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Can Weather Shocks Give Rise to a Poverty Trap? Evidence from Nigeria

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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 from LSMS project, I study households' asset dynamics over about a decade. I find that households hit by the flood converge to multiple equilibria consistent with the poverty trap narrative. 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 finding, testing different asset indexes and flood definitions, as well as controlling for conflict-related events. 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

The persistence of poverty is a worrying issue that dooms the lives of millions of people and keeps researchers and policymakers puzzled. Global efforts in poverty alleviation achieved a decrease in the extreme poverty rate from 36% of the world population in 1990 to 10% in 2015. Yet, it is estimated that in the same year still 736 million people lived below the $1.90 extreme poverty line (World Bank, 2018). With COVID-19, researchers project a reversal in the trend (United Nations, 2020), with an increase of 68-100 million extreme poor (Mahler et al., 2020; Valensisi, 2020).

This situation is further aggravated by climate change which increases the frequency of extreme weather hazards. The poor are typically more vulnerable to such events, with dramatic consequences for their permanence in a poverty state. The number of people at risk of worsening their life conditions and compromising their survival is worryingly increasing. This calls for the analysis of 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 because of two main reasons: first, the poor lack the means to cope with large shocks, as their buffer stocks and savings are insufficient for consumption smoothing. Second, as climatic shocks hit whole communities simultaneously, traditional and informal insurance mechanisms fail at protecting the poorest.

The aim of this paper is to study the relationship of climate shocks and poverty persistence within the framework of poverty traps. Poverty traps are self-reinforcing mechanisms that reproduce poverty and make it persistent (Azariadis and Stachurski, 2005). A poverty trap can be understood as "a critical minimum asset threshold, below which families are unable to successfully educate their children, build up their productive assets, and move ahead economically over time. Below the threshold lie those who are ruined, who can do no better than hang on and who are offered no viable prospects for economic advance over time. Those above the threshold can be expected to productively invest, accumulate, and advance" (Carter et al., 2007, p. 837). The 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. So far, the main contribution on the link between poverty traps and weather shocks is from Carter et al. (2007), which find some evidence of poverty traps following a shock in Honduras and in Ethiopia. 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 effective representation of the consequences of an extreme weather shock can be seen in Figure 1. The household starting with lower asset levels (A_{bp}) falls below the threshold, while the other one is able to avoid the same fate, even though recovery is a long process. Its length can depend on the choice and availability of coping strategies. The research questions 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?

Figure 1: Asset shocks that can result in poverty traps.

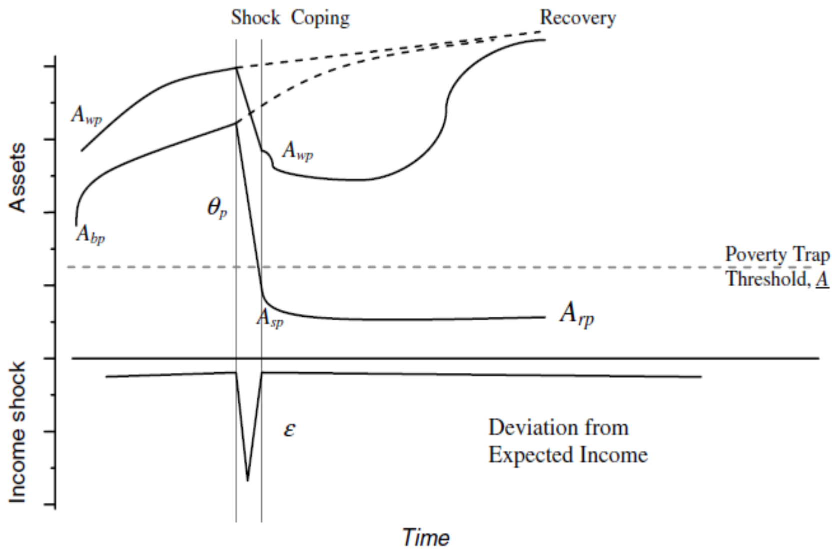


Figure 1. *Asset shocks and poverty traps.*

Source: Carter et al., 2007

In order to answer my research questions, I focus on the case of Nigeria. The country's share of population living with less than 1.90$ per day was 53.5% in 2010 (World Bank, 2021), or 62.6% according to the national estimate (Table 1), despite sustained GDP growth[1]. In recent years evidence has shown raising poverty, inequality and polarization (Clementi et al., 2017, 2016; Eigbiremolen, 2018; Jaiyeola and Bayat, 2020; World Bank, 2016). The context of the country is extremely complex. 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). Referring to Niger Delta region, 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).

Table 1: Poverty estimates of Nigeria

	2004		**2010**		**2019**	
	Headcount ratio	**Poverty gap**	**Headcount ratio**	**Poverty gap**	**Headcount ratio**	**Poverty gap**
Nigeria	64.2	27.4	62.6	26.2	40.1	12.9
Rural	73.4	32.7	69	30.3	52.1	17.4
Urban	52.2	20.5	51.2	19.1	18	4.5

Source: National Bureau of Statistics of Nigeria (2020, 2012). Please note that these have been computed from survey data with different recall methods, therefore they are not comparable (Clementi et al., 2016).

This paper contributes mainly to two strands of the literature: the empirical literature that tests for poverty traps and the literature on climate shocks and poverty. In particular, it extends available empirical evidence on poverty traps to the case of Nigeria, so far neglected by this literature despite its high and persistent poverty rates. It also provides evidence of the effects of the flood on different subgroups of the population.

[1] GDP growth rates ranged between 5% and 9% annually in the period 2004-2014, while more recently there has been a slowdown (World Bank, 2021).

Contrary to most of previous analysis on poverty traps based on pastoralist communities, the case of Nigeria is rather challenging. Asset representation cannot be based solely on tropical livestock units but need to combine different assets' ownership to better represent wealth. For this reason, different asset aggregation methods are examined. Moreover, as studying whether poverty traps exist is empirically demanding, several methods are applied following the literature. First, non-parametric and parametric regressions are estimated. Second, convergence and post-shock growth models are estimated alongside with a panel threshold model. Non-parametric results show non-linear dynamics for the whole sample and for subsamples: non-flooded households converge to one high equilibrium, while flooded households converge to (at least) two equilibria. Parametric results confirm the existence of such non-linearities. Panel threshold estimations confirm the existence of such threshold among flooded households. 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 for the creation of a poverty trap after the flood. Robustness checks validate these findings and improve the identification of the flood-affected households.

This paper is structured as follows: the next Section contextualizes this work in the literature on poverty traps and in the literature of climate vulnerability, Section 3 presents the methodological approaches used, Section 4 presents the dataset and the way flood extent was measured, Section 5 presents summary statistics and Section 6 describes the main results. Section 7 tests the validity of these results with robustness checks, while Section 8 concludes with some policy recommendations.

2. Literature review

2.1 Literature on poverty traps

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

A visual representation is given in Figure 2, where on the x-axis there is the asset level in the starting period and on the y-axis the level in the following period. The 45-degree line represents the case in which asset levels are constant across periods. The two other curves represent the case of convergence (the dotted line) and of the trap (the wiggly S-shaped line). The former portrays the canonical dynamics of wealth, associated to diminishing returns to assets: no matter the initial asset level, it is possible to start a process of accumulation of wealth that eventually pushes everyone along the same growth path (unconditional convergence). When convergence is not observed, in the second case, there can be club convergence or multiple equilibria. The latter is consistent with the concept of poverty traps and the existence of thresholds at which the return on assets is locally increasing (Carter and Barrett, 2006). The initial wealth stock is determinant for the type of dynamic. At the unstable equilibrium $\Lambda(A_m)$, asset dynamics bifurcate (Adato et al., 2006): below the threshold, households converge to the low equilibrium poverty trap asset level, in which the process of saving little by little is doomed to bring little success. Above the threshold, households can exploit the ascending path and grow (Carter and Barrett, 2006).

Figure 2: Asset dynamics with and without a poverty trap

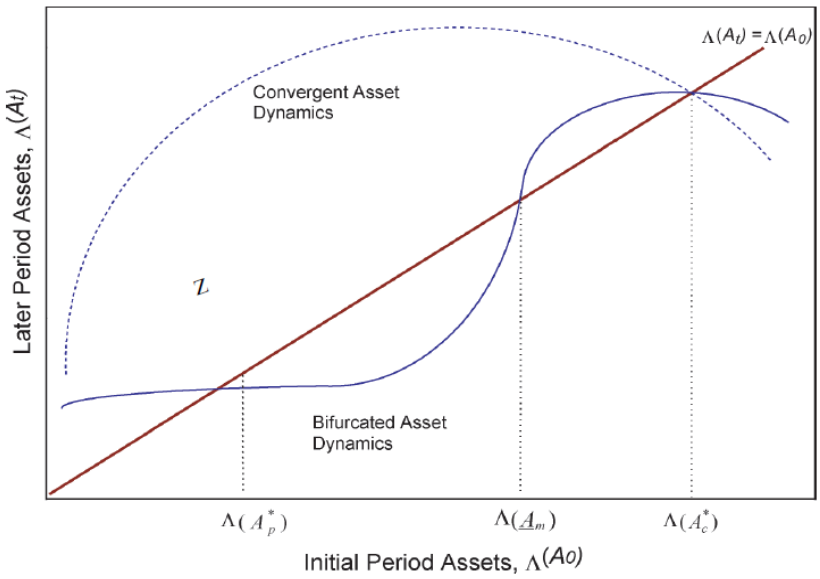


Figure 1. Hypothetical asset dynamics

Source: Adato et al., 2006

Poverty traps can emerge when income dynamics are nonlinear and create multiple equilibria (Barrett et al., 2018). This can happen because of some exclusionary mechanisms that trap households at the individual, community or regional levels (Barrett and Carter, 2013). These mechanisms can include human capital, savings propensity, discount rates and geographic factors (Carter and Barrett, 2006), natural capital such as land size (Coomes et al., 2011), technological indivisibilities (in the case of complementary assets) and credit constraints (Balboni et al., 2020), social networks and social capital (Chantarat and Barrett, 2013), poor nutrition and health, behavioural patterns about risk and time preferences, missing capital markets, lack of insurance, and fragile resource governance (Barrett et al., 2018).

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

Multiple financial market failures create a trap of this kind. This trap assumes inability to borrow, fixed intrinsic ability and two types of technology. Borrowing and insurance are not feasible, which implies that the endowments correspond to expected assets in the future, and that risk and shocks can have persistence effects. Multiple financial market failures have the behavioural consequence that instead of smoothing consumption, households smooth assets instead (Carter and Lybbert, 2012; Scott, 2019; Zimmerman and Carter, 2003). Additionally, risk taking by risk averse agents is 'anomalous' when they are close to the Micawber threshold (Lybbert et al., 2004) and risk reducing schemes foster investments (Barrett and Carter, 2013). Poverty traps call for specific policy action. Filling the gap to reach the threshold would suffice to propel households put the household on the way out of poverty. Safety nets can have large spillover and multiplier effects (Barrett and Carter, 2013). Access to credit, insurance and savings can dissolve poverty traps.

Empirical studies in this context have found mixed evidence. Cases where poverty traps were found are linked to 'simple' contexts, for example pastoralists in Ethiopia and Kenya, where one livestock index can represent a household's wealth. In more structured contexts, methods of aggregation of different assets have been proposed (Adato et al., 2006). Nonetheless, identifying poverty traps is not easy from the methodological and empirical point of view (cfr. Section 3 on Methodology)[2]. Cases where poverty traps have not been identified are linked both to the absence of such traps and to data and methodological issues[3].

2.2 Literature on climate vulnerability and the poor

Climate change brings about large alterations in the form of both extreme climate events[4] and slow changes. Extreme events, our focus, are becoming more frequent, therefore studying them is increasingly relevant. They typically affect places unevenly. At the same time, the impact of these events is heterogeneous across world regions, as the vulnerability of each place depends also on non-climatic factors, i.e. social, economic, cultural, political, and institutional factors (IPCC, 2014). 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). In Africa, for example, it is projected that extreme events such as floods and droughts will be more frequent, desertification will advance due to changes in rainfall and land use intensification, grain yields

[2] Poverty traps have been identified in Ethiopia (Carter et al., 2007; Lybbert et al., 2004; Lybbert and Barrett, 2007; Santos and Barrett, 2006), Northern Kenya (Barrett et al., 2006), South Africa (Adato et al., 2006; Carter and Ikegami, 2007; Carter and May, 2001; Woolard and Klasen, 2005), Bangladesh (Balboni et al., 2020), Burkina Faso (Carter and Lybbert, 2012), rural Mozambique (Laajaj, 2017), Honduras (Carter et al., 2007).

[3] Examples of works that do not find poverty traps are based in Pakistan (Naschold, 2013), India (Arunachalam and Shenoy, 2017; Naschold, 2012), rural Bangladesh (Quisumbing and Baulch, 2013), Hungary and Russia (Lokshin and Ravallion, 2004), rural China (Jalan and Ravallion, 2004), Mexico (Antman and McKenzie, 2005), Madagascar (Barrett et al., 2006), nor in a panel of eight countries (McKay and Perge, 2013).

[4] For example, heat waves, droughts, floods, cyclones, and wildfires.

will suffer, the sea level will rise, and variations in river water availability will be larger (Abeygunawardena et al., 2009).

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, diarrhea, 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[5] (Hallegatte et al., 2020). The longer-term situation will depend on the type of coping strategy a household can afford to adopt, for example, withdrawing children from school or reducing health expenses can have permanent dramatic consequences (Hallegatte et al., 2020). Where agriculture is mainly rain-fed, the relationship between rainfall variability and food poverty is 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).

Poor people are especially vulnerable to climate variations. They live in places that generally are very vulnerable on the geographical, environmental, socioeconomic, institutional and political basis (Abeygunawardena et al., 2009). Moreover, climate change worsens the impact of other hazards (IPCC, 2014), acting as a threat multiplier and making harder poverty eradication efforts (Hallegatte et al., 2015).

The poor are overly exposed, both directly and indirectly. Directly, they are more vulnerable because they live in fragile buildings (McGuigan et al., 2002), have all their assets in physical form (Winsemius et al., 2018) and gain their income from agricultural production, also vulnerable. Hence, shocks can bring households below the poverty line, depleting their wealth stock and impeding the asset accumulation process (Carter et al., 2007). The poor are more vulnerable also because they know less about climate change and adaptation practices (Dercon et al., 2005), enjoy 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). Being excluded from social protection means that also risk, left uninsured, affects *ex-ante* the type of investments that are carried out, including human capital investment (Elbers et al., 2007; Hallegatte et al., 2018). Indirectly, climate change brings about spikes in food prices and augmented food insecurity (IPCC, 2014), it affects mobility, physical and mental health (Hallegatte et al., 2018), water and biodiversity regulation, political instability and conflict, forced migration, economic growth (Dercon et al., 2005).

Empirical works confirm that the poor tend to be among the most hit groups by weather shocks 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. Shocks are found to have long-lasting effect (for example in Ethiopia, Dercon et al., 2005). An analysis of global exposure to flood risk and droughts for 52 countries highlights how in Africa

[5] 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).

the poor are disproportionately exposed to both drought and flood. Concerning flood risk, urban areas are the riskiest (Winsemius et al., 2018). Using a large sample of household surveys in sub-Saharan Africa in combination with spatial biophysical data, Azzarri and Signorelli (2020) find positive association between per capita consumption and long term humidity and but negative association between per capita consumption and temperature.

Such vulnerabilities can lead to the adoption of coping strategies that further limit the household's future responsive capacity. Indeed, diversification and risk-coping strategies are costly, as households cannot benefit from specialization gains (Elbers et al., 2007). Risk coping and risk management strategies reduce income, make poverty and the impact of negative shocks persistent (Jalan and Ravallion, 2004). For example, withdrawing children from school, selling assets, reducing consumption, and doing criminal activities can have long-lasting consequences (Barrett 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 defense structures permanently reduces economic output in affected regions" (Leichenko and Silva, 2014, p. 547). Evidence on climate-induced poverty traps is mixed so far. Climate change can also trap people that are too poor to migrate, the most vulnerable. For example, geographically disadvantaged areas in Zambia show little or no migration (Nawrotzki and DeWaard, 2018).

On the policy side, interventions are needed to reduce vulnerability, improve adaptation capacity as well as including the poor as main target (Abeygunawardena et al., 2009). Adaptation practices can reduce the impact of climate change and are positively associated with food security (Ali and Erenstein, 2017). Unfortunately, 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). Therefore, the choice of the policies will determine what the final impact of climate change on poverty is (Hallegatte et al., 2015).

3. Methodology

Testing empirically for a poverty trap is no easy task, because of the presence of non-linearities, the unstable nature of such equilibrium points (therefore there will not be many observations around the threshold), the limited length of available panel data, the heterogeneity across households and potential measurement errors. 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 with past asset holdings. Given the non-linearities, non-parametric techniques are 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. These use polynomials to model such non-linearities. Limits of this approach include the underlying assumptions on the functional form and its requirement of having observations at all asset levels, which is hard to expect given the unstable nature of the threshold (Scott, 2019). Therefore, several authors have used the parametric and non-parametric methods to test the relationship between current and past asset levels (Giesbert and Schindler, 2012; Naschold, 2013, 2012). The combination of methods allows researchers to exploit the advantages of each of them but keeping in mind each method's pitfalls. In order to have a poverty trap, the relationship between current and past assets has to be non-linear and non-convex. To demonstrate this, some difficulties emerge: First, one estimates individual households' transition equations though the cross-sectional variation. Second, data might show missing data for the S-shaped curve, which would be invisible to tests, or the non-convex region might be small. Third, econometric techniques might be insufficient (McKay and Perge, 2013). Nonetheless, these methods are the most effective available and 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 equation is not offset by the presence of more distance points which move the weight (Carter and Barrett, 2006). The relationship estimated can be seen in Equation 1:

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

where A_{it} are current asset holding of household *i* at time *t*, A_{it-1} are lagged asset holdings, the error term ε_{it} is assumed to be normally and identically distributed with zero mean and constant variance. The function f is a continuous function and can be estimated with local polynomial regression, locally nonlinear non-parametric LOESS, locally weighted scatterplot smoother (lowess), locally linear regressions, or different types of splines. Kernel weighted local linear smoothers are another form of local regression. 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).

2. Parametric approach

The parametric approach allows to control for covariates at time t-1. It can be estimated via OLS with fixed effects or other panel models. In equation 2,

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

asset growth of household i (ΔA_i) is a linear function of its fourth polynomial expansion at the baseline, household's baseline characteristics, community's and regional and time fixed effects. Polynomial expansion serves to capture the non-linearities are at the centre of distribution (Naschold, 2013, 2012).

This approach and the following approach can be complemented by a term $\beta_7 D(A_{it-1}, W_i, L, F)$, which mediates the impact of a shock (e.g. flood or drought) on asset grow by factors such as having access to nonfarm wage, labour market conditions and the availability of new land in the community (Carter et al., 2007; Giesbert and Schindler, 2012) and a set of coping strategies.

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. It was used also by Letta et al. (2018). It can be tested whether below-threshold households have the same asset patters as above-threshold households, as follows:

$$g_i = \begin{cases} \beta_A^{\ell} A_{it-1} + \beta_Z^{\ell} Z_i + v_i^{\ell} & \text{if } A_{it-1} < \gamma \\ \beta_A^{u} A_{it-1} + \beta_Z^{u} Z_i + v_i^{u} & \text{otherwise,} \end{cases} \tag{4}$$

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, and γ is the asset threshold. A poverty trap is found if households in the lower regime tend to a lower equilibrium. This is seen by comparing the coefficients.

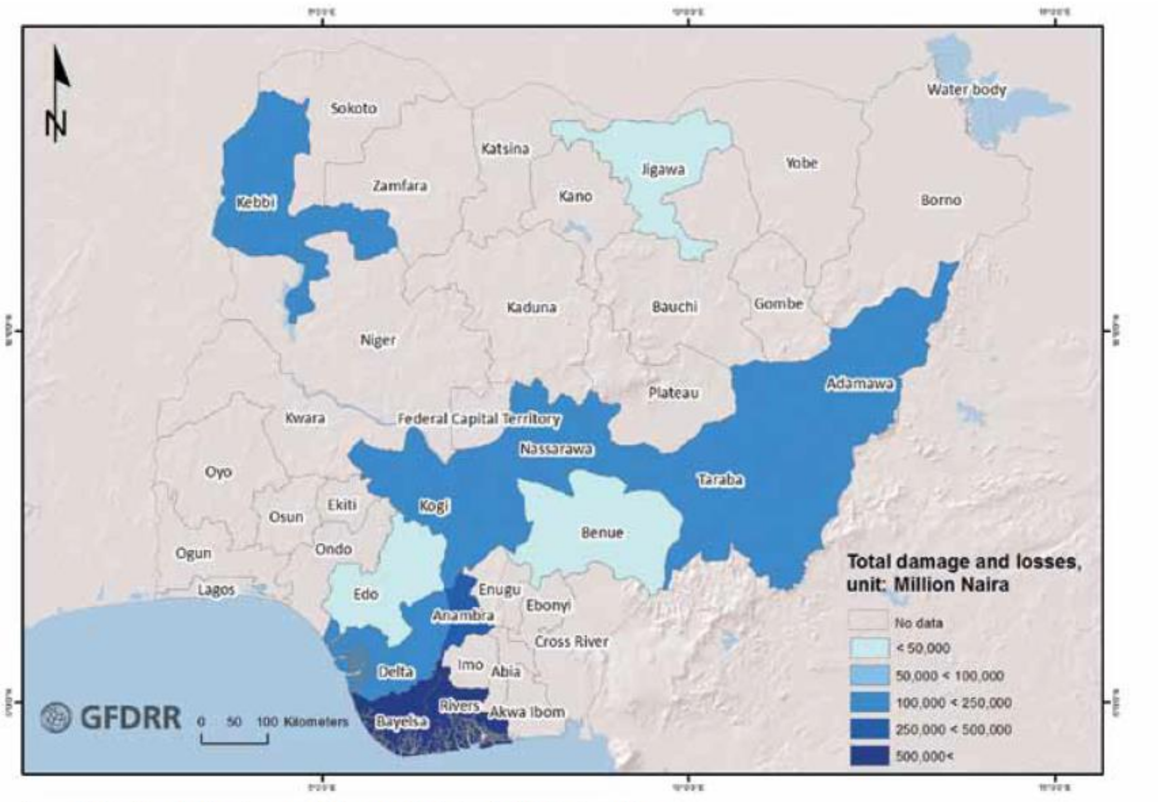
4. The data

This analysis is based on the General Household Survey 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. 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. Attrition totalled 10.4%.

4.1 Flood measurement

In 2012, Nigeria experienced severe flooding. 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. It was described as the worst flood in 40 years, killing 363 people, injuring 5,851 people and displacing 3.8 million people. The estimated overall damage and losses of the flood are estimated to total US$ 16.9 billion, a 1.4% impact on GDP (Federal Government of Nigeria, 2013). The floods involved 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 3).

Figure 3: Total damage and losses of the flood



Source: Estimations by the Assessment Team on the basis of official information.

Source: Federal Government of Nigeria, 2013, p. xxiv.

The peak of the flood occurred during the first visit of the second wave of the survey (Table 2). 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 2: 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

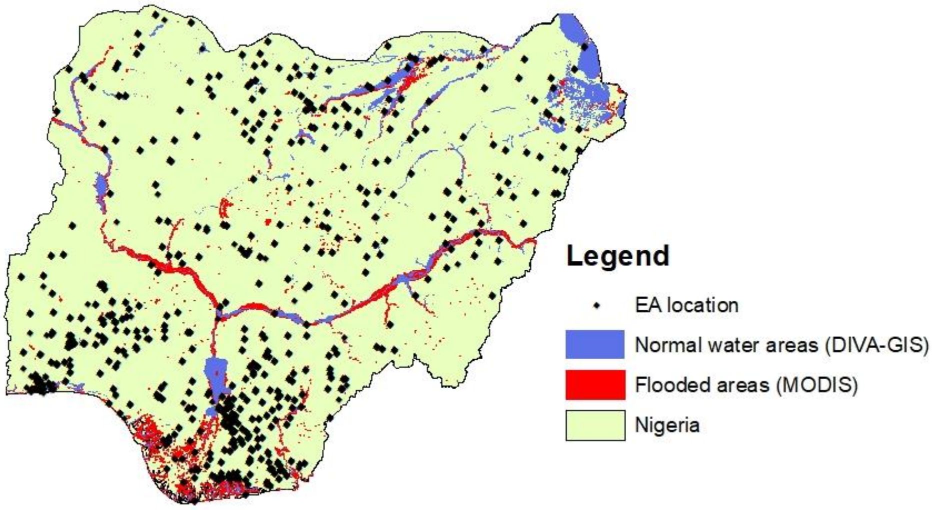
Source: own elaboration.

Satellite data was downloaded for the period 11 September - 3 November from the NASA's MODIS NRT (near real time) Floodmap website[6], which provides elaborations of two or more days of observations (Figure A5). 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 A6). 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[7]. MODIS' released products for the period of interest are 2-days products. Compared to data from one single observation, these can give a first remedy to issues of cloud coverage, 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[8]. Since there are only products of two days for the period of interest, 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. Those layers have been united to show the maximum extension of flooded area.

Households' enumeration areas were plotted in the map, and a 2 km buffer was constructed around them[9]. 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 522 (11.2%). Figure 4 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.

[6] https://floodmap.modaps.eosdis.nasa.gov/
[7] More recent MODIS products also incorporate a cloud shadow masking (Nigro et al., 2014).
[8] 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).
[9] Considering that EA coordinates provided in the dataset are modified for confidentiality issues 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 a robustness check different buffer sizes are evaluated (see Section 7).

Figure 4: 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)

5. Descriptive statistics

Table 4 reports the T-test of some key variables for the sample pre-shock (wave 1) for flooded and non-flooded households[10]. The two subsamples differ along many dimensions, for example soon-to-be flooded households are less engaged in agriculture but are more better off. They have higher access to financial resources band are more protected by safety nets. They have higher assets and consumption level. They are more likely to be involved in non-farm employment.

Table 3:T-test on rural sample by flood at baseline

Variables	N. flooded	Mean flooded	N. no flood	Mean no flood	MeanDiff
Number of people in the hh	522	5.670	4066	5.861	-0.190
Female headed hh	522	0.180	4066	0.143	0.037**
Age head of hh	522	48.13	4066	49.96	-1.831**
Head of hh married	519	0.792	4064	0.811	-0.0190
Head of hh widowed	519	0.118	4064	0.123	-0.00500
Years of education head of hh	520	7.475	4046	5.948	1.527***
Number of children <5yo	522	1.027	4066	1.133	-0.106*
HH dependency ratio	507	0.981	3933	1.110	-0.129***
Total livestock owned, tlu	522	0.503	4066	2.079	-1.577
Land owned, hectares	522	0.00800	4066	0.0420	-0.034***
HH cultivates crops/trees	522	0.347	4066	0.683	-0.337***
Asset index similar to DHS	506	0.332	3803	-0.158	0.490***
Daily consumption per capita, 2010 PPP + Paasche	522	4.249	4065	3.300	0.949***
HH receives remittances	522	0.259	4066	0.217	0.041**
HH received assistance	522	0.0360	4066	0.0140	0.022***
HH has borrowed	522	0.362	4066	0.362	0
Average maize yield	155	4969	2476	7807	-2.8e+03***
Available arable communal land	522	0.320	4066	0.263	0.057***
Community hires agric labourers	522	0.640	4066	0.875	-0.235***
Community's average agricultural wage	522	553.9	4066	634.0	-80.115***
Microfinance in the community	522	0.324	4066	0.152	0.171***
HH Distance in (KMs) to Nearest Market	522	57.88	4066	69.02	-11.135***
HH Distance in (KMs) to Town >20k	522	17.13	4066	19.72	-2.585***
HH withdraw a child from school	522	0.0940	4066	0.100	-0.00600

[10] The weights are not applied here.

A hh member works for a wage	522	0.326	4066	0.259	0.067***
A hh member is self employed	522	0.625	4066	0.468	0.156***
A hh member migrated for work/land reason	522	0.0130	4066	0.0170	-0.00400

Source: own elaboration using Nigeria GHS panel data

Looking at the frequencies of coping strategies by wave, those that have the highest frequency at wave 2 are withdrawing children from school, selling assets, 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 4: 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	HH sold assets
Panel A: Total sample										
1	9.9	26.7	48.6	22.2	2.7	36.2	.	1.7	0.1	1.7
2	10.2	25.8	50.9	2.2	3	37.1	14	3.5	0.3	3.1
3	2.3	25.7	57.7	4.9	3.1	17.7	4.9	11.1	0.4	2
4	3.9	29.9	50.8	34.5	3.9	14.9	2.2	18.3	0.7	8
Panel B: Flooded sample (2km)										
1	9.4	32.6	62.5	25.9	2.5	36.2	.	1.3	0.4	3.6
2	5.7	35.4	69.2	2.7	4.4	36.6	17.2	3.3	0.4	9
3	1.7	30.5	67.4	6.7	4.4	18.8	5.2	9.8	0.4	1.5
4	4.4	39	62.3	39	6.3	23.9	2.5	20.8	2.5	13.8

Source: own elaboration using Nigeria GHS panel data

5.1 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, and allow a forward-looking evaluation of poverty (Carter and Barrett, 2006). Asset-based approaches bring about three important contributions: (i) they shed light on a minimum asset bundle with which households can find their own exit out of poverty; (ii) they characterize the reliance on time to end poverty given people's access to social capital and financing opportunities; and (iii) they help designing safety nets (Carter and Barrett, 2006).

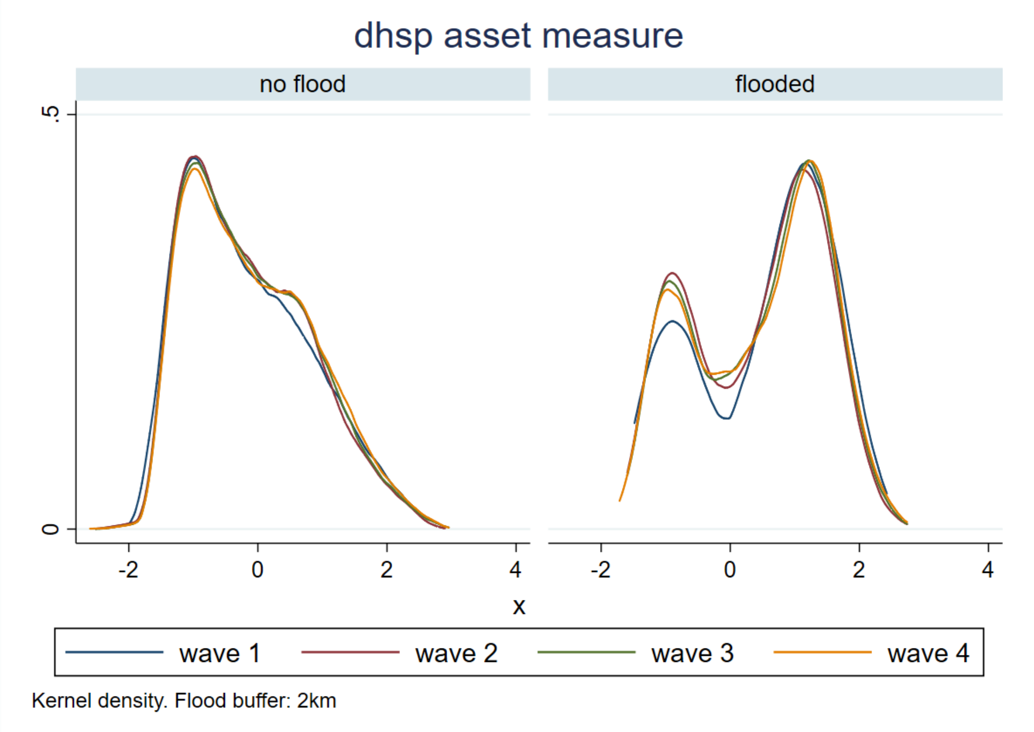
I followed DHS' methodology to create a comprehensive asset index (Rutstein, 2015). I selected all the variables that were common and had common categories across waves. For each yes/no variable, missing values were replaced with 0. For each continuous variable, missing values were replaced with the variable mean at the enumeration area. The aggregation of all these dimensions is done via principal components extraction[11] (Sahn and Stifel, 2003, 2000) and the first factor 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

[11] 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.

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 (McKay and Perge, 2013; Naschold, 2013, 2012).

Appendix A.1 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 measure can be seen split by flood occurrence in Figure 5. The flooded sample has a distribution with two peaks, giving a first clue about the presence of more equilibria.

Figure 5: Kernel density of asset index by flood, 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 5. Panel A provides transition percentages for the whole 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 percentages in the second initial quintile (60.9%).

Table 5: Transition matrices by asset quintiles, row percentages

Panel A: w1-w4 total sample						
Quintiles of assets, w1	Quintiles of assets, w4					
	1	2	3	4	5	Total
1	58.09	32.01	8.91	0.99	0	100
2	31.52	40.08	21.4	6.61	0.39	100
3	5.2	21.2	46.4	24.4	2.8	100

4	0.84	5.44	25.94	45.19	22.59	100
5	0	0.66	3.99	27.24	68.11	100
Total	20.15	19.85	20.15	20.07	19.78	100

Panel B: w2-w4 flooded sample (2km)						
	Quintiles of assets, w4					
Quintiles of assets, w2	1	2	3	4	5	Total
1	73.33	20	0	6.67	0	100
2	60.87	30.43	8.7	0	0	100
3	11.11	33.33	33.33	22.22	0	100
4	0	4.35	26.09	39.13	30.43	100
5	0	0	1.14	25	73.86	100
Total	16.46	8.86	7.59	21.52	45.57	100

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.

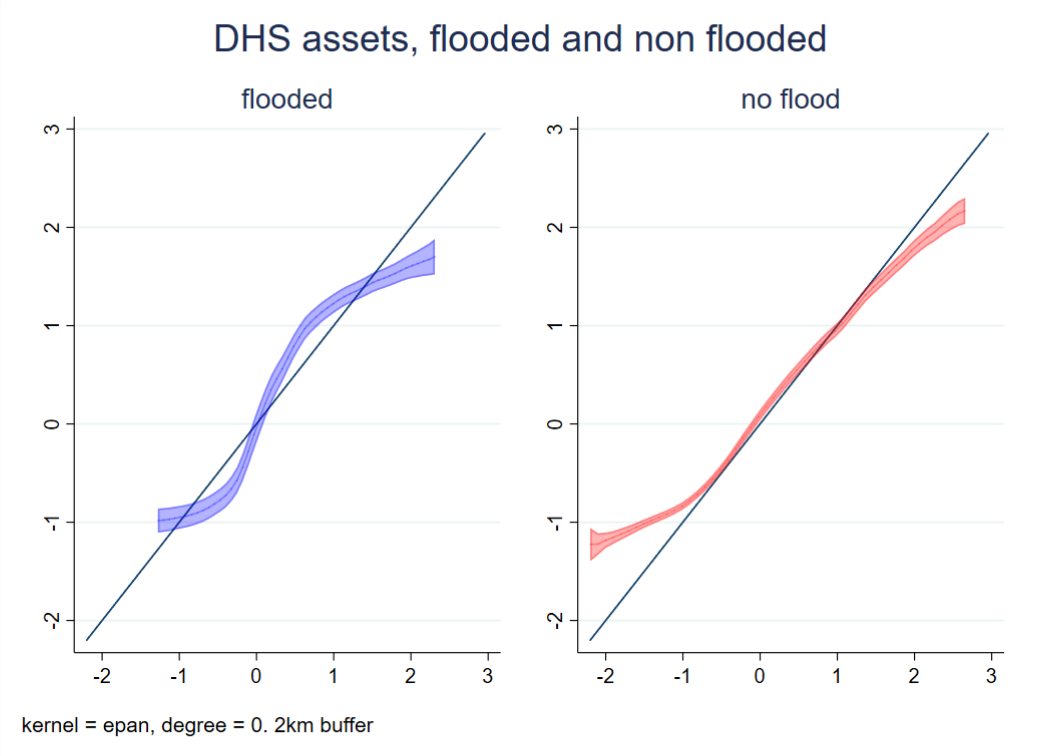
5.2 Non-parametric regression

Using non-parametric regressions in an exploratory way [12] shows some heterogeneity among subgroups, for instance rural and urban areas: urban households seem to converge to a high asset level, whereas rural household follow more strictly the 45-degree line. Rural households have a less clear path but certainly cross the 45-degree line below the crossing point of urban households. A similar trend happens for households that do agriculture and those that operate outside agriculture. The gender of the household head also seems to matter for asset ownership and dynamics. Bivariate relations suggest the presence of more equilibria for male-headed households, one very high and one very low, while for female-headed households there seem to be converge to a single equilibrium in the middle of the other two (similar to what is found by Dillon, A. & Quiñones (2011) for Northern Nigeria and by Edet and Etim (2014) for Southern Nigeria). The education level of the household head also matters for asset dynamics, as expected education is positively associated with higher equilibria. Moreover, households with a source of income from somewhere else (internal and international migrants) are able to converge to a single high equilibrium, while the rest of the households have one low and one high equilibria.

Concentrating on the flooded and non-flooded sample and restricting the time dimension from wave 2 (when the shock has happened) to wave 4 (Figure 6), the two curves look very different. The blue one (flooded) shows a wiggly shape, compatible with the poverty traps shape, while the red one is very flat. 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, 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).

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

Figure 6: Local polynomial smooth, by flood



Source: own elaboration using Nigeria GHS panel data.

6. Results

6.2. 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 a OLS model. Lagged asset are modelled also with the squared, third and the fourth degree terms[13] (Barrett et al., 2006; Giesbert and Schindler, 2012; McKay and Perge, 2013; Naschold, 2013, 2012). All regressions include household characteristics (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 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 to a town with more than 20,000 inhabitants, and a dummy for rural areas), as well as the dummy for flooded areas

[13] 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 the fourth polynomial is the most appropriate, even though the t-test does not find relevant differences among mean predicted values across all specifications. After the fourth polynomial, no other coefficient is statistically significant.

and its interactions with some of the variables mentioned above. Table 6 reports the coefficients of the variables of interest. Columns 1 and 2 use as dependent variable the asset change from wave 4 to wave 1 (2018/19 – 2010/11), while columns 3 and 4 consider the asset change after the shock (2018/19 –2012/13)[14]. The latter explicitly takes into account the occurrence of the flood shock using as starting period wave 2. 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 β_1 is between -2 and 0 and all other β_{2-4} are all equal to zero. The null is rejected in all columns and indeed β_1 is found between -2 and 0, however β_2=β_3=β_4=0 is rejected only in the first and last column, indicating convergence for the flooded sample 'before' the shock and for the whole sample after the shock.

Table 6: Parametric regression, long differences, OLS

Y= asset growth	**W1-W4**		**Y= asset growth**	**W2-W4**	
	(1) All sample	**(2) Flood sample**		**(3) All sample**	**(4) Flood sample**
3-Lag assets	**-0.350*** **	**-0.739*** **	2-Lag assets	**-0.292*** **	-0.279
	(0.054)	(0.282)		(0.044)	(0.207)
3-Lag assets^2	-0.004	0.198	2-Lag assets^2	-0.010	**0.281** **
	(0.046)	(0.141)		(0.034)	(0.137)
3-Lag assets^3	**-0.052** **	0.006	2-Lag assets^3	**-0.030** **	**-0.227** **
	(0.021)	(0.138)		(0.013)	(0.110)
3-Lag assets^4	0.012	-0.032	2-Lag assets^4	0.009	0.033
	(0.013)	(0.053)		(0.008)	(0.045)
Model	OLS	OLS		OLS	OLS
Observations	1,329	150		1,345	148
Adjusted R-squared	0.197	0.239		0.151	0.156
F-test all lags=0	0.000	0.000		0.000	0.000
F-test lags 2-4=0	0.054	0.554		0.151	0.009

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 center, as well as some interactions with flood, time and zone dummies, rural. Robust standard errors and panel weights. Flooded defined with 2 km buffer

Table 7 reports the same estimation for the remaining relevant time period pairs. Non-linearities are mostly present in the first two columns (wave 3 - wave1) where indeed convergence is rejected. It cannot be rejected for the shorter period difference (wave 4 -wave 3).

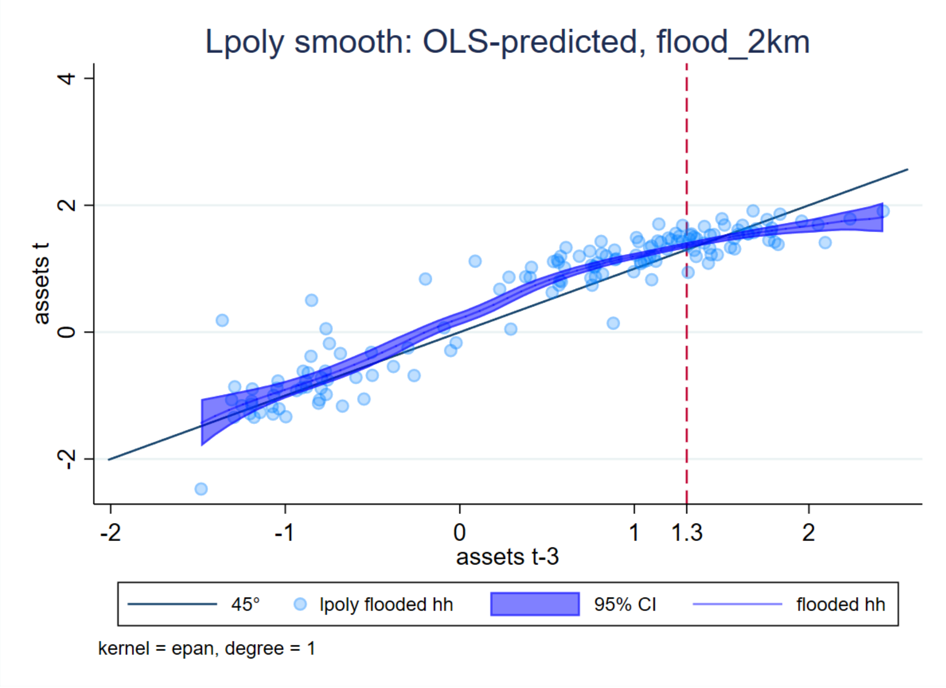
Table 7: Parametric regression, other time differences, OLS

Y= asset growth	**W1-W3**		**Y= asset growth**	**W3-W4**	
	(1) All sample	**(2) Flood sample**		**(3) All sample**	**(4) Flood sample**
2-Lag assets	-0.309***	-0.041	1-Lag assets	**-0.303*** **	-0.145
	(0.027)	(0.091)		(0.047)	(0.275)
2-Lag assets^2	-0.060***	-0.111**	1-Lag assets^2	0.048	0.165
	(0.021)	(0.054)		(0.034)	(0.154)
2-Lag assets^3	-0.027***	-0.210***	1-Lag assets^3	-0.005	-0.160
	(0.010)	(0.062)		(0.019)	(0.124)
2-Lag assets^4	0.013**	0.075***	1-Lag assets^4	-0.008	0.032
	(0.006)	(0.022)		(0.009)	(0.050)
Model	OLS	OLS		OLS	OLS
Observations	4,150	482		1,395	152
Adjusted R-squared	0.189	0.292		0.149	0.182
F-test all lags=0	0.000	0.000		0.000	0.002
F-test lags 2-4=0	0.001	0.000		0.292	0.234

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

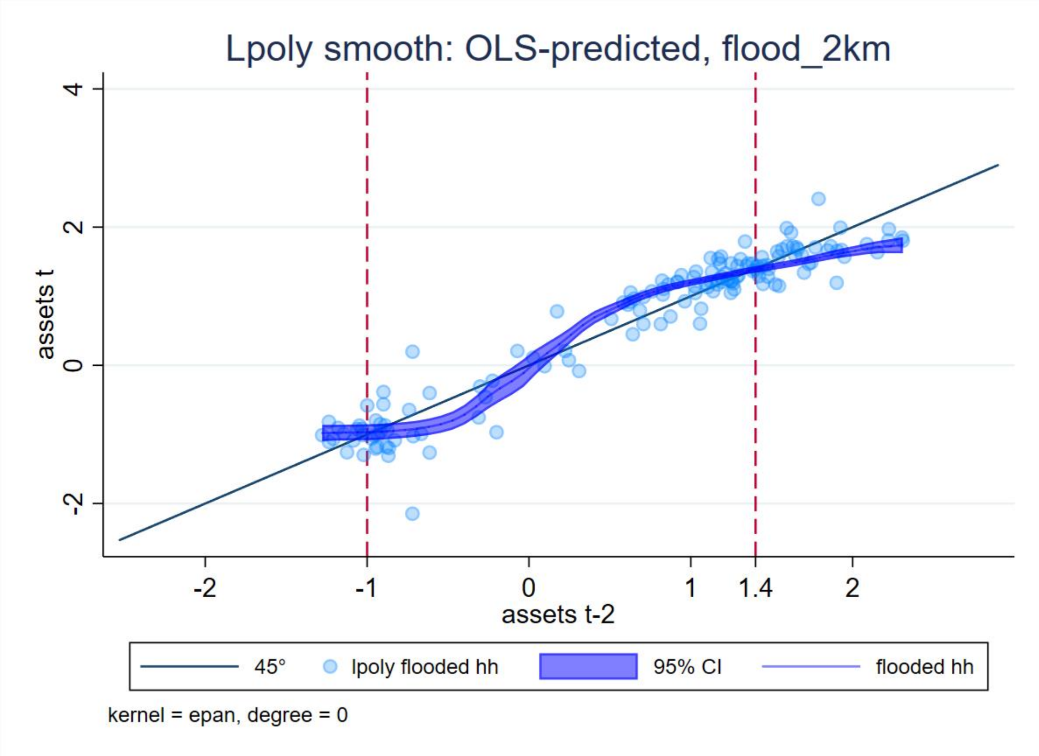
These results can also be appreciated graphically with a non-parametric regression, by predicting fitted values of the growth variable, adding to it its lag and plotting it against the lag itself, as done by Giesbert and Scldhindler (2012) and Naschold (2013) (Figure 7 reports the long difference for flooded households, Figure 7 the post-shock difference for flooded households again). Kernel-weighted local polynomial smoothing is used. In the case of Figure 7, the asset recursion function crosses the 45-degree line only once, at around 1.3 asset scores. Since it crosses the line from above, this is a stable equilibrium to which all households should converge. It is interesting to note how after the shock (Figure 8) a second equilibrium can be found at low levels of assets (at -1 asset scores) and the transition curve takes an S shape. This indicates that 'initial' conditions that are created with the flood lead to a bifurcation in which a poverty trap is found at -1 asset scores. Conversely, in Figure 7 where the initial assets considered are before the shock, no low-level equilibrium can be identified.

Figure 7: OLS-predicted asset change from wave 1- wave 4, flooded sample (2km buffer)



Source: own elaboration using Nigeria GHS panel data.

Figure 8: OLS-predicted asset change from wave 2-wave 4, flooded sample (2km buffer)

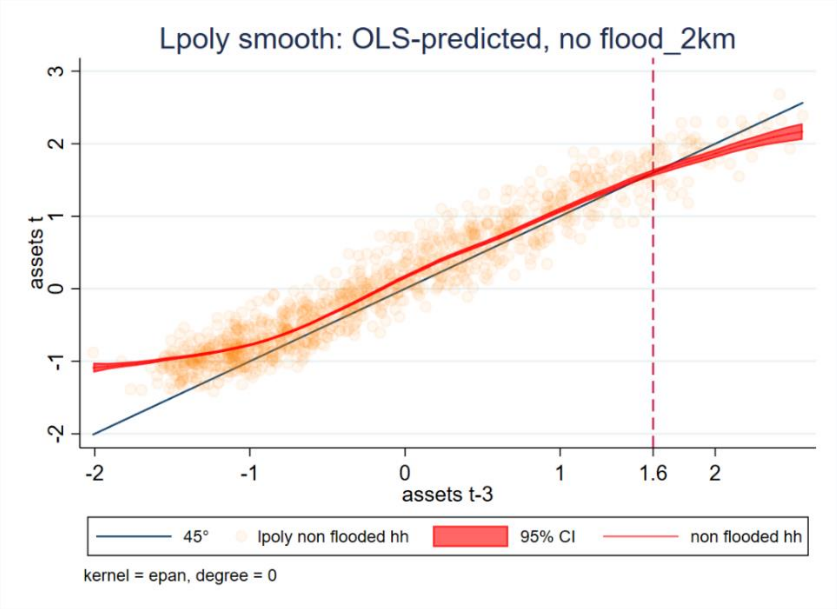


Source: own elaboration using Nigeria GHS panel data.

Further periods' local polynomial regressions (reported in the Appendix A_2) confirm the creation of a poverty trap at -1 after the shock (difference from wave 4 to wave 3, Figure A1), and confirm the absence of the same if the period spans before the flood occurrence (in the case of the difference from wave 3 to wave 1, Figure A2). In the latter case, convergence is confirmed.

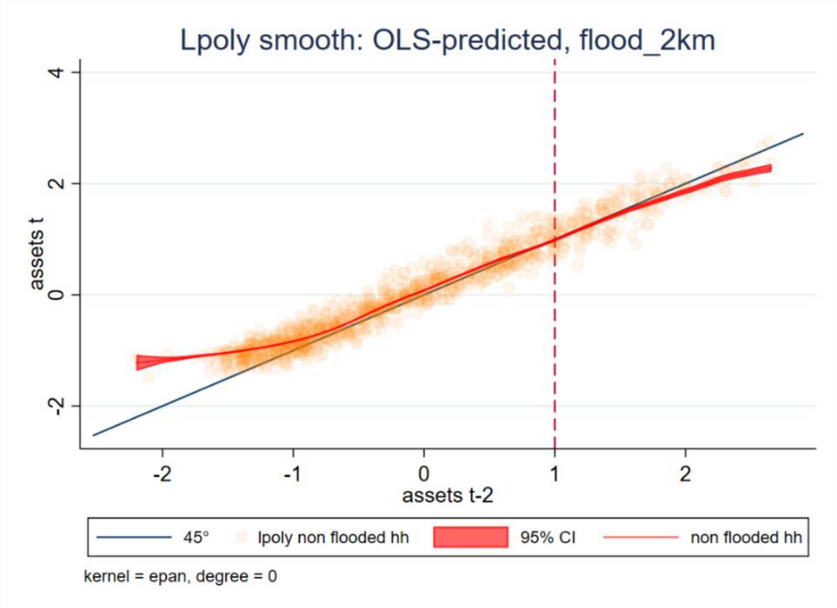
Looking at non-flooded households, for any periods the transition curve is rather flat and crosses the 45-degree line only at a higher level, suggesting convergence (Figures 9 and 10).

Figure 9: OLS-predicted asset change from wave 1-wave 4, non-flooded sample



Source: own elaboration using Nigeria GHS panel data.

Figure 10: OLS-predicted asset change from wave 2-wave 4, non-flooded sample



Source: own elaboration using Nigeria GHS panel data.

6.4 Threshold estimation

Next, I check whether among flooded households 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). A mildly significant low-level threshold is found for the flooded households using one lag and the 5-km buffer (Table 8), which confirms the existence of a low-level equilibrium that was observed before[15]. Repeating the same analysis for specific time intervals and checking for a second break point do not add new information to the picture, as the sample is not large enough[16]. Adding controls to the threshold regression yields a slightly lower threshold but still significant.

Table 8: fixed effects panel threshold regression, flooded sample only, pooled waves from 2 to 4

Model	Threshold	Lower	Upper
Th-1 (no controls)	-0.549	-0.679	-0.512
Th-1 (with controls)	-0.666	-0.739	-0.661

Threshold effect test (bootstrap = 400):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Th-1 (no controls)	77.297	0.071	15.010	0.060	13.859	15.435	20.278
Th-1 (with controls)	70.591	0.065	18.210	0.020	13.797	15.366	19.471

Coefficients	no controls	with controls
Below threshold# lag_assets	-0.323***	-0.328***
	(0.093)	(0.076)
Above threshold# lag_assets	-0.078	-0.099**
	(0.048)	(0.048)
age head of hh		0.001
		(0.002)
number of people in the hh		0.038***
		(0.012)
Head is female widow		-0.135**
		(0.054)
HH Distance in (KMs) to Nearest Market		-0.000
		(0.000)
HH Distance in (KMs) to Nearest Population Center with +20,000		0.000
		(0.001)
Available arable communal land		-0.180***
		(0.037)
Rural dummy		-0.431**
		(0.170)
HH cultivates crops/trees		-0.031
		(0.045)
Total livestock owned, tlu		-0.005
		(0.005)
HH suffered income shock past 2yrs		-0.022
		(0.025)
Crop loss: climate, pest, violence		0.063
		(0.052)
HH receives remittances		0.075*
		(0.044)
HH received assistance		-0.041
		(0.049)
HH has borrowed		0.013
		(0.029)
Community hires agric labourers		0.013
		(0.035)
Constant	0.439***	0.452**
	(0.044)	(0.175)
R2_Within	0.03	0.12
R2_Between	0.88	0.07
R2_Overall	0.76	0.05
N	1,095	1,095

* *p*<0.1; ** *p*<0.05; *** *p*<0.01. Note: the dependent variable is the asset index, and the threshold variable is the lagged asset index

[15] This is compatible with the one identified graphically if a 5-km buffer is used instead of the 2-km buffer used so far. Using the 2-km buffer does not give any significant threshold since the sample size is too small.
[16] A second non-significant threshold is identified at 1.6236, which also reminds us of the non-parametric high equilibrium.

Now that I have identified a threshold beyond simple visualization, I can estimate what happens below and above it. As Carter et al. (2007) do, I performed a short OLS regression of asset growth for the flooded households, below and above the estimated threshold of -0.67 (Table 9). The coefficients on lagged assets are both very significant and different from each other. The coefficient in the low growth regime is, as expected, 'sharply negative'. The one in the higher-growth regime is nonetheless also quite negative (in Carter et al., it was close to zero). This again confirms the finding of a poverty trap for flooded households.

Table 9: Post-shock regression, flooded households only

	w2 - w4		Pooled w2 w3 w4	
	below -0.66	**Above -0.66**	**below -0.66**	**Above -0.66**
L2.assets	-0.446***	-0.233***		
	(0.077)	(0.047)		
L.assets			-0.943***	-0.183***
			(0.163)	(0.040)
age head of hh	0.016	0.022	-0.038**	0.021
	(0.015)	(0.015)	(0.019)	(0.014)
c.agehead#c.agehead	-0.000	-0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
number of people in the hh	0.017*	0.020*	0.016*	0.016
	(0.009)	(0.011)	(0.008)	(0.010)
Head is female widow	-0.149*	-0.126*	-0.124	-0.040
	(0.085)	(0.074)	(0.110)	(0.067)
HH Distance in (KMs) to Nearest Market	-0.002	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)
HH Distance in (KMs) to Nearest Population Center with +20,000	0.003*	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Available arable communal land	-0.402***	-0.333***	-0.023	-0.274**
	(0.100)	(0.113)	(0.124)	(0.107)
Rural dummy	0.031	0.031	-0.692*	0.001
	(0.134)	(0.087)	(0.368)	(0.077)
HH cultivates crops/trees	-0.195*	-0.117		
	(0.099)	(0.076)		
Total livestock owned, tlu	-0.034**	0.004	-0.019	0.009
	(0.016)	(0.011)	(0.013)	(0.010)
HH suffered income shock past 2yrs	0.010	-0.133**	-0.094	-0.155***
	(0.067)	(0.061)	(0.077)	(0.055)
Shock: dwelling damaged past 2yrs	-0.096	-0.164	0.220	-0.273
	(0.249)	(0.356)	(0.306)	(0.315)
Crop loss: climate, pest, violence	0.059	-0.128	0.203**	-0.208*
	(0.095)	(0.129)	(0.097)	(0.119)
HH receives remittances	0.162**	0.067	0.201**	0.099*
	(0.075)	(0.065)	(0.095)	(0.058)
HH received assistance	-0.183	-0.137	-0.036	-0.063
	(0.111)	(0.119)	(0.133)	(0.111)
HH has borrowed	-0.074	0.002	-0.123	-0.007
	(0.081)	(0.076)	(0.083)	(0.068)
Community hires agric labourers	0.209**	0.070	0.211	-0.053
	(0.098)	(0.077)	(0.186)	(0.070)
L2.jobnfexist	-0.040	0.171**	0.122	0.143*
	(0.082)	(0.086)	(0.091)	(0.076)
Adj R-squared	0.29	0.13	0.50	0.15
N	178	267	86	265
Zone#Year	yes	yes	yes	yes

* p<0.1; ** p<0.05; *** p<0.01
OLS

6.6 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 shown explicitly. These are non-farm wage (negative but not significant), remittances (positive and significant), borrowing (negative and significant) and assistance programmes participation (mixed sign, not significant). Table 10 additionally indicates that withdrawing children from school is positively related to asset growth (please note that the asset index does not include human capital, which likely suffers from such a choice).

Table 10: Parametric regression for coping strategies OLS, flooded sample

	(1)	(2)	(3)	(4)	(5)
2-Lag assets	-0.279	-0.253	-0.263	-0.281	-0.281
	(0.207)	(0.206)	(0.207)	(0.208)	(0.208)
2-Lag assets^2	0.281**	0.303**	0.275**	0.282**	0.288**
	(0.137)	(0.138)	(0.137)	(0.138)	(0.138)
2-Lag assets^3	-0.227**	-0.263**	-0.226**	-0.226**	-0.228**
	(0.110)	(0.113)	(0.110)	(0.111)	(0.111)
2-Lag assets^4	0.033	0.043	0.034	0.033	0.032
	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)
L2.non farm wage	-0.072	-0.070	-0.096	-0.071	-0.075
	(0.086)	(0.086)	(0.088)	(0.087)	(0.086)
L2.remittances	0.780***	0.788***	0.795***	0.777***	0.784***
	(0.120)	(0.121)	(0.122)	(0.122)	(0.119)
L2.assistance	-0.013	-0.002	0.015	-0.016	0.019
	(0.494)	(0.494)	(0.499)	(0.496)	(0.503)
L2.borrow	-0.058	-0.060	-0.061	-0.058	-0.061
	(0.097)	(0.098)	(0.097)	(0.098)	(0.097)
L.withdraw children from school		0.294***			
		(0.110)			
L2.non farm_self-employment			-0.084		
			(0.081)		
L2.insurance				-0.069	
				(0.242)	
L2.migration					-0.276
					(0.238)
R-squared	0.32	0.33	0.33	0.32	0.33
N	148	148	148	148	148
Controls	yes	yes	yes	yes	yes
Zone	yes	yes	yes	yes	yes

* *p*<0.1; ** *p*<0.05; *** *p*<0.01. OLS vce robust option. 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 insurance contract, having some members migrate (all destinations).

7. Robustness checks

7.1 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[17]. The non-parametric regression graph shows again an S-shaped transition curve, with three equilibria. Nonetheless, this restricts the flooded sample further, and the formal estimation of a threshold yields no significant results.

[17] 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 flooded water. 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.

Changing the buffer radius helps understand how the results are sensitive to this choice. Two new buffer sizes are calculated for 5 and 10 km. The 5 km buffer comprehends 1,064 households, whereas the 10 km buffer affects 2,034 households (43.65%). 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).

7.2 Different asset indexes

Using a different asset aggregation method (polychoric PCA) does not alter the main results (Table 11).

Table 11: Parametric regression, long differences, OLS with polychoric PCA asset index

Y= asset growth	**W2-W4**	
	All sample	**Flood sample**
2 Lag assets	-1.237***	-2.096*
	(0.226)	(1.149)
2 Lag assets^2	1.669***	1.232
	(0.441)	(2.034)
2 Lag assets^3	-1.075***	-0.261
	(0.309)	(1.253)
2 Lag assets^4	0.219***	-0.006
	(0.070)	(0.252)
Model	OLS	OLS
Observations	1,258	139
Adjusted R-squared	0.163	0.201
F-test all lags=0	0.000	0.000
F-test lags 2-4=0	0.001	0.019

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 center, as well as some interactions with flood, time and zone dummies, rural. Robust standard errors and panel weights. Flooded defined with 2 km buffer.

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 the time period is not driving the results, it is testes in Table 12.

Table 12: Parametric regression, long differences, OLS with asset index without durables

Y= asset growth	**W2-W4**	
	All sample	**Flood sample**
2 Lag assets	**-0.455*** **	**-0.872*** **
	(0.052)	(0.175)
2 Lag assets^2	-0.056	-0.180
	(0.043)	(0.216)
2 Lag assets^3	**-0.060*** **	0.041
	(0.019)	(0.066)
2 Lag assets^4	0.005	0.057
	(0.013)	(0.070)
Model	OLS	OLS
Observations	1,345	148
Adjusted R-squared	0.151	0.156
F-test all lags=0	0.000	0.000
F-test lags 2-4=0	0.000	0.613

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 center, as well as some interactions with flood, time and zone dummies, rural. Robust standard errors and panel weights. Flooded defined with 2 km buffer.

7.3 Conflicts

Since the period of analysis, Nigeria has suffered an escalation of violence and conflict events, especially in some zones (north-east primary). 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[18]) (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 13). Results are unchanged. The conflict occurrence has usually a negative correlation with asset growth but in a case where it is positive and significant. Predicting asset change and plotting it with local polynomial smoothing yields the same results as before.

Table 13: Parametric regression, long differences, OLS. Conflict as dummy for events>0

Y= asset growth	**W1-W3**			**W2-W4**	
	All sample	**Flood sample**		**All sample**	**Flood sample**
3-Lag assets	-0.347***	-0.736***	2-Lag assets	-0.301***	-0.595**
	(0.055)	(0.281)		(0.045)	(0.233)
3-Lag assets^2	-0.001	0.195	2-Lag assets^2	0.001	0.415***
	(0.046)	(0.139)		(0.034)	(0.145)
3-Lag assets^3	-0.056**	0.010	2-Lag assets^3	-0.028**	-0.152
	(0.022)	(0.136)		(0.013)	(0.116)
3-Lag assets^4	0.013	-0.035	2-Lag assets^4	0.007	-0.005
	(0.013)	(0.052)		(0.008)	(0.046)
Conflict=1	-0.068	0.615		0.027	0.676***
	(0.048)	(0.453)		(0.043)	(0.237)
L.conflict	0.073	-0.225		0.027	-1.587***
	(0.056)	(0.517)		(0.047)	(0.347)
L2.conflict	0.038	-0.733		-0.022	-0.453*
	(0.070)	(0.492)		(0.064)	(0.230)
Model	OLS	OLS		OLS	OLS
Observations	1,309	150		1,345	148
Adjusted R-squared	0.198	0.245		0.148	0.244
F-test all lags=0	0.000	0.000		0.000	0.000
F-test lags 2-4=0	0.033	0.530		0.148	0.002

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 center, as well as some interactions with flood, time and zone dummies, rural. Robust standard errors and 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 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).

A second variable created is the same dummy but restricted to those events in which there are fatalities. Results are unchanged[19] (Table 14).

Table 14: Parametric regression, long differences, OLS. Conflict as dummy for fatalities>0

Y= asset growth	**W1-W3**			**W2-W4**	
	All sample	**Flood sample**		**All sample**	**Flood sample**
3-Lag assets	-0.355***	-0.785***	2-Lag assets	-0.297***	-0.674***
	(0.055)	(0.266)		(0.044)	(0.232)
3-Lag assets^2	0.002	0.166	2-Lag assets^2	0.002	0.388***
	(0.046)	(0.135)		(0.034)	(0.137)

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

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

3-Lag assets^3	-0.052**	0.015	2-Lag assets^3	-0.029**	-0.142
	(0.021)	(0.133)		(0.013)	(0.112)
3-Lag assets^4	0.012	-0.030	2-Lag assets^4	0.006	-0.001
	(0.013)	(0.051)		(0.008)	(0.043)
Conflict=1	0.107	0.705**		0.068	0.542***
	(0.088)	(0.311)		(0.070)	(0.182)
L.conflict	0.069	0.015		0.068	0.171
	(0.091)	(0.270)		(0.074)	(0.221)
L2.conflict	-0.196*	-0.228		-0.096	0.374
	(0.118)	(0.465)		(0.125)	(0.294)
Model	OLS	OLS		OLS	OLS
Observations	1,309	150		1,345	148
Adjusted R-squared	0.200	0.246		0.150	0.203
F-test all lags=0	0.000	0.000		0.000	0.000
F-test lags 2-4=0	0.047	0.662		0.130	0.011

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 center, as well as some interactions with flood, time and zone dummies, rural. Robust standard errors and 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).

8. Conclusions

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

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 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 this study, the flood divides the population in two groups, the treatment and the control groups, allowing for insightful comparisons. 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.

In order to determine whether the 2012 flooding event created a poverty trap, this analysis used a combination of methods. First, with descriptive aim, 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. Second, parametric regressions confirmed the absence of convergence for flooded households after the shock. Predicting the asset change and using it in non-parametric regressions, shows how a poverty trap is identified at -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 points are stable and the middle one is of unstable nature. Third, panel threshold estimations provided significant evidence in favour of the presence of one threshold splitting the sample for flooded households, although a second threshold could not be identified with statistical robustness. The low-level threshold corresponded to the one identified graphically.

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 threshold. Households that suffered the flood shock presented different growth dynamics depending on the initial wealth, signalling that those households that suffered extensive asset destruction converged to a low-level equilibrium. These findings provide empirical evidence for the creation of a poverty trap after the flood. Robustness checks confirmed the general findings, while highlighting the limitations of the sample size.

This paper provides empirical evidence of the creation of a poverty trap in Nigeria after 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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Appendix

A.1

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

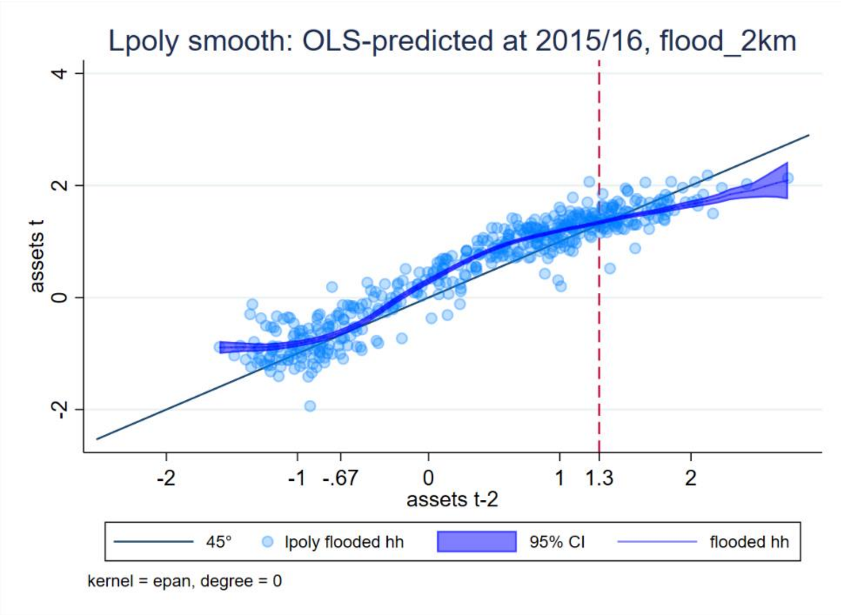
Components	DHS assets, quintiles 1	2	3	4	5	Total	
	mean	mean	mean	mean	mean	mean	Factor1
wall==mud/compacted earth	0.81	0.75	0.27	0.08	0.01	0.38	-0.08
wall==mud brick (unfired)	0.05	0.09	0.06	0.03	0.01	0.05	-0.01
wall==burnt bricks	0.00	0.01	0.02	0.02	0.02	0.01	0.00
wall==concrete	0.00	0.10	0.62	0.85	0.96	0.51	0.09

wall==wood	0.01	0.02	0.01	0.01	0.00	0.01	-0.01
wall==iron sheets	0.00	0.00	0.01	0.01	0.00	0.01	0.00
wall==other (specify)	0.12	0.03	0.01	0.00	0.00	0.03	-0.03
roof==grass	0.56	0.08	0.02	0.01	0.00	0.13	-0.08
roof==iron sheets	0.35	0.83	0.90	0.89	0.78	0.75	0.00
roof==clay tiles	0.03	0.01	0.00	0.00	0.00	0.01	-0.02
roof==concrete	0.00	0.01	0.02	0.02	0.02	0.01	0.00
roof==plastic sheeting	0.00	0.01	0.01	0.01	0.01	0.01	0.00
roof==abestos sheet	0.00	0.02	0.03	0.04	0.13	0.05	0.01
roof==other (specify)	0.05	0.05	0.03	0.02	0.05	0.04	-0.01
floor==sand/dirt/straw/mud	0.91	0.37	0.09	0.03	0.01	0.28	-0.13
floor==smooth cement	0.08	0.61	0.89	0.95	0.81	0.67	0.00
floor==wood	0.00	0.02	0.01	0.01	0.00	0.01	-0.01
floor==tile	0.00	0.00	0.01	0.02	0.17	0.04	0.02
floor==other (specify)	0.00	0.00	0.00	0.00	0.01	0.00	0.00
cookfuel==firewood	0.99	0.96	0.87	0.59	0.15	0.71	-0.08
cookfuel==coal	0.00	0.00	0.02	0.04	0.03	0.02	0.01
cookfuel==grass	0.00	0.00	0.00	0.01	0.01	0.00	0.00
cookfuel==kerosene	0.00	0.02	0.10	0.34	0.60	0.21	0.06
cookfuel==electricity	0.00	0.00	0.00	0.01	0.02	0.01	0.01
cookfuel==gas	0.00	0.00	0.00	0.01	0.20	0.04	0.05
cookfuel==other	0.00	0.00	0.01	0.01	0.00	0.00	0.00
water, wet s.==pipe borne water	0.02	0.05	0.07	0.10	0.16	0.08	0.02
water, wet s.==bore hole/hand pump	0.14	0.24	0.35	0.44	0.48	0.33	0.03
water, wet s.==well/spring protected	0.13	0.16	0.13	0.13	0.08	0.12	-0.01
water, wet s.==well/spring unprotected	0.32	0.18	0.07	0.03	0.01	0.12	-0.04
water, wet s.==surface water: pond, river, lake	0.22	0.15	0.07	0.03	0.01	0.10	-0.03
water, wet s.==rain water	0.15	0.21	0.27	0.20	0.08	0.18	-0.01
water, wet s.==tanker/truck/vendor	0.00	0.01	0.02	0.03	0.03	0.02	0.01
water, wet s.==other	0.01	0.01	0.01	0.04	0.15	0.04	0.03
toilet==none	0.49	0.33	0.28	0.16	0.03	0.26	-0.04
toilet==toilet on water	0.00	0.02	0.02	0.04	0.04	0.02	0.01
toilet==flush to sewage	0.00	0.00	0.01	0.06	0.23	0.06	0.04
toilet==flush to septic tank	0.00	0.00	0.03	0.12	0.49	0.13	0.06
toilet==pail/bucket	0.00	0.01	0.00	0.01	0.00	0.01	0.00
toilet==covered pit latrine	0.21	0.36	0.47	0.47	0.18	0.34	0.00
toilet==uncovered pit latrine	0.21	0.19	0.12	0.08	0.02	0.12	-0.03
toilet==v.i.p latrine	0.01	0.02	0.01	0.02	0.01	0.02	0.00
HH does not share its toilet facility	0.39	0.50	0.44	0.44	0.62	0.48	0.02
HH owns a mobile phone	0.40	0.63	0.81	0.93	0.98	0.75	0.06
HH uses electricity	0.03	0.21	0.56	0.85	0.97	0.52	0.09
HH mem has a bank account	0.02	0.10	0.27	0.55	0.90	0.37	0.08
# cattle, cows owned by hh	4.29	0.92	0.32	0.17	0.07	1.15	-0.02
# oxen owned by hh	0.25	0.13	0.02	0.01	0.00	0.08	-0.02
# donkey/horse owned by hh	0.76	0.03	0.01	0.01	0.01	0.16	0.00
# goats owned by hh	7.32	2.75	1.45	4.41	0.43	3.27	0.00
# sheep owned by hh	2.46	1.21	0.53	0.24	0.10	0.91	-0.03
# pigs owned by hh	0.12	0.08	0.08	0.13	0.35	0.15	0.00
# chickens owned by hh	8.14	6.03	4.00	3.81	16.24	7.64	0.00
# other poultry owned by hh	1.29	0.53	0.17	0.09	0.40	0.50	-0.01
# other livestock owned by hh	0.03	0.03	0.06	0.08	0.03	0.05	0.00
HH owns radio	0.49	0.52	0.54	0.63	0.64	0.56	0.01
HH owns tv	0.00	0.07	0.30	0.76	0.97	0.42	0.09
HH owns fridge	0.00	0.00	0.03	0.18	0.61	0.16	0.07
HH owns satdish	0.00	0.00	0.01	0.04	0.31	0.07	0.06
HH owns generator	0.01	0.07	0.15	0.33	0.68	0.25	0.07
HH owns aircond	0.00	0.00	0.00	0.00	0.09	0.02	0.04
HH owns computer	0.00	0.00	0.00	0.01	0.19	0.04	0.05
HH owns iron	0.05	0.13	0.22	0.56	0.90	0.37	0.08
HH owns fan	0.00	0.04	0.27	0.79	0.97	0.41	0.09
HH owns bike	0.21	0.23	0.21	0.17	0.10	0.18	-0.01
HH owns motorbike	0.23	0.35	0.35	0.40	0.24	0.31	0.00
HH owns trailer	0.02	0.01	0.00	0.00	0.00	0.01	-0.01
HH owns car	0.01	0.02	0.03	0.07	0.36	0.10	0.05
HH owns boat	0.01	0.00	0.00	0.00	0.00	0.00	0.00
HH owns canoe	0.01	0.01	0.01	0.01	0.00	0.01	0.00
Land owned, hectacres	0.08	0.05	0.03	0.02	0.01	0.04	-0.01
HH members per room	2.35	2.15	2.04	2.17	2.11	2.16	-0.01
HH uses domestic help	0.00	0.00	0.01	0.02	0.06	0.02	0.02
HH owns land	0.08	0.08	0.04	0.03	0.03	0.05	-0.01

Source: own elaboration using Nigeria GHS panel data

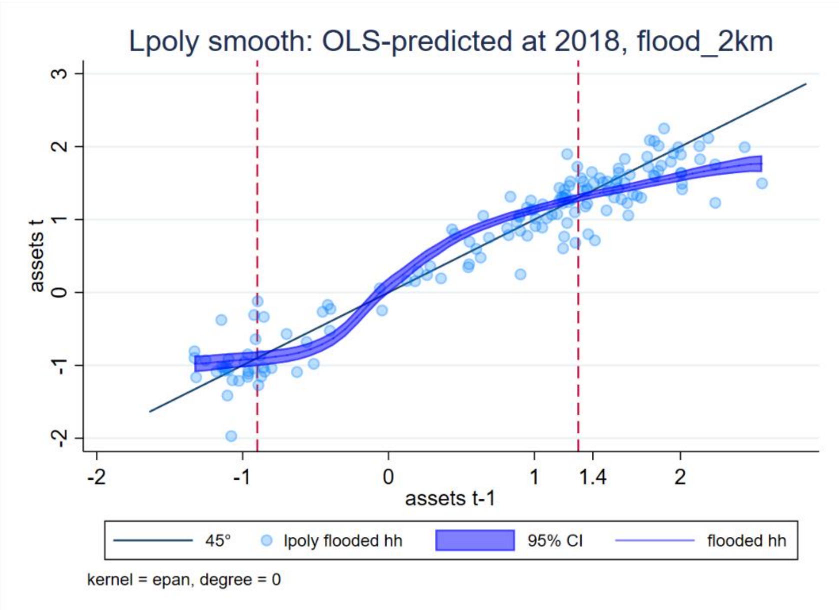
A.2

Figure A 1: OLS-predicted asset change from wave 1 - wave 3, flooded sample (2km buffer)



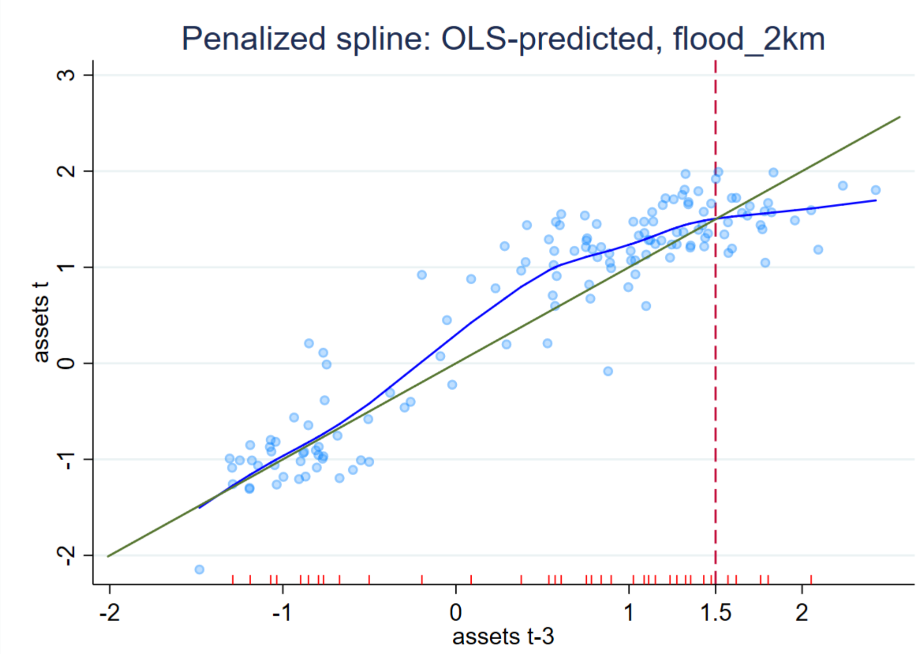
Source: own elaboration using Nigeria GHS panel data.

Figure A 2: OLS-predicted asset change from wave 3-wave 4, flooded sample (2km buffer)



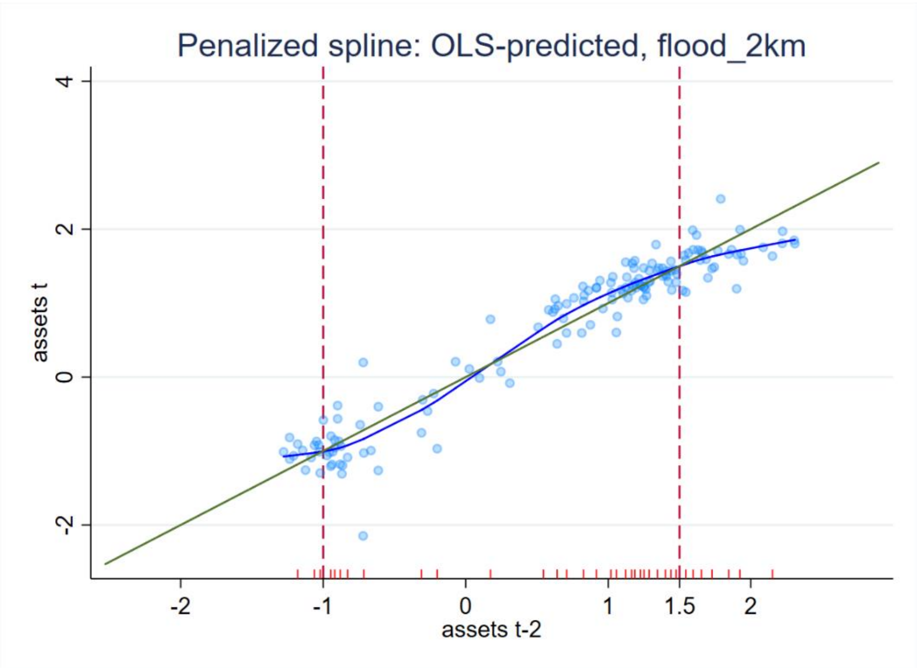
Source: own elaboration using Nigeria GHS panel data.

Figure A 3: OLS-predicted asset change w1-w4. Penalized spline, flooded with 2km



Source: own elaboration using Nigeria GHS panel data

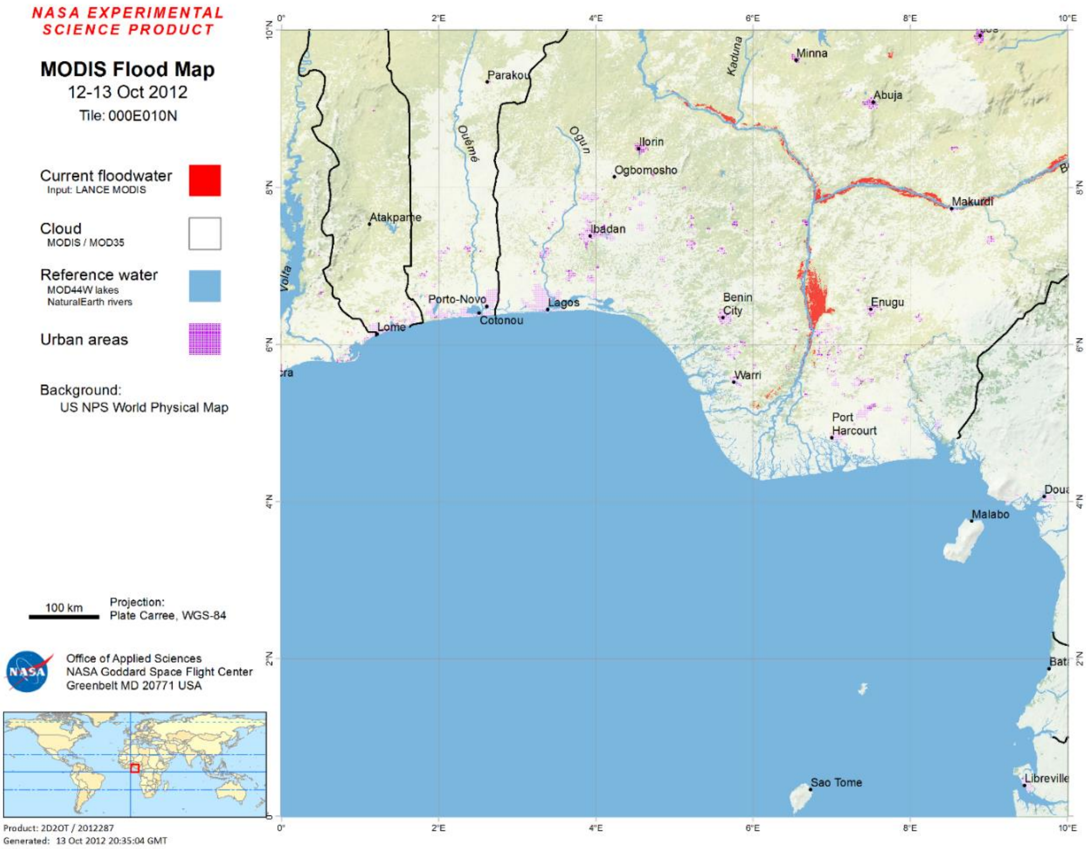
Figure A 4: OLS-predicted asset change w2-w4. Penalized spline, flooded with 2km



Source: own elaboration using Nigeria GHS panel data

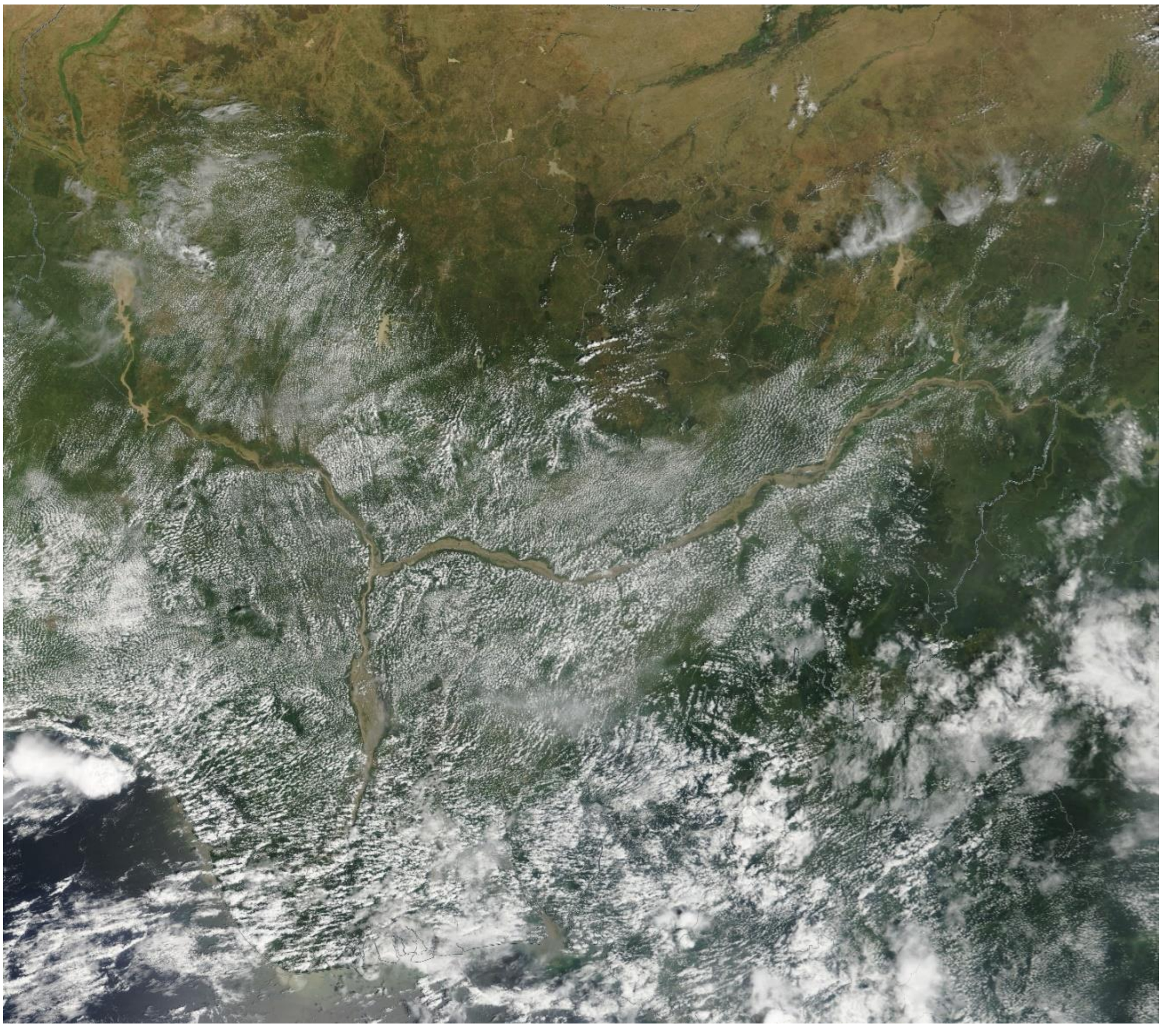
A.3

Figure A 5: 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 6: Terra MODIS True Color Corrected Reflectance snapshot 13 October 2012



Accessed from Earthdata.nasa.gov