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 code Q540; O120

Introduction

Worldwide extreme poverty persists despite recent improvements, yet COVID-19 is expected to push 68-100 million people in extreme poverty (Mahler et al., 2020; Valensisi, 2020). This situation is further aggravated by climate change which increases the frequency of extreme weather hazards. The poor, disproportionately exposed, lack the means to cope with large shocks, and traditional and informal insurance mechanisms fail when shocks hit communities simultaneously.

The aim of this paper is to study the relationship of climate shocks and poverty persistence within the framework of poverty traps. The medium-term consequences of an extreme weather shock can be different for households depending on their initial assets. Households starting with lower asset levels risk falling below the threshold and remain trapped there, while better-off households might suffer temporary drawbacks but recover in time (Carter et al., 2007). 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?

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, which suffered in 2012 the worst flood in 40 years, with almost 4 million people displaced. 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 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, despite sustained GDP growth[1]. 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 needs to combine different assets' ownership information to better represent wealth. For this reason, different asset aggregation methods are examined.

Theoretical Framework

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.

[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).

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

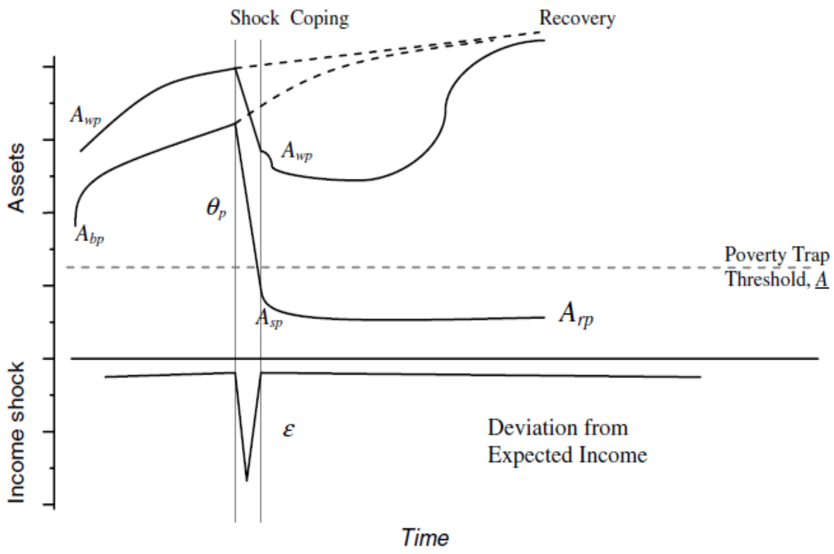


Figure 1. *Asset shocks and poverty traps.*

Source: Carter et al., 2007

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). 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 on Methodology). Cases where poverty traps have not been identified are linked both to the absence of such traps and to data and methodological issues.

Climate change brings about large alterations in the form of both extreme climate events 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, 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 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 (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 (for instance Amare et al., 2018; De Laubier-Longuet Marx et al., 2019; Ngoma et al., 2019). 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 the poor are disproportionately exposed to both drought and flood. Concerning flood risk, urban areas are the riskiest (Winsemius et al., 2018). 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).

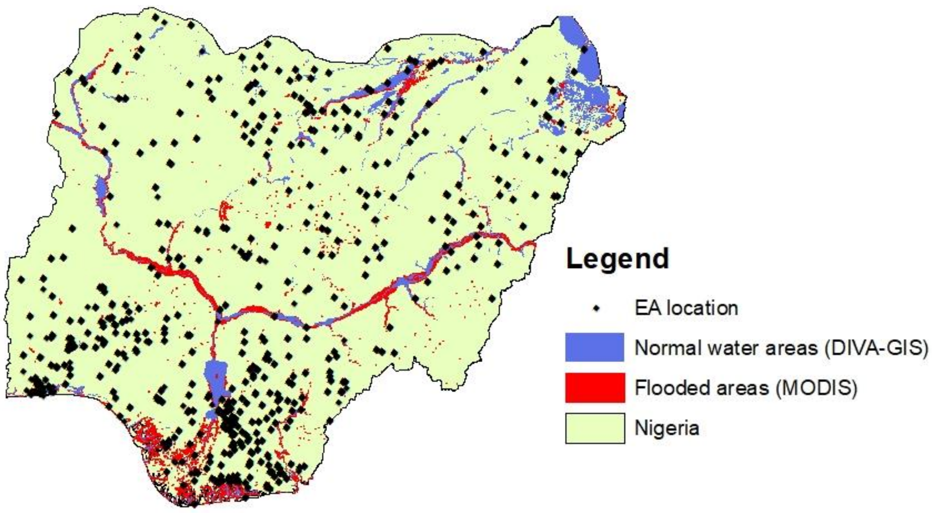
Methodology

Some methodological choices are needed to identify the relevant groups (flooded and non-flooded) and define a wealth index.

I identify flooded areas with satellite image data from NASA's MODIS Near Real Time Floodmap products or the period 11 September - 3 November (Figure 1). 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. 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. 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. 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. 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 2 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.

Figure 2: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)

To represent household wealth, I build an 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 & 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 & Barrett, 2006). I followed DHS' methodology to create a comprehensive asset index (Rutstein, 2015) using information on households' durables, agricultural tools, livestock, dwelling characteristics, land owned, aggregated with principal components extraction (Sahn & Stifel, 2003, 2000),. The asset index is calculated on the pooled sample (McKay and Perge, 2013; Naschold, 2013, 2012).

Testing empirically for a poverty trap is no easy task. In the literature, different methods have been used: 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 (Adato et al., 2006; Barrett et al., 2006; Lybbert et al., 2004). The relationship estimated can be seen in Equation 1:

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

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 is estimated with local polynomial regression. To allow for covariates, complementary parametric approaches are needed, modelling non-linearities with polynomials of lagged assets (Giesbert & Schindler, 2012; McKay & Perge, 2013; Naschold, 2013). In equation 2,

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

the 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. Both have their drawbacks but combined they can provide useful insights. I further test for convergence and look at post-shock growth with a panel threshold model, which is able to identify structural breaks in panel data (Carter et al., 2007; Hansen, 2000; Wang, 2015). It can be tested whether below-threshold households have the same asset patters as above-threshold households, as follows (equation 3):

$$g_i = \begin{cases} \beta_A^{\ell} A_{it-1} + \beta_Z^{\ell} \mathrm{Z}_i + v_i^{\ell} & \text{if } A_{it-1} < \gamma \\ \beta_A^{u} A_{it-1} + \beta_Z^{u} \mathrm{Z}_i + v_i^{u} & \text{otherwise,} \end{cases} \tag{3}$$

here 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. Then it can be tested whether below-threshold households have the same asset patters as above-threshold households. I provide comparisons for the flooded and non-flooded samples for different subperiods.

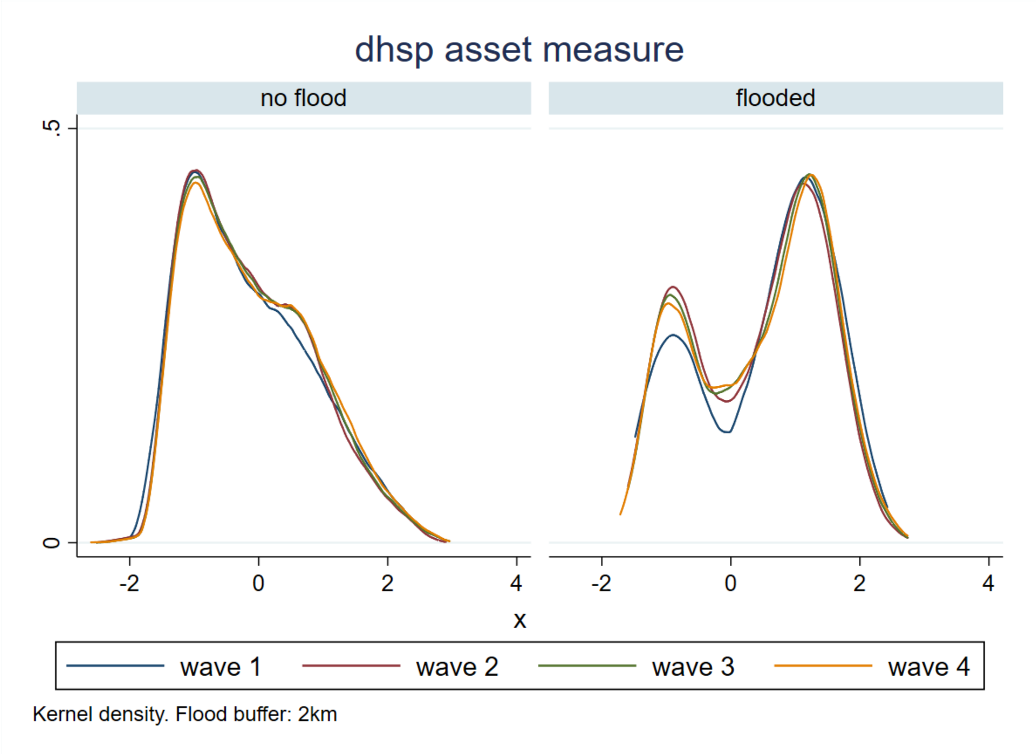
Data

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 a probability proportional to the size of the EA. In each of these, 10 households were randomly chosen. Due to nonresponse, 4,851 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%.

Descriptive statistics

Figure 3 represents the distribution of the asset measure, split by flood occurrence. The flooded sample has a distribution with two peaks, giving a first clue about the presence of more equilibria.

Figure 3: Kernel density of asset index by flood, all waves



Source: own elaboration using Nigeria GHS panel data

Table 1 reports the T-test of some key variables for the sample pre-shock (wave 1) for flooded and non-flooded households[2]. 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 and are more likely to be involved in non-farm employment.

[2] The weights are not applied here.

Table 1: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
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 (Table 2), 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 2: 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

Results

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 (Table 3). The estimator is a OLS model. Lagged asset are modelled also with the squared, third and the fourth degree terms[3] (Barrett et al., 2006; Giesbert & Schindler, 2012; McKay & Perge, 2013; Naschold, 2012, 2013). 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 and its interactions with some of the variables mentioned above. Table 3 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)[4]. 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 3 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 $\beta_{2\text{-}4}$ 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.

[3] 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.

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

Table 3: 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 4 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).

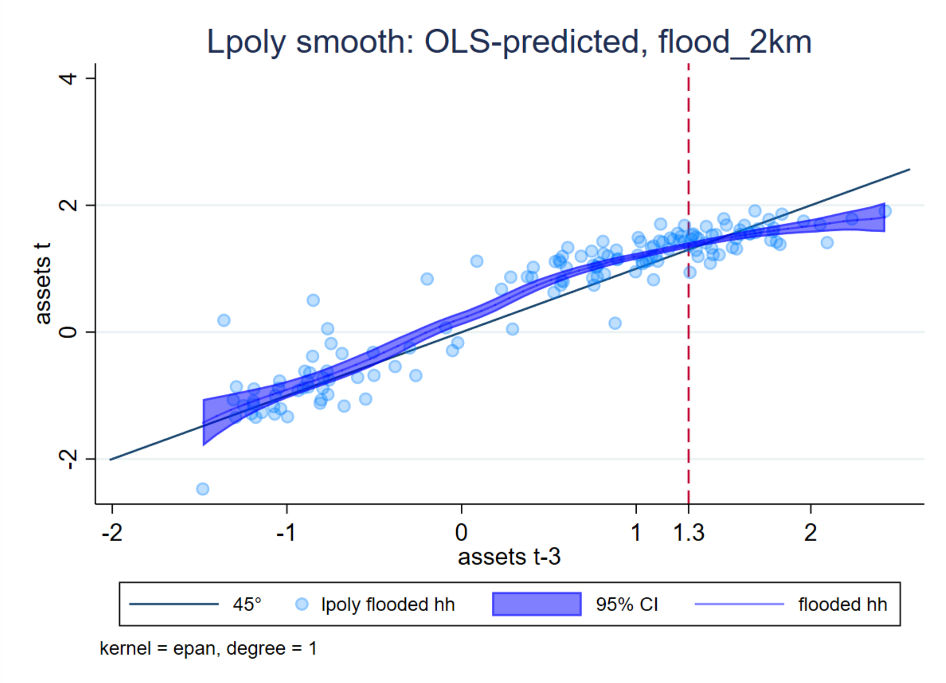
Table 4: Parametric regression, other time differences, OLS

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

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

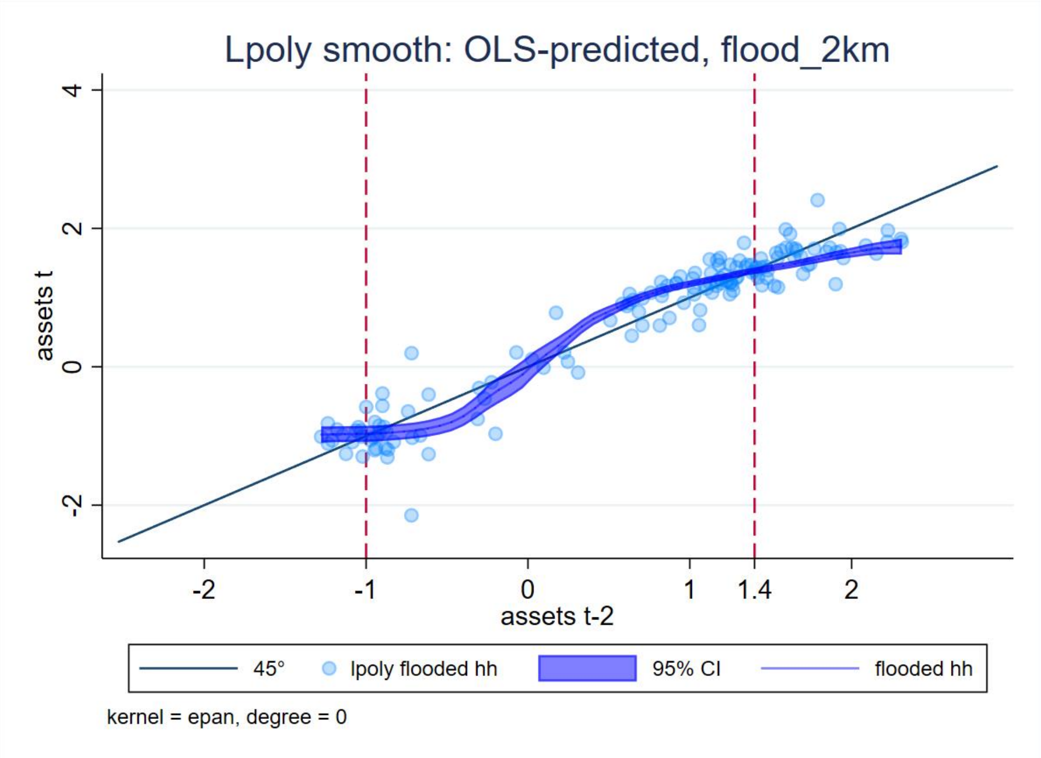
Predicting the dependent and using it for nonparametric regression shows how flooded households indeed have three equilibria, of which one is the poverty trap. The asset recursion function for flooded households has the usual S shape of poverty traps (see in Figures 4 the pre-shock patterns, with only one equilibrium, and in Figure 5 the post-shock patterns, with three equilibria). In the case of Figure 4, 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 5) 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. Further periods’ local polynomial regressions (not reported) confirm the creation of a poverty trap at -1 after the shock, 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). In the latter case, convergence is confirmed. Non-flooded households, on the contrary, have a flat curve and only converge to a high equilibrium (Figures 6 and 7).

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



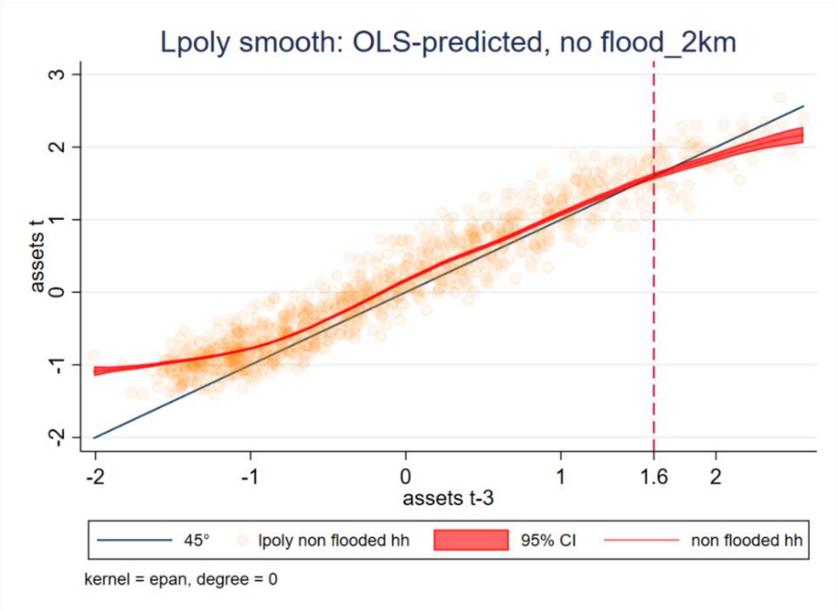
Source: own elaboration using Nigeria GHS panel data.

Figure 5: OLS-predicted asset change from wave 2-wave 4, flooded sample (2km buffer)



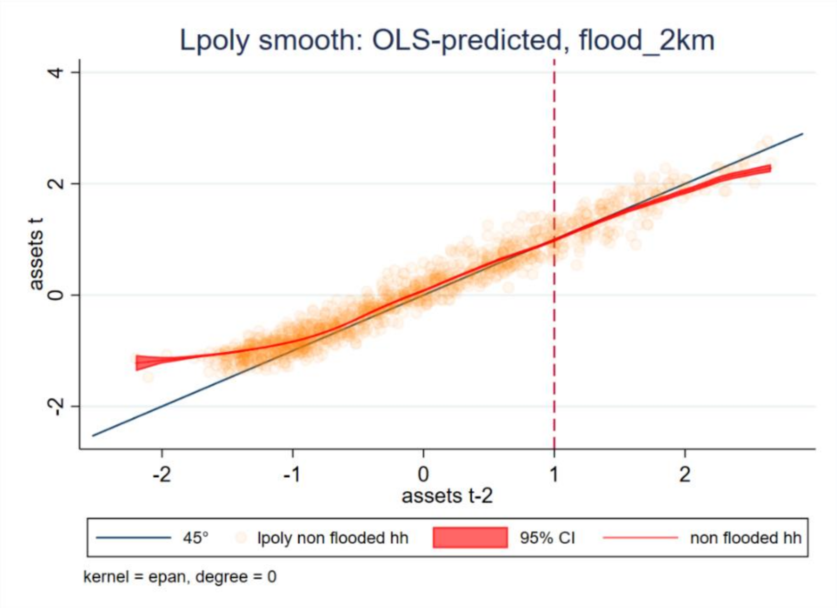
Source: own elaboration using Nigeria GHS panel data.

Figure 6: OLS-predicted asset change from wave 1-wave 4, non-flooded sample



Source: own elaboration using Nigeria GHS panel data.

Figure 7: OLS-predicted asset change from wave 2-wave 4, non-flooded sample



Source: own elaboration using Nigeria GHS panel data.

Panel threshold estimations (Hansen, 2000; Wang, 2015) confirm the existence of a mildly significant threshold among flooded households using one lag and the 5-km buffer (Table 5). 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[5]. Adding controls to the threshold regression yields a slightly lower threshold but still significant.

[5] A second non-significant threshold is identified at 1.6236, which also reminds us of the non-parametric high equilibrium.

Table 5: 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

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 (Table 6). 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. 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). All these findings provide empirical evidence for the creation of a poverty trap after the flood (Carter et al., 2007).

Table 6: 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*** (0.077)	-0.233*** (0.047)		
L.assets			-0.943*** (0.163)	-0.183*** (0.040)
age head of hh	0.016 (0.015)	0.022 (0.015)	-0.038** (0.019)	0.021 (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* (0.009)	0.020* (0.011)	0.016* (0.008)	0.016 (0.010)
Head is female widow	-0.149* (0.085)	-0.126* (0.074)	-0.124 (0.110)	-0.040 (0.067)
HH Distance in (KMs) to Nearest Market	-0.002 (0.001)	0.000 (0.001)	0.001 (0.002)	-0.000 (0.001)
HH Distance in (KMs) to Nearest Population Center with +20,000	0.003* (0.002)	0.001 (0.002)	0.000 (0.002)	0.001 (0.001)
Available arable communal land	-0.402*** (0.100)	-0.333*** (0.113)	-0.023 (0.124)	-0.274** (0.107)
Rural dummy	0.031 (0.134)	0.031 (0.087)	-0.692* (0.368)	0.001 (0.077)
HH cultivates crops/trees	-0.195* (0.099)	-0.117 (0.076)		
Total livestock owned, tlu	-0.034** (0.016)	0.004 (0.011)	-0.019 (0.013)	0.009 (0.010)
HH suffered income shock past 2yrs	0.010 (0.067)	-0.133** (0.061)	-0.094 (0.077)	-0.155*** (0.055)
Shock: dwelling damaged past 2yrs	-0.096 (0.249)	-0.164 (0.356)	0.220 (0.306)	-0.273 (0.315)
Crop loss: climate, pest, violence	0.059 (0.095)	-0.128 (0.129)	0.203** (0.097)	-0.208* (0.119)
HH receives remittances	0.162** (0.075)	0.067 (0.065)	0.201** (0.095)	0.099* (0.058)
HH received assistance	-0.183 (0.111)	-0.137 (0.119)	-0.036 (0.133)	-0.063 (0.111)
HH has borrowed	-0.074 (0.081)	0.002 (0.076)	-0.123 (0.083)	-0.007 (0.068)
Community hires agric labourers	0.209** (0.098)	0.070 (0.077)	0.211 (0.186)	-0.053 (0.070)
L2.jobnfexist	-0.040 (0.082)	0.171** (0.086)	0.122 (0.091)	0.143* (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

Finally, coping with a shock is highly dependent on which strategies the households can adopt. Extending the parametric regression to a series of binary variables (Table 7) shows some interesting correlations: non-farm wage (negative but not significant), remittances (positive and significant), borrowing (negative and significant) and assistance programmes participation (mixed sign, not significant).

Table 7: 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).

Robustness checks

Some robustness checks are carried out: the variation of the buffer for flood definition, using alternative asset measures, controlling for conflict and violence escalation. Going beyond the dichotomic flood variable, a measure of flood intensity is created to count the maximum times the buffer's polygons are flooded. 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. 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). These validate these findings and improve the identification of the flood-affected households.

Using a different asset aggregation method (polychoric PCA) does not alter the main results (Table 8).

Table 8: 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 9.

Table 9: 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.

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[6]) (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 & Rocca, 2021) and it is modelled with 3 lags, to account for the evolution of conflict (Table 10). 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 10: 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[7].

Discussion and Conclusion

Most studies on poverty traps have concentrated on more homogeneous settings; Nigeria is a more complex and heterogeneous case, which requires nontrivial asset aggregation. 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 along the distribution of wealth.

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

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

In order to determine whether the 2012 major flooding event created a poverty trap in Nigeria, this analysis used a combination of methods: the bivariate nonparametric regression, the parametric regressions and panel threshold model. The identification of a thresholds 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. 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, as well as investing in infrastructure to reduce the impact of future floods.

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