	(0.258)	(0.341)
Lag income (tercile n.3)	-0.425	-0.081	-0.640*	-0.782**	0.162
	(0.344)	(0.319)	(0.375)	(0.346)	(0.406)
Drought SPEI 7	-0.180	-0.047	-0.117	0.085	-0.839*
	(0.309)	(0.301)	(0.294)	(0.255)	(0.469)
Observations	6,594	6,594	6,594	6,594	3,296
R-squared	0.717	0.701	0.742	0.760	0.618
Number of households	3,297	3,297	3,297	3,297	1,648
R2 within	0.718	0.701	0.742	0.760	0.618
R2 between	0.0793	0.0488	0.0342	0.00289	0.346
R2 overall	0.187	0.151	0.146	0.192	0.304
Threshold (lag asset index)	2.201	50.28	53.04	2.632	19.90
Prob	0.010	0.010	0.000	0.030	0.000
Trim	0.01	0.01	0.01	0.01	0.01
Obs. above the thr	6,432	133	229	3,323	115
% Obs above the thr.	98%	2%	3%	50%	3%

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

3.6.2 Tests of heterogeneity

To shed light on the heterogeneity in the diversification level, we split the sample between those who have a non-diversified portfolio and those with a more diversified portfolio using two different approaches, i.e., according to the number of times a household has the diversification index below the average across rounds (Table 3.16) and splitting the sample using the initial diversification level (Table 3.17) [113]. In the former case, a threshold can be identified for all outcomes for both classes. Results

[113] In the first approach, we count the number of times a household has the diversification index below the average, and we separate households in two classes: those with low diversification (with 3 or more times below-average diversification) and those with high diversification (less than 3 times with low diversification) (Table 3.16). In the second approach we just split the sample according to the households' initial diversification level (Table 3.17). Both approaches entail a certain degree of arbitrariness, nevertheless they provide some information about the evolution of diversification. Using the lagged diversification as a threshold variable is not suited either, as the resulting thresholds (not significant) are found too close to the extremes of the variables: zero (full specialization) and above 0.6 (where the max of the range is 0.7).

confirm the relations emerged in Table 3.13. Interestingly, the dummy for climatic shocks has a significantly negative coefficient only for low diversification households in the case of all-asset and durables growth (columns 1 and 3). This could signal again the ability of more diversified households to cope with shocks.

Who are those with a high diversification index? A t-test shows that they have lower all-assets, agricultural assets (implements/land and livestock), lower yields, have more education, earn larger shares from self-employment, farm and non-farm wage and transfers, while less from crop and livestock, have less land, lower-quality dwelling and lower income and food consumption score. Unpacking the industry of self-employment, high-diversification households earn significantly higher shares of income from manufacturing, transport and services. Looking at wage income, those with high diversification have higher shares from agriculture employment, utilities, construction, commerce and transport.

Table 3.16: Panel threshold fixed effect regression, by diversification class

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All assets growth		Durables growth		Agricultural assets growth		Farm implements growth		Livestock growth	
Diversification level:	low diversif.	high diversif.	low diversif.	high diversif.	low diversif.	high diversif.	low diversif.	high diversif.	low diversif.	high diversif.
Drought SPEI 7	-2.476***	-0.100	-2.432***	-0.254	-1.523	0.173	-1.427	-0.741	-0.387	-0.174
	(0.769)	(1.035)	(0.839)	(1.094)	(0.976)	(0.995)	(0.981)	(0.706)	(0.567)	(0.515)
(Lower regime) lag diversification	-0.009	0.004	-0.013	0.004	-0.003	0.010	-0.011	-0.006	0.001	0.010
	(0.013)	(0.011)	(0.013)	(0.012)	(0.015)	(0.012)	(0.012)	(0.010)	(0.008)	(0.007)
(Higher regime) lag diversification	0.165*	0.268***	0.240**	0.297***	-0.281**	-0.099**	-0.358	0.038	-1.733***	-0.159*
	(0.092)	(0.095)	(0.110)	(0.100)	(0.141)	(0.044)	(0.219)	(0.122)	(0.458)	(0.095)
Observations	1,064	964	1,064	964	1,064	964	1,064	964	548	472
R-squared	0.619	0.548	0.557	0.511	0.633	0.550	0.694	0.609	0.628	0.508
Number of households	266	241	266	241	266	241	266	241	137	118
R2 within	0.619	0.548	0.557	0.511	0.633	0.550	0.694	0.609	0.628	0.508
R2 between	0.092	0.115	0.042	0.102	0.022	0.064	0.014	0.001	0.111	0.031
R2 overall	0.231	0.212	0.158	0.188	0.211	0.170	0.289	0.226	0.289	0.209
Threshold (lag asset index)	51.989	46.691	56.017	47.818	57.322	26.204	62.714	30.588	20.780	13.560
Prob	0.060	0.000	0.000	0.000	0.000	0.000	0.020	0.070	0.000	0.000
Trim	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	74	89	62	98	71	361	28	88	17	54
% Obs above the thr.	3.6%	4.4%	3.1%	4.8%	3.5%	17.8%	1.4%	4.3%	1.7%	5.3%

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

We also report results after splitting the sample at the median of income diversification level at wave 1 (0.204) (Table 3.17). This aims at shedding light on the amount of initial diversification which is 'good' for asset accumulation. A statistically significant threshold can be identified for each asset type. The thresholds for the same asset are higher in the case of higher diversification with respect to low diversification for all assets and durables (columns 1-4), while for agricultural assets, farm implements and livestock the opposite is true. While for the households below the threshold the coefficient of diversification is never significant (except in the case of the all-assets index for which there is a positive though only slightly significant coefficient), for those above the threshold there is a significant and consistently negative coefficient for all the cases in which diversification is low. This means that when the income portfolio is quite specialized and assets are above a certain threshold, increasing diversification is negatively correlated with asset growth. For households with a more diversified portfolio and assets above the threshold, further diversification is positively related to asset accumulation (livestock growth being the only exception). This time the dummy for climatic shocks has a significantly negative coefficient only for some above-median diversification households.

A t-test on the difference of the means for households belonging to the two groups shows that those with high diversification index have higher durables and lower agricultural asset indexes (both farm implements and livestock), less productivity, higher hired labour, have more education, earn more from self-employment, non-farm wage and transfers, while less from crop and livestock, have less land, better quality dwelling and higher income and food expenditure.

Table 3.17: Panel threshold fixed effect regression, low and high diversification based on diversification at round 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All assets growth		Durables growth		Agricultural assets growth		Farm implements growth		Livestock growth	
Diversification level:	low diversif.	high diversif.	low diversif.	high diversif.	low diversif.	high diversif.	low diversif.	high diversif.	low diversif.	high diversif.
Drought SPEI 7	0.736	-3.058***	0.723	-2.969***	-0.111	-1.063	-0.852	-1.311*	0.137	-0.329
	(0.840)	(0.953)	(0.875)	(1.078)	(0.997)	(0.943)	(0.957)	(0.791)	(0.648)	(0.298)
(Lower regime) lag diversification	0.020	0.007	0.021	0.003	-0.010	-0.001	0.000	-0.009	0.008	0.004
	(0.012)	(0.013)	(0.014)	(0.015)	(0.017)	(0.011)	(0.013)	(0.010)	(0.009)	(0.005)
(Higher regime) lag diversification	-0.218***	0.387***	-0.122***	0.462***	-0.471***	0.102	-0.498***	0.143**	-1.799***	-0.085
	(0.052)	(0.072)	(0.043)	(0.087)	(0.140)	(0.073)	(0.140)	(0.072)	(0.470)	(0.053)
Observations	996	1,032	996	1,032	996	1,032	996	1,032	568	452
R-squared	0.628	0.598	0.562	0.546	0.637	0.564	0.691	0.644	0.607	0.579
Number of UPHI3	249	258	249	258	249	258	249	258	142	113
R2 within	0.628	0.598	0.562	0.546	0.637	0.564	0.691	0.644	0.607	0.579
R2 between	0.132	0.069	0.067	0.044	0.091	0.000	0.076	0.008	0.124	0.053
R2 overall	0.266	0.200	0.195	0.152	0.253	0.126	0.319	0.203	0.293	0.105
Threshold (lag asset index)	34.586	52.429	26.402	55.329	57.322	46.382	36.624	21.333	26.160	11.450
Prob	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Trim	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	241.000	72.000	325.000	68.000	71.000	146.000	72.000	169.000	12.000	62.000
% Obs above the thr.	0.119	0.036	0.160	0.034	0.035	0.072	0.036	0.083	0.012	0.061

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

3.7. Conclusions

Although it is qualitatively well known that households' income diversification is neither equally feasible nor equally rewarding for all and depends on the range of options available to them (Barrett, Reardon, et al., 2001; Barrett, Bezuneh, et al., 2001; Ellis & Freeman, 2004; Otsuka & Yamano, 2006), there are only a few studies that empirically test this hypothesis.

With specific reference to Tanzania, previous studies showed that non-farm income shares rise with food consumption quintiles in peri-urban areas (Lanjouw et al., 2001) and with food and non-food consumption (Khan & Morrissey, 2020). In particular, Khan & Morrissey (2020), using the first three waves of the Tanzania LSMS dataset, highlighted some heterogeneity according to the activity: wage outside of agriculture and self-employment have a welfare-enhancing role, while agricultural wage entails no association with higher consumption. Moreover, substantial gender differences emerge in the profitability and access to the various activities. Similarly, we found that the role of diversification is heterogenous across the wealth distribution, livelihood strategies (proxied by the different asset indexes), and in presence of shocks. Specifically, we found evidence that income diversification fosters asset accumulation, specifically the accumulation of durables, only for the better assets-endowed households. This appears in contrast to the findings in other contexts in which diversification of income benefits the poorest quintiles the most (Asfaw et al., 2018, 2019; Tran & Vu, 2020), while it is consistent with other studies on Tanzania that find that better-off households diversify more (Dercon & Krishnan, 1996; Dimova et al., 2021; Ellis & Mdoe, 2003). In particular, consistently with Dimova et al. (2021) findings, we show that income diversification is driven by asset accumulation motivation as opposed to poorer households that diversify because of survival motivations.

Moreover, our results show that income diversification for better-endowed households is negatively correlated with agricultural asset growth (in particular, livestock growth). This suggests a tendency to reduce investments/disinvesting in agriculture only for wealthier household, in line with the structural transformation process that is occurring in Sub-Saharan Africa and, specifically, in Tanzania. A similar relationship was found in Albania and in Ethiopia[114]. Conversely, for poorer households, specifically livestock-poor households, the more they diversify the more they accumulate livestock. This positive relationship resonates the results of Ellis & Freeman (2004) for four African countries and of Hertz (2009) for Bulgaria. This possibly highlights that the relationship between livestock and non-farm income is self-reinforcing as non-farm income can be invested to accumulate livestock (Ellis & Freeman, 2004) and, at the same time, livestock is an asset that can be sold to overcome the barriers to enter non-farm business activities.

[114] In Albania this occurred for both subsistence and commercial farmers (Kilic et al., 2009), while in our case it is so only for wealthier agricultural households. In Ethiopia, both livestock-rich and livestock-poor households show a positive relation between the share of off-farm income in total income and expenditure growth, with a larger coefficient for wealthier households (Bezu et al., 2012).

Furthermore, we found that income diversification only partially mitigates the negative impact of climatic shocks on agricultural assets accumulation for poorer households, while it is more effective in doing so for better-endowed households. Indeed, income diversification plays a role as a tool for managing agricultural risk (Arslan et al., 2018; Gao & Mills, 2018; Tankari, 2020), both ex-ante, i.e., against climate variability and ex-post, i.e., against climate shocks (Barrett, Reardon, et al., 2001). Indeed, income diversification provides an imperfect mechanism for coping ex-post with climatic shocks. Ex-ante, it is hard to say. Other studies showed that in Zambia farmers use income diversification to cope with shocks, as it is a more prompt mechanisms than crop diversification, which is preferred as an ex-ante strategy (Arslan et al., 2018). In Bangladesh, it is ex-ante risk that increases income diversification responses, but only where flood risk is low (Bandyopadhyay & Skoufias, 2015).

For durable assets, no significant effect of shocks is found, possibly suggesting an asset smoothing behaviour as emphasized by Letta *et al.* (2018) who found that while poor and rich households in Tanzania smooth their assets against temperature shocks, poorer households do so at the expense of their consumption. This may suggest the existence of a climate-induced poverty trap. Interestingly, the poverty trap hypothesis, i.e. starting conditions matter for future growth (Balboni et al., 2021), seems at work also in our sample of households, but with the important qualification that income diversification interacts with household asset endowment levels, favouring only the households above a specific diversification threshold. In fact, splitting the sample according to their diversification level at the beginning of the analysed period, we find that for households above the asset threshold more diversification negatively correlates with asset growth when diversification was low at the beginning. In other words, when the income portfolio is quite specialized and assets are above a certain threshold, increasing diversification is negatively correlated with asset growth. Conversely, considering households that are wealthier in assets, we find that for the ones having initially more diversified income portfolios further diversification is positively related to asset growth.

As income diversification generally allows asset accumulation for better-off households, this suggests that although income diversification is spread along the wealth distribution, it does not represent a pathway out of poverty for all. Rather, besides the important entry barriers already emphasized by many authors (Barrett *et al.* 2001a; Drall & Mandal 2021; Reardon 1997), there are also wealth thresholds limiting the potential of diversification. Nonetheless, we find that also poorer households may benefit from income diversification, it depends on the household specific livelihood strategy. In our sample, this is the case only for the ones engaged in livestock rearing activities.

The asset accumulation role of income diversification for better-off households calls for policy interventions targeting the less-endowed households. Policies would include fostering agricultural productivity for sustaining the incomes of the less-endowed households, through complementary interventions in infrastructure, access to financing and to the markets, especially in more remote areas (Dimova et al., 2021), and directly in agriculture for food security (Dedehouanou & McPeak, 2020;

Reardon et al., 2000). Improving the access to risk management tools, such as insurance[115] and social safety nets, could help households to engage in income diversification for sake of seizing opportunities rather than forced into it because of necessity.

A second implication of our results is that wealth inequality plays a crucial role in qualifying the diversification outcomes as well as the opportunities the households can access (Addai et al., 2022; Barrett, Reardon, et al., 2001). Indeed, while diversification of income is negatively correlated with poverty in Tanzania, a large share of households that diversify are poor, implying that many nonfarm activities, which are the most accessible to the poorest, are unproductive (Diao et al., 2018). Interventions should be therefore aimed at lowering access barriers to the most profitable activities, such as the provision of information, financial capital, education and infrastructure (Reardon et al., 2000), so that they can pave the way out of poverty.

In conclusion, our study shows that the effect of diversification is heterogeneous and crucially depends on the interaction of diversification with asset endowment, livelihood strategies, and risk exposure. However, further studies are needed to confirm/disconfirm the validity of our findings in other contexts exploring the mechanism leading to this result. Furthermore, more analyses based on primary data collected ad hoc to shed light on the specific off-farm activities which may be more suitable for specific group of households to enhance their welfare outcomes and reduce the risk exposure to shocks are needed as well. Unfortunately, this kind of analysis was not possible with LSMS-ISA dataset.

[115] The need to diversify income sources (and crop) decreases if insurance opportunities are available (Bozzola & Smale, 2020).

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Appendix 1. Data cleaning

Particular care was devoted to the cleaning of the data. Despite the general high quality of the LSMS datasets, some challenges emerged. For instance, the private transfers module in wave 2 questionnaire was formulated very differently from the other waves' questionnaires. This led to an underestimation of those transfers, which were therefore imputed from the households' average from wave 1 and wave 3. A similar exercise was done for each asset ownership and livestock dummies whenever the module was missing in a 'middle' year (i.e., for which the information was available both in the previous and in the following wave).

Also, to correct for missing questions in wave 1 for the months and weeks worked, in order to calculate annual wages, we imputed months and weeks from the median for the same sector in the second wave. This was especially relevant for agricultural wage labour, which has a more casual temporal pattern.

Whenever possible, outliers were corrected[116], if not they were dropped. In particular, two households of the balanced sample were dropped because of plausible but extremely high levels of income (one is a very well remunerated public administrative job, one has a huge chicken farm[117]) which we deemed not in line with the sample. Finally, 32 households were dropped because reporting zero gross income in 'non-middle' years (i.e., the first or the last wave, or when information was missing in two or more consecutive waves).

Appendix 2. Wealth index construction

The choice of which assets might be relevant to proxy households' wellbeing and their accumulation process is not a trivial task and can influence the final result (Howe et al., 2008). Therefore, we started from a core of key assets (agricultural and non-agricultural) and then proceed to add the remaining ones[118] one by one and later, cumulatively. Results were very stable but showed a pattern in which durables and agricultural assets moved in different directions, looking at how the all-asset index changed sign whenever a durable or agricultural asset was added stepwise. This is also why we chose to use different asset indexes as outcomes.

[116] Outlier detection involved inspecting the tails of the density distribution of the main variables over time, comparing averages, min, max and percentiles over time, and so on.

[117] The huge chicken farm reported having 2,000 chickens in wave 4 and 2,500 in wave 5, but they reported selling 20,000 chickens for 62 million TSh (unit price =3,100 TSh) (the median price of chicken during the same wave was 8,000 TSh). Although a correction was possible, such a large super-specialized household was not in line with our sample. The second case regarded a person with the very high monthly wage from a job in public administration, and was coherent with its own previous and following observations. So, there was no error but again we perceived that this household had little to do with the rest of our sample. The removal of the two households did not change the interpretation of our results.

[118] We did not include those that had very low ownership rates.

We computed each asset index by extracting the PCA first component (Filmer & Pritchett, 2001). On the one hand, this approach lacks a monetary equivalent that makes its interpretation more difficult. On the other hand, it needs to be interpreted in a relative way and can provide a measure of inequality (McKenzie, 2005). PCA approach has indeed been criticized for the weighting used especially with binary data (Naveed et al. 2021; Vyas & Kumaranayake 2006), although it seems not to be a serious concern (Howe et al., 2008). Assessments of validity of these asset indexes have been based on the comparison with consumption measures, which most likely capture different socio-economic dimension (Howe et al., 2008). Despite two decades of discussion over the alternatives (multiple correspondence analysis or MCA, exploratory factor analysis of the tetrachoric PCA (Naveed et al., 2021), factor analysis (Sahn & Stifel, 2003)), PCA is still used as one of the most suitable approaches for several reasons. In fact, it is computationally simple and it does not poses measurement problems, such as seasonality, recall bias, measurement error, as monetary measures usually do. Furthermore, PCA works well with binary as well as continuous variables (while categorical variables need to be transformed into binary variables).

Appendix 3. Sensitivity of the threshold

The number of observations above the thresholds is quite small in all models. Whether this is an issue depends on the stability of threshold and of its location. This issue was already pointed out in the Hansen seminal paper (1999, p. 349): "It is undesirable for a threshold $\hat{\gamma}$ to be selected which sorts too few observations into one or the other regime. This possibility can be excluded by restricting the search in (8) [the equation of the estimator for γ] to values of γ such that a minimal percentage of the observations (say, 1% or 5%) lie in each regime". However, in the Wang (2015) paper, which developed the Stata "xthreg" command, there is no explicit reference to how this issue can be addressed, but for trimming. This procedure trims a proportion of the threshold variable on both sides at 1% (default).

Similar to Seo & Shin (2016), it can be useful to report also the number of observations below the threshold in percentage terms (while all tables in the text report the percentage of observations above). In our case, with a trimming proportion of 1%, the share of observations below the thresholds is between 95% and 98%. Increasing the trimming of the threshold variable means that we are excluding larger proportions of the threshold variable at the tails of the distribution. If we increase it to 2%, results are almost unchanged and the threshold values are slightly lower, leaving between 95 and 96% of observations in the low regime. This means that above the threshold there are between 40 and 103 observations (Table A3.1).

Table A3 1: Sensitivity check: number of observations above the thresholds identified and percentage of households in the low regime. Long small panel W1-W5.

trim		(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
0.01	Obs. above the thr	103	45	62	100	29
	% Obs below the thr.	95%	98%	97%	95%	97%
0.02	Obs. above the thr	103	96	87	100	40
	% Obs below the thr.	95%	95%	96%	95%	96%
0.03	Obs. above the thr	133	122	350	169	62
	% Obs below the thr.	93.4%	94.0%	82.7%	91.7%	93.9%
0.04	Obs. above the thr	163	172	350	164	82
	% Obs below the thr.	92.0%	91.5%	82.7%	91.9%	92.0%

As the trim proportion increases, the number of observations above the threshold increases but with 4% trimming coefficients start losing statistical significance. This is suggestive that the structural break is consistently located at the higher end of asset indexes' distribution.

Furthermore, we find a similar result using a larger sample size such as the first three waves only, i.e., the short panel without refreshed observation units that took place in wave 4 (Table A3.2). At 1% trim, between 50% and 98% of observations are in the lower asset regime (in the case of all-asset is 2%, but this is due to the very low-level threshold identified). This means that the observations above the thresholds are between 115 and 3,323. At 4%, between 2% (durables) and 96% of observations belong to the low regime (corresponding to a number of observations in the high regime between 134 and 6,461), but results lose some significance.

Table A3 2: Sensitivity check: number of observations above the thresholds identified and percentage of households in the low regime. Large short panel W1-W3.

trim		(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
0.01	Obs. above the thr	6432	133	229	3323	115
	% Obs below the thr.	3%	98%	97%	50%	97%
0.02	Obs. above the thr	6397	1841	395	3346	230
	% Obs below the thr.	3.0%	72.1%	94.0%	49.3%	93.0%
0.03	Obs. above the thr	6331	1837	1009	3319	264
	% Obs below the thr.	4.0%	72.1%	84.7%	49.7%	92.0%
0.04	Obs. above the thr	6432	6461	263	3324	134
	% Obs below the thr.	2.5%	2.0%	96.0%	49.6%	95.9%

All these checks, showing the relative stability of results up to a certain degree of trimming (3%), means that having few observations above the threshold is not driving our results and confirms that the structural breaks are actually located at the high end of the asset distribution.

Appendix 4. Additional estimations

Table A 14: T-tests for mean differences between households above and below the thresholds of Table 3.13

	(1) All-assets	(2) Durables	(3) Agricultural assets	(4) Livestock
Mean differences (Above th.- below th.)				
All-asset index	34.164***	34.876***	8.905***	8.714***
Durables	38.573***	40.624***	0.571	1.64
Agricultural assets	1.62	-1.239	40.733***	33.674***
Farm implements	0.797	1.835	26.960***	21.631***
Livestock (TLU)	-0.044	-0.573	13.831***	18.672***
Productivity (harvest/labour)	1.359	0.408	3.824***	3.806**
HH labour hours spent on plot total	-55.852***	-64.889***	175.271***	198.491***
Hired labour days spent, all activities	29.439***	10.06	23.565***	-0.655
Mean yield	96.118***	121.993***	-22.44	-76.151**
N. income sources (off farm)	0.138	0.102	-0.372***	-0.435***
Education adult	2.734***	2.179***	-1.573***	-2.816***
Education (highest)	3.706***	2.595***	-0.744*	-1.499***
Share of income (self-employment)	0.113***	0.172***	-0.103**	-0.05
Share of income (agricultural wage)	-0.065***	-0.076**	-0.059**	-0.03
Share of income (nonfarm wage)	0.158***	0.103**	-0.065*	-0.111**
Share of income (crop)	-0.169***	-0.171***	0.001	0.01
Share of income (tree)	-0.01	-0.01	-0.037***	-0.022
Share of income (livestock)	-0.048	-0.074*	0.312***	0.216***
Share of income (transfers)	0.02	0.056**	-0.049**	-0.013
Land owned (size ha)	-0.720***	-0.645**	3.686***	3.103***
N. cattle	-0.893	-0.924	20.804***	31.525***
N. oxen	-0.093	-0.082	1.984***	3.327***
N. donkey horses	-0.02	-0.02	0.280***	0.111**
N. goats	0.837	-1.204*	5.799***	6.137***
N. sheep	-0.447	-0.484	3.576***	4.281***
N. pigs	0.848***	-0.077	-0.291	-0.454
N. chicken	13.330***	11.329***	8.131***	9.615***
N. poultry	-0.31	-0.484	2.857***	4.029***
Household owns its dwelling	0.073*	0.044	0.103**	0.044
Household has safe drinking water	0.072	0.044	-0.063	-0.155*
Dwelling has cement floors	0.627***	0.625***	-0.133**	-0.073
Household has functioning electricity	0.591***	0.773***	-0.087**	-0.089*
Household has private running water	0.280***	0.253***	-0.175***	-0.151*
Household has a private flush toilet	0.285***	0.309***	-0.078**	-0.066
Food Consumption Score	18.098***	16.027***	7.390***	10.684***
Per Capita Daily Caloric Intake	349.137***	366.444***	-410.199***	-511.744***
Gini Simpson Index of Diet Diversity	0.151***	0.141***	-0.031	-0.003
Annual food expenditure ($ PPP)	1.087***	1.139***	-0.096	-0.246
Income (total) in 2017ppp/day/pc	2.483***	1.576**	-0.687	-1.448**
Income diversification (Gini-Simpson)*	4.075*	3.783	-12.985***	-12.291***
Sh. selfemp from primary sector	-0.008	-0.008	-0.008	-0.006
Sh. selfemp from mining	-0.007	-0.007	0.009	-0.013
Sh. selfemp from manufacturing	-0.042*	-0.041	-0.003	-0.052
Sh. selfemp from utilities	-0.001	-0.001	-0.001	
Sh. selfemp from construction	-0.004	-0.005	0.011	-0.005
Sh. selfemp from commerce (wholesale, retail, hotels)	0.157	0.042	-0.165	-0.035
Sh. selfemp from transport, storage, communication	0.016	-0.01	0.006	-0.018
Sh. selfemp from financ, real estate, business services	0	0	0	0
Sh. selfemp from services comm, soc and personal services	-0.065	-0.055	-0.157	-0.302

Table A 15 (continued): T-tests for mean differences between households above and below the thresholds of Table 3.13

	(1) All-assets	(2) Durables	(3) Agricultural assets	(4) Livestock
Mean differences (Above th.- below th.)				
Sh. wage from primary sector	-0.208***	-0.217***	-0.103*	-0.092
Sh. wage from mining	-0.005	-0.005	-0.005	-0.006
Sh. wage from manufacturing	0.022	0.049**	-0.002	-0.015
Sh. wage from utilities	0.034***	-0.005	-0.005	-0.008
Sh. wage from construction	-0.053**	-0.052	-0.019	-0.041
Sh. wage from commerce (wholesale, retail, hotels)	-0.036	-0.015	-0.025	-0.057
Sh. wage from transport, storage, commutation	0.019	0.011	-0.011	-0.013
Sh. wage from financial, real estate, usiess services	0.008	-0.005	-0.005	-0.007
Sh. wage from services (comm, soc and pers services)	3.833***	0.134	-0.201	-0.077

* The income diversification is multiplied by 100.

Table A 16: Panel threshold fixed effect regression, absolute threshold (all asset index)

	(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
(Lower regime) lag diversification	-0.003	-0.004	-0.003	-0.045***	0.011**
	(0.008)	(0.009)	(0.009)	(0.013)	(0.005)
(Higher regime) lag diversification	0.233***	0.300***	-0.053*	0.002	-0.022
	(0.065)	(0.098)	(0.031)	(0.009)	(0.016)
Lag all assets	-1.059***				
	(0.028)				
Lag durables		-1.037***			
		(0.032)			
Lag agricultural assets			-1.051***		
			(0.034)		
Lag farm implements				-1.254***	
				(0.039)	
Lag livestock (TLU)					-1.005***
					(0.062)
Lag income (tercile n.2)	0.036	-0.037	0.501	0.739	-0.490*
	(0.422)	(0.430)	(0.544)	(0.493)	(0.295)
Lag income (tercile n.3)	1.272**	1.621**	-0.362	0.270	-0.407
	(0.600)	(0.653)	(0.686)	(0.698)	(0.405)
Drought SPEI 7	-1.324**	-1.079	-0.648	-1.095*	-0.724
	(0.651)	(0.715)	(0.697)	(0.634)	(0.696)
Observations	2,028	2,028	2,028	2,028	1,020
R-squared	0.587	0.530	0.594	0.662	0.544
Number of households	507	507	507	507	255
R2 within	0.587	0.530	0.594	0.662	0.544
R2 between	0.105	0.064	0.037	0.009	0.079
R2 overall	0.224	0.169	0.187	0.259	0.218
Threshold (lag all-assets index)	48.710	50.082	32.290	6.043	30.941
Prob	0.000	0.000	0.500	0.270	0.190
Trim	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	103	96	231	581	6
% Obs above the thr.	5.1%	4.7%	11.4%	28.6%	0.6%

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth) and an explanatory variable. The threshold variable is lagged all-assets for all columns. The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

Table A 17 Farm implements and its components, average over time, rural and agricultural sample.

Round	Total farm implements, normalized	Land owned, hectares	HH owns storage facility (%)	HH owns sprayer (%)	HH owns any tractor (%)
1	9.265	1.543	8.876	8.284	0.000
2	9.959	1.756	7.101	8.087	2.959
3	8.175	1.562	8.481	4.536	2.761
4	6.997	1.235	5.917	6.706	3.550
5	4.930	1.180	1.183	3.748	2.959

Table A 18: Panel threshold fixed effect regression, self-reported shocks.

	(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
(Lower regime) lag diversification	-0.005	-0.004	-0.005	-0.012	0.012**
	(0.008)	(0.009)	(0.009)	(0.008)	(0.005)
(Higher regime) lag diversification	0.220***	0.289***	-0.249**	0.072	-0.257***
	(0.063)	(0.091)	(0.113)	(0.071)	(0.070)
Lag all assets	-1.058***				
	(0.028)				
Lag durables		-1.036***			
		(0.031)			
Lag agricultural assets			-1.022***		
			(0.034)		
Lag farm implements				-1.273***	
				(0.039)	
Lag livestock (TLU)					-0.931***
					(0.069)
Climate shock	-0.789*	-1.046**	-0.137	0.203	0.448*
	(0.426)	(0.416)	(0.595)	(0.534)	(0.257)
Agricultural shock	1.531***	1.387***	1.342**	1.054**	0.031
	(0.379)	(0.397)	(0.522)	(0.507)	(0.234)
Income shock	-2.944*	-3.360*	-0.446	-1.007	-0.447
	(1.624)	(1.773)	(0.815)	(0.744)	(0.368)
Price shock	-0.305	-0.317	-0.607	-0.293	-0.630**
	(0.380)	(0.412)	(0.470)	(0.471)	(0.264)
Health shock	0.295	-0.180	0.499	0.556	0.018
	(0.367)	(0.394)	(0.425)	(0.387)	(0.187)
Conflict shock	1.044	1.936	0.329	1.021	0.586
	(1.347)	(1.417)	(0.887)	(0.897)	(0.588)
Observations	2,028	2,028	2,028	2,028	1,020
R-squared	0.593	0.535	0.602	0.664	0.571
Number of households	507	507	507	507	255
R2 within	0.593	0.535	0.602	0.664	0.571
R2 between	0.107	0.062	0.037	0.010	0.090
R2 overall	0.226	0.166	0.191	0.260	0.242
Threshold (lag asset index)	48.949	56.017	57.621	28.835	20.200
Prob	0.000	0.000	0.000	0.270	0.000
Trim	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	98	62	67	105	29
% Obs above the thr.	4.8%	3.1%	3.3%	5.2%	2.8%

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, shock and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.

Table A 19: GMM panel-data model allowing threshold and endogeneity.

	(1) All-assets growth	(2) Durables growth	(3) Agricultural assets growth	(4) Farm implements growth	(5) Livestock growth
(Lower regime) lag diversification	-0.115	0.092	-0.017	0.036	-0.015
	(0.133)	(0.062)	(0.065)	(0.061)	(0.011)
(Higher regime) lag diversification	0.454**	-0.190	-0.305	-1.904**	-0.050
	(0.207)	(0.159)	(0.494)	(0.842)	(0.139)
Threshold (lag asset index)	16.432***	16.669***	47.819***	36.709***	10.972***
	(2.750)	(4.226)	(3.549)	(2.515)	(1.613)
N. of households	507	507	507	507	255
N. of time periods	4	4	4	4	4
Bootstrap replications for linearity test	100	100	100	100	100
Bootstrap p-value	0.000	0.000	0.000	0.000	0.000

All features of the model have been set to replicate the threshold model. *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Instruments included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, a drought variable and wave dummies. Assets indexes are rescaled to range from 0 to 100.

Table A 20: Panel threshold fixed effect regression, interaction with climatic shocks. Sensitivity of the SPEI index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All assets growth		Durables growth		Agricultural assets growth		Farm implements growth		Livestock growth	
	SPEI 9	SPEI 12	SPEI 9	SPEI 12	SPEI 9	SPEI 12	SPEI 9	SPEI 12	SPEI 9	SPEI 12
Drought SPEI	-0.400	-0.372	-0.026	-0.092	-2.298*	-2.165**	-2.584**	-1.848*	-1.750**	-1.679**
	(0.857)	(0.782)	(0.898)	(0.822)	(1.204)	(1.053)	(1.120)	(0.985)	(0.760)	(0.747)
(Low regime) lag diversif. # drought	-0.036	-0.055**	-0.054*	-0.063**	0.058**	0.037	0.032	0.005	0.025*	0.026*
	(0.026)	(0.024)	(0.028)	(0.025)	(0.029)	(0.026)	(0.028)	(0.024)	(0.015)	(0.015)
(High regime) lag diversif. # drought	0.106	0.102	0.101	0.100	1.720***	1.711***	0.282***	0.291***	0.277	0.272
	(0.082)	(0.082)	(0.100)	(0.100)	(0.316)	(0.315)	(0.036)	(0.031)	(0.291)	(0.292)
Observations	2,028	2,028	2,028	2,028	2,028	2,028	2,028	2,028	1,020	1,020
R-squared	0.568	0.570	0.517	0.518	0.603	0.603	0.664	0.665	0.544	0.544
N. of households	507	507	507	507	507	507	507	507	255	255
R2 within	0.577	0.579	0.517	0.518	0.603	0.603	0.664	0.665	0.544	0.544
R2 between	0.111	0.110	0.072	0.072	0.033	0.033	0.008	0.008	0.075	0.075
R2 overall	0.210	0.211	0.158	0.159	0.186	0.186	0.261	0.260	0.215	0.215
Threshold (lag asset index)	48.710	48.710	47.391	47.391	50.495	50.495	8.518	14.053	5.850	5.850
Prob	0.060	0.030	0.050	0.050	0.000	0.000	0.010	0.010	0.220	0.280
Trim	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Obs. above the thr	103	103	101	101	99	99	539	294	132	132
% Obs above the thr.	5.1%	5.1%	5.0%	5.0%	4.9%	4.9%	26.6%	14.5%	12.9%	12.9%
Drought + (low regime) lag diversif.	-0.436	-0.426	-0.080	-0.155	-2.240	-2.128	-2.552	-1.843	-1.725	-1.653
P-value	0.604	0.731	0.934	0.993	0.058	0.670	0.020	0.057	0.022	0.025
Drought + (high regime) lag diversif.	-0.295	-0.269	0.074	0.007	-0.579	-0.454	-2.302	-1.558	-1.473	-1.406
P-value	0.731	0.579	0.928	0.847	0.631	0.040	0.041	0.109	0.076	0.087

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. Each column reports the results of the same model; the only difference is the asset index, thus affecting the dependent (asset growth), an explanatory variable and the threshold variable (lagged assets). The regime-dependent variable is the Gini-Simpson index of income diversification (off-farm only). Controls included: gender of the household head, education of the household head (inverse hyperbolic sine transformed), age of the household head (inverse hyperbolic sine transformed), size of the household (count), income terciles, drought and panel wave dummies. Asset indexes are rescaled to range between 0 and 100.