# Can weather shocks give rise to a poverty trap? Evidence from Nigeria

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## 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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# Introduction

Currently, 494 million people live under the extreme poverty line of 1.90$ per capita per day[1]. 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)[2]. The poor are typically more vulnerable to such events because as their buffer stocks and savings are insufficient for consumption smoothing[3]. The poor tend to be among the most hit groups by weather shocks[4]. 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[5] (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

[1] https://pip.worldbank.org/home [accessed on 9 January 2023]
[2] 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).
[3] 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.
[4] 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.
[5] 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).

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 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. 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[6] (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[7]. 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, 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).

[6] For instance conflicts among farmers and herders, also in Nigeria (Eberle et al., 2020).
[7] 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: Asset shocks that can result in poverty traps.*

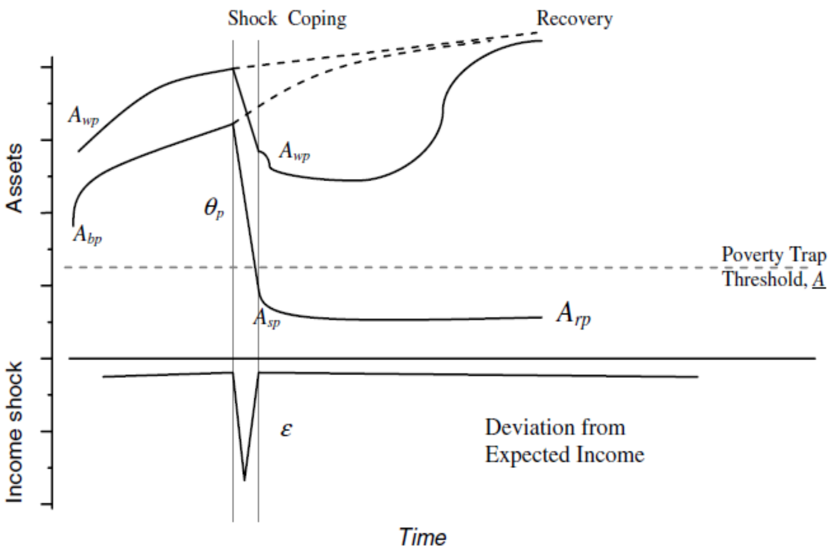



Figure 1. *Asset shocks and poverty traps.*

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[8] 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[9]. 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,

[8] 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).
[9] 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).

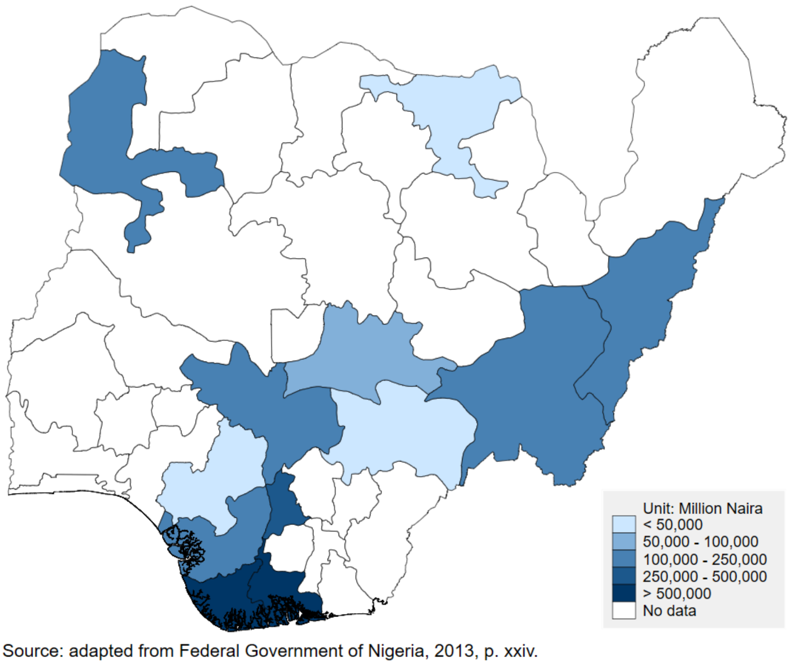
the existence of a poverty trap could be due to fast population growth and loss of capabilities, bad governance and corruption, bad transportation and oil extraction (Ibaba and Ebiede, 2010).

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[10]. 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 2).

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

*Figure 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[11] (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[12] 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

[11] 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).
[12] 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.

over a decade from 2010 top 2019. I identify flooded households and neighbouring non-flooded 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.

## 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[13].

## 2.1 Flood measurement

The peak of the flood occurred during the first visit of the second wave of the survey (Table 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: 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[14], 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[15]. MODIS'

[13] 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.
[14] https://floodmap.modaps.eosdis.nasa.gov/ [accessed before 2022; since then, the website has been revisited].
[15] More recent MODIS products also incorporate a cloud shadow masking (Nigro et al., 2014).

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[16], which during a flood is plausibly thick. Products of 3 or 14 days are more effective because they include observations for a longer period 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[17]. 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.

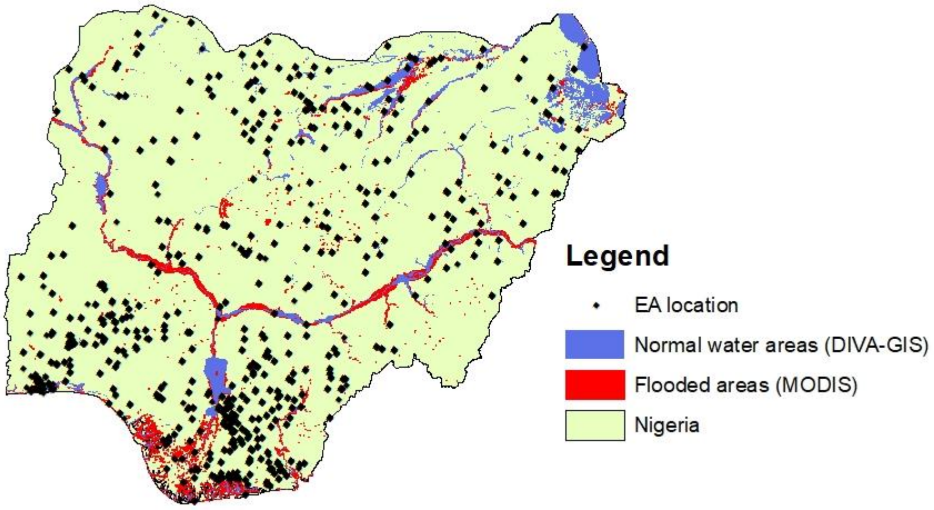
Households' enumeration areas were plotted in the map, and a 2, 5 and 10 km buffer was constructed around them. I then build a rural-urban buffer, which has a radius of 2 km in urban areas and 5 km in rural areas[18]. The variable that was constructed takes the value of one if the area around the village intersects some inundated pixel, zero otherwise. Flooded households, according to this variable, are 793 (17.4%). Figure 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.

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

[17] 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).

[18] 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).

*Figure 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*)

## 3. Methodology

Testing empirically for a poverty trap is no easy task[19]. 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.

1. 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

[19] 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).

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 $\varepsilon_{it}$ 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[20]. 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 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.

2. 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 $i$ ($\Delta A_i$) 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

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

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[21].

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.

3. 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:

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

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, $\gamma$ 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.

## 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 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[22] (in

[21] 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.

[22] The donut approach, or the rings method, relies on the physical proximity of treated and control units (relying

Figure 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.

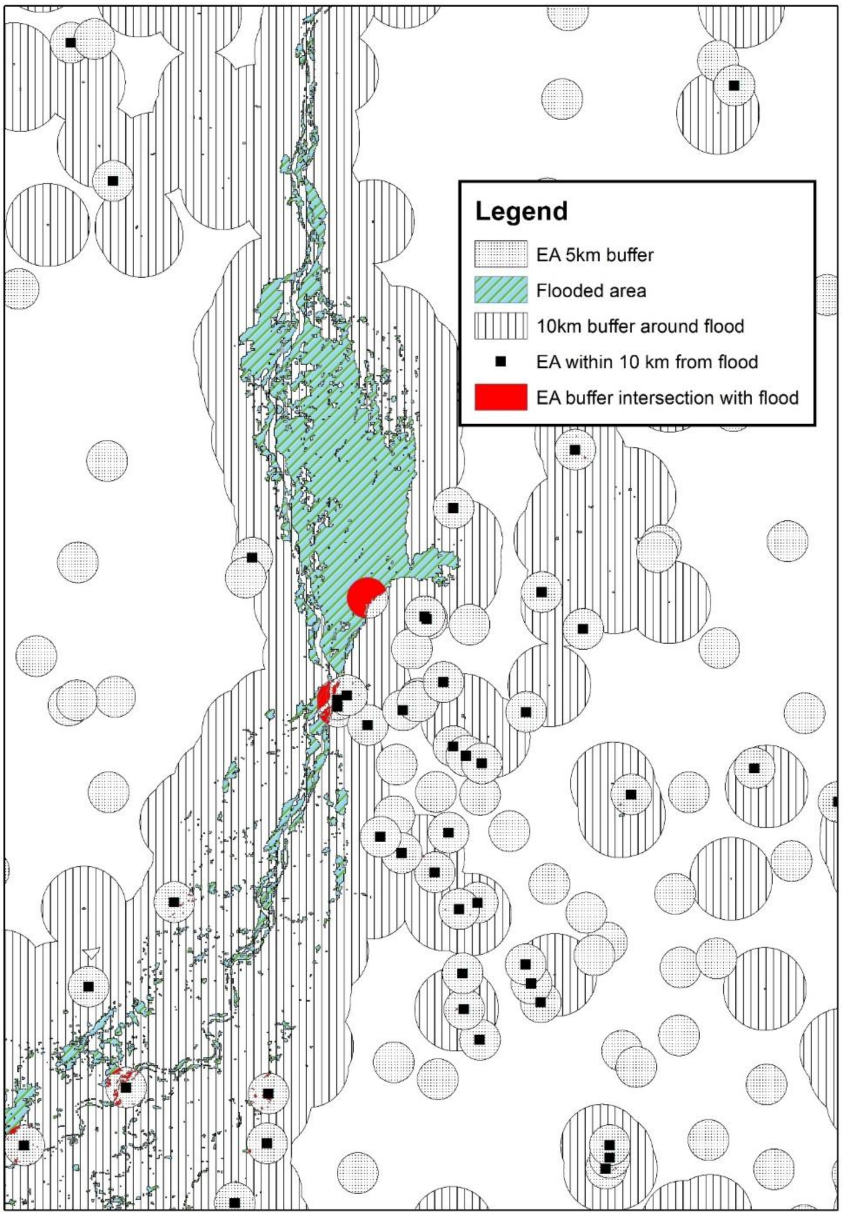
A second source of concern for the identification is the effect of the previous large flood of 2010[23]. Data collection of the first wave started in August but the majority of households were interviewed during the month of September. Indeed, flooding during the post-planting visit posed some difficulties 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 6.4). Alternatively, we use as a proxy for flooded areas the distance from the closest inland water during normal times[24] (cf. Section 6.2).

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.

[23] 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).

[24] Retrieved from https://diva-gis.org/gdata

*Figure 4: Visual representation of the donut approach to flooded areas*




Source: own elaboration using Nigeria GHS panel data.

## 4. Descriptive statistics

Table 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[25]. 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 opportunities and lower wages, live more distant from towns and recur more often to the withdrawal

[25] The weights are not applied here.

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 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 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 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

### 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[26] (Rutstein, 2015). The aggregation of all these dimensions is done via principal components extraction[27] (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 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[28], 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.

[26] 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.

[27] 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.

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

*Figure 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 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 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 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

# 5. Results

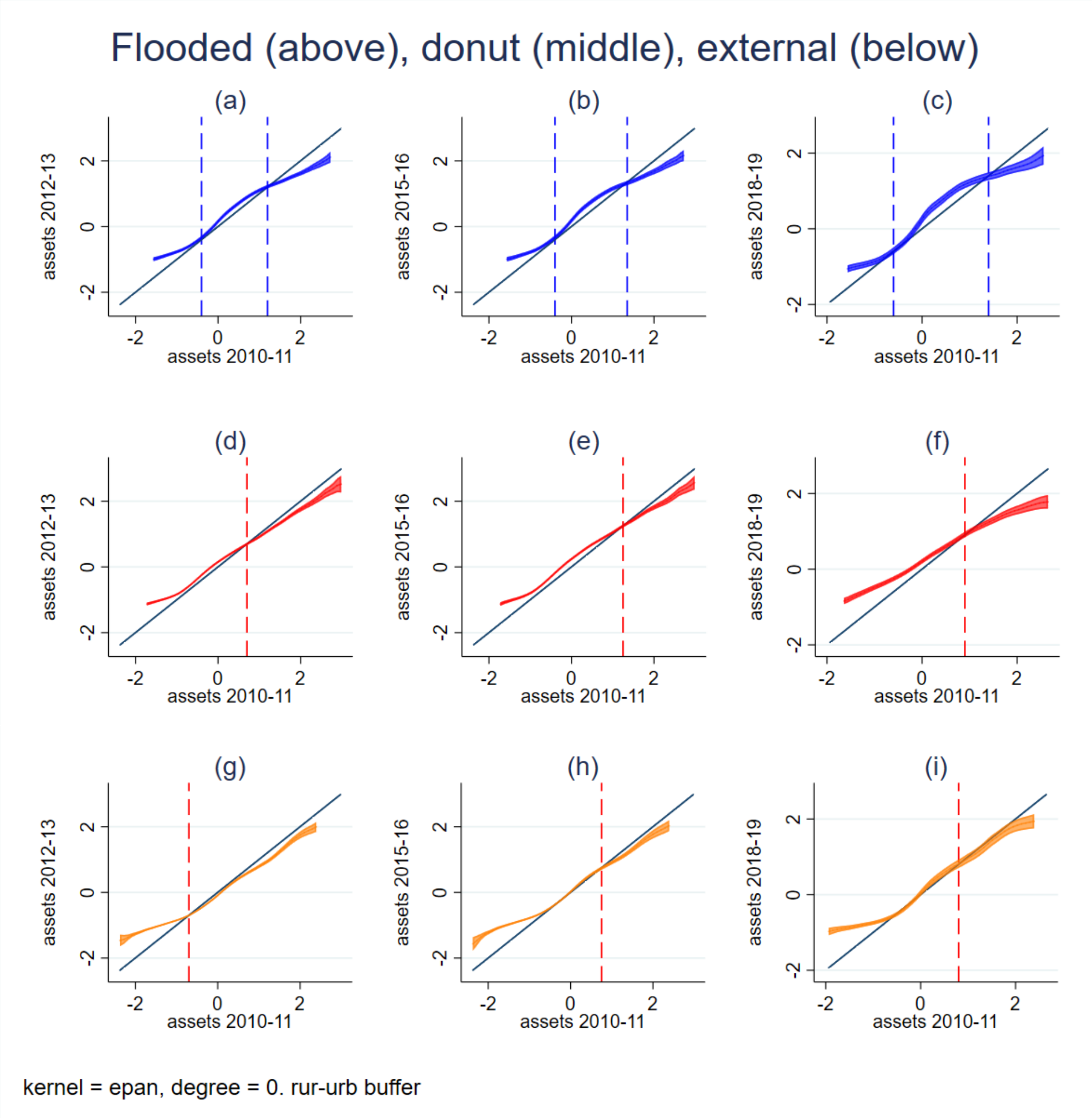
## 5.1 Non-parametric regression

Using non-parametric regressions in an exploratory way[29] 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 7, panels a, b and c) and if we start in wave 2 (Figure 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 6, panels d, e and f, and Figure 7, panels b and e). Similarly, external households are very flat and cross the diagonal only once (Figure 6 panels g, h, I and Figure 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).

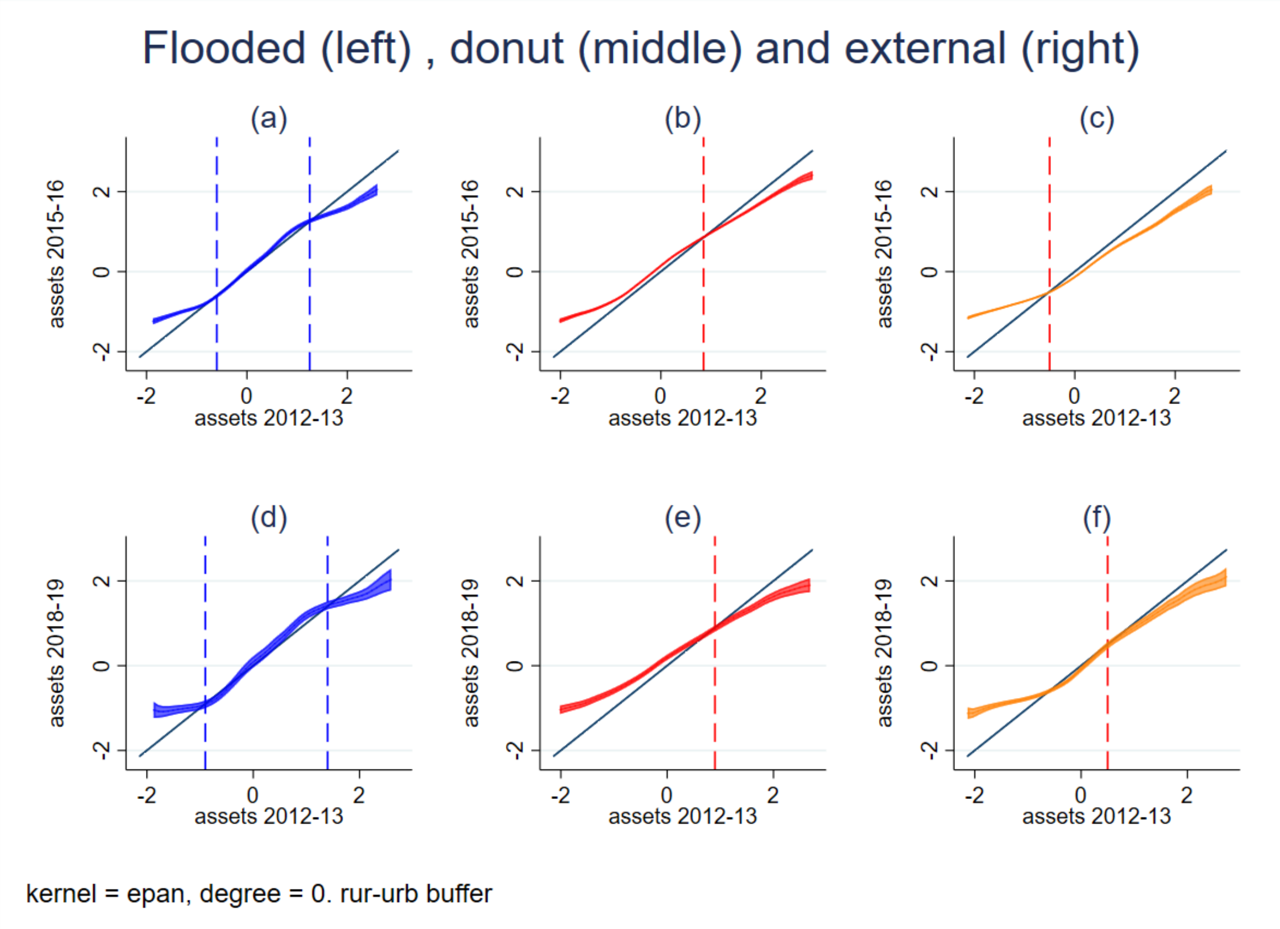
[29] Since these report only bivariate relationship, graphs are not reported but are available upon request.

*Figure 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 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.

## 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[30] (Barrett et al., 2006; Giesbert and Schindler, 2012; McKay and Perge, 2013; Naschold, 2013, 2009). Table 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)[31].

[30] 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.

[31] 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 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 $\beta_1$ is between -2 and 0 and all other $\beta_{2\text{-}4}$ are all equal to zero. The null is rejected in all columns and indeed $\beta_1$ 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).

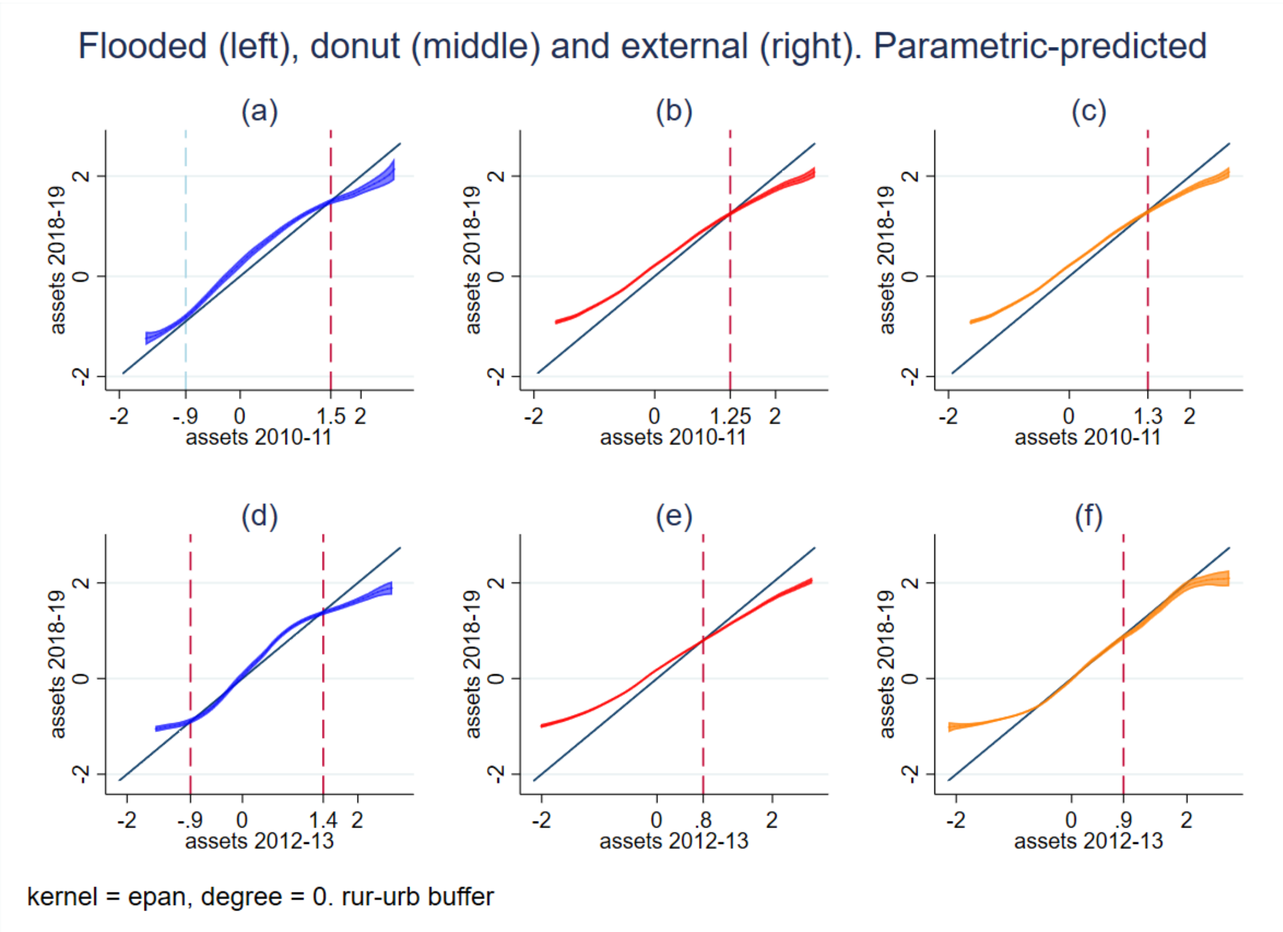
*Table 6: Parametric regression, long differences until 2018-19 (extended panel), OLS*

| | (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 8 provides the corresponding graph to the estimates of Table 6, therefore with 2018/19 final assets. Kernel-weighted local polynomial smoothing is used[32]. 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[33] 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 8: OLS-predicted asset change to wave 4, local polynomial smooth*




Source: own elaboration using Nigeria GHS panel data.

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

33 Since it crosses the line from above, this is a stable equilibrium.

We repeat the analysis in Table 7 using as final period the third wave but maintaining the same sample[34]. Now columns 1-3 report the asset change from wave 3 to wave 2 (2015/16 –2010/11), while 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 7: Parametric regression, long differences until 2015-16 (same sample as Table 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 |

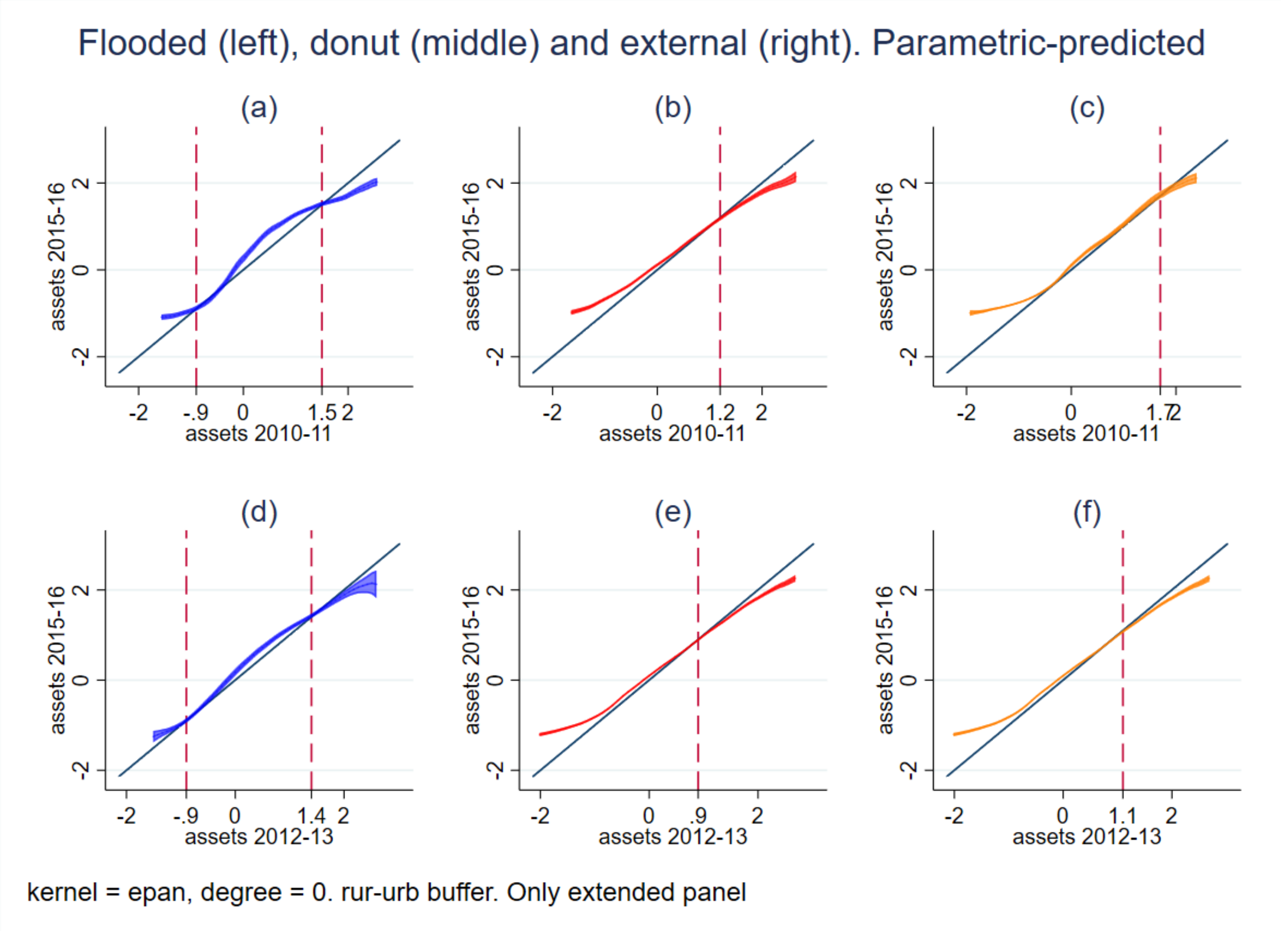
p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), 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 9 shows local polynomial smooth functions from predicting asset growth in the parametric exercise of Table 7. The final period assets are those of 2015/16. Despite showing dynamics

[34] 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 coefficient of the lagged assets is the lowest for flooded households, as in Table 6 and partly 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).

over a shorter period, Figure 9 confirms the results of Figure 8. The low-level equilibrium identified is the same as before (-0.9 asset scores).

*Figure 9: OLS-predicted asset change to wave 3, local polynomial smooth*




Source: own elaboration using Nigeria GHS panel data.

# 6. Robustness checks

## 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[35] . The non-parametric regression graph shows again an S-shaped transition curve for flooded households, with three equilibria (Figure A6, left panel).

[35] 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.

Nonetheless, this restricts the flooded sample further, and the formal estimation of a threshold yields no significant results.

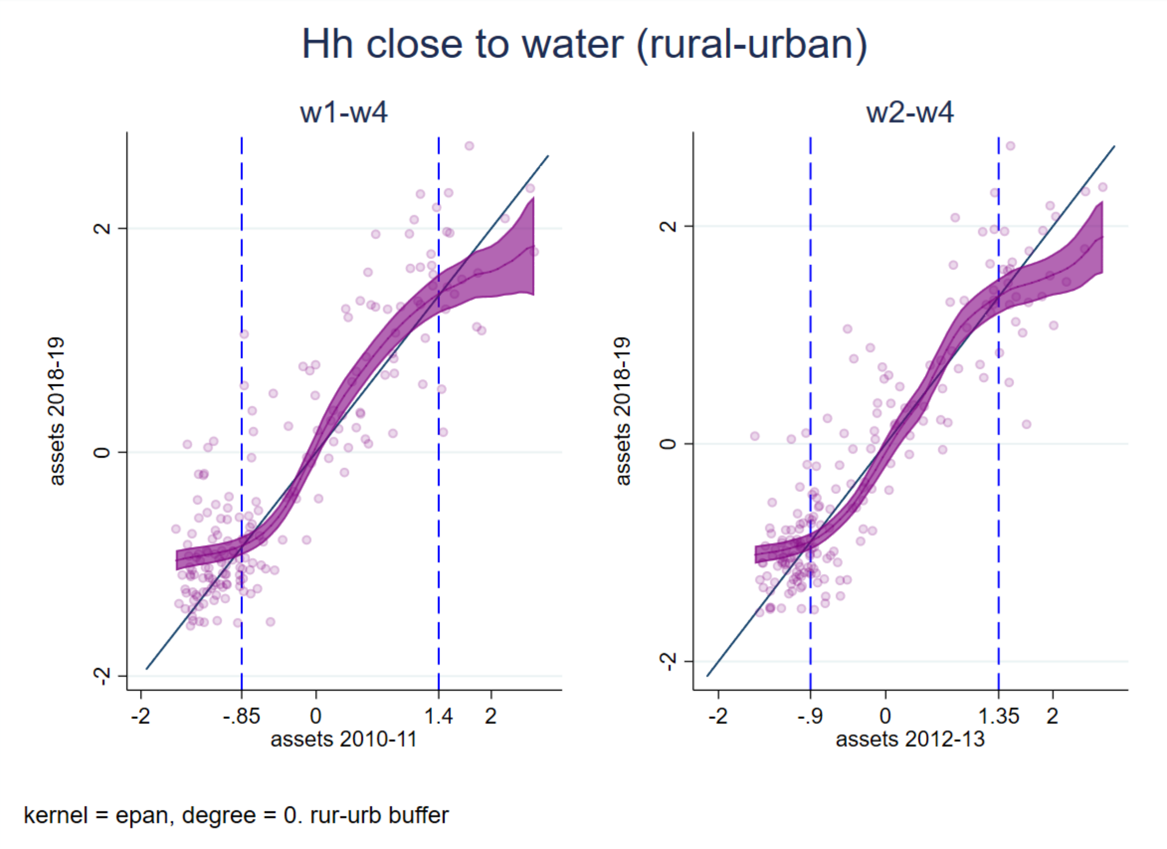
Changing the buffer radius helps understand how the results are sensitive to this choice[36]. The current buffer is either 2 or 5 km radius, according to the rural/urban zone. Three new buffer sizes are calculated for 2 (Figure A 6, right panel), 5 (Figure A 7, left panel) and 10 km (Figure A 7, right panel). 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.

## 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[37]). Non-parametric regressions show S-shaped dynamics with two stable equilibria, very similar to the results with the previous definition (Figure 10).

[36] See also Appendix 2 for a focus on sensitivity and convergence.
[37] See also Appendix 2 for sensitivity tests of the distance to water and convergence.

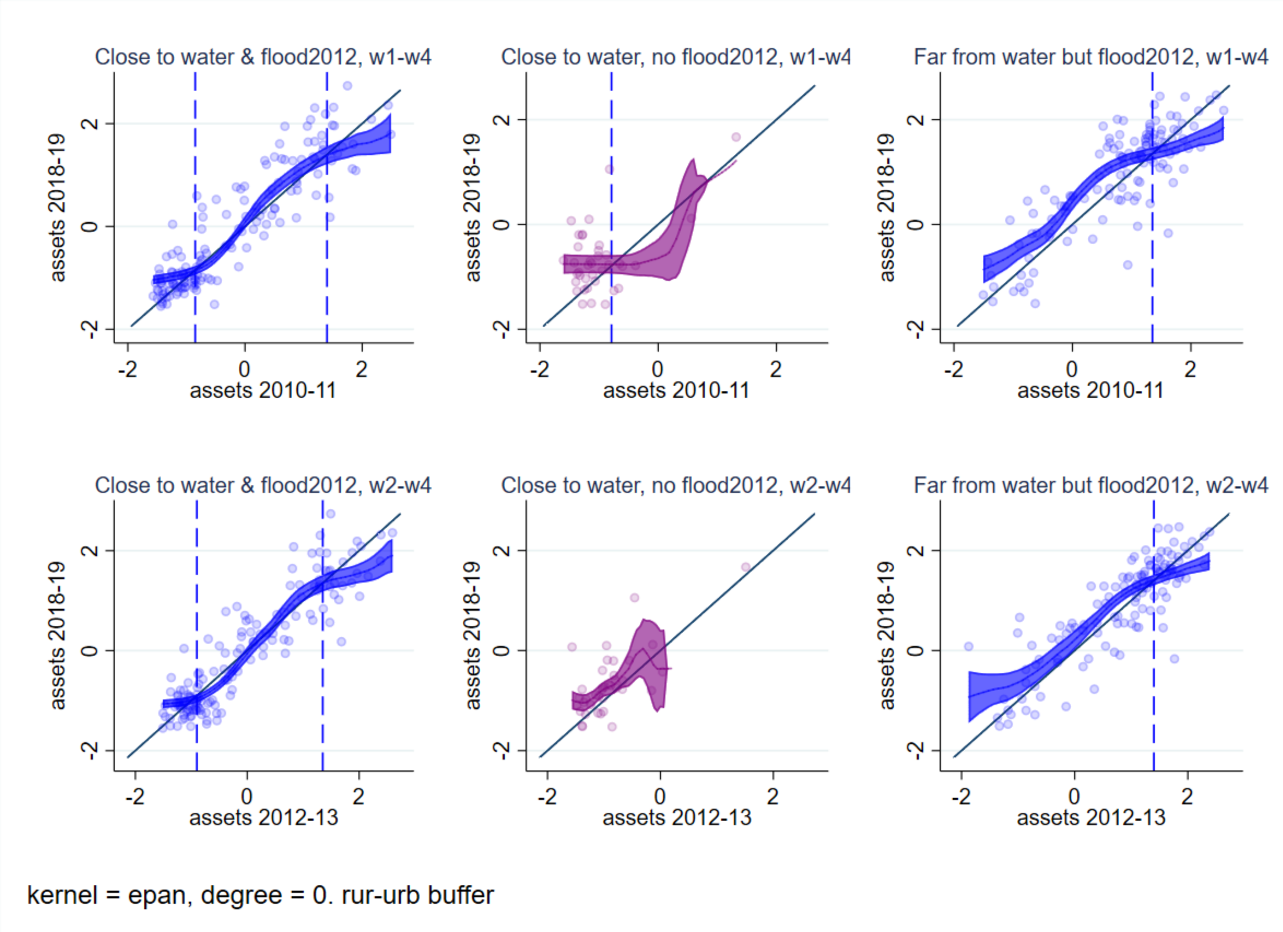
*Figure 10: Local polynomial smooth, households close to water*




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 (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 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 11: Intersections of households in proximity of water and flood of 2012*




Source: own elaboration using Nigeria GHS panel data.

## 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.

## 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[38]) (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[39] (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[40], 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[41]. 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).

# 7 Extension of results

## 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[42] (Table 8). The estimated thresholds are at 1.315 (significant) asset scores for the flooded sample and 0.816 for the external sample. For flooded households, the effect of lagged

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

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

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

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

[42] The sample is otherwise too small.

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[43]. 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 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 |
| R-squared | 0.690 | 0.700 | 0.693 |
| Number of hhid | 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 |

[43] Table available upon request.

| Prob | 0.000 | 0.507 | 0.060 |
|---|---|---|---|

* $p$<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 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 9: Post-shock regression, flooded households only, pooled w2-w3-w4 (one lag).*

| | (1)<br>Below 1.315 | (2)<br>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.

## 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[44], 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.

*Table 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* | | |

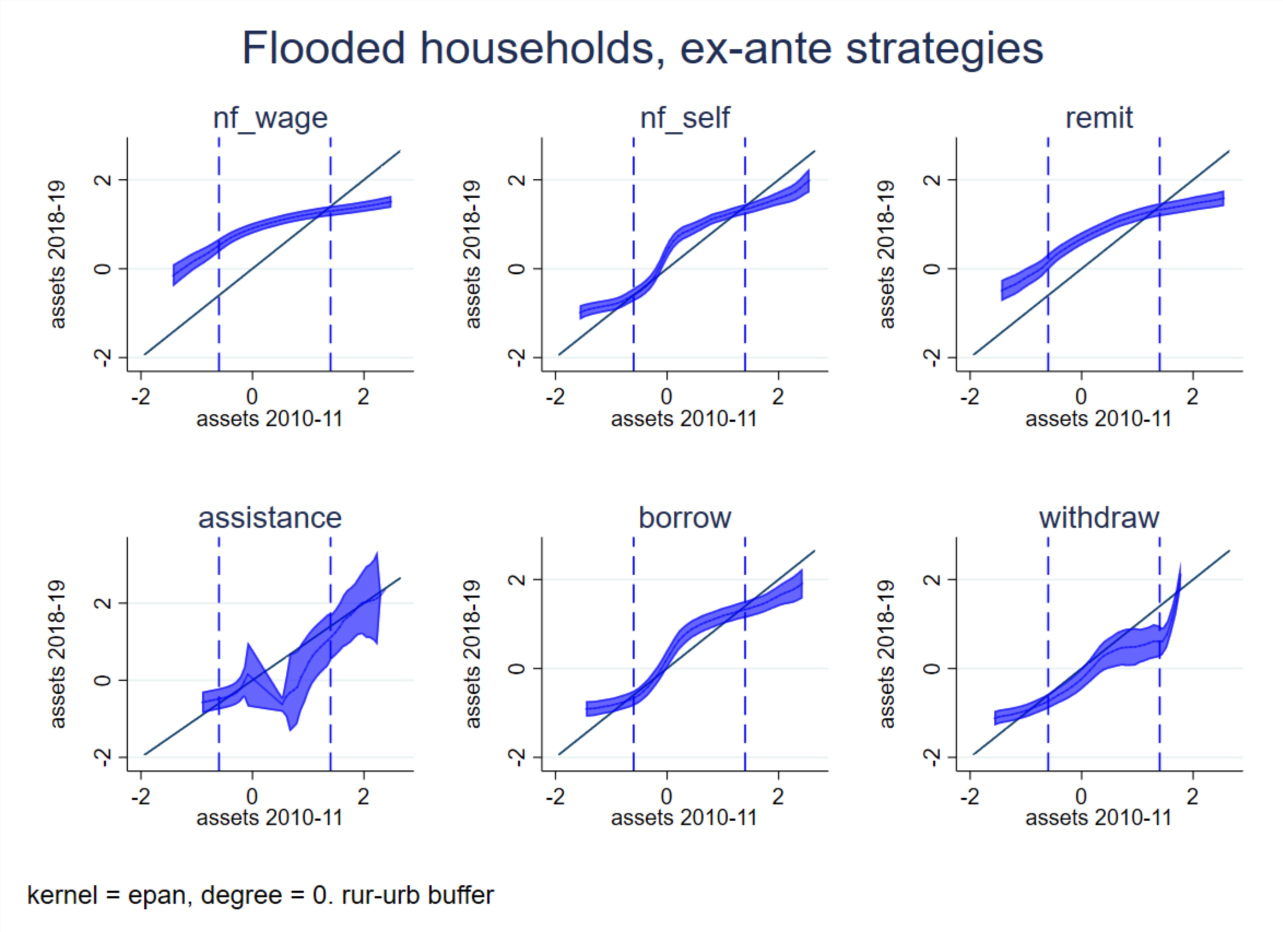
[44] Please remember that the asset index does not include human capital, which most likely suffers from such a choice.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | (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 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 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 7.

## 7. 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[45]. 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 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.

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

Plausibly, it is recurrent climatic shocks among vulnerable populations that trap people in poverty[46], 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[47]. 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.

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[46] 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).

[47] 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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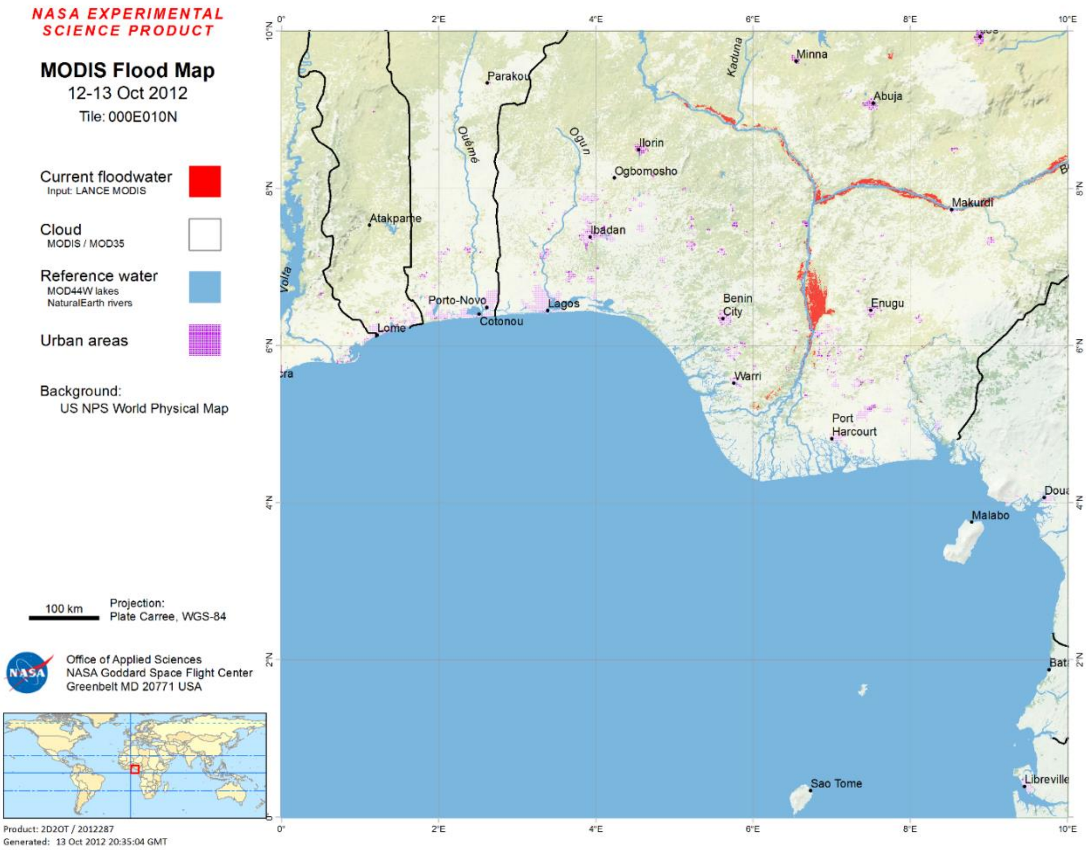
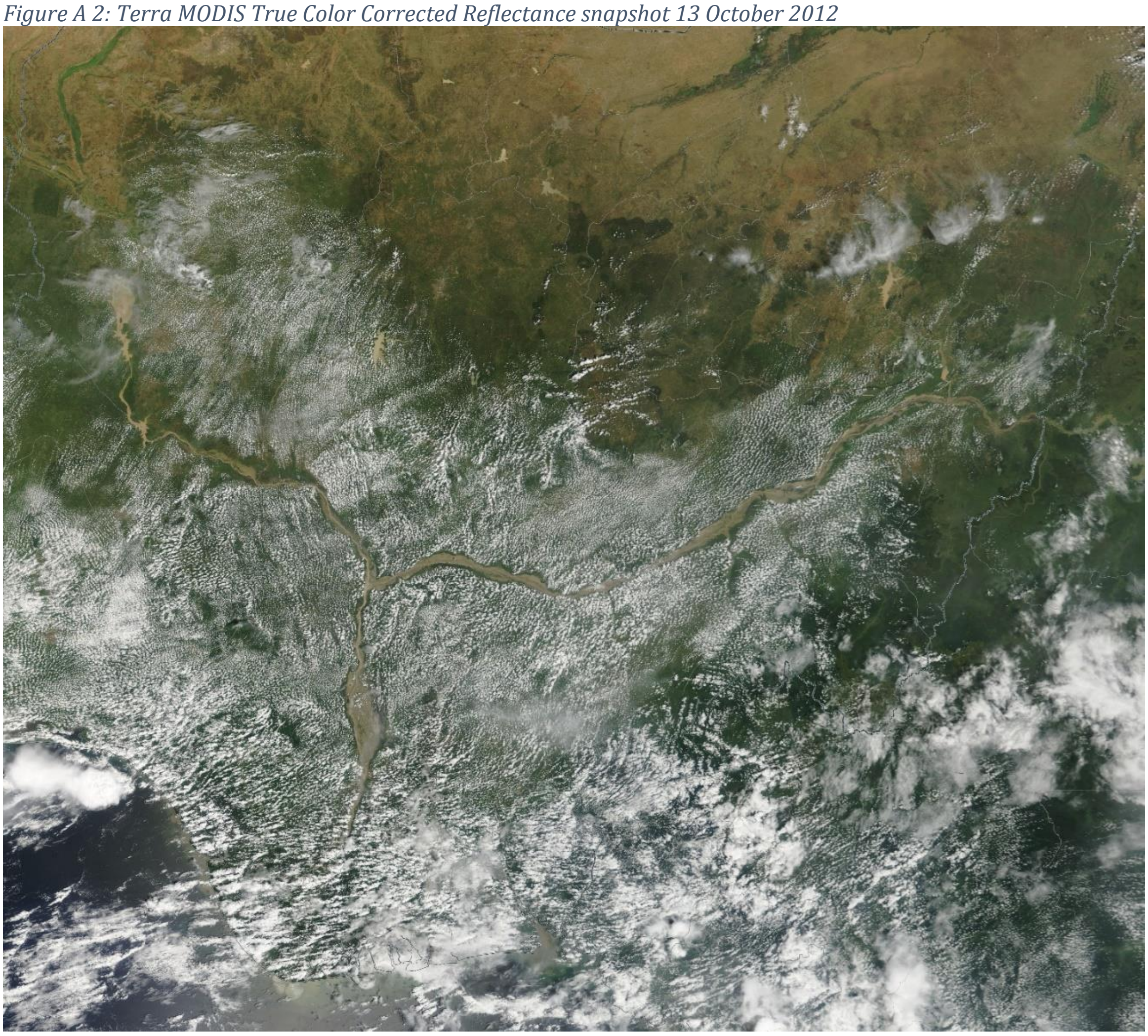
# Appendix 1

*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 |
| 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

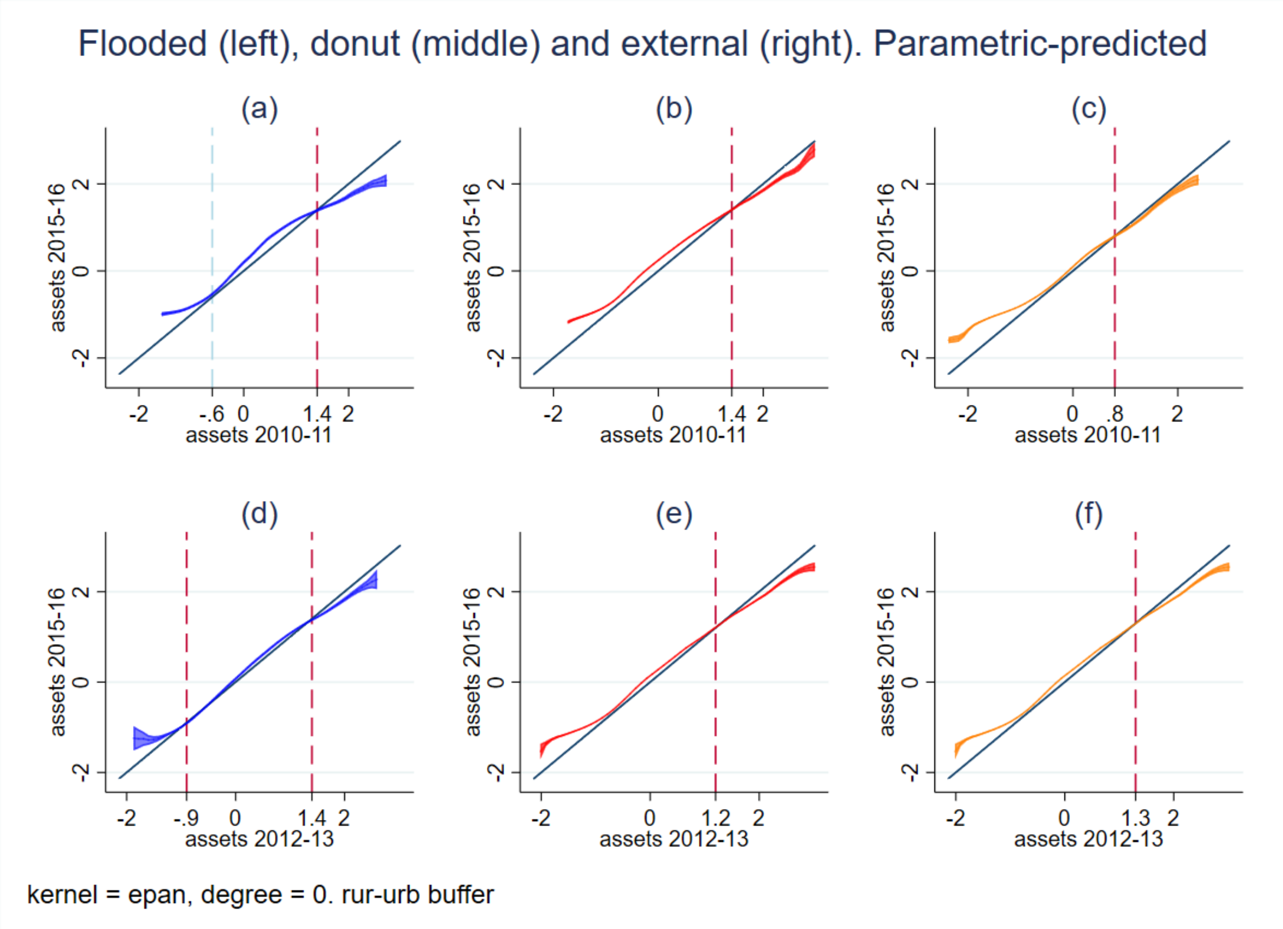
*Table A 2. Parametric regression, long differences until 2015-16 (shorter large panel), OLS*

| | (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 |

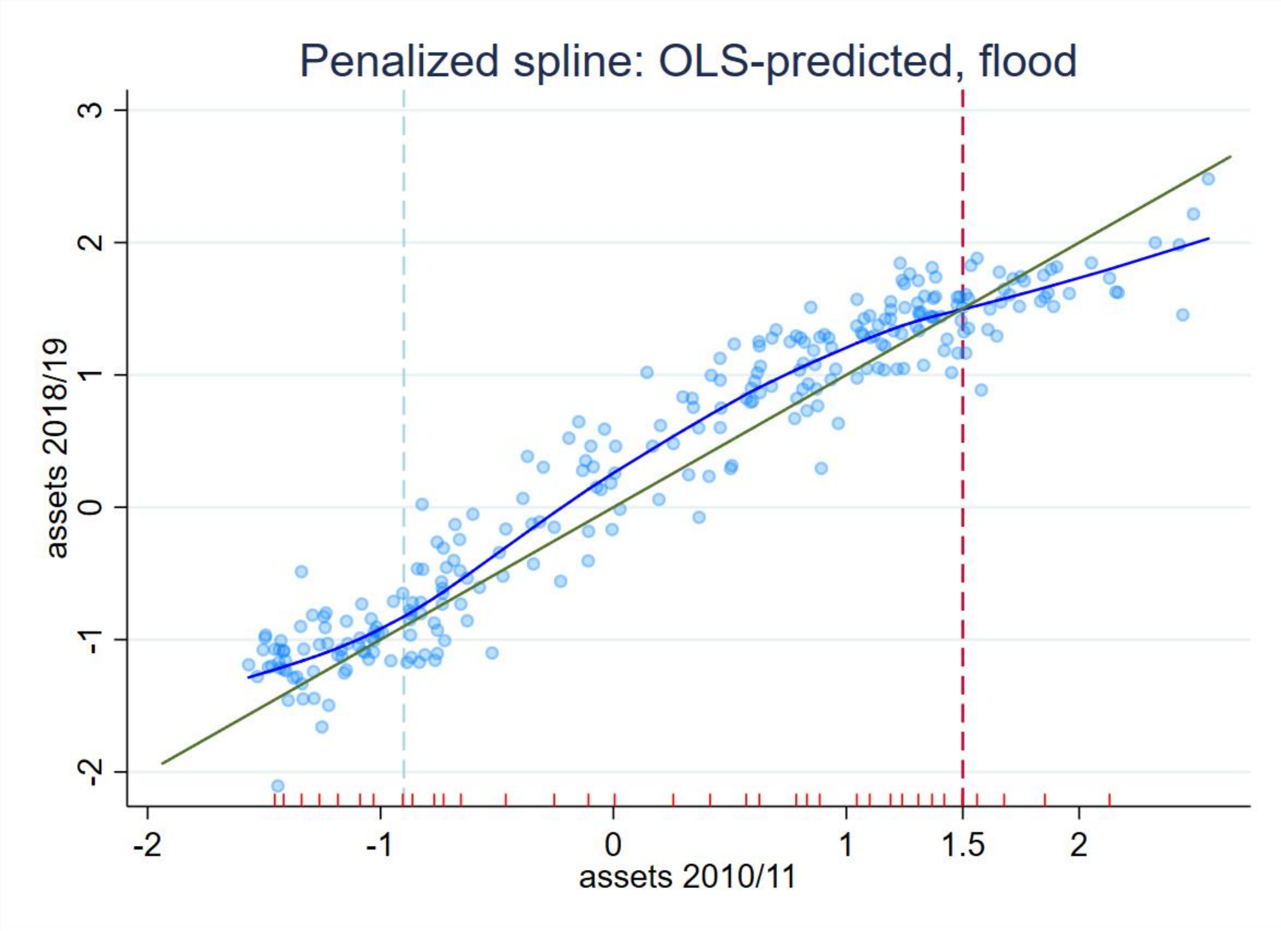
p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), 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*



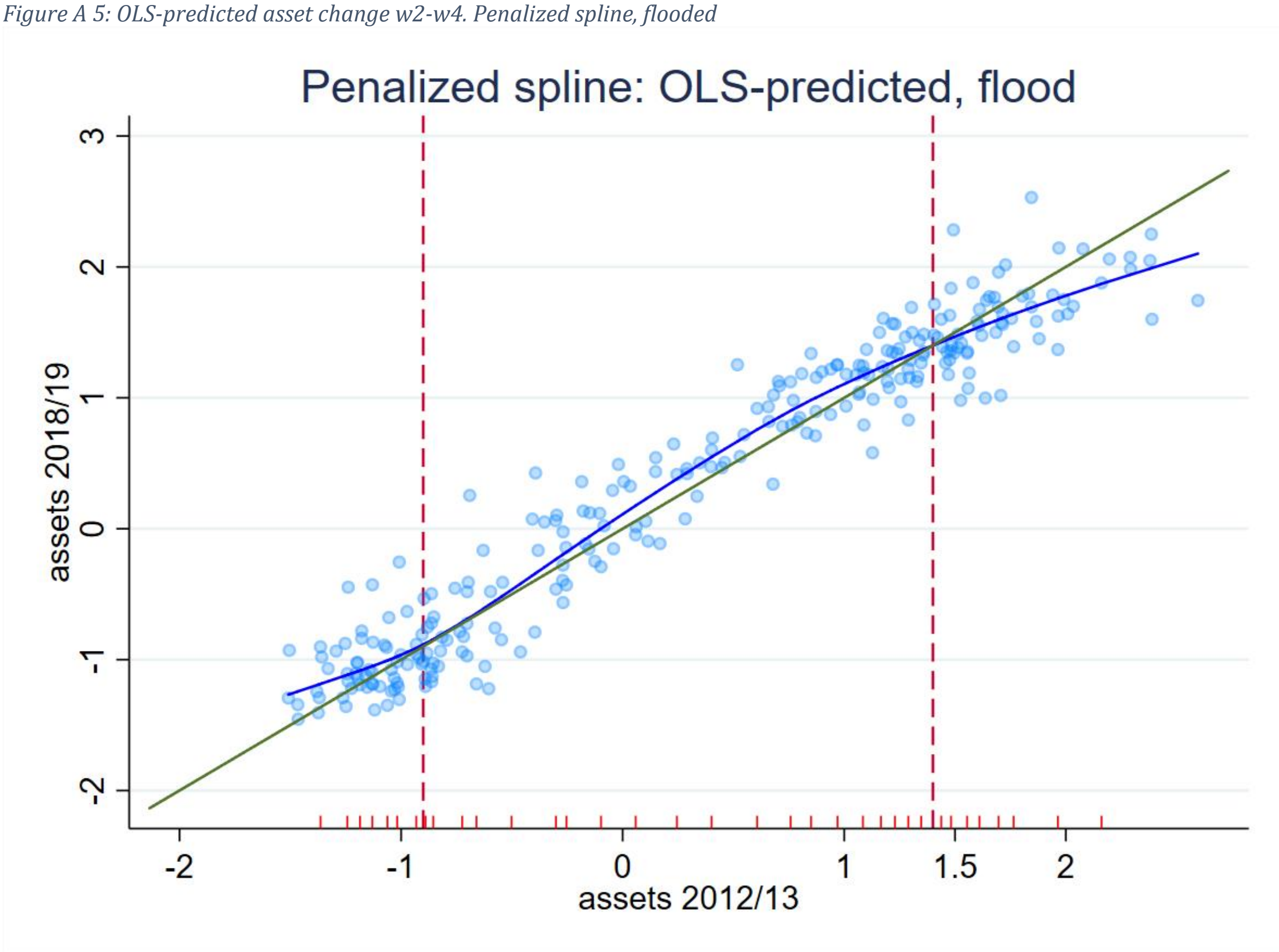

Source: own elaboration using Nigeria GHS panel data. Large panel up to w3.

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



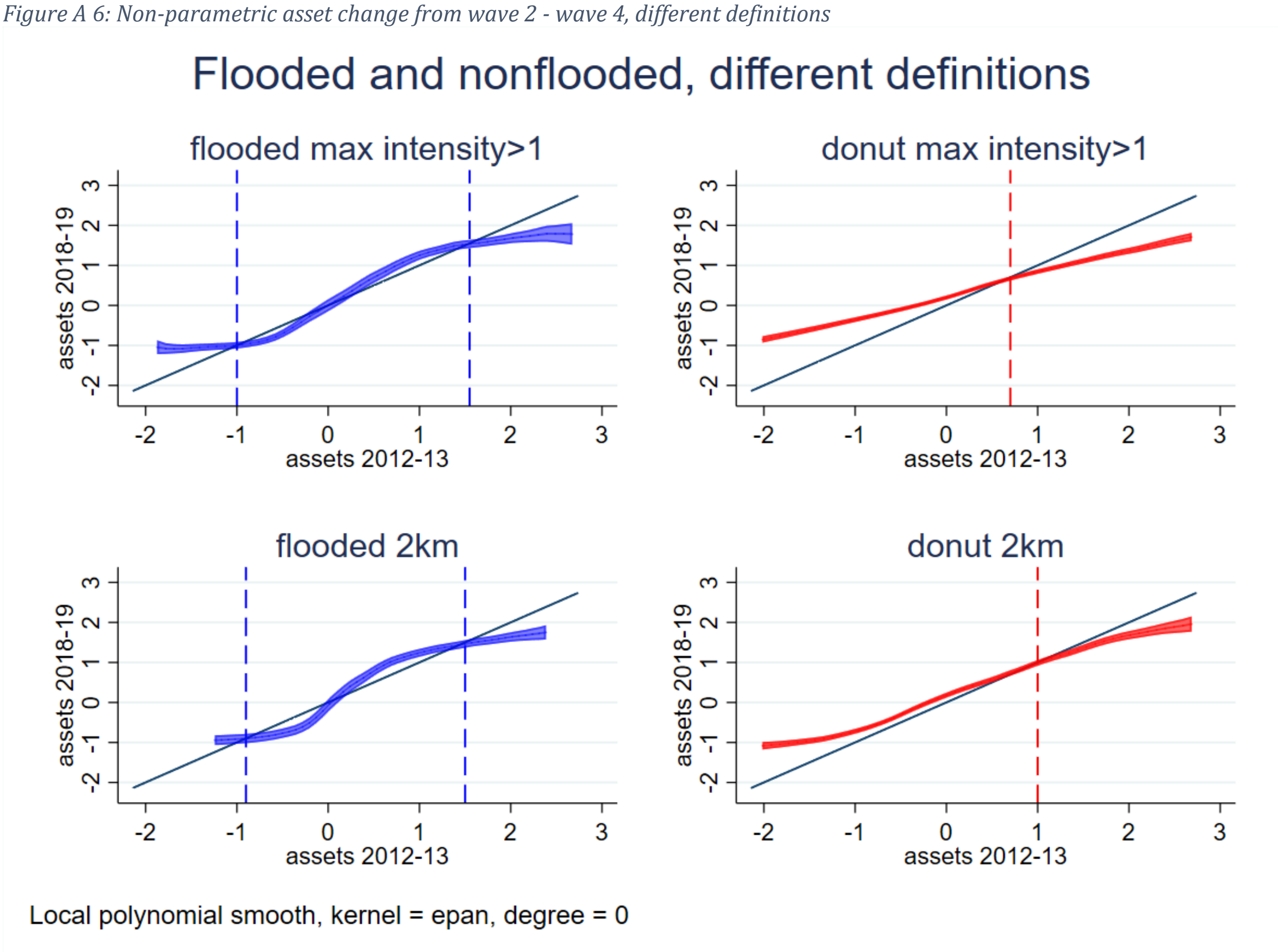

Source: own elaboration using Nigeria GHS panel data

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



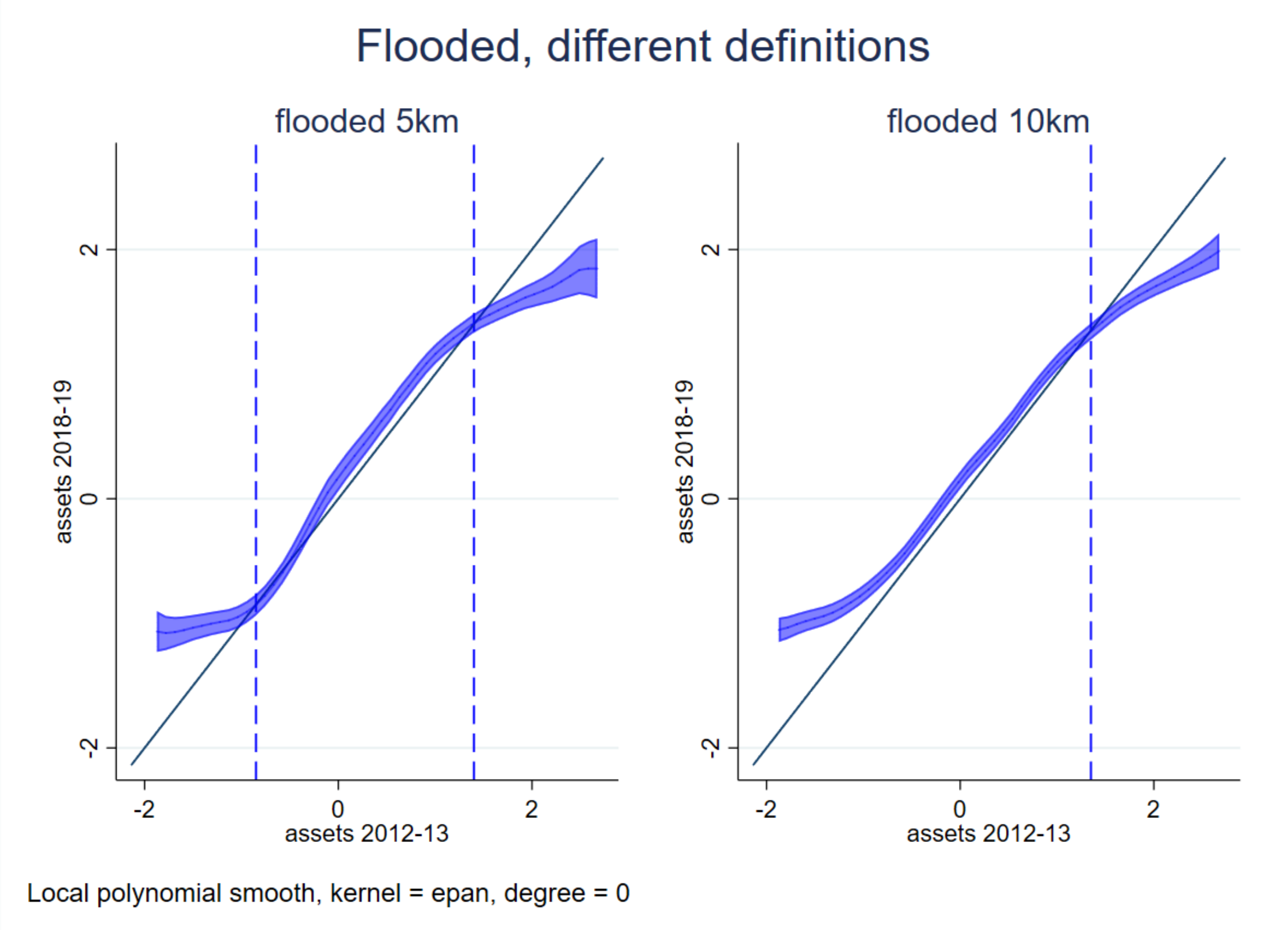

Source: own elaboration using Nigeria GHS panel data

*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 3: 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 4: 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 5: 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 6: 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 |
|---|---|---|---|---|---|---|

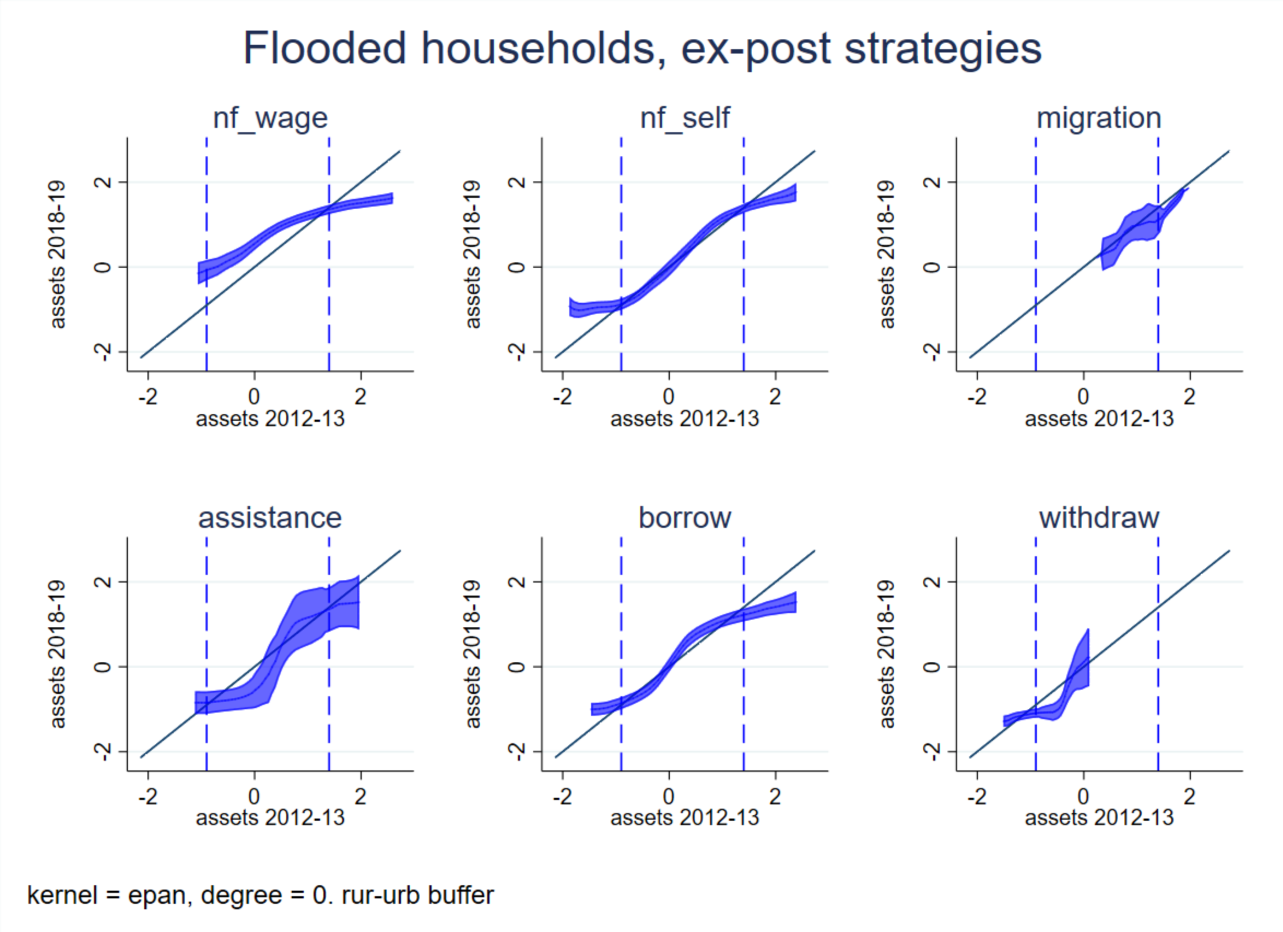
p<0.1; ** p<0.05; *** p<0.01. All regressions control for (lagged) socio-demographics, income diversification dummies (wage jobs, remittances, assistance, borrowing, crop income), mitigating factors (availability of communal land, availability of agricultural jobs, agricultural wage offered, microfinance), 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 7: 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 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.