NIGERIA

IFPRI

STRATEGY SUPPORT PROGRAM| WORKING PAPER

JULY 2023

Anticipatory cash transfer for climate resilience: Evidence from northeast Nigeria

Bedru Balana, Dolapo Adeyanju, Clare Clingain, Kwaw S. Andam, Alan de Brauw,

Ishaku Yohanna, Olukunbi Olarewaju, and Molly Schneider

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
IFPRI

INTERNATIONAL RESCUE COMMITTEE

NiMet
Nigerian Meteorological Agency

UPPER BENUE RIVER BASIN DEVELOPMENT AUTHORITY

CENTRE FOR DISASTER PROTECTION

CONTENTS

TABLES

FIGURES

ACRONYMS/ABBREVIATIONS

CSI	Coping Strategy Index
FCS	Food Consumption Score
HH	Household
ICT	Information and Communication Technology
ID	Identification
IFPRI	International Food Policy Research Institute
IRC	International Rescue Committee
LCSI	Livelihood Coping Strategy Index
LGA	Local Government Area
LR	Likelihood Ratio
NEMA	National Emergency Management Agency
NiHSA	Nigeria Hydrological Service Agency
NiMET	Nigeria Meteorological Agency
NPC	National Population Commission
OLS	Ordinary Least Square
PAP	Pre-Analysis Plan
PCA	Principal Component Analysis
RCT	Randomized Control Trial
rCSI	Reduced Coping Strategy Index
SEMA	State Emergency Management Agency
TLU	Tropical Livestock Units
UBBDA	Upper Benue Basin Development Authority
UNDRR	United Nations Office for Disaster Risk Reduction
UNOCHA	United Nation's Office for the Coordination of Humanitarian Affairs
USD	United States Dollar
WI	Wealth Index

ABSTRACT

This paper presents the findings from an experimental study designed to assess the impacts of one-off large lump sum cash transfers on food security, climate adaptive actions, and climate resilience of smallholders in climate-risk and conflict-affected communities in northeast Nigeria. This pilot intervention was supported by Google.org and implemented by the International Rescue Committee (IRC) in collaboration with the international Food Policy Research Institute (IFPRI). The central hypothesis of the intervention was that when climate vulnerable communities have timely access to information and the financial and social resources to act upon that information, they will avoid negative coping strategies and build more diversified and climate resilient livelihoods. A one-off lump sum of anticipatory cash was transferred to a randomly sampled treatment households in flood-prone areas in northeast Nigeria when triggered by the climate data risk thresholds. Comparable households in a control group received an equal amount of cash post-flooding shock. The main purpose of the study was to assess the impacts of anticipatory cash against the traditional humanitarian post-shocks supporting mechanism. We collected baseline and endline data from a sample of 1450 experimental households (725 'treatment' and 725 'control') and analyzed the data using econometric models. Several outcome indicators including food security, climate adaptive and resilience actions, and wellbeing measures were used to assess the intervention. The results indicate that anticipatory cash has significant impacts on increasing the number of pre-emptive climate adaptive actions and enhancing future resilience to climate shocks. On other hand, anticipatory cash transfers do not seem to have significant impacts on short-term food and non-food consumption expenditures compared to post-shock cash transfers. Our findings indicate that one-off large sum anticipatory transfer could lead households to build their climate resilience capacity, and hence a promising intervention to reduce the vulnerability of households to future climate shocks. Based on the findings we have two key recommendations: (1) Given the generally positive findings on household's climate adaptive and climate resilience capacity, we suggest humanitarian agencies and governments to consider anticipatory interventions such as anticipatory cash transfers as a mechanism for both meeting basic needs and improving climate resilience of households if quality data and analytics exist to predict a high probability of climate shocks. (2) As climate shocks continue to worsen and humanitarian funding needs remain unmet for both emergencies and early recovery, anticipatory approach may be critical to meeting the short- and long-term needs of climate- and conflict-affected households.

Keywords: Anticipatory cash, Coping strategies, Climate resilience, Flooding, Smallholders

***JEL**. D06, H43, H48, I31, Q54*

1. INTRODUCTION

The rising frequency and intensity of climate variability and extreme weather events including unpredictable rainfall and temperature, flooding, and drought threaten food production, livelihoods, and food security of farm households in sub-Saharan Africa (Di Falco et al., 2011; Di Falco and Veronesi, 2013; Hasegawa et al., 2015; Chonabayashi et al., 2020; Kuang et al., 2020; Tesfaye and Tirivayi, 2020). According to the United Nations Office for Disaster Risk Reduction (2021), frequent and intense floods, droughts and storms account for up to 90 percent of natural hazards worldwide. The climate crisis is intersecting with and compounding other drivers of severe food crisis, including conflict and economic downturns. Climate change has become the primary factor affecting agricultural productivity and is deeply intertwined with food crises in the world (Nyathi et al., 2022). The negative impacts of climate variability and change are felt more in developing countries like Nigeria than the developed world due to limited coping strategies available to poorer populations (Adekola and Lamond 2018; Akinloye 2018) and 'adaptation deficits'[1]to climatic shocks (Calzadilla et al., 2013; Fankhauser and McDermott, 2014; Asfaw et al., 2018). Poorer households with fewer livelihood assets, limited coping strategies, and dependent on climate sensitive economic activities such as subsistence farming are highly vulnerable to climatic shocks (Calzadilla et al., 2013; Fankhauser and McDermott, 2014; Gitz et al., 2016; Asfaw et al., 2018; Clarke et al., 2022).

Nigeria is highly vulnerable to climate-related shocks and ranks high among the countries that are susceptible to climate change (Ebele and Emodi, 2016; Elias and Omojola, 2015). Many states in the country increasingly suffer perennial flooding (Echendu, 2020; 2021), especially during the rainy season which occurs between March and November annually. In 2012, Nigeria experienced one of its largest floods in a century, causing the displacement of over 2.3 million people, 363 deaths, and impacted the livelihoods of over 16 million people (Adekola and Lamond, 2018; Adelekan and Asiyanbi, 2016; Boamah et al., 2015). Total economic losses were estimated at US$16.9 billion (Tiwari and Tiwari, 2015). Several studies show that annual flooding has led to more displacements than any other climate disaster in Nigeria (Boamah et al., 2015; Echendu, 2021; Tiwari and Tiwari, 2015; United Nation's Office for the Coordination of Humanitarian Affairs (UNOCHA), 2022a).

The situation is particularly severe in northeast states of Nigeria that have experienced decades of climatic shocks, insecurity, and consequent humanitarian crises (Madu, 2016; Federal Ministry of Environment, 2014; Hassan et al., 2019; Kamta et al., 2020). In recent years, the frequency of flooding in the northeastern states Adamawa, Borno, and Yobe has shown significant increases. In 2019, these states faced the worst floods in seven years, which affected over 300,000 people and had casualties five times more than those reported in previous years (UNOCHA, 2020). More recently, the flooding incidence that followed the 2022 rainy season led to loss of life, injuries, and damage to infrastructure, property, and agricultural land thereby

[1] Adaptation is generally described as those responses by individuals, groups and governments to climatic change or other stimuli that are used to reduce their vulnerability or susceptibility to adverse impacts (Bradshaw et al., 2004). Adaptation deficit entails a situation in which a country experiences a lack of institutional, economic, and technological means to facilitate the adaptation process (Asfaw et al., 2018).

impacting livelihoods and food security (UNOCHA, 2022). A study on the effects of recent flooding in Nigeria shows that Adamawa state is among the most affected states with an estimated 260,000 people exposed to floods and around a 1,000 km^2 of land submerged across the state (REACH Initiative, 2022). This is attributed to heavy rainfalls (average of above 2000 mm and can reach 4000 mm in southern Nigeria) between the months of July and October 2022 (as compared to the overall annual average of 1000 mm) that caused an overflow of the Lagdo dam in neighboring Cameroon and increased flow of the Benue River. Besides climate variability, protracted and frequent violent conflicts including the Boko Haram insurgence and herder-farmer conflicts further disrupt agricultural activities and food supply chains that worsen food insecurity and malnutrition (Obi and Eboreime, 2017; Baliki et al., 2018; Adelaja and George, 2019).

As climate shocks have become increasingly prevalent, governments and humanitarian organizations have stepped in to provide time-bound support to those worst affected. This support can take the form of food aid, temporary shelter, or basic services, but increasingly, support is provided in the form of one-off cash transfers (Dietrich and Schmerzeck, 2019; Ferraro and Simorangkir, 2020; Pople et al., 2021). However, most humanitarian aids largely focus on responding to post-shock crises (Nobre et al., 2019; Pichon, 2019; Levine et al., 2020). This has raised a need for early/anticipatory actions to improve household preparedness and limit the devastating long-term impacts of climate shocks. If targeted properly, anticipatory actions can potentially help households to better prepare and respond to climate shocks, reduce vulnerability, and increase household resilience to shock (de Perez et al. 2015, Gros et al. 2022).

Findings from few existing studies indicate the positive impacts of anticipatory actions on various household level outcomes. Examples include a simulation-based study of anticipatory interventions on household level outcomes (Giuffrida et al., 2017); evaluation of the costs, benefits and returns on investment of ex-ante actions compared to ex-post responses (Gros et al., 2019; Nobre et al., 2019); and assessments of the impacts of anticipatory cash transfers on household welfare (Gros et al., 2019; Tanner et al., 2019; Hill et al., 2019; People et al., 2021). However, most of the existing studies on the benefits or impacts of anticipatory actions are based on either observational or quasi-experimental data (Levine et al., 2020; Pople et al., 2021). There is limited randomized experimental evaluations of the impact of anticipatory cash transfers in response to forecast based climatic shocks in the humanitarian sector (Puri et al., 2017; Levine et al., 2020; Pople et al., 2021). We attribute this dearth of empirical evidence to various factors. First, it is difficult to justify the ethics of a randomized control trial in life-or-death situations. Second, the need for speed with the lack of transparency in implementation obfuscates the identification of a valid counterfactual. Third, it is challenging to conduct a baseline when it is unknown a priori where a disaster will strike, particularly since disasters ex-post disrupt the supply of basic services and infrastructure, including those needed for data collection. As a result, little is known on the impacts of cash transfers beyond the immediate consumption support they provide, and how their impact is affected by their timing and targeting (Pople et al., 2021).

We study the differential impacts of anticipatory vs. post-shock one-off lump sum cash transfers for a fast onset climate shock (flooding) by randomly assigning the eligible population in anticipatory and post-shock cash transfer treatment groups. Thus, recipients of post-shock cash transfers are considered as ‘controls’ against the anticipatory cash recipients ‘treatment’ group. Our present study thus has several distinguishing features compared to past studies: (1) Data has come from a randomized experiment against observational or quasi-experimental studies such as that of Pople et al. (2021) where the identification strategy was based on exogenous variations in administrative constraints. (2) We collected data through in-person surveys compared to phone interviews. In-person surveys improve data quality and enable the collection of more detailed information than phone interviews. (3) Unlike past studies that considered only a few welfare indicators (Gros et al, 2019) or the cost-effectiveness of ex-ante actions (Nobre et al., 2019), our study included several measures of welfare including the short-term food consumption score (FCS), reduced coping strategy index (rCSI), livelihood coping strategy index (LCSI), and wellbeing indicators. (4) With the exception of Pople et al. (2021), many studies had imbalanced counterfactuals and used relatively small sample sizes. Our study is based on a balanced counterfactual and a relatively large sample size of 1450 study households.

The main objective of this study was to evaluate the welfare and other household level impacts of this anticipatory cash transfers against the conventional post-shock approach of cash transfers. Based on the balance test, our samples are well balanced across the pre- and post-shock groups, showing that the two groups are comparable across major socio-demographic variables measured at the baseline. Thus, our research design enables us to generate valid counterfactuals to assess anticipatory cash transfer as against post-shock cash. To the best of our knowledge, the present cash transfer intervention design is the first of its kind in cash transfer experimental design implemented in a conflict-prone environment that combined an anticipatory action with a conventional post-shock humanitarian response.

The remaining parts of the paper are organized as follows. Section 2 provides the description of ‘cash for climate resilience’ intervention. The study methods including research design, data collection and econometric strategies are presented in section 3. Sections 4 and 5 respectively present descriptive and econometric results. The last section concludes the paper with some policy recommendations.

2. CASH FOR CLIMATE RESILIENCE INTERVENTION

The International Rescue Committee’s (IRC) global mission is to help people whose lives and livelihoods are shattered by conflict and disaster, including the climate crisis, to survive, recover and gain control of their future. The IRC and Google.org have formed a partnership in Nigeria to catalyze a transformation in humanitarian preparedness and response to complex climate crises, investing in foundational innovations to create new products and services, as well as research to understand what works. This partnership is expected to advance innovations in responding to climate change induced risks for conflict- and crisis-affected people by integrating predictive analytics with cash assistance that will result in improved coping strategies, increased capacity for decision making, and more diversified and profitable livelihoods. The goals of the intervention project include:

1. **Intervention**: To reduce the use of negative coping strategies and support households to build resilience against climate shocks by providing climate risk reduction transfer and early warning messaging to smallholder farmers.

2. **Research**: To assess the effectiveness of use of early warning systems and impacts of anticipatory cash transfers versus post-shock cash transfers to mitigate the level of shock and stress experienced by smallholder farmers in the event of a hazardous climatic event.

3. **Expected outcome**: Households reduce the use of negative coping strategies, improve food security and income, and build resilience to climatic shocks.

The IRC's central hypothesis is that when climate vulnerable communities have timely access to information and the financial and social resources to act upon that information, they will avoid negative coping strategies and build more diversified and climate resilient livelihoods. Community members are acutely aware of how their environment is changing due to climate change, and these communities are rich with knowledge on climate change adaptation and mitigation measures. However, resource constrained communities lack effective systems to disseminate real-time information about climate risks and their potential severity and many households in resource constrained environments do not possess the financial means to implement adaptive or mitigation measures that would allow them to protect or adapt their livelihoods during a stress and/or shock. This is especially true in conflict-affected communities, where a lack of social cohesion and inter-community economic linkages can exacerbate vulnerabilities.

To test this hypothesis, the IRC piloted the climate risk reduction transfer in Adamawa state in northeast Nigeria with smallholder farmers and livestock owners. The project adopted a systems approach, working within and with the existing ICT systems (radio, SMS, voice, mobile, etc.), agriculture extension providers, and other key stakeholders within the government and community. The pilot project transferred a lump sum of anticipatory cash transfer to a sample of 725 flood-prone households when triggered by the climate data platform risk thresholds. As controls to this anticipatory cash transfer, an equal number of comparable households ('control group') received equal amount of cash transfer post flooding shock. All households received early warning messages prior to the floods through community-based early warning workers. The pilot intervention/study focused on flooding because it is a predictable climatic shock with available well-established prediction data compared to other climate shocks.

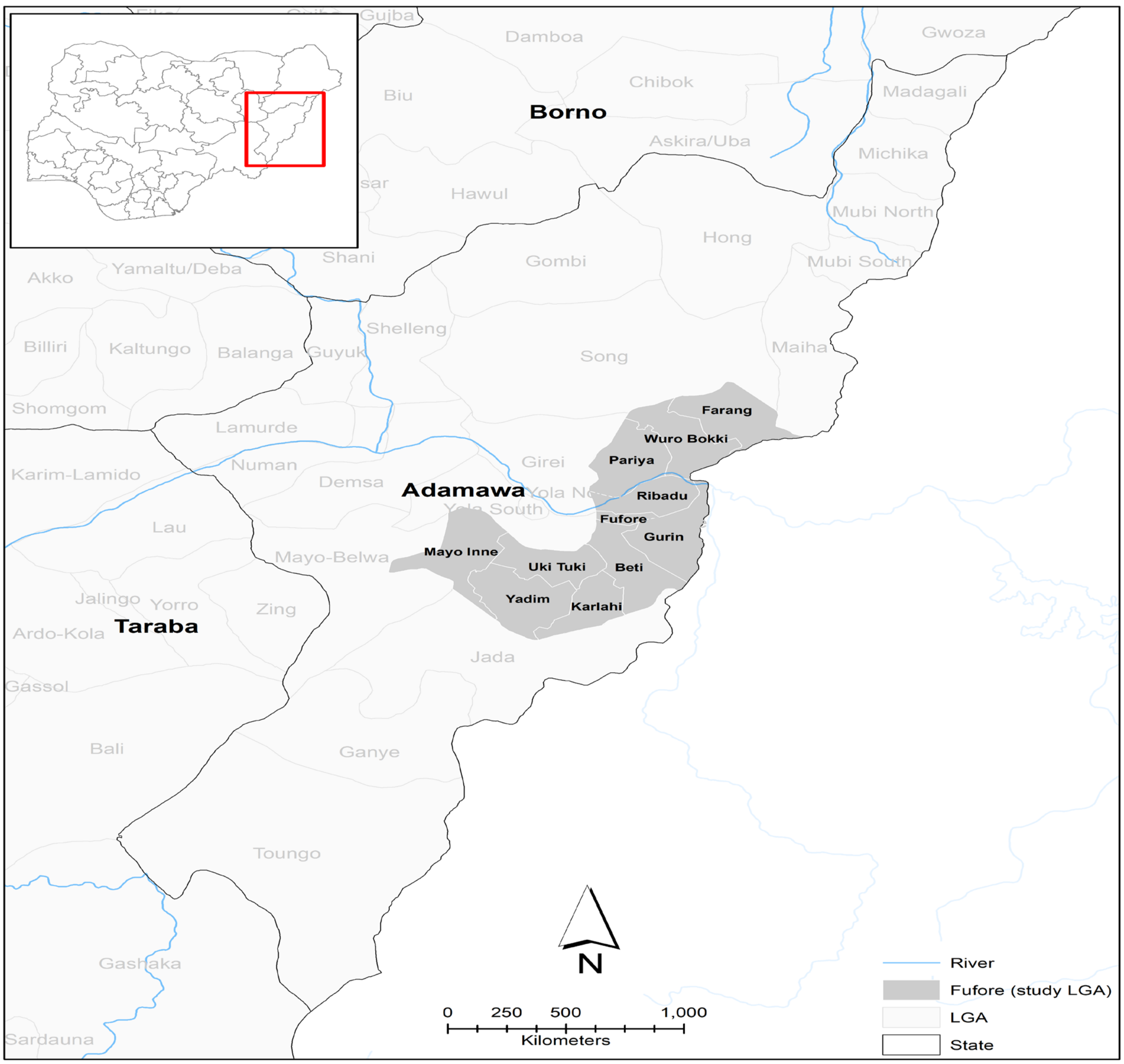
3. MATERIALS AND METHODS

3.1 The study area

The project was implemented in Fufore Local Government Area (LGA) of Adamawa state, northeast Nigeria situated between latitude 9^0 13^1 North and longitude 12^0 39^1 East (Figure 1). Fufore has a total land area of about 5,169 km^2 with an estimated population of 207,286 inhabitants (National Bureau of Statistics, 2010). The area experiences distinct dry and wet seasons with temperature and humidity varying with season. The wet season is between April and October with an average annual rainfall of 750 to 1000mm. The dry season period is between December and March and characterized by dry, dusty, and hazy northeast trade winds that blow over the area from Sahara Desert. Temperatures are relatively high almost all the year round, reaching about 42^0C during the dry season. The area is drained by a series of rivers and streams such as River Benue which takes its source from Cameroon, River Faro, and Ine., which all encourage arable cropping, livestock rearing, and fishing. The major crops cultivated include millet, rice, beans, soyabean, and sorghum.

Based on flooding severity, six communities situated close to the River Benue floodplain, Faro River and the Ladgo dam in Cameroon were targeted. These communities include Dulobwatiye, Ribado, Dasin_Hausa, Farangfarang, Rico and Gembiusi. Most rural households in Fofure LGA depend on the floodplain along the Upper River Benue for their agricultural production due to water availability during the off-season. Although the floodplains are suitable for cultivation in the off-season, these farmers are exposed to flooding risk in the main rainy season and vulnerable to the impact of climate change. IRC's assessment had identified recurrent flooding as a major hazard due to its impact on the livelihoods of smallholder farmers.

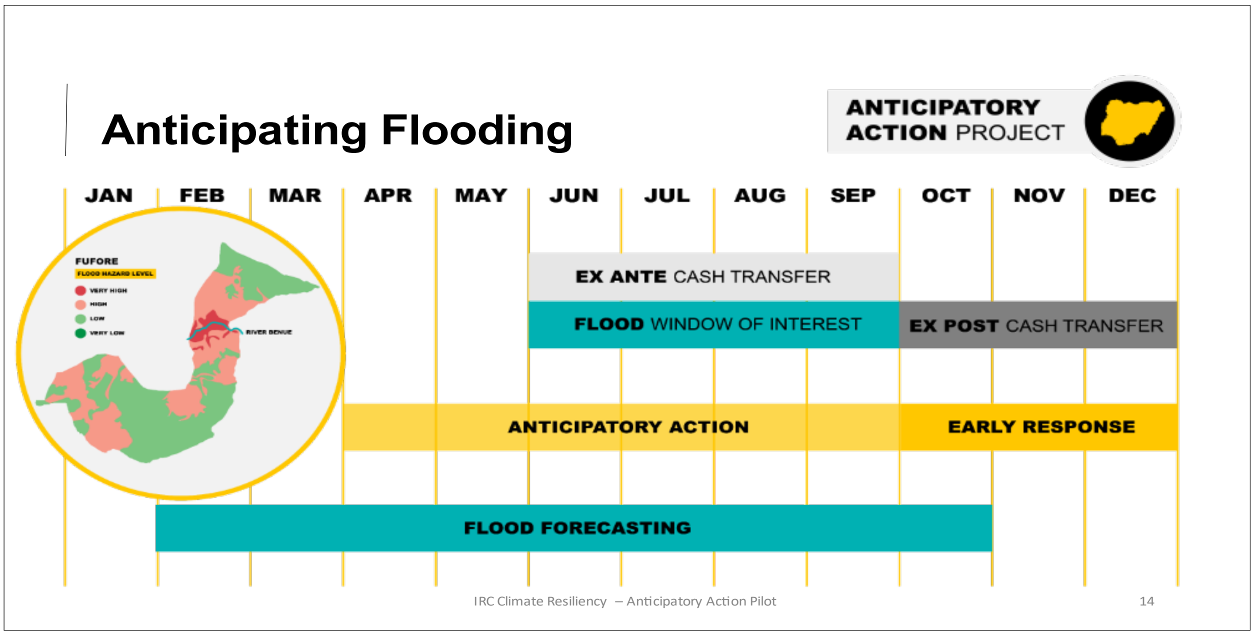
Figure 1. Map of the study area



3.2 Readiness and activation triggers for cash transfer

The IRC collaborated with the Nigeria Hydrological Service Agency (NiHSA), the Nigeria Meteorological Agency (NiMET) and the Upper Benue Basin Development Authority (UBBDA) to set forecast-based thresholds and provide evidence on hydrological and meteorological parameters for triggering anticipatory cash transfer. The collaboration focused on real-time monitoring of water level, discharge, and rainfall, data sharing, and early warning information dissemination to inform anticipatory action. These parameters were selected and monitored from existing gauge stations close to the communities of intervention. The analytics, data, thresholds set for these parameters and detailed descriptions of setting the thresholds are provided in Annex 1.

Figure 2. Flooding calendar (window of interest) and trigger development process



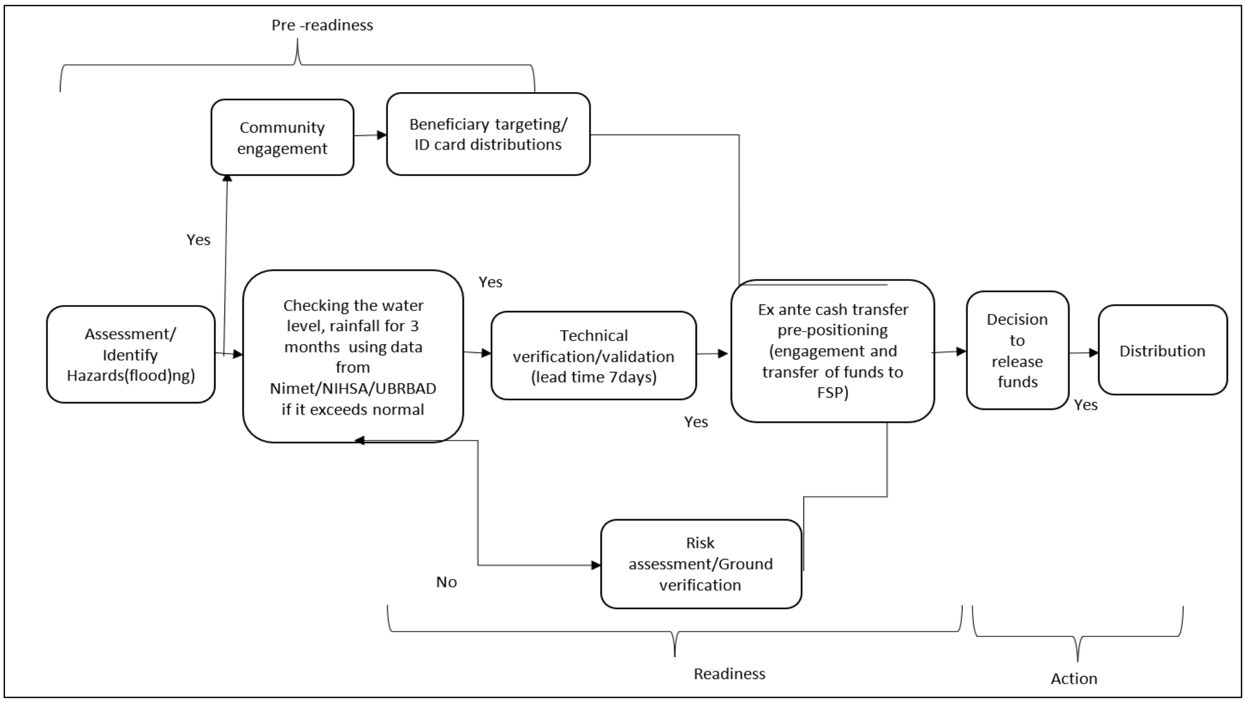
Source: IRC (2022)

The intervention also includes early warning messages by ten trained and experienced community early warning volunteers selected from the National Emergency Management Agency (NEMA), the State Emergency Management Agency (SEMA), Fufore LGA, and community leaders (see Annex 2 for the contents of early warning messages). The volunteers were trained in the warning systems of disaster risk reduction messaging, early action, and climate smart adaptation. This included information on planting early, use of drought resilient crops varieties, and early harvesting.

3.3 Anticipatory and post-shock cash transfer

On 27 July 2022, the IRC provided a pre-shock cash transfer of N195,000 (~400 USD) to 725 households ('treatment group') across the six communities in anticipation of the impending flooding. At the time of the cash distribution, the flash flooding water had cut-off three of the six study communities (Dulobatiye, Farang-Farang and Rico) from accessing to the main transport route. These communities were no longer accessible by vehicle or motorbike, leaving wooden boat as the alternative means of transport. Figure 4 presents the schematic processes through which forecast-based anticipatory cash distribution decisions were made and implemented. An equal number of households i.e., 725 randomly assigned households ('control group') received same cash transfer on 7 November 2022 after the flood receded and access was manageable.

Figure 3. Decisions and implementation process of anticipatory cash transfer



Source: IRC (2022)

3.4 Sampling frame and sample selection

To construct a sampling frame from which to select participants for the intervention, the IRC conducted a blanket registration of all households in the six communities identified as the most historically affected by floods and climatic shocks in Fufore LGA. The registration process resulted in 2,095 households eligible for selection. Once the sampling frame was constructed, 1,450 participants were selected using stratified random sampling with proportional allocation by community and gender. The sample function in R statistical software was used to randomly select household IDs with equal probability from the pool of eligible men and women within each community (Table 1).

Table 1. The distribution of sample households (by gender and community)

Gender	Study communities						
	DulloBwatiye	Farangfarang	Rico	Ribado	Gembeusi	Dasin Hausa	Total
Male	81	41	60	238	138	245	803
Female	122	31	13	211	138	132	647
Total	203	72	73	449	276	377	1450

Source: IRC Field Survey (2021)

3.5 Data Collection

Baseline data were collected from the sample of 1450 experimental households before the intervention. Interviews were conducted by ten enumerators conversant with both the English and local Hausa language. Enumerators were provided rigorous face-to-face training on the study design, survey protocol, and research ethics. The endline survey was conducted with the same households five months after the implementation of the baseline survey. The questionnaires for both baseline and endline surveys were pre-tested in a suburb of Yola town that were not part of the study communities. Surveys were conducted in-person and at the end of each survey day, enumerators uploaded the data to the server and senior researchers undertook quality checks. Debriefs were held either at the end of the day or the start of the following day.

Baseline data collection took place over a 17-day period between 25 April and 31 May 2022. Since Ramadan had ended close to when baseline data collection was due to start, the survey was first administered in the majority of Christian communities and to reduce response bias a seven-day recall period was used for food security related questions. Some cross-checking questions were added to capture whether the household had recently been fasting. Similar field planning and survey administration procedures were pursued for the endline data collection administered in December 2022, five months after the baseline survey. A larger pool of enumerators (twenty) was used for endline survey to complete data collection before the 2022 Christmas holiday.

3.6 Outcome measures

The inception document of the IRC/Google.org pilot project identified four major outcome areas to examine the impacts of anticipatory cash transfers (outcome 1- 4 in Table 2). In constructing the indicators of these outcome areas, we follow a pre-analysis plan (PAP) registered in the American Economic Association Registry[2]. We included two additional impact areas, i.e., household aggregates and expenditures on food and non-food consumption, to further assess the effects of anticipatory cash transfers on household assets, consumption, and investment decisions. Annex 3 provides detailed descriptions of the construction of food consumption score (FCS), reduced coping strategies index (rCSI), and livelihood coping strategies index (LCSI).

[2] The pre-analysis plan (PAP) can be accessed here: https://www.socialscienceregistry.org/trials/9652

Table 2. Outcome areas and their indicators

Outcome areas	Indicators
Outcome 1: Increase in climate adaptive actions	• Number of pre-emptive actions adopted. • Household labor re-allocation in response to flooding (including migration) • Number of post-shock actions taken
Outcome 2: Increase in climate resilience	• Livelihood diversification • Productive investment (agricultural assets) • Productive investment (productive livestock)
Outcome 3: Reduction/avoidance of negative coping strategies	• Reduced Coping Strategy Index (rCSI) • Livelihood Coping strategy Index (LCSI)
Outcome 4: Household welfare	• Food consumption score (FCS) • Wellbeing indicator measured using an 11-scale Cantril's ladder of life satisfaction (measure of 'scarcity mindset')
Outcome 5: Household aggregates	• Agricultural income (crop and livestock) • Non-transfer and non-agricultural incomes (from non-farm employment and small businesses) • Number of livestock (in tropical livestock units) • Value of durables household and agricultural assets
Outcome 6: Food vs. non-food consumption	• Expenditure on food • Non-food household expenditure

3.7 Estimation strategy

We specify three empirical models (equations 1 – 3) to examine the impacts of anticipatory cash transfers on various household level outcomes including short-term food consumption, coping strategy indices, asset changes, and wellbeing indicators.

3.7.1 Average treatment effect of anticipatory cash (without controls)

We consider anticipatory cash transfers as a randomized experiment where a sample of 1450 households from the eligible beneficiary population of interest were randomly drawn and the experimental sample is then divided randomly into two groups: (1) the treatment group (anticipatory cash recipients), and (2) the control group (post-shock cash recipients). The unbiased treatment impact can be estimated using a standard linear model as expressed in equation 1.

$$Y_i = \varphi + \beta . preshock_i + \psi_c . v_i + \varepsilon_i \quad \text{-------------------------(1)}$$

where Y_i is the outcome of interest for household i and pre_shock_i is a dummy variable taking a value of 1 if household i received cash before the flooding and zero for post-flood cash recipient households. We control geographic differences across the study communities using fixed effects (ψ_c); v_i is a community dummy taking 1 for each of the five community and zero for the base category (the most remote Farang-farang community); and ε_i is a zero mean error term uncorrelated to the treatment dummy. To correct for heteroskedasticity of the error terms, we estimate robust standard errors. φ is a constant term, β measures the average treatment effect.

3.7.2 Average treatment effect of anticipatory cash (with controls)

In the second specification, we augmented equation 1 by adding observable covariates/controls.

$$Y_i = \varphi + \beta.preshock_i + \gamma.X_i + \psi_c.v_i + \varepsilon_i \quad \text{------------------(2)}$$

where the $Y_i, \varphi, \beta,\ v_i\ and\ \varepsilon_i$ are as described in equation 1; X_i is a vector of controls identified by a LASSO regression[3] to control for observable imbalances across groups and increase precision in our estimates and γ is a vector of coefficients for the controls.

3.7.3 Heterogeneity analysis by wealth index

The impacts of anticipatory cash transfer likely vary by household's wealth status. Asset endowments (land, livestock, and durable household assets) can serve as good proxies for the wealth status of households. Instead of treating each asset category as a separate wealth indicator, we generated a wealth index from these three assets using the method of principal component analysis. We then categorized households into five wealth quintiles. To conduct the heterogeneity analysis, we estimate a fully interacted model (i.e., the wealth index with treatment dummy) using the bottom 20 percent households as the base category as expressed in equation 3.

$$Y_i = \varphi + \beta_1.T_i + \beta_2.WI_{2i} + \beta_3.WI_{2i} * T_i + \beta_4.WI_{3i} + \beta_5.WI_{3i} * T_i + \beta_6.WI_{4i} + \beta_7.WI_{4i} * T_i + \beta_8.WI_{5i} + \beta_9.WI_{5i} * T_i + \gamma.X_i + \psi_c.v_i + \varepsilon_i \quad \text{---(3)}$$

Where $WI_{2i}, WI_{3i,} WI_{4i}\ and\ WI_{5i}$ are the four wealth index quintiles (excluding the bottom wealth quintile as a base category); T_i a treatment dummy (i.e., pre-shock cash); β_1 measures the average effects anticipatory cash; β_2 , β_4, β_6 and β_8 respectively measure the wealth effects for households at the second, third, fourth and fifth wealth quintiles relative to the bottom 20 percent households; and β_3 , β_5, β_7 and β_9 respectively capture the interaction effects of anticipatory cash and wealth for the households in the second, third, fourth and fifth wealth quintiles relative to households in the bottom wealth quintile. Other notations are as explained in Equations 1 and 2.

4 DESCRIPTIVE RESULTS

4.1 Characteristics, flood experience, and balance tests

Table 3 describes the sample and compares the mean value of household characteristics between treatment and control groups across a set of variables including demographics, assets, livelihood activities, and access indicators assessed at the baseline. The balance test results show that households are well balanced across the treatment and control groups. The p-values for tests of equality between the two groups (column 8) are insignificant for all variables, indicating that randomization was successful in creating a good counterfactual.

The mean age of the household head was 45 years and female household heads account for 23 percent of the sample while household heads had about 6 years of formal education, indicating a low level of literacy. The household size, defined as people who live and dine together, was nearly double the 5-person average reported by the National Population Commission (NPC)

[3] LASSO regression was used to identify a set of control variables used in equations 2 and 3.

(2019). The low dependency ratio indicates that there are proportionally more working adults in the household who can support the children and the elderly. Total durable asset owned was valued at approximately[4] ₦152,245 (~332 USD) while households earn an average of ₦241,058 (~526 USD) annually. Agriculture accounts for a larger share of total income, indicating that households are primarily farmers who cultivate an average of 2.89 hectares.

Table 3. Balancing test and descriptive statistics

Variables	Pooled	Post-shock		Pre-shock		Diff	P-value
	Mean	N	mean	N	Mean		
Age of household head	44.97	724	44.87	722	45.06	0.19	0.806
Gender of household head	0.23	724	0.23	724	0.23	0.01	0.803
Education of household head (years)	5.62	722	5.43	721	5.80	0.37	0.173
Household size	9.58	724	9.48	724	9.68	0.20	0.465
Dependency ratio	1.76	724	1.79	724	1.74	-0.05	0.593
Total value of asset	152245	724	155010	724	149899	-5110	0.758
Agric income	202545	724	214863	724	190787	-24075	0.210
Non-agriculture income	38513	724	32308	724	44825	12517	0.143
Total income	241058	724	247171	724	235612	-11559	0.596
Land size (ha)	2.89	724	3.08	724	2.70	-0.38	0.122
Livestock No. (TLU)	1.05	724	1.02	724	1.08	0.06	0.751
Access to Credit (yes)	0.33	724	0.32	724	0.35	0.03	0.241
Access to extension (yes)	0.18	724	0.17	724	0.18	0.01	0.679
Group membership (yes)	0.34	723	0.33	724	0.35	0.01	0.631
Household engage in non-farm activities	0.42	724	0.41	723	0.43	0.02	0.508
Household engage in wage employment	0.01	724	0.01	724	0.01	0.00	0.562
Household engage in self-employment	0.41	724	0.40	724	0.42	0.02	0.488
Walking distance from road (in minutes)	56.01	724	56.43	724	55.40	-1.03	0.665
Food consumption score (FCS)	33.95	723	33.84	724	34.07	0.22	0.793
Reduced coping strategy index (rCSI)	16.28	724	16.49	724	16.08	-0.41	0.368
Flood experience (yes)	0.95	724	0.96	724	0.94	-0.02*	0.095

Notes: Diff. reports the pre-shock mean minus the post-shock mean.
Source: Authors' computation (Field survey, 2022)

Respondents had limited access to credit and extension services, and only about one-third are members of local social groups or associations. This low access to credit services could be attributed to the remoteness of the study areas. Given that the majority of households are farmers, limited access to basic agricultural services may have serious consequences for household productivity and food security. About 42 percent of the households reported they engage in one or more non-farm activities with wage employment accounting for one percent and self-employment for 41 percent. The average walking distance to the nearest motorable road is about 56 minutes. The average food consumption score (FCS) of 33.95 indicates that households fall within the 'borderline' category, i.e., below the acceptable score of 42 points and above. This reflects the prevalence of food insecurity among the sampled households. Similarly, the average reduced coping strategy index (rCSI) of 16.28 for the pooled sample at the baseline indicates that

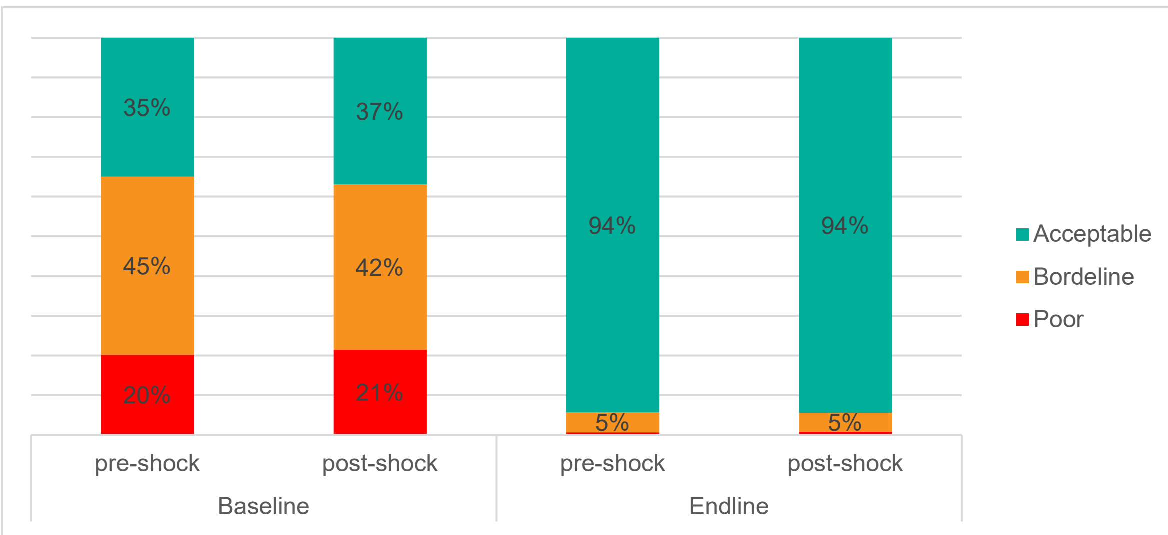
4 The official exchange rate at the time of baseline survey (July 2022) was 1USD = ₦ 417 and during the endline survey (December 2022) 1USD= ₦444.

households adopted 'stress' coping strategies. The data also shows that respondents were vulnerable to flooding, with 95 percent reporting previous flooding experience.

4.2 Food Consumption Score (FCS)

The food consumption score is a household-level composite score based on dietary diversity, food frequency, and relative nutritional importance of different food groups. It is based on the frequency of household consumption of different food groups over a seven-day recall period. The FCS score classifies households into three categories (*poor, borderline,* and *acceptable*). Figure 4 shows that about 63 percent and 65 percent of the control and treatment households respectively fell within the poor and borderline categories of FCS at the baseline. The endline results show that household food consumption scores drastically improved where almost all the households became food secure (94 percent survey households in both the treatment and control groups were at acceptable food consumption level). These results align with the other measures of food security (rCSI and LCS) that show notable improvement in household food security at endline.

Figure 4. Food consumption categories at baseline and endline

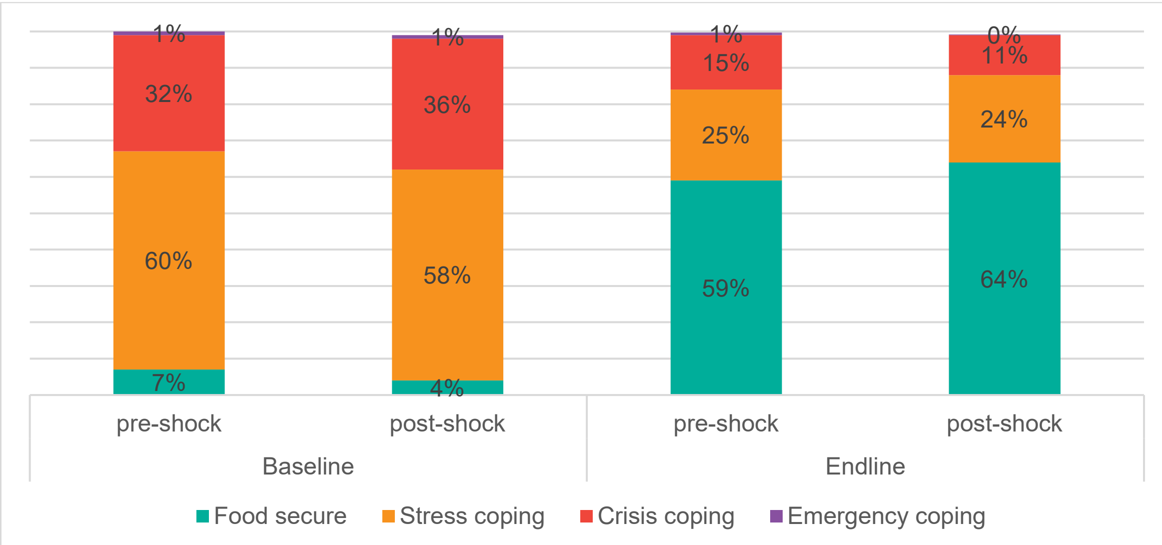


4.3 Reduced Coping Strategies Index (rCSI)

A coping strategy index is a behavioral indicator of household food security status. The CSI measures how households cope with a shortfall in food for consumption with results presented in a simple numeric score. The CSI is based on the many possible answers to a single question: 'What do you do when you don't have adequate food and don't have the money to buy any?' The 'reduced' CSI (rCSI) includes a standardized set of five coping strategies and preset weights reflecting their respective severity. As detailed in Annex 3, scores of the rCSI can be grouped into four categories (*food secure, stress, emergency*, and *crisis*). Results show that only 4 to 7 percent of survey households were food secure at the baseline (Figure 5). Fifty-eight and sixty percent of the treated and control households, respectively adopted stress coping strategies at the baseline.

At the endline, however, we observed a significant upward movement in the percentage of households that were food secure (64 percent of control and 59 percent of treated households). Similarly, the percentage of households that used stress and crisis coping strategies notably reduced.

Figure 5. Reduced coping strategy at baseline and endline

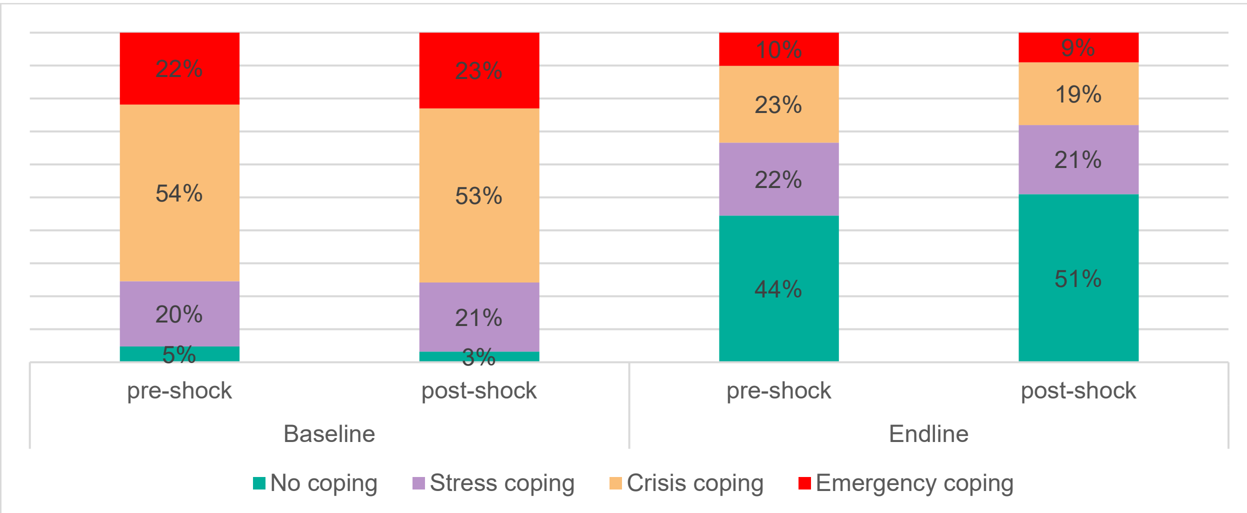


4.4 Livelihood coping strategies (LCS)

The livelihood coping strategies index (LCSI) is used to better understand the longer-term coping and productive capacities during crisis and thus indicates households' resilience to future access of food. It is constructed using the responses to ten selected (context-specific) questions on coping strategies adopted by households during crisis. The responses to these questions are summarized into levels of severity (*none, stress, crisis, or emergency*) that indicate the coping strategies adopted (Annex 3). We anticipate that both treated and control households will employ different coping strategies, which will likely impede their ability to adapt to or recover from climate shocks. We examined the percentage of beneficiaries who reported using any of the coping strategies associated with the LCS (stress, emergency, and crisis). The baseline results presented in Figure 6 show that most of the households (over 50 percent) in both groups used *crisis* strategies at the baseline to deal with longer-term food shortages. This indicates that households were vulnerable to climate shocks prior to the cash intervention. Over 20 percent used emergency strategies, while only very few (three percent of the control and 5 percent of treatment households) did not adopt any livelihood coping strategy and subsequently are food secure.

In contrast, the endline survey results show a significant increase in the percentage of households that did not use any coping strategy, while the percentage of beneficiaries who used *crisis* coping strategies decreased significantly by 64 percent and 54 percent, respectively, for the control and treatment groups. Similarly, the proportion of households that used stress and emergency coping strategies decreased. These findings could imply that the cash transfer was beneficial to both groups, regardless of the treatment status and period of cash disbursement.

Figure 6. Livelihood coping strategy at baseline and endline



4.5 Extent of flood damage

Figures 7 and 8 show self-reported flood damages for a pooled sample and disaggregated by treatment status. All survey households reported crop losses because of the 2022 flooding. In contrast, less than one-tenth of the treatment and control groups reported livestock loss while only 10 percent of the control and 9 percent of treatment households reported property loss.

To further explore the extent of flood damage, households were asked to estimate the extent to which their production and household assets were damaged during the flooding. The extent of asset damage disaggregated by treatment status is presented in Figure 10. Approximately 40 percent of the treated households and 47 percent of the control households reported complete crop loss, while only 3 percent reported crop loss of less than 25 percent. A higher proportion, 42 percent of treated and 32 percent of control households reported livestock losses of up to 50 percent. Approximately 25 percent of the two groups reported property loss. Both groups had nearly identical crop and property loss experiences, with more treatment (42 percent) than control (32 percent) households reporting approximately 50 percent livestock loss.

Both groups had almost similar experiences in terms of crop and property loss while more treatment (42 percent) than control (32 percent) households reported about 50 percent livestock loss.

Figure 7. Extent of asset damage (pooled sample)

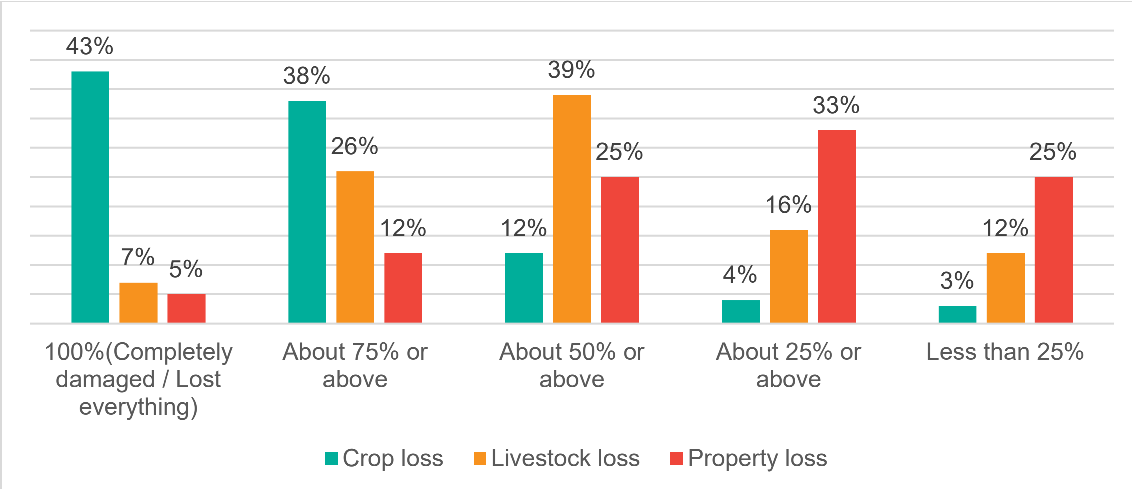
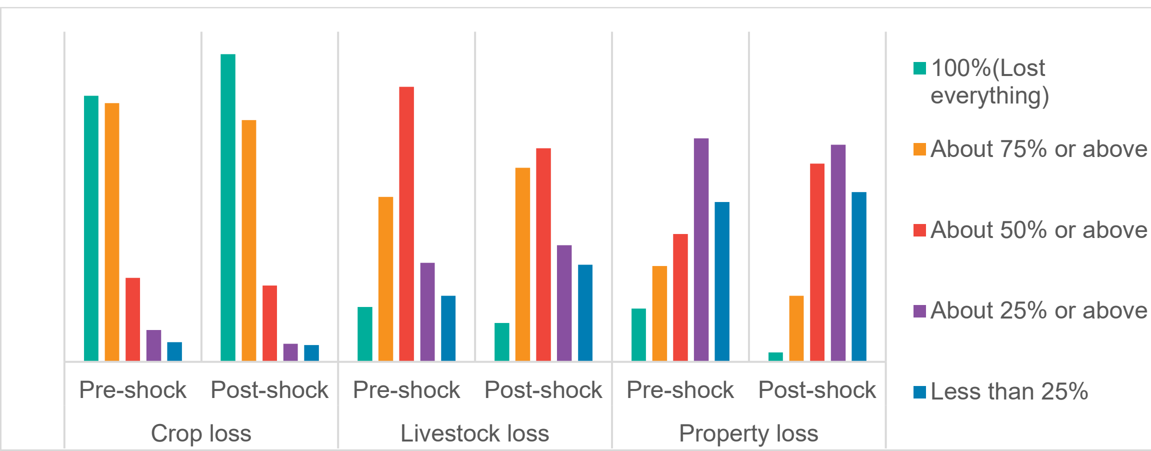


Figure 8. Extent of asset damage disaggregated by treatment status.



4.6 Utilization of IRC cash transfer

Figure 9 presents the percentage of the IRC cash spent on various items. We found that both treatment and control households spent over 70 percent of the cash (about 136,500 Naira) on non-food items, followed by asset procurement, climate-preparedness actions (48 percent), and about 45 percent was spent on meeting food needs. Control and treated households saved approximately 14 percent and 11 percent, respectively.

Figure 9. Percentage of cash spent on items

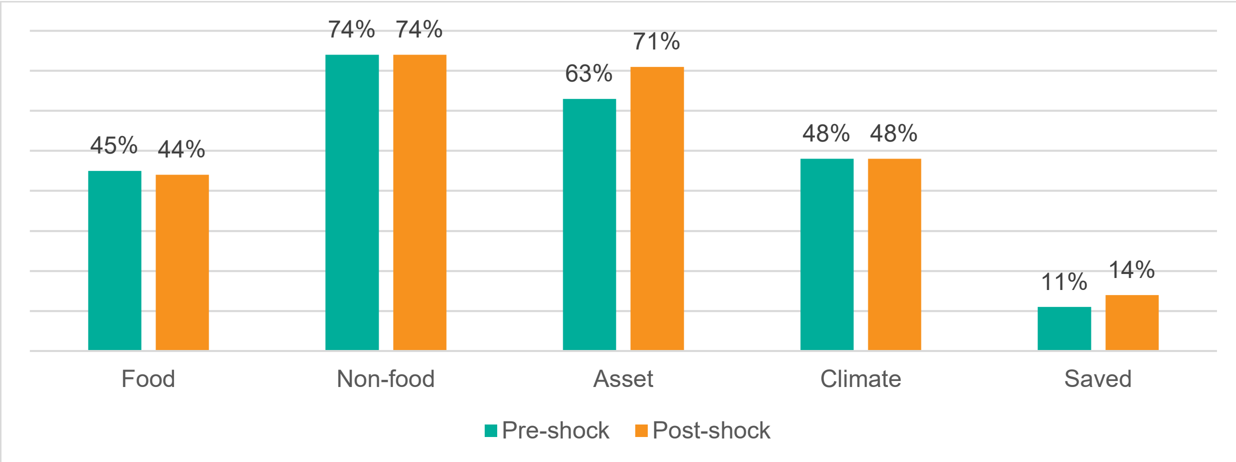
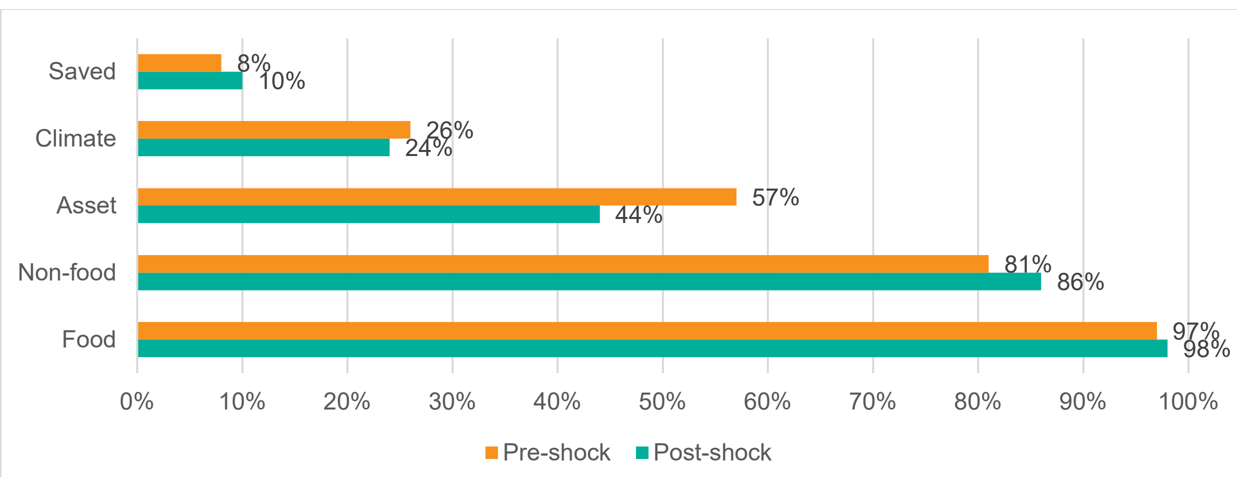


Figure 10 shows that almost all treated (98 percent) and control households (97 percent) households used the cash on meeting food needs followed by non-food needs. A very small percentage did not spend the cash at all. In comparison to the control group, a higher proportion of treated households spent the money on productive assets (57 percent) and climate-resilient activities (26 percent). These results corroborate existing evidence studies that households mostly spend cash transfers on food items (Schady and Rosero, 2008; Fiszbein and Schady, 2009; Pople et al., 2021).

Figure 10. Utilizations of IRC cash transfers (by treatment status)



Based on household self-reported flood damage measured at endline survey, almost all survey households (over 99 percent) of both control and treatment households reported crop loss due to the 2022 flooding. Conversely, less than one-tenth of both groups reported livestock loss while only 10 percent of control households and 9 percent of treatment households reported property loss. These results imply that the 2022 flooding affected the lives and livelihoods of smallholders since crop production is predominant among the sampled households.

5 ECONOMETRIC RESULTS

5.1 Impacts on food consumption

Table 4 report estimation results (with and without controls/covariates) of the effects of anticipatory cash on food consumption score (FCS). The control variables (covariates) were selected using the LASSO[5] regression. We also included lagged values of outcome variable (FCS at the base line i.e., t=0) and community fixed-effects in the regression model with covariates. Variance-covariance of the regression estimates were clustered by communities.

Table 4. Effects of anticipatory cash transfer on FCS (with and without controls) (n=1447)

	FCS	FCS
Treatment (Anticipatory cash)	0.623 (0.974)	0.431 (0.552)
Lagged dependent variable (FCS, t=0)	-	0.074** (0.024)
Cons.	63.31*** (0.669)	61.51*** (1.659)
Household level controls?	No	Yes
Community fixed effects?	No	Yes
F(1, 1445) for pre-shock=post-shock	0.430	0.031
P-values (treatment var)	0.511	0.511
Pre-flood cash recipients mean dep var.	63.312 (17.67)	63.312 (17.67)
Post-flood cash recipients mean dep var.	63.935 (18.35)	63.935 (18.35)

Source: Estimation results using survey data (2022), Adamawa, Nigeria.
Note: Unit of observation is a household at the endline. FCS=food consumption score. The controls or covariates include household head age, education, gender, household size, income, wealth score, extension access, credit access, membership local groups, and disability index. Community fixed effects are included. Standard errors are in parentheses. Statistical significance denoted with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As the results show in Table 4, we do not see significant differences in food consumption scores between anticipatory and post-shock cash recipients. Several factors could have contributed to this. First, most of the households in the study communities are food producers who primarily consume from their own production. Since it is common for households to store food items from previous production seasons for consumption smoothing, they may not have used the transfers to purchase food. Second, the existence of strong social capital (family members, friends, and relatives) in the survey communities may have resulted in food sharing, which is particularly common in rural areas. Third, there may be spillover effects as far as food consumption is concerned. For instance, pre-shock cash recipients might have lent some money or food to their counterparts in the control group to smooth consumption, which could have contributed to the absence of differential impacts in food consumption between the two groups. Fourth, considering the large amount of the transfer and the economic status of the beneficiaries, recipients may be keen to invest transfers on large durable assets in addition to food. This is consistent with

[5] LASSO (least absolute shrinkage and selection operator) is a regression analysis method that performs both variable selection and regularization to enhance the prediction accuracy statistical models. https://statalasso.github.io/docs/lassopack/

Haushofer and Shapiro (2013) who found that households are more likely to spend unconditional lump-sum transfers on durables rather than on food. Also, our results are consistent with Gros et al. (2022) who found no discernible effects of forecast-based-cash on the food consumption of recipient households in Mongolia. Fifth, by observing anticipatory cash recipients in neighboring households, control households might have anticipated cash transfer too at some time during the agricultural season so that they might have taken similar decision on food consumption. Finally, it might signify the household's pre-existing behavioral norm to stock up on food ahead of the flood season.

5.2 Impacts on livelihood diversification

The results presented in Table 5 show that anticipatory cash transfer has a statistically significant impact on household's labor re-allocation decision including migration. This is consistent with the common climate adaptation argument that re-allocating labor to other activities is less risky activities than farming (Sabates-Wheeler et al., 2008). For instance, wages from working on other people's farms or formal employment can improve food security as they provide income during the lean seasons caused by weather variability (World Bank, 2009). Thus, migrant labor is perceived as a positive adaptation strategy (Weldegebriel and Prowse, 2013) which could help households to cope with weather shocks. This result corroborates Ardington et al. (2009) who found that cash transfers facilitated labor migration in South Africa.

However, our results do not provide evidence of positive impact on diversified crop production, mixed crop-livestock farming, and non-farm business activities. One plausible explanation could be that the period is too short for adjusting to a more climate resilient livelihood activity, or, due to prior negative experience and perceived risks of future flooding, households were discouraged from investing in crop diversification or non-farm businesses. This is consistent with Weldegebriel and Prowse (2013) who attribute the insignificance of cash transfer on non-farm activity generation in Ethiopia to the absence of demand for non-farm rural enterprises during climate shocks.

Table 5. Effects of anticipatory cash transfer on livelihood diversifications (n= 1447)

	Labor re-allocation (inc. migration)[1]		Diversify crops[2]	Mixed crop-livestock[3]	non-farm activities[4]
	Coef.	Margins			
Treatment (Pre-flood cash recipient)	0.236*	0.034	0.074	0.087	0.132
	(0.142)	(0.019)	(0.115)	(0.107)	(0.114)
Cons.	-1.753***	-	0.848***	-0.466**	-0.886***
	(0.104)	-	(0.081)	(0.076)	(0.081)
Household level controls?	No	No	No	No	No
Community fixed effects?	No	No	No	No	No
LR Chi2(1)	2.75	-	0.41	0.67	0.24
P-values (treatment var)	0.098	0.08	0.52	0.41	1.34

Source: Estimation results using survey data (2022), Adamawa, Nigeria.
Note: Unit of observation is a household at the endline survey. Outcome variables are: 1. Family labour re-allocation (e.g., migrated to work elsewhere) (yes/no). 2. Household diversified crop production (cultivating more than one crop) (yes/no). 3. Household engaged in mixed crop-livestock farming (yes/no). 4. Household engaged in supplementary non-farm activities (yes/no). Standard errors are in parentheses. Statistical significance denoted with * p < 0.10, ** p < 0.05, *** p < 0.01.

5.3 Impacts on households' climate adaptative actions

Table 6 shows that pre-shock cash payment had significant impacts on the number of pre-emptive actions taken by households in anticipation of flood shocks. Consistent with prior expectations, households who received cash prior to the flood had increased capacity to reduce the potential consequences of flood on their households, thereby increasing their resilience to hazards, both prior to and during the immediate threat of the disaster (Aguirre et al., 2019). However, there is no significant difference between the anticipatory and post-shock cash recipients in terms of the number of post-shock actions adopted. This could be because the post-shock group also received cash after the flooding and thus could have invested in post-shock recovery actions.

Table 6. Effects of anticipatory cash transfer on pre-emptive and post-shock actions (n= 1439)

	Number of pre-emptive actions			Number of post-shocks actions		
	(OLS)	(Poisson)	(Margins, (dy/dx))	(OLS)	(Poisson)	(Margins, (dy/dx))
Treatment (Pre-shock cash)	0.175*	0.081***	0.169*	0.106	0.052	0.106
	(0.101)	(0.036)	(0.075)	(0.082)	(0.036)	(0.075)
Cons.	2.136***	0.688***	--	1.889***	0.753***	--
	(0.232)	(0.026)	--	(0.185)	(0.082)	--
Household level controls?	No	No	No	No	No	No
Community fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
F(6,1439) OLS;	1.23	--	--	1.239	--	--
LR chi2(6) Poisson	--	13.26	--	--	16.99	--
P-values (treatment var)	0.084	0.021	0.021	0.198	0.156	0.156

Source: Estimation results using survey data (2022), Adamawa, Nigeria.
Note: Unit of observation is a household at the endline survey. Statistical significance denoted with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Impacts on household level aggregates

Table 7 shows that anticipatory cash transfers had statistically significant effect on household's seasonal incomes from non-farm employment and small business incomes and incomes from agriculture (crops and livestock) measured at endline. Anticipatory cash could have helped households either to take the necessary preemptive actions to safeguard small businesses and minimize crop damages (Davis and Pozarny, 2012). These results are consistent with those reported in Table 6 related to the positive impacts of anticipatory cash on the number of preemptive actions. This could particularly hold considering the large amount of cash disbursed. However, there is no significant difference in the possession of durable assets and number of livestock measured at the endline between the anticipatory and post-shock cash recipients. This could be because of fear of possible displacement and risks of losing their livestock and durable assets because of the flooding. Evidence abounds that previous flooding in the Northeastern region have led to destruction of livestock assets including livestock and durable assets (Echendu, 2020, 2021; REACH Initiative, 2022).

Table 7. Effects of anticipatory cash transfers on household aggregates

	Non-transfer & non-agric. income[1]	Agriculture income[2]	Livestock numbers[3]	Durable assets[4]
Treatment (Pre-flood cash recipient)	0.534** (0.193)	50738* (21836)	0.437 (0.293)	0.135 (0.232)
Cons.	3.546*** (0.094)	-338005*** (10614)	1.192** (0.362)	5.921 (0.129)
Initial conditions (lagged values) controls?	Yes	Yes	Yes	Yes
Community fixed effects?	Yes	Yes	Yes	Yes
P-values (treatment var)	0.040	0.068	0.196	0.586
Pre-flood cash recipients mean dep var.	6.67[a] (5.83)	70115[b] (220625)	1.576 (9.725)	5.823 (5.679)
Post-flood cash recipients mean dep var.	6.57[a] (5.74)	60293[b] (157311)	1.144 (5.687)	5.687 (4.684)

Source: Estimation results using survey data (2022), Adamawa, Nigeria.
Note: Unit of observation is a household at the endline. Outcome variables are: (a) non-transfer income (also non-agricultural) including incomes from non-farm employment and small business/trade in log form (in Naira); (b) Agricultural income (incomes from crop production and livestock sources) (in Naira). Here, we used the 'changes in agriculture income' (i.e., endline minus baseline); (c) Number of livestock in tropical livestock units (TLU) (#); and (d) Value of durables household and agricultural assets (in Naira). [a]The means were calculated from the log transformed values. [b]Means are calculated from total agricultural incomes for the treatment and control groups. Standard errors are in parentheses and statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 reports regression results of the utilization of cash transfers. The results show that anticipatory cash transfers have positive and statistically significant effects on the long-term investment decisions in productive agricultural assets and livestock. Productive investments enhance household's future income generating capacity and reduce their vulnerability of future shocks. Thus, anticipatory cash has shown an interesting long-term resilience capacity building implication. However, we do not find significant differences between anticipatory and post-shock cash recipients' food purchases and expenditures on non-food household items.

While Table 9 reports the impacts of anticipatory cash on wellbeing measures, Table 10 presents estimation results by households' wealth status. Studies show that exposure to severe climatic shocks negatively affect life satisfaction and anticipatory cash could potentially mitigate mental and psychological pressure associated with crises (Pople et al., 2021). Our study does not find significant differences in wellbeing measures between the pre- and post-cash households. One possible explanation could be that during the endline survey both treatment and control groups had already received the cash transfer and hence both groups were likely to link their wellbeing with the cash they received irrespective of the timing. Table 11 shows that for all seven outcome indicators that explore heterogenous impacts there is little evidence that the impacts vary by wealth groups.

Table 8. Effects of anticipatory cash transfer on food and nonfood expenditures and productive investments

	Utilization of IRC cash transfer				
	CONSUMPTION EXPENDITURE		INVESTMENT EXPENDITURE		
	(1) Food expenditure (y/n)[1]	(2) Nonfood household expenditures (y/n)[1]	(3) Invested on productive agric. assets (y/n)[2]	(4) Invested on productive livestock (y/n)s[3]	(5) Invested on nonfarm small business (y/n)s[4]
Treatment (anticipatory cash)	-0.368	-0.123	0.496***	0.352***	-0.173
	(0.352)	(0.112)	(0.106)	(0.146)	(0.153)
Cons.	3.926***	0.783***	-0.490***	-1.878***	-1.763***
	(0.269)	(0.080)	(0.076)	(0.109)	(0.105)
Controls (covariates)	Yes	Yes	Yes	Yes	Yes
Community fixed effects?	Yes	Yes	Yes	Yes	Yes
P-values (treatment var)	0.297	0.271	0.000	0.016	0.259

Source: *Source*: Authors' estimations using econometric models and survey data 2022 (Adamawa, Nigeria)
Note: Unit of observation is a household at the endline. Outcome variables were derived from the series of questions on the utilization of the IRC transfer; (a) Purchased basic food items for household consumption (yes/no); (2) Spent of personal/household expense (clothing, health, education, transport); (3) Invested in productive agriculture assets (e.g., farm equipment/tools, water pumps,); (4) Bought productive livestock (e.g., dairy cow, oxen…); and (5) Invested in non-farm business (new or expansion). Standard errors are in parentheses. Statistical significance denoted with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Effects of anticipatory cash transfer on wellbeing measures

	Model-1 (OLS)	Model-2 (Ordered logit)	Model-3 (Logit)		Model-4 (Logit)		Model-5 (Logit)	
	Cantril's 11 point ladder scale	Gallup's grouped 3-categroy scale	'Thriving' (Cantril's scale: >=7)	Margins (dy/dx) (Thriving)	'Struggling' (Cantril's scale: 5 & 6)	Margins (dy/dx) (Struggling)	'Suffering' (Cantril's scale: <=4)	Margins (dy/dx) (Suffering)
Anticipatory cash	-0.037 (0.062)	-0.045 (0.109)	-0.257 (0.274)	-0.009 (0.010)	0.029 (0.113)	0.006 (0.024)	0.021 (0.111)	0.004 (0.024)
Selected covariates								
Age HH head	-0.003 (0.002)	-0.004 (0.003)	-0.028*** (0.011)	-0.001** (0.000)	0.001 (0.003)	0.000 (0.000)	0.002 (0.003)	0.000 (0.000)
Gender HH head	-0.152** (0.074)	0.054 (0.133)	-0.785* (0.445)	-0.029* (0.016)	0.182 (0.137)	0.039 (0.029)	-0.094 (0.135)	-0.021 (0.031)
Total HH income	3.445** (1.350)	6.210** (2.570)	5.050 (3.990)	1.890 (1.150)	5.130* (2.750)	1.150* (5.940)	-6.870** (2.970)	-1.520** (6.560)
HH wealth index	0.105*** (0.019)	0.189*** (0.34)	0.187** (0.073)	0.007** (0.003)	0.161*** (0.357)	0.035*** (0.007)	-0.194*** (0.036)	-0.043*** (0.007)
Social capital - membership	0.559*** (0.065)	0.632*** (0.114)	1.414*** (0.288)	0.053*** (0.012)	0.350*** (0.118)	0.070*** (0.015)	-0.586*** (0.116)	-0.130*** (0.025)
Disability index	-0-157*** (0.037)	-0.263 (0.070)	0.153 (0.160)	0.006 (0.006)	-0.325*** (0.073)	-0.071 (0.015)	0.292*** (0.071)	0.064*** (0.015)
Cons.	3.317*** 0.109)	/cut1=0.434 /cut2=3.264	-2.660*** (0.502)	-	-0.784*** (0.201)	-	0.501** (0.199)	-
Com. fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model diagnostics	F (7, 1435) = 23.80	LR chi2(7) = 50.60	LR chi2(7) =50.60	-	LR chi2(7) =64.93	-	LR chi2(7) =97.80	-
P-values (treatment)	0.550	0.682	0.348	0.349	0.792	0.792	0.848	0.848

Source: *Source*: Authors' estimations using econometric models and survey data 2022 (Adamawa, Nigeria). *Note*: Unit of observation is a household at the endline. The outcome variable is household's wellbeing indicator measured: (1) using Cantril's 11-points (0-10) self-reported life evaluation ladder scale (numbered zero at the bottom to 10 at the top). In model-1 Cantril's scale was assumed continuous and thus use of OLS. (2) Grouping Cantril's 11-point scale into three categories following the Gallup approach. This results in a ordered wellbeing indicator (1=suffering, 2=struggling, and 3= thriving) and thus use of ordered logit model. (3) In models 3, 4 and 5; we run a binary logit model for each of the Gallup's category. The controls were chosen based on their high potential to be associated with the wellbeing – demographic (age and gender), household total income, wealth index constructed from household durable assets, land and livestock using principal component analysis, social capital indictor, and disability index constructed from the six disability indictors. Standard errors are in parentheses. Statistical significance denoted with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Effects of anticipatory cash transfer on various outcomes (by wealth quintile)

	Consumption and coping strategies			Climate adaptive actions		Climate resilience actions		Wellbeing
	(1) FCS	(2) rCSI	(3) LSCI	(4) Number pre-emptive actions	(5) Number post-shock actions	(6) Productive agric. assets	(7) Productive livestock	(8) Cantril's 11-point ladder
Anticipatory cash	-1.660 (2.073)	-0.532 (1.111)	-0.158 (0.121)	0.117 (0.223)	0.040 (0.183)	0.172 (0.259)	0.810 (0.552)	-0.002 (0.142)
Lagged values	0.111*** (0.029)	-0.029 (0.029)	0.064 (0.035)	-	-	-	-	-
Wealth_q2	0.284 (2.076)	0.404 (1.110)	-0.014 (0.121)	0.278 (0.224)	0.153 (0.183)	0.266 (0.257)	1.355*** (0.520)	0.114 (0.143)
Anticipatory x Wealth_q2	4.248 (2.940)	1.386 (1.573)	0.137 (0.171)	-0.343 (0.317)	-0.211 (0.259)	0.439 (0.355)	-0.708 (0.655)	-0.019 (0.202)
Wealth_q3	3.138 (2.056)	1.303 (1.101)	0.013 (0.120)	0.068 (0.222)	0.050 (0.182)	0.562 (0.250)	1.437*** (0.514)	0.075 (0.141)
Anticipatory x Wealth_q3	2.225 (2.935)	-0.920 (1.573)	-0.015 (0.171)	0.314 (0.317)	0.168 (0.259)	0.313 (0.351)	-0.532 (0.644)	0.053 (0.202)
Wealth_q4	4.827 (2.083)	1.494 (1.114)	0.031 (0.121)	0.636** (0.225)	0.346* (0.184	0.838*** (0.250)	1.895*** (0.501)	0.302* (0.143)
Anticipatory xWealth_q4	0.871 (2.939)	-2.332 (1.573)	-0.101 (0.171)	0.190 (0.317)	0.342 (0.259)	0.373 (0.351)	-0.442 (0.621)	-0.133 (0.202)
Wealth_q5	6.977*** (2.127)	1.886 (1.134)	-0.011 (0.123)	0.526** (0.228)	0.421** (0.187)	0.783*** (0.254)	1.834*** (0.506)	0.607*** (0.145)
Anticipatory xWealth_q5	3.586 (2.994)	-1.023 (1.579)	0.083 (0.171)	0.072 (0.317)	-0.029 (0.260)	0.506 (0.254)	-0.374 (0.623)	-0.058 (0.202)
Cons.	56.55*** (1.731)	-7.219*** (0.994)	-0.736*** (0.112)	1.694*** (0.159)	1.798*** (0.130)	-0.990*** (0.187)	-3.325*** (0.455)	3.069*** (0.101)
Community fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Authors' estimations using econometric models and survey data 2022 (Adamawa, Nigeria). *Note*: Unit of observation is a household at the endline. The outcome areas include food consumption, coping strategies, climate adaptive actions, climate resilience actions, and a measure of wellbeing. The q2, q3, q4, and q5 are the second, third, fourth, and fifth wealth quintiles. Households in the bottom 20 percent (1st quintile) are used as a base category. So, the FCS= food consumption score. rCSI= reduced coping strategy index. LCSI=livelihood coping strategy index. (6) productive agric. assets and (7) productive livestock refer to specifically the use of IRC cash transfer on purchase of agricultural assets and productive livestock. Standard errors are in parentheses. Statistical significance denoted with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 CONCLUSIONS AND RECOMMENDATIONS

This paper has presented the findings from an experimental study designed to assess the impacts of anticipatory cash transfer on food security, climate adaptive actions and climate resilience of smallholder crop and livestock producers in climate prone and conflict-affected communities in northeast Nigeria. This pilot intervention was initiated and supported by Google.org and IRC. The IRC's central hypothesis was that when climate vulnerable communities have timely access to information and the financial and social resources to act upon that information, they will avoid negative coping strategies and build more diversified and climate resilient livelihoods. To test this hypothesis, the IRC piloted climate risk reduction cash transfer with smallholder farmers and livestock owners. The pilot project transferred a lump sum of anticipatory cash to 725 randomly sampled households ('treatment') when triggered by the climate data platform risk thresholds. Comparable households ('controls') in the intervention communities received an equal amount of cash post-flooding shock.

Baseline and endline data were collected from a sample of 1450 experimental households pre- and post-intervention (July 2022 and December 2022, respectively). To ensure the validity of comparison group, balance tests were performed across a set of variables including demographics, assets, livelihood activities, and access indicators assessed at the baseline. The balance test shows that randomization was successful in creating a valid comparison group. Four outcome areas were identified at the outset by the pilot project including food security indicators, adaptive actions, climate resilience, and household well-being. Two additional outcome areas were identified by the research team during the study. We assessed the impacts of anticipatory cash transfers on the six outcomes using a set of sixteen indicators. Our key findings include:

1. In terms consumption based short-term food security indicator (i.e., food consumption score), we do not find significant differences between anticipatory and post-shock cash recipient households.

2. Anticipatory cash transfers have significant impacts on the number of pre-emptive actions taken by households in anticipation of floods, but no significant impacts on the number of post-shock actions.

3. Anticipatory cash transfers have positive and statistically significant impacts on productive investments (agricultural assets and productive livestock). Productive investments could enhance a household's future income generating capacity and reduce their vulnerability to future shocks, thus improving long-term resilience capacity.

4. Finally, our results do not show significant differences in measures of subjective well-being between the pre- and post-cash households. Similarly, our heterogeneity analyses show that the impacts of anticipatory cash on various outcome measures are not sensitive to household wealth status, which may imply that households in the study communities are generally economically poor.

Key Recommendations

1. Given the positive impacts of anticipatory cash on household's climate resilience capacity and it was just as effective at supporting households to meet basic needs as standard post-shock cash transfer programs, we suggest humanitarian agencies and governments consider using anticipatory cash transfers where suitable. However, we would like to highlight that not all humanitarian contexts in which climate shocks occur will be conducive to anticipatory action.

2. Humanitarian agencies thus should weigh the feasibility of anticipatory actions against other climate risk mitigation and resilience activities and should strongly consider anticipatory action: (a) if there are quality data and analytics to predict a high probability climate shock, and (b) there is adequate time to intervene ahead of the onset or peak effects of the shock based on predictions, allowing households time to safely act and have sufficient resources with which to act.
3. As climate shocks continue to worsen and humanitarian funding needs remain unmet for both emergencies and early recovery, anticipatory approaches may be critical to meeting the short- and longer-term needs of climate- and conflict-affected households.
4. Future research should examine the impacts of varying cash transfer amounts and gather more granular, high-frequency data to understand how anticipatory cash interventions may influence food security and well-being throughout the course of the flood season.

REFERENCES

Adelaja, A., & George, J. (2019). Effects of conflict on agriculture: Evidence from the Boko Haram insurgency. *World Development*, *117*, 184–195.

Ariom, T. O., Dimon, E., Nambeye, E., Diouf, N. S., Adelusi, O. O., & Boudalia, S. (2022). Climate-smart agriculture in African countries: A Review of strategies and impacts on smallholder farmers. *Sustainability*, *14*(18), 11370.

Baliki, G., Brück, T., & Stojetz, W. (2018). Drivers of resilience and food security in North-east Nigeria: Learning from micro data in an emergency setting. *Final Report to the Food and Agriculture Organization*.

Clarke, B., Otto, F., Stuart-Smith, R., & Harrington, L. (2022). Extreme weather impacts of climate change: an attribution perspective. *Environmental Research: Climate*, *1*(1), 012001.

Coughlan de Perez, E., van den Hurk, B., van Aalst, M. K., Jongman, B., Klose, T., & Suarez, P. (2015). Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts. *Natural Hazards and Earth System Sciences*, *15*(4), 895–904.

Dietrich, S., & Schmerzeck, G. (2019). Cash transfers and nutrition: The role of market isolation after weather shocks. *Food Policy*, *87*, 101739.

Ebele, N. E., & Emodi, N. V. (2016). Climate change and its impact in Nigerian economy. *Journal of Scientific Research & Reports*, *10*(6), 1–13.

Elias, P., & Omojola, A. (2015). Case study: The challenges of climate change for Lagos, Nigeria. *Current Opinion in Environmental Sustainability*, *13*, 74–78.

Federal Ministry of Environment. (2018). *Federal Republic of Nigeria First Biennial Update Report (BUR1) of the Federal Republic of Nigeria under the United Nations Framework Convention on Climate Change (UNFCCC)*. https://www4.unfccc.int/sites/SubmissionsStaging/NationalReports/Documents/218354_Nigeria-BUR1-1-Nigeriapercent 20BUR1_Finalpercent 20(2).pdf

Ferraro, P. J., & Simorangkir, R. (2020). Conditional cash transfers to alleviate poverty also reduced deforestation in Indonesia. *Science Advances*, *6*(24), eaaz1298.

Filmer, D., & Scott, K. (2012). Assessing asset indices. *Demography*, *49*(1), 359–392.

Fiszbein, A., & Schady, N. R. (2009). *Conditional cash transfers: reducing present and future poverty*. World Bank Publications.

Gitz, V., Meybeck, A., Lipper, L., Young, C. de, & Braatz, S. (2016). Climate change and food security: risks and responses. *Food and Agriculture Organization of the United Nations (FAO) Report*, *110*, 2–4.

Gros, C., Bailey, M., Schwager, S., Hassan, A., Zingg, R., Uddin, M. M., Shahjahan, M., Islam, H., Lux, S., & Jaime, C. (2019). Household-level effects of providing forecast-based cash in anticipation of extreme weather events: Quasi-experimental evidence from humanitarian interventions in the 2017 floods in Bangladesh. *International Journal of Disaster Risk Reduction*, *41*, 101275.

Gros, C., Easton-Calabria, E., Bailey, M., Dagys, K., de Perez, E. C., Sharavnyambuu, M., & Kruczkiewicz, A. (2022). The effectiveness of forecast-based humanitarian assistance in anticipation of extreme winters: a case study of vulnerable herders in Mongolia. *Disasters*, *46*(1), 95–118.

Haider, H. (2019). *Climate change in Nigeria: impacts and responses*.

Hassan, A. G., Fullen, M. A., & Oloke, D. (2019). Problems of drought and its management in Yobe State, Nigeria. *Weather and Climate Extremes*, *23*, 100192.

Hjelm, L., Mathiassen, A., Miller, D., & Wadhwa, A. (n.d.). *Creation of a Wealth Index*.

Kamta, F. N., Schilling, J., & Scheffran, J. (2020). Insecurity, resource scarcity, and migration to camps of internally displaced persons in northeast Nigeria. *Sustainability*, *12*(17), 6830.

Levine, S., Wilkinson, E., Weingärtner, L., & Mall, P. (2020). Anticipatory action for livelihood protection. *Overseas Development Institute*.

Maxwell, D., & Caldwell, R. (2008). The Coping Strategies Index: A tool for rapid measurement of household food security and the impact of food aid programs in humanitarian emergencies. *Field Methods Manual*, *2*.

National Bureau of Statistics. (2010). Annual Abstract of Statistics, 2010. www.nigerianstat.gov.ng

National Population Commission (NPC). (2019). *2018 Demographic and Health Survey Key Findings*. www.population.gov.ng

National Population Commission (NPC). (2019). *2018 Demographic and Health Survey Key Findings*. www.population.gov.ng

Nobre, G. G., Davenport, F., Bischiniotis, K., Veldkamp, T., Jongman, B., Funk, C. C., Husak, G., Ward, P. J., & Aerts, J. C. J. H. (2019). Financing agricultural drought risk through ex-ante cash transfers. *Science of the Total Environment*, *653*, 523–535.

Nyathi, D., Ndlovu, J., Phiri, K., & Muzvaba, N. E. (2022). Climate Change and Food Insecurity: Risks and Responses in Bulilima District of Zimbabwe. In *Handbook of Climate Change Across the Food Supply Chain* (pp. 421–436). Springer.

Obi, F. A., & Eboreime, E. (2017). How boko haram is devastating health services in North-East Nigeria. *The Conversation*.

Obioha, E. E. (2008). Climate change, population drift and violent conflict over land resources in northeastern Nigeria. *Journal of Human Ecology*, *23*(4), 311–324.

Obioha, E. E. (2009). Climate variability, environment change and food security nexus in Nigeria. *Journal of Human Ecology*, *26*(2), 107–121.

Olarewaju, O. A. (2021). Insecurity in northern Nigeria: Implications for maternal and child health. *Clinical Epidemiology and Global Health*, *12*, 100869.

Pichon, F. (2019). *Anticipatory humanitarian action: What role for the CERF*. Working Paper 551). London: Overseas Development Institute. Retrieved from ….

Pople, A., Hill, R., Dercon, S., & Brunckhorst, B. (2021). *Anticipatory cash transfers in climate disaster response*.

Raj, S., Roodbar, S., Brinkley, C., & Wolfe, D. W. (2022). Food Security and climate change: Differences in impacts and adaptation strategies for rural communities in the Global South and North. *Frontiers in Sustainable Food Systems*, *5*.

Rutstein, S. O. (2015). Steps to constructing the new DHS Wealth Index. *Rockville, MD: ICF International*.

Schady, N., & Rosero, J. (2008). Are cash transfers made to women spent like other sources of income? *Economics Letters*, *101*(3), 246–248

Schleussner, C.-F., Donges, J. F., Donner, R. v, & Schellnhuber, H. J. (2016). Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries. *Proceedings of the National Academy of Sciences*, *113*(33), 9216–9221.

Shiru, M. S., Shahid, S., Alias, N., & Chung, E.-S. (2018). Trend analysis of droughts during crop growing seasons of Nigeria. *Sustainability*, *10*(3), 871.

The World Bank Group. (2021). *Climate Risk Profile: Nigeria*. www.worldbank.org

United Nations Office for the Coordination of Humanitarian Affairs. (2020). *Humanitarian Needs Overview: Nigeria*. www.humanitarianresponse.info/en/

United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA). (2022). *Current developments affecting the humanitarian response: Nigeria*. www.unocha.org

Washington Group. (2021). *Creating Disability Severity Indicators Using the WG Short Set on Functioning (WG-SS)*. http://www.washingtongroup-disability.com/.

ANNEXES

Annex 1. Analytics and data for setting triggers thresholds for anticipatory action

Trigger readiness and activation thresholds for flooding response were set by the Nigeria Hydrological Service Agency (NiHSA), the Nigeria Meteorological Agency (NiMET) and the Upper Benue Basin Development Authority (UBBDA) based on historical rainfall, water level and discharges flooding hydrograph records (Tables A1.1, A1.2, and A1.3). The trigger readiness and activation monitoring system were designed based on water level, discharge, and the rainfall flooding thresholds. These parameters were monitored daily, and the data were shared with IRC.

Table A1.1. Upper Benue River Basin Development Authority threshold

Upper Benue River Basin Development Authority threshold			
Gauge station/River threshold	**Normal**	**Warning**	**Peak/flooding**
Wurobokki, River Benue. Zero Level: 170.395	2.5-3.5m	4.0-5m	5.5 m and above
Dasin Hausa, River Benue, zero level: 93.820	3.0-4.5m	5.5.0m-6.5	6.5m and above
Jimeta Bridge, River Benue, Zero Level: 151.166	1.5- 3.5m	4.5m- 5.5m	7.0 and above

Source: UBBDA (2021)

Table A1.2. Nigeria Hydrological Service Agency threshold

Nigeria Hydrological Service Agency threshold		
Gauge station/River	**Warning**	**Peak/flooding**
Wurobokki, River Benue. Water levels	5.0m - 6.0m	6.5m above
Wurobokki, River Benue. Discharge levels	2290m^3/sec	2780m^3/sec

Source: NiHSA (2021)

Table A1.3. Nigeria Meteorological Agency Dekad threshold

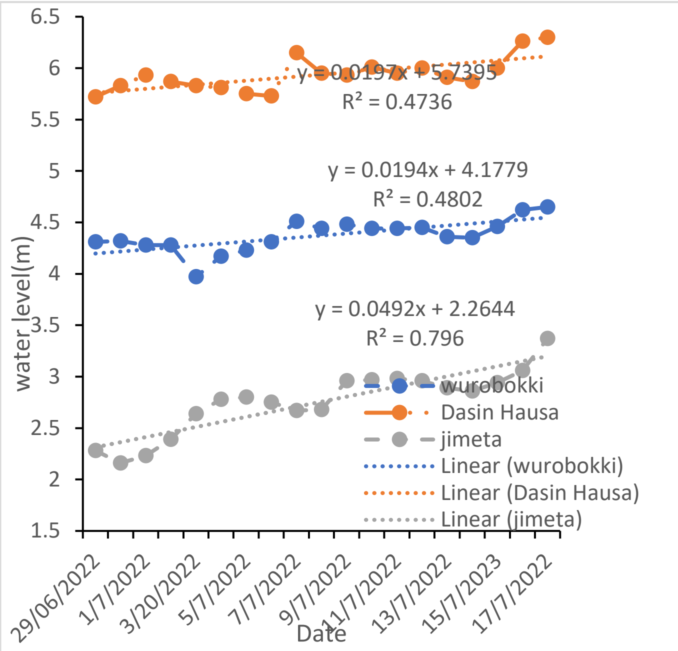
Months	From 1 to 10	From 11 to 21	From 21 to 31	Total
June	44.73mm	47.81mm	46.31mm	138.85mm
July	46.86mm	53.66mm	59.2mm	159.72mm
Aug	51.2mm	69.64mm	75.39mm	196.23mm
Sep	69.54mm	65.37mm	54.49mm	189.4mm
Oct	38.19mm	19.81mm	9.88mm	67.88mm

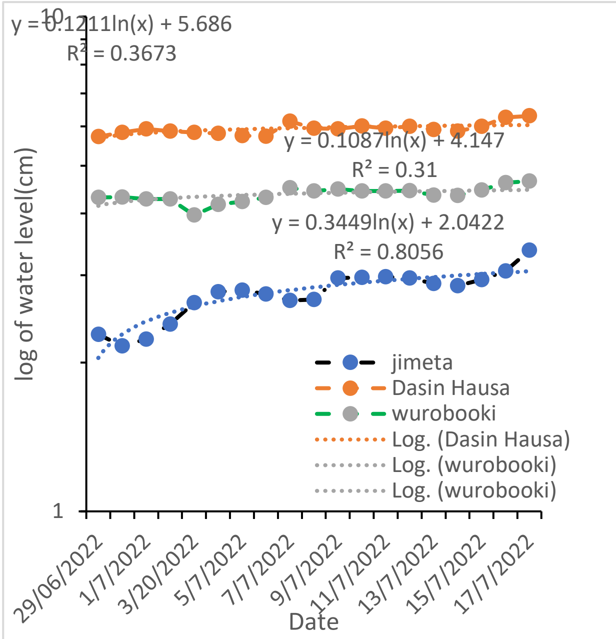
Source: NiMET (2021)

A. Triger readiness

On 17July 2022, the data from the UBBDA indicated that the water level downstream at Dasin Hausa gauge station had increased to 6.33m as against the 5.72m on 29 June 2022, which exceeds the set thresholds 6.0 m warning and 6.5m peaking flooding thresholds. Also, the water level upstream at Wurobokki gauge station had increased from 4.3m on 29 June 2022 to 4.65 on 17 July 2022, which is between 4.5m and 5m warning and peak/flooding threshold (see Figure A1.1). Also, to note that the river channel at Dasin Hausa is very narrow compared to the Wurobokki, which account for the water level difference in the upstream.

Figure A1.1. Water level across the three-gauge stations between June 29 to July 17, 2022





B. Trigger Activation decision

Following the onset of the rains, the IRC distributed clients ID cards and was preparing to release the pre-shock cash assistance in the coming week once an activation threshold has been reached. On 21 July 2022, the IRC communicated with the NiHSA, the NiMET and the UBBDA to confirm/validate the rise in water level, rainfall and discharge and the predicted excess rainfall that will cause flooding in the communities of intervention in the coming days, to activate the provision of pre shock anticipatory cash transfer to soon to be affected households. The trigger decision was taken to give households ample lead time of at least sevendays to purchase goods and other items in the next few weeks.

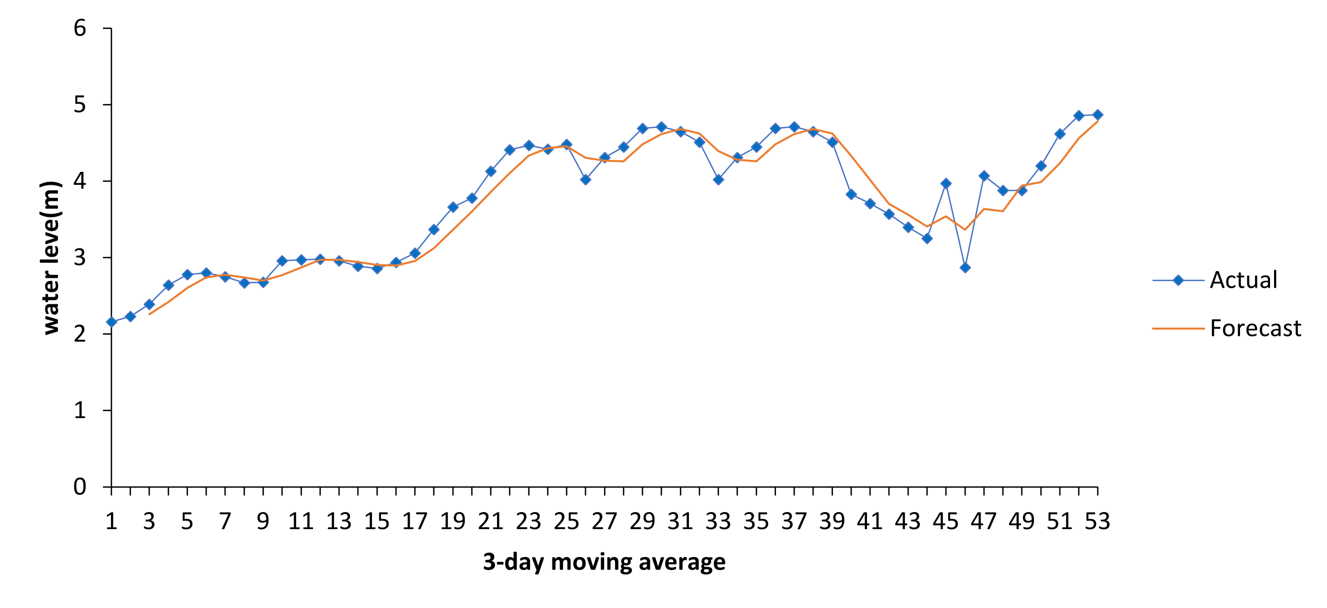
On 22 July 2022, the IRC received confirmation from the NiMET that they anticipate rainfall increase in the coming Dekads, in line with what you noted in the technical document and recommended to proceed with your proposed action plan. This was also confirmed by the NiHSA, and the UBBDA.

C. Monitoring of hydrological: Water level and discharge

After the cash disbursement, the IRC continued to monitor the rainfall, water level and the water discharge in the three gauging stations.

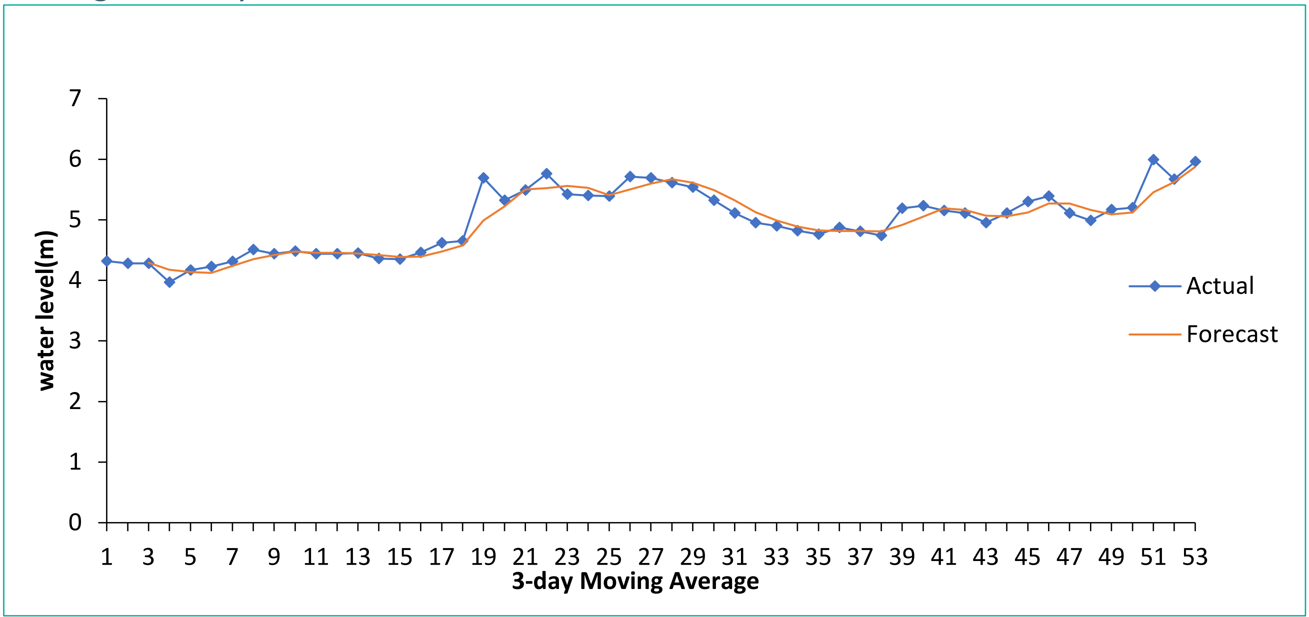
Jimeta guage station: On 27 July 2022, the water level at the Jimeta gauge station increased to 4.71m with a 3-day moving average of 4.8m from 2.8m on 29 June 2022, which exceeds the UBBDA threshold of 4.5m for warning (Figure A1.2). Although, the water level had dropped to 2.9m with a 3-day moving average of 3.6m on 15 August 2022, due to the early cessation of the rains associated with the August break phenomenon, it has increased again to 4.87m with a 3-day moving average of 4.7m on 21 August 2022. The water level had returned to its previous level of flooding with the return of the rain.

Figure A1.2. Three-days moving average for Jimeta gauge station between 29 June - 21 August 2022.



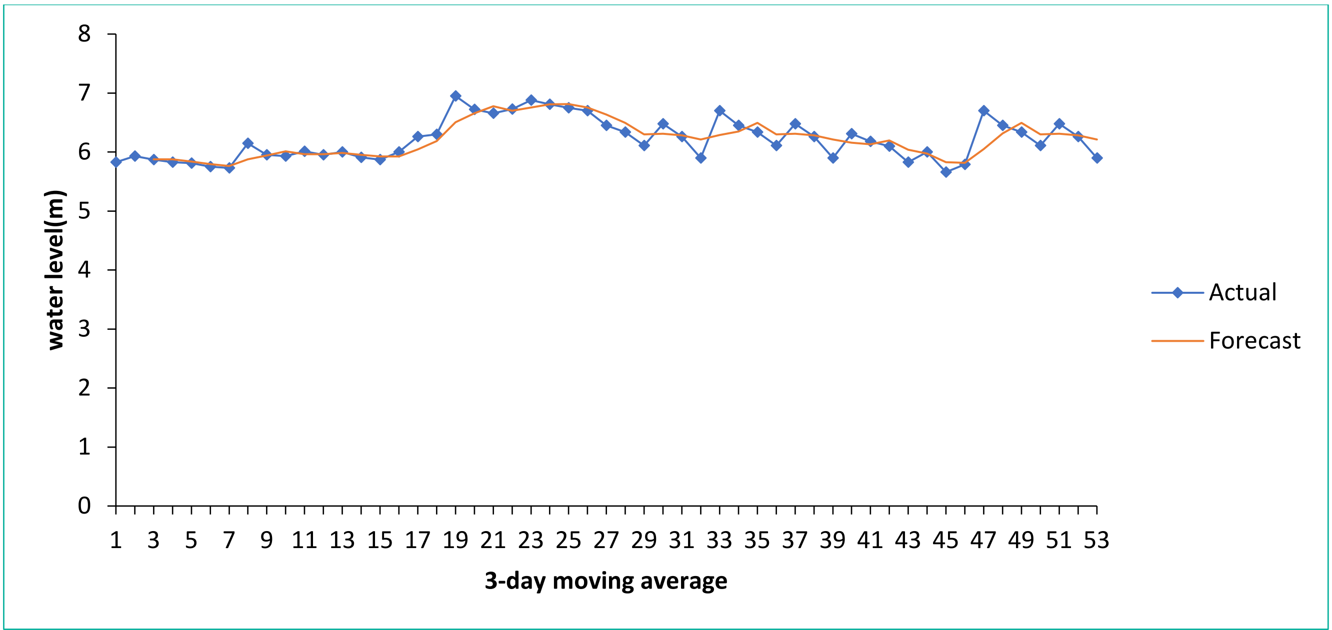
Wurobokki gauge station: On 25 July 2022, the water level at the Wurobokki gauge station increased to 5.71m with a 3-day moving average of 5.5m from 4.31m on 29 June 2022, which exceeds the UBBDA thresholds between 4.0 -5m and 5.5m (see Table A1.1). Although, the water level had dropped to 4.82 m with a 3-day moving average of 4.89m on 2 August 2022, due to the early cessation of the rains associated with the August break phenomenon, it has increased again to 5.96m with a 3-day moving average of 5.87m on 21 August 2022. The water level had returned to its previous level of flooding with the return of the rain. Also, data from the NiHSA indicated that on 27 July 2022, the water level increased to 5.5m from 3.92m on 29 June 2022 and decrease to 4.97m on 31 June 2022. The data from the two agencies shows a similar trend.

Figure A1.3. Three-days moving average at Wurobokki gauge station (29 June and 21 August 2022)



Dasin Hausa gauge station: On 27 July 2022, the water level at the Dasin Hausa gauge station increased to 6.48 m with a 3-day moving average of 6.3 m from 5.7 m on 29 June 2022, which exceeds the UBBDA thresholds between 5.5m-6.5 (see Table A1.1). Although, the water level had dropped to 5.66 m with a 3-day moving average of 5.8 m on 12 August 2022, due to the early cessation of the rains associated with the August break phenomenon, it has increased again to 5.9 m with a 3-day moving average of 6.2m 21 August 21, 2022.

Figure A1.4. Three-day moving average for Dasin Hausa gauge station (29 June and 21 August 2022)



On 14 August 2022, the water level decreased significantly due to the early cessation of the rains due to the August break phenomenon. Although, the months of July and August were forecasted to experience mild dry of 8 days according to NiMET Seasonal Climate Prediction 2022, the dry spell persisted for up to 18 days, which severely lower the water level. This was reported by farmers to have affected crops see pictures below.

D. Monitoring of meteorological parameters: Rainfall

On July 22, the rainfall data from NiMET indicated that the rainfall will exceed the normal dekad of 51.2mm of rainfall for the 1st of August thresholds with a probability of 80%. Though moisture index in the 3rd Dekad of July (**20th - 31st**) indicates that the soil is currently not as wet as in the previous Dekad, having recorded a rainfall amount of 124.2 mm, there is a risk of probable maximum rainfall that could occur and result in flash flood in any Dekad of August; PMP for any 10 days in August is 122 mm and has a return period of 5-years(see Table A1.4).

Table A1.4. Dekadal rainfall monitoring data

Dekad	Accumulated rainfall (in 10 days)	Corresponding Dekadal (10 days normal rainfall)
1st to 10th of June,2022	52.5mm	44.7mm
11st to 20th of June,2022	81.3mm	47.8mm
21st to 30th of June,2022	84.5mm	46.3mm
1st to 10th of July,2022	20.8mm	46.9mm
11th to 20th of July,2022	113.9mm	53.7mm
20th to 31st of July,2022	124.2mm	59.2mm
1st to 10th of August,2022	-----	51.2mm

E. Assessing flood footprint

The flood footing print in the past 8 years was assessed using web-based remote sensing Satellite images of Sentinel 1 images from 2015 to 2019. Flooding occurred on annual basis with the month of September having the highest frequency of flooding in the region. The extent of the flood footprints varies with 2019 having the highest footprint covering about 5,249.14 ha, representing a 34 percent increase in the area affected by flooding compared to the previous years. The result showed that more farmlands were being affected by flooding. This confirms the reports that farmers are moving land upland to clear new virgin lands because of the flooding, which further contributes to the problem of climate change.

Figure A1.5. Water level across three gage stations

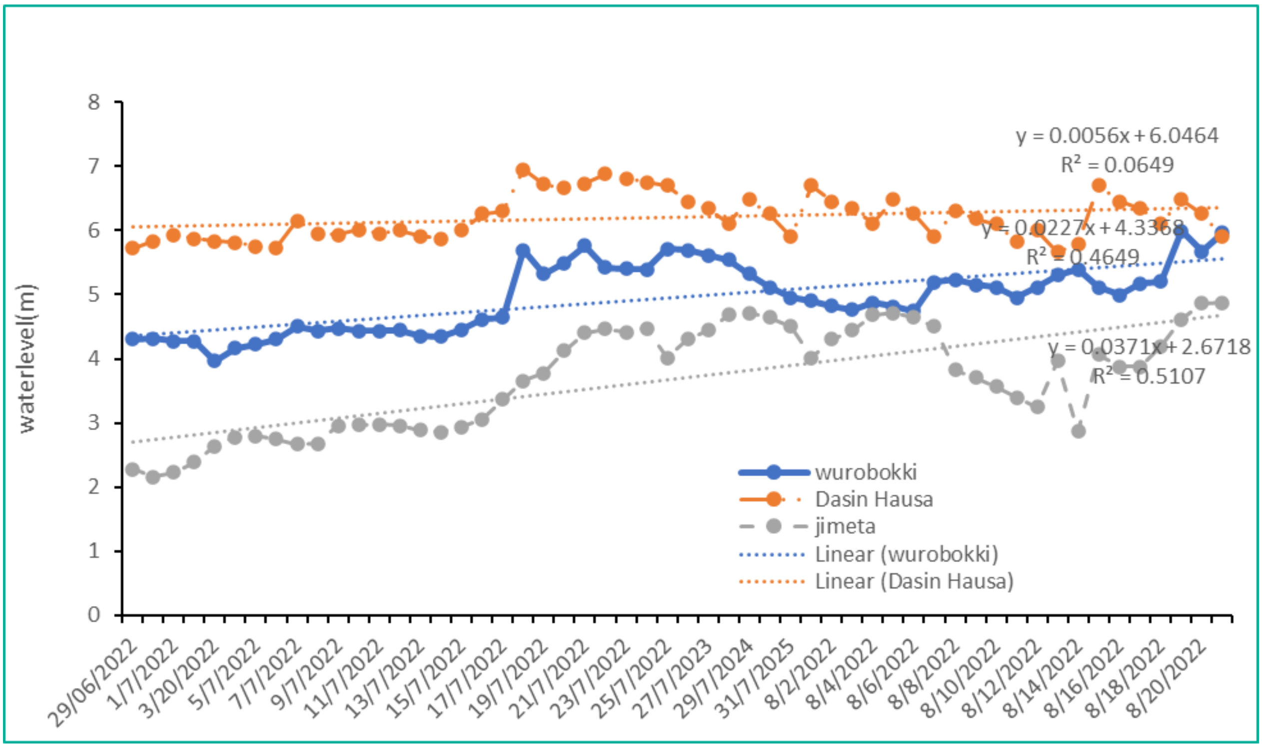
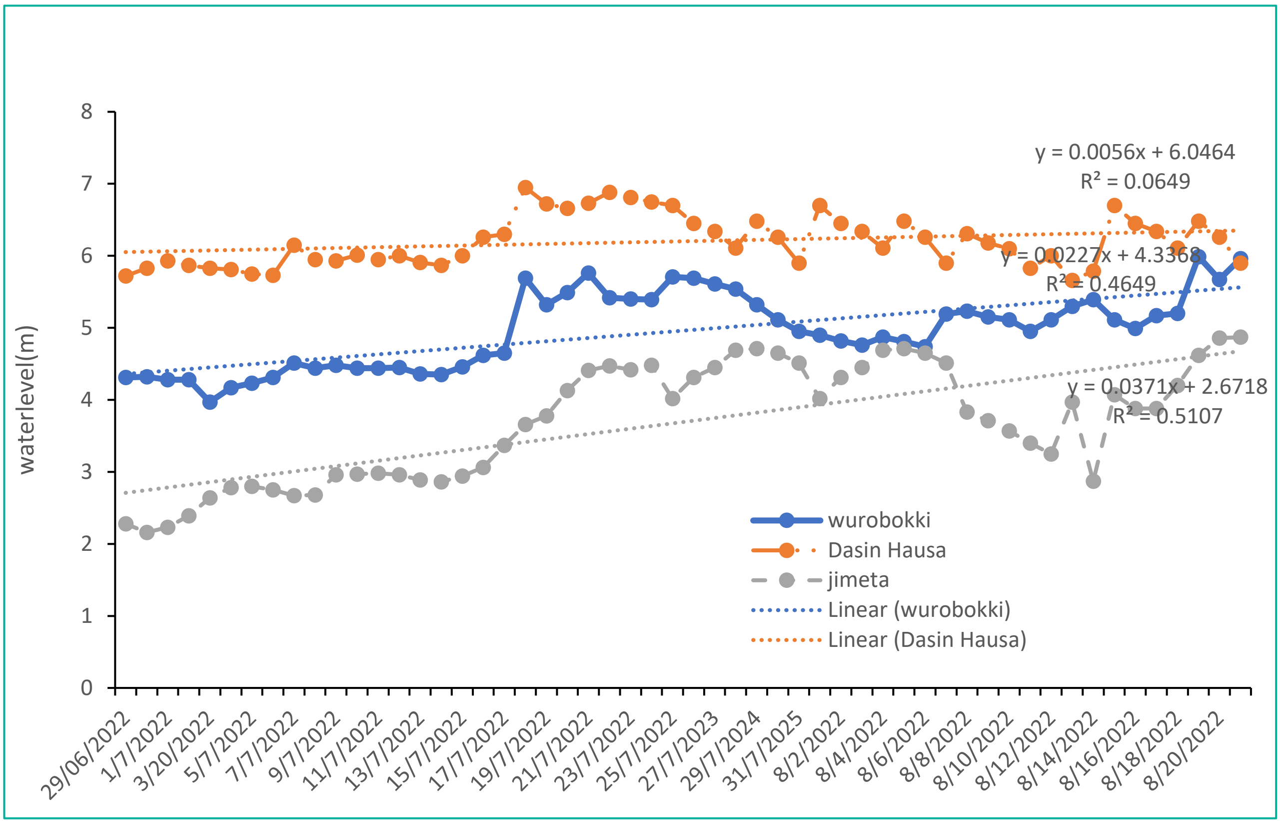


Figure A1.6. Comparison of NiHSA, UBBDA, and Fanfair water level and discharges at Wurobokki between 29 June to August 2022



Annex 2. Early warning Messages delivered to community through community-based early warning system workers

No.	Messages	Specific content of the message	Message delivery timing
1	Flood alert information received from hydro met agencies	Information on heavy rain in the coming weeks Communities to be calm and not to panic because of the flood information Information on impending flood based on forecast Communities to check the change in color of water in the river Benue as well as floating materials such as leaves	July
2	Disaster risk preparedness messaging	Advisories to evacuate children, livestock to safer areas, if told to do so ignore rumour and be calm Not to enter flood water Not allow children to enter or near flood water Not to drink flood water or use it for cooking Not to leave harvested crops in the field Listen to instruction that may come from local media including from the early warning system volunteers Avoid driving through the flooded and standing water	July
3	Public health education, awareness of disaster management (when state government declared cholera outbreak in the state because of the flooding)	Use clean water for brushing, preferably drinking water Cook or prepare food with clean water Wash hand often using soap and clean water Cook food well, cover food always and eat food hot or warm Wash fruits and vegetables well before eating Avoid consumption uncooked food during flood period Use proper latrine, avoid contact with human feaces Keep kitchen and kitchen materials always clean	July to August
4	The dry spell that set in before the main flooding	Created awareness that dry spell can be part of the challenges posed by climate change The communities to adjust to the temporary dry spell period Manual weeding of their farmland during the period is a good idea For those that have irrigation facilities, they can complement to supply water if they observe wilting of crops Engage in off-farm income generation activities such as petty trading	August
5	Introduction to Climate-smart agriculture (an official and organized training to early warning volunteers was conducted on the 22nd September, 2022)	To seek advisories from ministry of agriculture before going into any form of crop production Early planting of crops to harvest earlier before flooding Planting of early maturing crop varieties always Communities to prepare and engage in dry season irrigation farming Harvesting rainwater for use during dry season Cultivating flood tolerant crops such as rice	September/October
6	Tips for improving community emergency preparedness	To identify communities with special needs Creating and educational material for passing information on ways to protect themselves and homes from disaster Creation of notification system at the center of the town that would alert residence of emergency within shortest period of time eg town crier or whistle blower The need to discuss at community level on the evacuation plan and communities sensitized on the process and steps to follow	October to November

Source: IRC (2022)

Annex 3. Construction of indices

1. Food Consumption Scores (FCS)

The Food Consumption Score (FCS) was constructed using information on household-level food consumption gathered from a list of food items/groups specific to Nigeria (Table A3.1). The beneficiaries were asked about the number of days each food group was consumed within the household over the last 7days preceding the survey. The consumption frequencies of the food groups were summed, and any frequency value greater than seven was capped at seven. Next, the value obtained for each food group was multiplied by its assigned weight (Table A3.1). The FCS was computed as the sum of the weighted value of the eight food groups assessed. Food consumption score is computed as FCS = $\Sigma F_i X_i$

where F_i represents the different food groups, and i is the different food items. X_i denotes the consumption frequency of each food group over a week period. Finally, the continuous FCS was categorized into appropriate thresholds of food consumption groups as follows: 0 to 28 (poor), 28.5 to 42 (borderline), and above 42 (acceptable) following (United Nations World Food Program, 2008), as presented in Table A3.2.

Table A3.1. Food groups and weight

Food Items	Food Groups	Weight
Maize, rice, pasta, bread, and other cereals	Cereals and Tubers	2
Beans. Peas, groundnuts and cashew nuts	Pulses	3
Cassava, Yam, Arrow roots/Cocoyam, and potatoes		
Vegetables and leaves	Vegetables	1
Fruits	Fruit	1
Beef, goat meat, poultry, pork, eggs, fish, other meat, and seafoods	Animal protein	4
Milk and other milk products	Milk	4
Sugar, honey, and sugar products	Sugar	0.5
Edible oils, fats, and butter	Oil	0.5

Source: United Nations World Food Programme (2008)

Table A3.2. Classification of Food Consumption Scores

Threshold	Profile
0-28	Poor food consumption
28.5 – 42	Borderline food consumption
>42	Acceptable food consumption

Source: United Nations World Food Programme (2008)

2. Reduced coping strategy index (rCSI)

The Coping Strategies Index (CSI) was used to identify specific local coping strategies adopted by the households. The CSI is a context-specific indicator of food insecurity that counts and weighs household coping behaviors (Maxwell et al. 2008). It measures the frequency and severity of a household's coping strategies for dealing with food shortage. Within the context of this report, the "reduced" CSI (rCSI) was constructed using a standardized set of five households coping strategies in response to inadequate access to food and preset weights reflecting their respective severity. Using a household-level questionnaire, respondents were asked how often they used a particular coping strategy within a 7-day recall period as well as the severity of each strategy adopted (i.e., what degree of food insecurity do they suggest?). The final score for each coping strategy adopted was obtained by multiplying its relative frequency by the severity ranking/weight. The sum of these scores was computed to obtain the rCSI as a quantitative indicator of household food security status. The rCSI was categorized into 4 (Table A3.3).

Table A3.3 Recommended rCSI thresholds

IRC Recommended RCSI Category Threshold Values	
rCSI Category	rCSI score range
Food secure	0 to 3
Stressed	4 to 18
Crisis	19 to 42
Emergency	43+

Source: Global Food Security Cluster website Updated: July 2021

3. Livelihood coping strategy index (LCSI)

The livelihood-based coping strategies index (LCSI) was used to assess longer-term household coping and productive capacities and their future impact on food access. In constructing the index, we adapted the International Rescue Committee (IRC) Livelihood-based Coping Strategies Index (LCSI) which is based on the original Coping Strategies Index (CSI) developed by Maxwell and Caldwell (2008). Drawing on IRC's master lists and adapting to the local context, we collected data on 10 coping strategies, including four stress strategies, three crisis strategies and three emergency strategies.

Stress strategies indicate a reduced ability to deal with future shocks as the result of a current reduction in resources or increase in debts.

Crisis strategies are often associated with the direct reduction of future productivity.

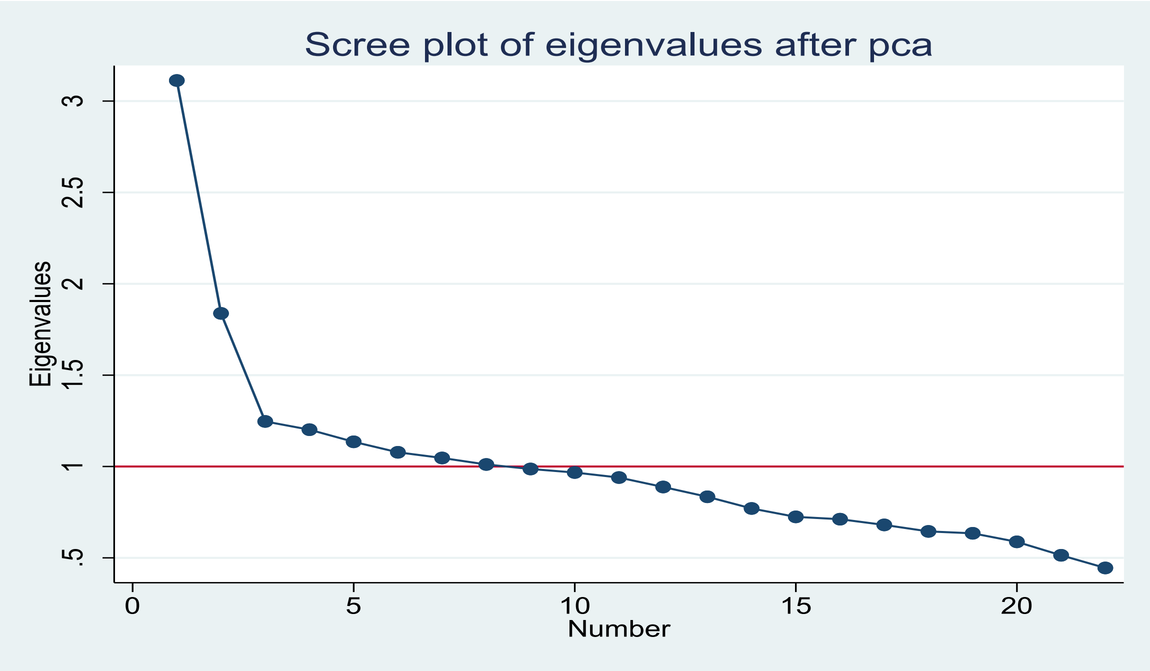
Emergency strategies also affect future productivity but are more difficult to reverse or more dramatic in nature than crisis strategies.

Beneficiaries were asked if their households had engaged in the selected coping strategies due to a lack of resources to meet domestic needs in the 30days preceding the survey. In addition, we collected information about households who did not employ a particular livelihood-coping strategy. The LCSI responses were categorised into four levels of severity (none, stress, crisis, or emergency) according to the most harmful strategy used.

4. Household Wealth Index

We constructed the household wealth index based on the indicators developed by WFP (Hjelm et al., n.d.), following the general approach utilized for DHS (Rutstein, 2015). Using Principal Component Analysis (PCA), we combined a set of household durable and livestock assets, as well as housing/dwelling construction materials, to create a composite index. The asset variables were all dichotomous while the housing characteristics was regrouped into binary variables following WFP approach (Hjelm et al., n.d.). Of the twenty-two components extracted in the first stage of the PCA, only the first eight were significant based on the Kaiser criterion of an eigen-value greater than one (Figure A1). The wealth index was constructed using the first component which has the largest eigenvalue and explains most of the variations in the data (Filmer & Scott, 2012). Subsequently, households were classified into five wealth quintiles based on their assigned scores.

Figure A3.1. Scree plot of eigen values after PCA



5. Disability index

Following the Washington Group (2021)), we measured disability over six Washington Group (WG) disability questions, assessed on four response categories as presented in Table A3.4. Scores were assigned to each response option and disability severity scores were derived by summing the values (scores) for the six questions. The score was grouped into four severity categories as None, mild, moderate, and severe.

Table A3.4 The six disability questions of Washington Group (WG)

Question	*Scale*
Do you have difficulty seeing, even if wearing glasses?	*1= No - no difficulty; 2= Yes – some difficulty; 3= Yes – a lot of difficulty; 4=Cannot do at all*
Do you have difficulty hearing, even if using a hearing aid?	*1= No - no difficulty; 2= Yes – some difficulty; 3= Yes – a lot of difficulty; 4=Cannot do at all*
Do you have difficulty walking or climbing steps?	*1= No - no difficulty; 2= Yes – some difficulty; 3= Yes – a lot of difficulty; 4=Cannot do at all*
Do you have difficulty (with self-care such as) washing all over or dressing?	*1= No - no difficulty; 2= Yes – some difficulty; 3= Yes – a lot of difficulty; 4=Cannot do at all*
Do you have difficulty remembering or concentrating?	*1= No - no difficulty; 2= Yes – some difficulty; 3= Yes – a lot of difficulty; 4=Cannot do at all*
Using your usual (customary) language, do you have difficulty communicating, for example understanding or being understood?	*1= No - no difficulty; 2= Yes – some difficulty; 3= Yes – a lot of difficulty; 4=Cannot do at all*

Source: Washington Group (2021)

ABOUT THE AUTHORS

Bedru Balana is a Research Fellow in Development Strategies and Governance Unit (DSGU) of IFPRI, based in Abuja. **Dolapo Adeyanju** a Research Analyst in IFPRI's DSGU, Nigeria Office, Abuja. **Kwaw Andam** is a Senior Research Fellow in DSGU of IFPRI and Program Leader of IFPRI-Nigeria, based in Abuja. **Alan de Brauw** is a Senior Research Fellow in the Markets, Trade, and Institutions Unit at IFPRI, based in Washington DC. **Clare Clingain** is a Senior Research Coordinator in the Economic Recovery and Development Technical Unit at the International Rescue Committee (IRC), based in New York. **Olukunbi Olarewaju** is a Senior Economic Recovery and Development (ERD) Manager at the IRC, based in Maiduguri. **Ishaku Yohanna** is an Economic Recovery and Development (ERD) Manager at IRC, based in Adamawa. **Molly Schneider** is a senior programme manager- Agriculture, Resilience, and Water at Winrock International, based in New York.

ACKNOWLEDGEMENTS

The IRC and IFPRI gratefully acknowledge the generous support of Google.org, which made this research and its learnings possible. IFPRI-Nigeria acknowledges research funding from the USAID Feed the Future Nigeria Agriculture Policy Activity. We thank the Nigeria Hydrological Service Agency (NiHSA), the Nigeria Meteorological Agency (NiMET), and the Upper Benue Basin Development Authority (UBBDA) for collaboration on hydrological and meteorological data.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
1201 Eye St, NW | Washington, DC 20005 USA
T. +1-202-862-5600 | F. +1-202-862-5606
Email: ifpri@cgiar.org | www.ifpri.org | www.ifpri.info

IFPRI-ABUJA
c/o Office 11, Second Floor, Solution Plaza
23, Ibrahim Tahir Lane,
Cadastral Zone B05, Utako
Abuja | Nigeria
ifpri-nigeria@cgiar.org | nssp.ifpri.org /

Funding for this work was provided by Google.org. This publication has been prepared as an output of the Google/IRC Anticipatory Action Project and has not been independently peer reviewed. Any opinions expressed here belong to the author(s) and are not necessarily representative of or endorsed by IFPRI.