Disasters without diversification: Long-term labor responses to floods in Nigeria

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This version: January 16, 2026
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Abstract

Climate change is expected to decrease agricultural productivity across much of the world through both higher temperatures and more frequent extreme weather events. Migration and non-farm labor are potential coping and adaptation strategies, yet little evidence exists on how weather shocks affect households' long-term labor allocation, migration, and livelihoods. This paper studies the impacts of the catastrophic 2012 floods in Nigeria using four rounds of nationally-representative panel data on 5,000 households collected from 2010-2019 in a difference-in-differences framework exploiting spatial variation in community-level flood exposure. We find that flood exposure reduces household crop production value by 33% and consumption per capita by 13% on average, with fairly persistent magnitudes over seven years post-exposure. Households in flooded communities persistently increase their supply of labor to their existing activities. There is no evidence of diversification of household livelihoods as a coping or adaptation strategy, though *ex ante* diversified households are more resilient to the flood shock. The likelihood of household and individual migration also increases but only after a delay of several years. These patterns suggest that household face constraints in their livelihood responses to climate shocks. Methodologically, we also show that floods detected by satellite imagery fail to identify a majority of exposure reported in the surveys and lead to different estimated effects. Despite other studies showing short-term livelihood diversification responses to floods, these results suggest they are more likely to entrench households in low-productivity agriculture, adding to concerns of how climate change may constrain structural transformation.

JEL codes: J22, O13, Q10, Q54

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1 Introduction

Climate change is predicted to reduce agricultural productivity in many parts of the world due to increases in temperatures and precipitation variability (Nath, 2025; Ortiz-Bobea et al., 2021). This has important implications for low- and lower-middle-income countries (LMICs) where a large share of the population depends on small-scale agricultural production for their livelihoods. The scope for on-farm adaptation and mitigation is limited (Hultgren et al., 2025; Kala et al., 2023; Pörtner et al., 2022), and there are also constraints to reallocating labor to non-farm alternatives (Albert et al., 2021; Alobo Loison, 2015), potentially increasing the costs of climate change (Cruz and Rossi-Hansberg, 2024). Climate change is also increasing the severity and frequency of extreme weather events (Coumou and Rahmstorf, 2012; Seneviratne et al., 2021), and it is unclear whether this will encourage or hinder such livelihood change or diversification for agricultural households. A large literature shows short-term migration or non-farm labor responses to weather shocks, but the literature on long-term impacts is smaller and has shown mixed results. This paper analyzes the long-term livelihood impacts of exposure to flood shocks in agricultural communities in LMICs by analyzing the effects of a major flooding event in Nigeria on household livelihood activities.[1]

Floods are a particularly important source of risk and damages, accounting for 44% of all disasters globally and 31% of all economic losses from 1970-2019 (World Meteorological Association et al., 2021). Over 170 million people in extreme poverty face high flood risk (Rentschler et al., 2022) and flood exposure is predicted to increase in most LMICs (Pörtner et al., 2022), with population growth driving large increases in exposure across much of sub-Saharan Africa (Rogers et al., 2025). Floods can completely destroy agricultural production, change perceptions of future production risk, and force short-term migration and non-farm work as coping strategies. But they may also decrease demand for non-farm goods and services and deplete assets needed to engage in non-farm activities. Consequently, it is unclear whether exposure to floods would result in a persistent reallocation of labor toward non-agricultural sectors. In 2012, excessive rainfall between September-November caused widespread flooding across much of Nigeria. The floods caused an estimated \$16.9 billion in damages and killed 431 people (Unah, 2021). Using four rounds of the nationally-representative General Household Survey-Panel (GHSP) from 2010-2019, we test whether community-level exposure to the 2012 floods affects household well-being and engagement in and income from household agriculture, non-farm household enterprise, and wage employment over time.

An initial consideration is how to measure flood incidence in survey communities. Existing work on the economic impacts of floods uses a variety of data sources including administrative data, satellite imagery or radar, survey or media reports, or some combination of these sources, but these sources suffer from different limitations and are often inconsistent with one another (Bangalore et al., 2025; Guiteras et al., 2015; Patel, 2025). We evaluate the correlations between several different measures of community flood exposure, focusing on one based on household survey reports

[1] We estimate impacts up to 7 years after the flood exposure event, so use 'long-term' primarily in contrast to the large literature studying 'short-term' effects in the one to two years after exposure.

in the GHSP and one based on MODIS satellite imagery from NASA's Near Real Time Global Flood Mapping product (NASA, 2024). These measures are not well-aligned: 48 communities are considered exposed to flooding in 2012 according to both measures compared to 86 using the survey measure only and 73 using the satellite measure only, with 290 not considered flooded by either. We find limited evidence that the disagreement is due to survey measurement issues. Communities where flooding is identified by satellite only are less rural and agricultural, suggesting areas where households may be less vulnerable and there less likely to report adverse flood effects. On the other hand, the MODIS-based measure misses more agricultural communities with limited fluvial flood hazard (from overflowing rivers) that experienced heavy rainfall in 2012, where clouds would have prevented satellite imagery from detecting floods. Given the limitations of the MODIS-based measure—flood incidence measures based on satellite radar are not available for 2012—we focus our analysis on a survey-based measure of community flood exposure and test the sensitivity of the results to different measurement approaches.

We estimate household effects of flood exposure in a difference-in-differences design comparing changes before and after the major flood events of 2012 for households that did and did not reside in communities exposed to those floods. To account for potential endogeneity in flood exposure, we balance the sample on recent flood history and underlying fluvial flood hazard, control for time-invariant correlates through household fixed effects, and recenter binary 2012 flood incidence around predicted incidence (as in Borusyak and Hull (2023)). The results are robust to different permutations of these approaches.

Community flood exposure causes large and significant immediate decreases in household consumption per capita, food security, asset value, and value of crop production. While household food security and asset values recover over time, consumption per capita does not, falling by 13% on average in survey rounds after 2012 relative to pre-flood levels. The apparent driver is a persistent decrease in the value of crop production, which falls by 33% on average following flood exposure with similar magnitude effects all the way through the 2018-19 survey round. These are economically large effects, particularly since they represent average effects of community-level flood exposure and less than half of households in communities flooded in 2012 report any direct adverse effects.

Decreased crop production value stems from a combination of decreases in area planted, average yields, and average sales prices. The production and yield effects are largest in the year of the floods but persist over subsequent seasons. Despite these reductions we find no evidence of agricultural exit or reallocation of labor away from agriculture following flood exposure. Instead, households exposed to floods are *more* likely to engage in farm production and *increase* supply of on-farm family labor relative to households in non-flooded communities over time. A 26% average increase in family crop labor hours does not appear to attenuate decreased crop production after the floods.

Nigerian households in the survey sample do not report commonly using migration or non-farm enterprises (NFEs) to cope with flood shocks; reducing consumption, selling assets, and both formal and informal assistance and loans are the most common coping strategies. In line with this, we find no average effects of flood exposure on household NFE engagement, labor hours, or income. The probability that the household moves or that any member migrates falls immediately after the floods but increases significantly 7 years later (by 6 and 10 percentage points, respectively). Delayed increases in migration suggest this is potentially a desirable but constrained flood response. Although flood exposure increases the count of household members engaged in wage work by 18%, this increase is concentrated on the intensive margin and is not associated with increases in wage income. In particular, only households engaged in *both* agricultural production and wage employment in the survey round before the floods increase their labor supply—to both activities—following flood exposure. The 2012 floods do not decrease consumption or assets for these already diversified households, suggesting substitution between consumption and leisure that is more constrained in other households. Increased labor hours in low-productivity crop production and in wage employment without corresponding income gains indicate important constraints to engaging in higher-return livelihood opportunities.

We do not find consistent heterogeneity in the impacts of the 2012 floods by measures of underlying flood hazard or recent flood exposure, though decreases in agricultural production value are driven by communities with higher flood hazard and any survey reports in the previous five years suggesting greater vulnerability in these areas. On the other hand, we find that households in communities that are closer to major markets have smaller decreases in the value of agricultural production and larger increases in engagement in wage work following floods than those in more isolated communities, though these differences are not associated with smaller decreases in consumption. Access to social safety nets, as measured by community-level reporting of different forms of social assistance programs, is associated with significantly smaller consumption decreases after floods but not with any difference in livelihood effects, suggesting a potential role of social programs in supporting flood recovery.

The results are qualitatively similar across different approaches to defining survey-based community flood incidence, but not when using a satellite-based measure. Strikingly, we find no consistent significant effects of satellite-based 2012 flood exposure on household outcomes, including in the 2012-2013 survey round. This is consistent with this measure not detecting any floods in a large number of communities with survey flood reports and classifying a similar number of communities with no flood reports as flooded. These differences highlight the importance of decisions around flood incidence measurement for economic analysis for both interpretation and validity.

In summary, we find no evidence of agricultural exit or livelihood diversification following flood exposure. Farm production value falls but the shares of total household income (including farm production value) from farm production, NFE, and wage employment are unchanged. Household livelihoods in this context are highly concentrated and remain so after the major 2012 flood exposure shock. The main labor supply responses involve intensifying engagement in existing activities with limited returns. While *ex ante* livelihood diversification appears to help mitigate flood shocks, it is not commonly used as an *ex post* coping strategy. Given the persistent reductions in agricultural productivity for years following flood exposure, the 2012 floods likely slowed down processes of structural transformation in Nigeria rather than contributing to them.

This paper contributes to our understanding of the dynamic impacts of weather-related disasters, particularly floods, on labor supply and livelihoods in sub-Saharan Africa, adding to a rich literature on the impact of climate shocks in LMICs. Many studies have analyzed the effects of floods on household outcomes in LMICs, though studies of its impacts on migration and labor supply have focused primarily on South Asia and on short-term effects (see Section 2 for an overview). In general, few studies of natural disasters in agricultural settings have analyzed long-term effects on measures of livelihood or labor supply other than migration.[2] Using measures of community exposure to a major flood event in Nigeria, we find persistent increases in household on-farm labor supply that do not prevent decreases in the value of farm production and household consumption per capita. Engagement in wage employment also increases but only among households with members already working for a wage before the floods, and there is no change in the concentration of household income or the income shares of different work activities. Migration appears to be one alternative to intensified agriculture production but does not increase until many years after the floods. The results indicate households in Nigeria struggle to recover from a significant agricultural production shock, and that access to non-farm opportunities is limited.

Our analysis of long-term labor allocation across activities following a weather shock also builds on the literature on factors encouraging or impeding structural transformation in LMICs (Alobo Loison, 2015; Gollin and Kaboski, 2023). Global reductions in agricultural productivity growth over the past few decades due to climate change have important implications for structural transformation.[3] While a large empirical literature studies the consequences of climate change and many studies have analyzed short-term labor supply responses to extreme weather events in LMICs,[4] there is limited evidence on the relationship between extreme weather events and livelihood diversification or structural change over the long-term in sub-Saharan Africa (Barrett et al., 2021). We show no evidence that flood adaptation or coping strategies push reallocation of labor from farm to non-farm activities as a result, though there are delayed effects on migration. Consistent with prior work on temperature-related decreases in agricultural productivity, we find decreasing food consumption and increasing agricultural labor following flood-driven reductions in agricultural productivity. The lack of agricultural exit or livelihood diversification following flood exposure suggests floods will slow down processes of structural transformation. This has important implications in a context of increasing flood risk, particularly as we show that more diversified households are more

[2] Some exceptions include Albert et al. (2021), Alfani et al. (2024), Efobi (2022), and Mueller and Osgood (2009b) on droughts, Kirchberger (2017) on earthquakes, Van den Berg (2010) on hurricanes, and Mueller and Quisumbing (2011), Patel (2025), and Sajid and Bevis (2021) on floods.

[3] See Auffhammer and Kahn (2018) and Kala et al. (2023) for discussions of potential responses for agricultural households in LMICs, and Albert et al. (2021), Colmer (2021), Cruz (2024), Cruz and Rossi-Hansberg (2024), Henderson et al. (2017), Liu et al. (2023), Nath (2025), and Pham (2025) for analyses of impacts of increasing temperatures on structural transformation.

[4] See e.g., Afridi et al., 2022; Bohra-Mishra et al., 2014; Branco and Féres, 2021; Chuang, 2019; Emerick, 2018; Franklin and Labonne, 2019; Grabrucker and Grimm, 2021; Gröger and Zylberberg, 2016; Ito and Kurosaki, 2009; Jayachandran, 2006; Jessoe et al., 2018; Kijima et al., 2006; Kleemans and Magruder, 2018; Kochar, 1995, 1999; Kubik and Maurel, 2016; Matsuura et al., 2023; Maystadt et al., 2016; Mueller, Sheriff, et al., 2020; Musungu et al., 2024; Noack et al., 2019; Rose, 2001; Yu et al., 2025.

resilient to floods.

Finally, we add to a growing literature on measurement concerns in evaluating the impacts of flood exposure (Bangalore et al., 2025; Chen et al., 2017; Guiteras et al., 2015; Patel, 2025; Saunders et al., 2025),[5] and to a broader literature on using remote sensing in economic analysis (Donaldson and Storeygard, 2016; Hansen et al., 2013; Jean et al., 2016; Yeh et al., 2020) and particularly the limitations of such measures (Fowlie et al., 2019; Gibson et al., 2021, 2025; Jain, 2020; Josephson et al., 2026; Sun et al., 2018). We find large differences in the communities identified as affected by the 2012 floods in Nigeria according to survey reports 'on the ground' and to satellite imagery 'from the sky' (building on previous work in Bangalore et al., 2025). Differences in vulnerability across communities as well as constraints in what floods can be detected by satellite imagery both play a role. While the limitations of different flood incidence measures are known, we highlight how they influence what types of flood events are captured and analyzed and how results should be interpreted. The vast majority of studies on the impacts of floods consider a single source of flood incidence data. The striking differences in estimated impacts under different measurement approaches in this paper suggest a need for more careful consideration of how to approach measurement as well as transparency and sensitivity checks in future research on floods.

2 Conceptual framework and literature

The structural transformation of economies is a key aspect of modern economic development. Structural change can include several types of transitions (Gollin and Kaboski, 2023), such as urbanization, shifting from informal to formal firms, and moving from artisanal self-employment to more complex firms. But perhaps the most obvious aspect is the reallocation of economic activity across sectors. Although this reallocation can be measured in different ways (Herrendorf et al., 2014), such as value added shares and final consumption expenditure shares, a common approach that relates directly to this paper involves analyzing changes in employment shares. Historically, structural transformation has involved decreasing employment in agriculture, hump-shaped employment shares in manufacturing, and increasing employment in services as a function of the level of economic development, though not all countries follow this trajectory (Sen, 2019).

Models of structural transformation emphasize the role of technological progress in driving reallocation across sectors, with different theories proposed based on uniform or sector-specific productivity increases (Herrendorf et al., 2014). In agriculture, innovation-driven productivity growth tends to *push* labor out, as decreasing amounts of labor are needed to meet finite demand for agricultural products. In manufacturing and services, productivity growth *pulls* labor in by increasing the marginal product of labor and therefore wages while lower prices and increased incomes drive increasing demand for manufactured goods and services. A large literature studies the drivers and constraints to structural transformation (see Gollin and Kaboski (2023) for a recent

[5] A much larger literature focuses just on the question of flood detection; see for example Kar et al. (2024), Li et al. (2018), Tellman et al. (2021), Yan et al. (2015), and Zhang et al. (2023).

overview), but it is clear that differences across contexts in productivity across sectors can affect whether and how structural change occurs.

These considerations make it important to consider how climate-related productivity shocks could affect structural transformation, particularly in developing countries with high shares of employment still engaged in agriculture. Climate change is decreasing agricultural productivity is most regions of the world (Nath, 2025; Ortiz-Bobea et al., 2021). Recent research suggests that current adaptive measures are insufficient to mitigate these effects (Hultgren et al., 2025; Kala et al., 2023; Pörtner et al., 2022) and that constraints to migration—an important adaptation pathway (see e.g., Ibáñez et al. (forthcoming))—increase the losses from climate change (Cruz and Rossi-Hansberg, 2024).

Studies on the impacts of climate change on structural transformation have focused on the effects of increasing temperatures and report mixed results. Two global analyses find that decreased agricultural productivity increases agriculture's share of employment as consumption expenditure falls and shifts towards subsistence goods (Cruz, 2024; Nath, 2025). There is more variation in country-specific studies. In India, Colmer (2021) finds that higher temperatures decrease agricultural productivity and increase non-agricultural employment in the short-term, but Liu et al. (2023) find that in the long-term, rising temperatures decrease non-agricultural employment due to lower local incomes and demand for non-agricultural goods and services. In Brazil, Albert et al. (2021) find that persistent increases in dryness lead to labor reallocation towards manufacturing locally and towards services in migration destinations. Finally, in Vietnam, Pham (2025) find that extreme heat leads to reallocation of labor away from agriculture in both the short-term and long-term, but only in more globally-integrated regions. In less-integrated regions, consumption expenditures fall and the agricultural labor share increases.

What is clear from the literature is that reallocating labor to a more productive non-farm activity would reduce losses from permanent or transitory decreases in agricultural productivity. In addition to increasing temperatures, climate change is also increasing the frequency and severity of extreme weather events. Many studies find that agricultural households respond to adverse weather events by increasing labor supply to non-agricultural activities in the same year,[6] in order to offset lost agricultural income and smooth household consumption. A growing body of evidence evaluates whether exposure to such shocks has persistent effects on household labor supply outcomes, but finds mixed effects on reallocation from farm to non-farm activities,[7] so the implications for structural transformation are unclear.

If structural transformation is most commonly the result of productivity *increases* in the agricultural and non-agricultural sectors, how might an agricultural productivity *decrease* from a weather-

[6]E.g., Afridi et al., 2022; Branco and Féres, 2021; Chuang, 2019; Colmer, 2021; Jayachandran, 2006; Kijima et al., 2006; Kochar, 1995; Kubik and Maurel, 2016; Matsuura et al., 2023; Mueller, Sheriff, et al., 2020; Noack et al., 2019; Rose, 2001.

[7]E.g., Albert et al. (2021) and Mueller and Osgood (2009a, 2009b) on drought in Brazil, Efobi (2022) on drought in Nigeria, Gray and Mueller (2012a) on drought in Ethiopia, Alfani et al. (2024) on drought in Morocco, Kirchberger (2017) on earthquakes in Indonesia, Liu et al. (2023) on temperature in India, and Pham (2025) on extreme heat in Vietnam.

related shock such as a flood promote labor reallocation? Several mechanisms may push households to exit agriculture or diversify their livelihood strategies. First, households may update their beliefs about risks and returns to agricultural production, though only if the shock is seen as an indicator of a changing risk profile and not as an extreme realization from an unchanged risk distribution. Second, the short-term non-farm labor and migration coping strategies documented in many studies to smooth consumption needs following shocks may help households learn about non-farm livelihood opportunities that are more productive that agriculture. Third, for weather disasters causing physical damages such as floods or cyclones, damage or loss of productive assets may change perceptions about sunk costs of remaining in agriculture. Forced displacement may similarly decrease the opportunity cost of allocating labor away from agriculture.

On the other hand, a variety of factors can constrain households wanting to respond to a shock by diversifying their livelihood activities or exiting agriculture. In developing contexts which often have high trade costs, low agricultural productivity can create a 'food problem' increasing the need to allocate land and labor to produce food and meet subsistence needs (Gollin et al., 2007; Nath, 2025). As documented in the studies on climate change and structural transformation, reduced agricultural productivity also decreases local incomes. This will on average reduce demand for non-agricultural goods and services and associated non-agricultural labor (Liu et al., 2023), limiting local non-farm opportunities which may already be low in rural agricultural areas with weak infrastructure (Barrett et al., 2021). Migration is a possible response, but resource constraints following a productivity shock can interact with other barriers to prevent migration in search of non-agricultural work. Even successful migrants may face high costs of living and lower wages in urban areas due to increased market competition (Auffhammer and Kahn, 2018), and many rural households and individuals prefer not to migrate away permanently (Lagakos et al., 2023). Even where there are non-farm opportunities, household strategies to smooth consumption after a shock can deplete household assets (Carter et al., 2007), reducing resources available to invest in new skills, activities, and technologies that could be needed to engage in new livelihood activities.

This conceptual framework highlights how adverse shocks to agricultural productivity could have different effects on household livelihood strategies depending on the context and household characteristics. In well-integrated areas with more developed labor markets, agricultural households with sufficient resources may reallocate labor to non-farm activities while in less-integrated areas and for poorer households, reduced incomes and limited alternatives may increase engagement in agriculture. Indeed, Mueller, Gray, and Hopping (2020) find that temperature and rainfall anomalies increase short-term out-migration in some African countries but decrease it in others and point to differences in non-farm opportunities and the need for subsistence production labor as potential mechanisms. Though a large literature documents displacement and migration following weather shocks in LMICs (Almulhim et al., 2024, results on the impacts of flood incidence are mixed. In a set of studies in different South Asian countries, three report increases in short-term out-migration following flood exposure (Balboni et al., 2023; Patel, 2025; Pavel et al., 2023), two report decreases (Chen and Mueller, 2019; Chen et al., 2017), two report null effects (Gray and

Mueller, 2012b; Mueller et al., 2014), and one reports mixed results (Maystadt et al., 2016).

While many studies find that flood exposure increases short-term non-farm labor activity, still drawing on evidence from South Asia (Akter, 2021; Chen et al., 2017; Gray and Mueller, 2012b; Maystadt et al., 2016; Mueller and Quisumbing, 2011; Vitellozzi and Giannelli, 2023), the small literature on long-term effects of floods on livelihood activities is less consistent. Mueller and Quisumbing (2011) find that wages in both farm and non-farm activities fall and that workers move into non-farm casual labor in the short-term following flood exposure in Bangladesh, but that these effects do not persist 5 years later. Sajid (2023) finds that flood exposure in the past decade in rural areas of India decreases both household wealth, non-agricultural work, and migration to urban areas while increasing engagement in agriculture. In contrast, Patel (2025) finds that floods in Bangladesh persistently increase migration and push employment out of agriculture, with effects are mitigated by prior adaptation to past flooding exposure.

The different results across these studies motivate further evaluation of the livelihood and labor supply impacts of flood exposure in a new context (without the monsoon-related flooding prevalent in South Asia), taking into consideration factors which could lead to differential effects. The conceptual framework suggests two key factors that could lead to heterogeneous effects of flood exposure on long-term household livelihood strategies. First, households in areas with high underlying flood hazard and with recent flood exposure are more likely to have already adapted and therefore be less affected by a given flood event. On the other hand, floods occurring in such areas may be more severe and create a greater need for livelihood-based coping strategies. Second, households with better connections to markets should have more access to non-farm work opportunities and be less reliant on household production for subsistence, and therefore respond more to a flood shock. We test whether heterogeneity along these dimensions can explain some of the differences in the literature on the livelihood effects of flood exposure.

3 Context and data

Floods are one of the most common types of natural disasters globally, accounting for 44% of all disaster events from 1970-2019 (World Meteorological Association et al., 2021). The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report finds that there is high confidence that climate change is increasing the risk and severity of flooding, due largely to increases in extreme precipitation events (Caretta et al., 2022). Tellman et al. (2021) estimate that the proportion of the global population exposed to floods has increased by 20-24 percent from 2000 to 2015, and find that this will increase further by 2030 under current climate change projections. Projected increases in flood risk are not distributed evenly over space; the largest projected increases are concentrated in South and Southeast Asia and Sub-Saharan Africa (Caretta et al., 2022). Rogers et al. (2025) estimate that by 2100, 63% of global flood exposure will be in the areas with the lowest GDP levels.

Nigeria is one of the countries with the largest change in the population exposed to floods. Tellman et al. (2021) estimate that this population nearly doubled from 2000 to 2015. Rogers et al.

(2025) project that it will nearly double again from 2020 to 2050, from 34 to 64 million at risk of 100-year floods of at least 10 cm. The Nigeria Hydrological Services Agency (NIHSA) reports that the frequency of flooding has intensified in recent years, disrupting agricultural production and livelihoods but also causing death, population displacement, and destruction of housing and other infrastructure (NIHSA 2021).

In 2012, catastrophic flooding affected 30 of 36 states between September and November as a result of excessive rainfall. The floods caused an estimated $16.9 billion in damages, displaced over 2.1 million people, and killed 431 people (Unah, 2021). Similar widespread floods in 2022 affected 33 of 36 states, displaced over 1.3 million people, and killed 603 (Oguntola, 2022).

Increasing flood risk and recent particularly severe national flood disasters make Nigeria a relevant context for studying the economic impacts of flood exposure and labor supply. Nigeria is also an important setting to study labor reallocation and structural transformation, with the largest population and economy in Africa. While 76% percent of Nigeria's GDP comes from non-agricultural sectors, around 70% of Nigeria's population is engaged in agriculture (Statista, 2023). Most of agricultural production is at a subsistence level and productivity is low such that Nigeria relies on imports to feed its population (FAO, 2022).

3.1 Survey data

The main data source for the analysis is Nigeria's General Household Survey Panel (GHSP).[8] The GHSP is a nationally-representative panel survey including approximately 5,000 households conducted by the Nigeria National Bureau of Statistics, and is part of the World Bank's Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). In each round, households are surveyed twice: once post-planting (around August-September) and once post-harvest (around February-March). Four survey rounds have been completed between 2010 and 2019, with two-thirds of the sample being replaced for the 2018-19 round. Figure A1 shows a timeline of GHSP data collection. Efforts to track households even if they move result in quite low levels of attrition: just 8% of households drop out of the sample between 2010 and 2015.[9]

The household survey includes detailed modules on household agricultural production, labor supply, income, assets, and socio-demographics. The primary household-level outcomes are measures of total annual income or production value by activity and engagement of members in different types of work. We consider three broad livelihood activities: household farm (crop and livestock) production, household non-farm enterprise, and any form of wage employment. In addition, we consider effects of flood exposure on measures of household consumption, food security, and wealth, and on a variety of crop production outcomes. We convert all monetary values to constant 2016 PPP USD, accounting for inflation and changes in purchasing power, and winsorize continuous variables at the 99th percentile.

Incomes are measured at the annual level over the 12 months prior to the post-harvest survey.

[8] See Appendix C for additional details.

[9] For the panel sample of the 2018-19 survey round, 95% of targeted households were tracked and included.

We assign a value of 0 for households not engaged in particular activities. In 2010, 40% of households reported at least one member engaged in wage employment at some point in the year. Household wage income the sum of individual earnings for all wage employment. Similarly, income from household non-farm enterprise (76% of households) is the sum of revenues from all enterprises. For household farm activities (69% of households), we estimate the value of all crop and livestock production, including output consumed by the household. The value of crop production is based on crop sales revenue plus the value of unsold production, calculated as the quantity not sold times the median price for sales of that crop in the community. We follow the same approach to value livestock products (e.g., animal labor, eggs, milk, meat, live animals). We also calculate total income from other sources, such as investments, remittances, and pensions.

Each household is associated with community-level data based on surveys with a group of community informants conducted at the same time as the household surveys.[10] The public survey data also include spatial characteristics calculated by the World Bank such as distances to markets and administrative centers, local climate and weather, and land cover.

3.2 Flood data

An important challenge in analyzing floods is determining how to measure flood incidence—where floods have occurred. The main raw data sources include government records, media reports, survey reports, precipitation data, river or other water gauges, and satellite imagery or radar, and all of these sources have been used in applied research studying the impacts of floods. Each source has different advantages and limitations.[11] The most common flood incidence measures in recent years draw on high-frequency and high-resolution satellite imagery or radar data, applying various algorithms to first identify surface water and then determine when and where to classify this as flooding.

Most of the economics literature on the household effects of flood exposure uses a single flood incidence measure and does not engage critically with flood remote sensing literature, echoing criticisms of economists' use of nighttime lights data (Gibson et al., 2025). Guiteras et al. (2015) were

[10] Communities are referred to as 'enumeration areas' (EAs) in the GHSP.

[11] Government and media reports can provide validated information on the timing and location of floods and are incorporated in many public databases of flood events such as the Dartmouth Flood Observatory (DFO, Brakenridge, 2023) and the EM-DAT International Disaster Database (Guha-Sapir et al., 2023). But media sources typically only approximate the spatial extent of flooding and are not comprehensive, with particularly limited coverage outside more populated and developed areas (Jones et al., 2023; Patel, 2025), while the level of detail in government flood records is highly variable. Survey reports provide direct evidence of areas affected by floods but are limited in their spatial and temporal coverage and subject to concerns around measurement error and reference dependence or adaptation. Local precipitation may be correlated with flooding, though the quality of the proxy is questionable (Chen et al., 2017; Guiteras et al., 2015; James and Schumacher, 2024), as most flood events result from the overflow of rivers and other bodies of water (fluvial floods) rather than local rainfall accumulation that is not absorbed or drained away (pluvial floods). Precipitation data may also be combined with hydrological models to predict flood incidence. Water gauges are limited in spatial extent and are more commonly used for validation of other flood measures than for measuring flood incidence. Satellite data sources have the advantages of high spatial and temporal coverage but may fail to capture floods that are of short duration or masked by clouds (an issue for imagery but not radar), buildings, trees, or topography. They are also sensitive to algorithm parameters selected to identify surface water and classify flood events.

among the first to highlight that different measures were poorly correlated, considering rainfall, satellite imagery, and survey reports in Bangladesh, but did not test flood impacts. Chen et al. (2017) find higher correlations between a more refined rainfall-based measure and a measure based on satellite imagery in Bangladesh, and estimate similar qualitative effects of flood exposure on out-migration. Akter (2021) considers survey reports and satellite imagery detection of floods in Pakistan and finds similar qualitative effects on men's and women's time use. In contrast, Saunders et al. (2025) report that choosing between measures of incidence based on satellite imagery (including state-of-practice and state-of-the-art models), a physical inundation model, rainfall deviations, and river gauges significantly affects the accuracy and timeliness of simulated flood index insurance payouts in Bangladesh.

In closely related work, Bangalore et al. (2025) compare different approaches to measuring incidence of Nigeria's 2012 floods. They evaluate three GHSP survey-based measures, two measures based on satellite imagery (public satellite radar data are not available for 2012), one based on media and government reports (the Dartmouth Flood Observatory (DFO) Archive; Brakenridge, 2023), and one combining DFO flood events with satellite imagery (the Global Flood Database; Tellman et al., 2021). The study finds significant disagreement across sources in which GHSP communities are identified as experiencing floods in 2012, and this leads to inconsistent estimates of the short-term effects of these floods on household agricultural production. We build on Bangalore et al. (2025) and other papers considering approaches to flood measurement by analyzing the drivers of disagreement between survey and satellite measures of community flood incidence in Nigeria in 2012,[12] and explore the implications of flood measurement approaches to estimating long-term effects of the 2012 floods.

First, we use a *survey-based* measure of flood incidence using household reports in the 2012-13 GHSP post-harvest round (conducted in February-April 2013).[13] We combine reports from separate questions in different parts of the survey on floods that caused harvest failures, loss of harvest, loss of property, and food insecurity. We count the number of households in each community reporting any type of flood exposure in 2012 (Figure A3), and define community flood incidence as having at least two households reporting flood exposure. This approach has the advantage of capturing flood events that affect households in different ways, though will not capture floods that do not affect households through these particular dimensions. Requiring more than one household flood report effectively treats isolated reports as measurement error, as a 'non-flood' shock (some households may report damage from heavy precipitation as a 'flood'), or as a highly-localized shock. This requirement could bias estimated effects downward due to some flooding among control observations, or upward by identifying effects of potentially more severe floods. We test the sensitivity of the results to different survey-based flood incidence measures, including reports of flood events in the community survey.

[12] The EM-DAT International Disaster Database surprisingly does not record any flood events in Nigeria in 2012. The DFO Archive identifies five broad polygons of flooded areas (Figure A2 Panel A) and the Global Flood Database only maps out three associated flooding events.

[13] See e.g., Freudenreich and Kebede (2022), Gray and Mueller (2012b), Mueller and Quisumbing (2011), and Stein and Weisser (2022) for examples of research on the household impacts of floods measured using survey reports.

Appendix C provides additional details on the specific survey questions used and correlations in flood reports across survey questions.

Second, we follow several economics papers (Akter, 2021; Chen et al., 2017; Guiteras et al., 2015; Sajid and Bevis, 2021; Vitellozzi and Giannelli, 2023) in using a *satellite-based* flood incidence measure using MODIS (Moderate Resolution Imaging Spectroradiometer) satellite imagery. In particular, we use NASA's Near Real-Time (NRT) 2-day 250 m resolution Global Flood Mapping product (NASA, 2024), taking their approach to identifying flood events as given.[14] We define pixels as having been exposed to floods if the NASA NRT product identifies any flood incidence in that pixel in 2012 (Figure A2 Panel B presents a map). We match GHSP communities to satellite flood incidence based on the community coordinates. These coordinates are randomly offset from the original community centroids in the public data, by 0-2km in urban areas and by 0-5km in rural areas (and up to 10km for a random 1% of rural communities). We therefore define a community as exposed to a satellite flood incidence if its offset coordinates are within 5 km of any flooded pixel, and test robustness to using a 10 km radius. Moving forward we refer to this as the 'MODIS' or 'satellite' flood measure.

We do not include a precipitation-based proxy of flood incidence due to the coarseness of publicly-available databases and limitations in using local precipitation deviations to identify flooding (Chen et al., 2017; Guiteras et al., 2015; James and Schumacher, 2024). As an additional source of flood data, we directly obtained a list of all local government areas (LGAs) where floods were reported in 2012 from the Nigerian National Emergency Management Agency (NEMA), and match this information to communities based on their location. NEMA is responsible for overseeing disaster management in Nigeria, and collects information on flood reports from State Emergency Management Agencies, other government agencies, and media sources.

Finally, data on fluvial flood hazard produced by the European Commission Joint Research Centre (JRC; Baugh et al., 2024) map the depth of inundation for floods of different return period at a 90 meter resolution. We focus on depths of 100-year floods, and calculate the mean and maximum depth within a 5 km radius of each survey community as a measure of local flood hazard. This measure does not capture pluvial flood hazard from heavy precipitation that is not absorbed or drained toward river networks, but fluvial flood hazard typically drives the largest share of flood exposure and risk. To complement this measure, we calculate the distance between each survey community and the nearest body of water using data from the Digital Chart of the World.

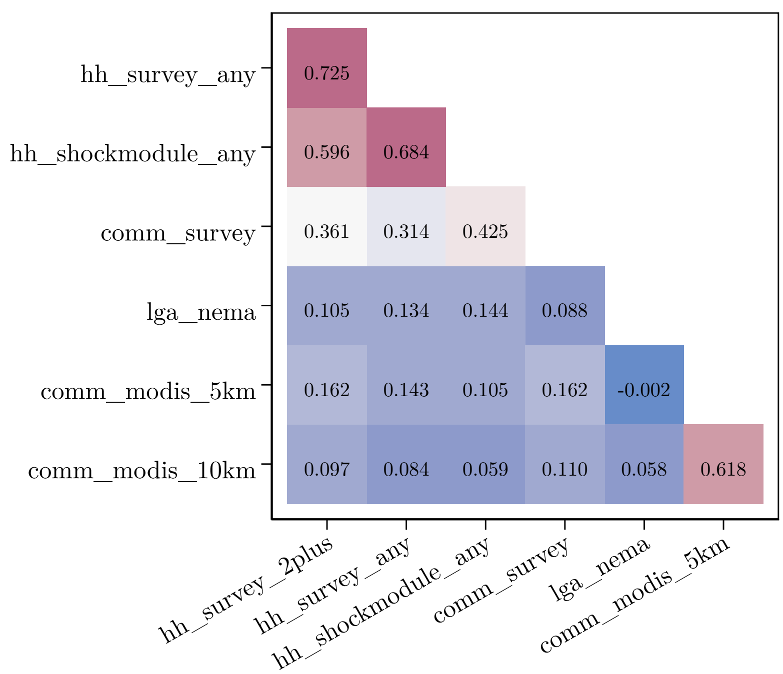
3.3 Analyzing flood detection across sources

The set of communities identified as exposed to floods in 2012 differs significantly depending on the survey measure. Figure 1 shows a heatmap of pairwise correlations between flood measures

[14] The algorithm identifies surface water using the Normalized Difference Water Index (NDWI), applies a permanent water mask to determine when this water is not expected, and then applies various corrections to deal with cloud and terrain shadow and other known issues in surface water detection. The NASA NRT product transitioned to a different format in 2022 and access to historical flood data has been restricted and is no longer possible through the online platform.

(Figure A4 maps exposed communities by definition). Measures based on the household survey are highly correlated with one another (values above 0.6), though measures based on household reports versus one based on informant reports in the community survey are less well-correlated (values between 0.3-0.4). But correlations between these measures and the satellite-based measure using MODIS imagery are very low, with none greater than 0.2. The correlation is highest when using a 5 km buffer to link communities to MODIS-detected floods and using the main survey-based flood definition, considering all flood-related questions and requiring at least two separate household reports. Neither survey- nor satellite-based flood measures are closely correlated with the NEMA data on flood incidence, both because the NEMA data are at the LGA level and therefore lose local variation in flood incidence and because the NEMA data do not include many LGAs where floods are reported by surveys or detected by satellite. NEMA records 2012 flood reports in the LGAs of 94 of the 465 GHSP communities, but captures only 21% of communities identified as flooded by satellite and 28% of those identified by survey. This was the first year where NEMA attempted to collect information on flooded areas across the country and efforts to document flooding were greatly increased in subsequent years.

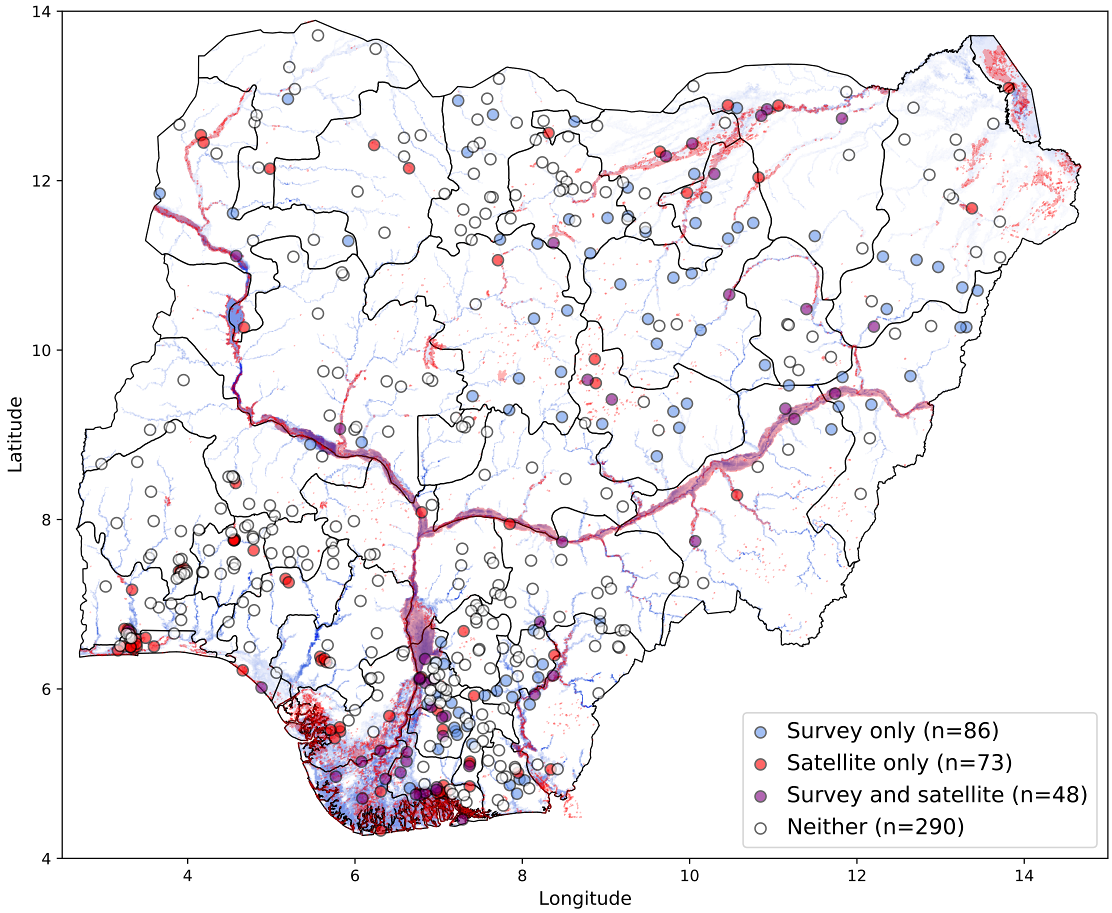
Figure 1: Correlations between different measures of community-level 2012 flood incidence



Note: This heatmap shows pairwise correlations between different measures of flood incidence in 2012 at the level of communities in the Nigeria GHSP. 'hh_survey_2plus' is the main survey-based measure, indicating at least two households reporting a flood in any survey module. 'hh_survey_any' is the same but only requires one household report. 'hh_shockmodule_any' indicates any household reporting a flood but only considering reports in the household shocks module. 'comm_survey' indicates a flood report by informants in the community survey. 'lga_nema' indicates floods reported by NEMA in the local government area (LGA) containing the community. 'comm_modis_5km' and 'comm_modis_10km indicate any flooded pixel identified in the NASA MODIS flood database within 5 and 10 km of the community centroid, respectively.

Figure 2 maps the locations of GHSP communities and their 2012 flood exposure status based on the main survey measure and the MODIS measure. The figure illustrates how widespread flooding was across the country and highlights differences in community flood exposure between the two measures. Of 497 GHSP communities, 134 have at least two household flood reports for 2012 and 121 are within 5km of a pixel identified as flooded by the MODIS measure, but just 48 communities are considered flooded according to both measures.

Figure 2: 2012 community flooding exposure, by flooding measure



Note: The maps shows the locations of communities included in the Nigeria GHSP, colored by their flood exposure in 2012. Flood incidence is based on either at least two survey reports of being affected by floods in the community or on the community being within 5 km of a pixel where flooding was identified in the NASA MODIS flood product. Pixels identified as flooded by MODISA are shown in red. The blue shading in the background corresponds to the depth of 100-year fluvial floods.

A possible explanation is survey measurement error or misreporting. Survey measurement error does not seem to drive the difference, as alignment between the survey and satellite measures only increases slightly when we require at least two households to have reported floods for the survey measure compared to one household (Figure 1). Strategic misreporting also does not seem an important factor, as on average 34% of households (10 households are sampled in most communities) report flooding in the 86 communities identified as flooded by survey only, compared to 50% on average in the 48 communities identified as flooded by both measures. Part of the mismatch may be due to the noise in the publicy-provided GHSP community coordinates,[15] but the correlation between the two measures is worse if we extend the radius for the MODIS measure to 10 km. Twenty-four of the 86 communities classified as flooded by survey only are within 10 km of a flooded pixel, and their true location may in fact overlap with the flooded area. But the other 62 are more than 10 km from any satellite-identified flooding, indicating other reasons for the mismatch in flood classification.

Different types of errors may explain communities identified as flooded by only one measure. The MODIS measure may be affected by two main sources of error which can explain many communities identified as flooded by the survey only: missing data due to cloud cover and gaps in temporal coverage, and an inaccurate masking of permanent or seasonal water. Most flooding in Nigeria is associated with periods of heavy rainfall so may be masked by clouds. The satellites also only take snapshots at particular points in time every 1-2 days so will miss flash floods where standing water does not persist. Related to this, survey respondents may report water-related damages from heavy rainfall that did not involve inundation as floods, as the surveys do not allow for separate reporting of such damages. Such events would not be captured by satellites.

There are 73 communities within 5 km of MODIS-detected flooded pixels but with no survey-reported floods. Flooding may have taken place near to these communities without causing damages that would be reported in the surveys, or the detected floods may have been sufficiently far away not to affect households. Another factor is that survey respondents only report floods that affect them in particular ways. Some floods detected by MODIS may not have affected households in the ways they are asked about (harvest loss, property loss, food insecurity). The correlation between survey reports and the MODIS measure is weaker if we only consider household reports in the shock module, showing the importance of including respondent reports in other parts of the survey. Reference dependence and adaptation may also be important factors (Guiteras et al., 2015): some communities are likely more accustomed to or adapted to floods and they may therefore not lead to reports of adverse household effects. Another source of error in the MODIS measure could further explain some of the mismatch: the flood detection algorithm may misclassify some expected or seasonal variation in surface water as flooding.[16]

We estimate a series of regressions of community characteristics on dummies for flood incidence under different combinations of the two measures to test whether there are systematic differences, and summarize the results in Table 1. Communities where 2012 floods are identified in both survey reports and MODIS imagery are primarily rural (73%), within 10 km of a body of water, have average 100-year flood inundation depth within 5 km of 1.5 m, and experienced 362 mm less precipitation in 2012 than their historical average (first column). The lower than average precipitation emphasized the limits of rainfall-based flood proxies, as floods can be driven by rainfall

[15] We were unable to obtain a dataset linking the true community locations to the MODIS flood incidence data from the World Bank LSMS team.

[16] Slayback (2024) notes that the NASA Global Flood Mapping product algorithm includes time compositing to deal with clouds and shadows, terrain and cloud shadow masking, Height Above Nearest Drainage masking, and a reference surface water mask based on water detection over previous years. It is not clear if the water mask accounts for seasonal water fluctuations.

in other areas or by very concentrated heavy rainfall in otherwise dry conditinos. Areas that are not classified as flooded according to either flood measure are 32 km farther from a body of water, have average 100-year flood inundation depth within 5 km of 0.1 m, and had similar precipitation in 2012 as usual, but are otherwise similar in terms of rural location and household characteristics (column β_3). This aligns with floods being primarily fluvial rather than pluvial and concentrated in areas with high underlying flood hazard.

Table 1: Differences in GHSP community characteristics by 2012 flooding status

	Mean: Both definitions N=48	β_1: Satellite only N=73	β_2: Survey only N=86	β_3: No flood N=290	$\beta_1 = \beta_2$ (*p-val*)	$\beta_1 = \beta_3$ (*p-val*)	$\beta_2 = \beta_3$ (*p-val*)
Rural	0.73	-0.40***	0.15*	-0.03	0.00***	0.00***	0.00***
	(0.45)	(0.08)	(0.08)	(0.07)			
HH distance to nearest major road (km)	8.54	-4.48***	-0.39	-2.90**	0.00***	0.11	0.01***
	(11.81)	(1.52)	(1.47)	(1.27)			
Diff. in annual precipitation from hist. avg. (mm)	-361.81	93.31	388.92***	296.69***	0.00***	0.00***	0.02**
	(605.01)	(71.04)	(68.87)	(59.57)			
Distance to nearest water area (km)	9.62	11.33**	15.94***	31.65***	0.22	0.00***	0.00***
	(13.98)	(5.22)	(5.06)	(4.38)			
Avg 100-year flood depth within 5 km	1.52	-0.79***	-1.35***	-1.40***	0.00***	0.00***	0.20
	(1.54)	(0.12)	(0.12)	(0.10)			
Baseline share HHs w/ >5 members	0.47	-0.08*	0.12***	-0.02	0.00***	0.06*	0.00***
	(0.27)	(0.04)	(0.04)	(0.04)			
Baseline share HHs below 1.90 USD/cap poverty line	0.34	-0.13***	0.17***	0.02	0.00***	0.00***	0.00***
	(0.31)	(0.05)	(0.05)	(0.04)			
Baseline share HHs w/ above-median asset value	0.52	0.05	-0.08*	-0.03	0.00***	0.02**	0.14
	(0.24)	(0.05)	(0.05)	(0.04)			
Baseline mean HH agricultural land (ha)	1.00	-0.78**	0.33	-0.22	0.00***	0.01***	0.04**
	(1.79)	(0.36)	(0.35)	(0.30)			
Baseline share HHs w/ crop production	0.69	-0.35***	0.24***	0.02	0.00***	0.00***	0.00***
	(0.39)	(0.06)	(0.06)	(0.05)			
Baseline share HHs w/ non-farm enterprise	0.78	0.00	0.00	-0.02	0.94	0.35	0.37
	(0.16)	(0.04)	(0.04)	(0.03)			
Baseline share HHs w/ wage employment	0.40	0.08*	-0.06	0.01	0.00***	0.03**	0.01**
	(0.25)	(0.05)	(0.04)	(0.04)			

Note: This table presents the results from regressions of community characteristics (in each row) on dummies for flood incidence in 2012 according to different measures. The reference group is communities considered flooded under both the survey-based and satellite-based measures. Baseline household data are from the GHSP 2010-11 survey round. The difference in annual precipitation from the historical average is the total precipitation for 2012 minus the annual average from 1960-1990.

Relative to communities identified as flooded according to both survey and satellite, communities classified as flooded according to satellite only are 40 percentage points (pp) less likely to be rural, are 4.5 km closer to a major road, are 11 km farther from a body of water, and have half the average level of flood hazard (column β_1). Households in these communities have 78% less agricultural land, are 35 pp less likely to be engaged in crop production, and are 13 pp less likely to be below the poverty line. The satellite-only measure is therefore more likely to identify floods in more urban, less agricultural settings with lower flood hazard. Households in these areas may be less likely to experience property and harvest destruction from floods due to more robust housing materials and less agricultural engagement and have access to more resources to cope with food insecurity, and so be less likely to report a flood shock. The lower flood hazard also suggests some possible false positives for the MODIS flood detection algorithm.

Communities identified as flooded according to the survey only are more likely to be rural, are

16 km farther on average from a body of water, face limited fluvial flood hazard, and experienced significantly more precipitation in 2012 (column β_2). These characteristics suggest that flood reports in these communities are more likely to represent pluvial floods or heavy rain-related damages that the MODIS imagery will often miss due to cloud cover. A flood measure based on satellite radar or a combination of radar and imagery would help overcome this limitation (see Patel (2025) for a thoughtful example of how this can be done), but public satellite radar data are not available for 2012. Households in these communities are also larger, more likely to be poor, and more likely to be engaged in crop production, meaning they are more vulnerable to the types of flood damages asked about in the survey.

In summary, the two flood measures identify different sets of flooded communities. While Guiteras et al. (2015) argue that survey reports of flooding in Bangladesh have little value relative to "objective" satellite-based measures because households "perceive exposure relative to their average environment" (p. 235), if we are interested in analyzing the effect of floods as an economic shock it is unclear whether a satellite measure should be preferred. The MODIS measure may capture some floods that are not reported in the surveys but also miss a large share of reported floods. The survey measure only captures floods that adversely affect households in specific ways, but it is arguably these types of events that are most relevant to study.

In this paper we focus our analysis on the impacts of survey-reported floods and test how the main effects differ by the choice of flood measure, because of the limitations in the MODIS measure. The effects we identify are of residing in a community where floods were severe enough to damage crops, property, or food security of at least two of ten surveyed households, relative to residing in a community with no survey-reported floods or floods that were less severe.

4 Empirical approach

We analyze the impacts of community exposure to floods in 2012 on household outcomes in subsequent years in a difference-in-differences framework. Specifically, we estimate two-way fixed effects regressions

$$Y_{icst} = \alpha + \beta Flood_c \times Post_t + \mu_i + \gamma_{st} + \lambda_{it} + \epsilon_{icst} \quad (1)$$

where outcome Y varies across households i, communities c, states s, and years t.[17] *Flood* is an indicator for having been a resident in 2012 of a community exposed to floods in 2012. Defining flood exposure at the community level avoids concerns about endogeneity in which households are directly affected. Floods, perhaps more so that drought or temperature shocks, have a strong idiosyncratic element where vulnerability may vary significantly across households even within a community, creating variation in the extent to which different households in flood-exposed communities are affected and the nature of those effects. Analyzing floods at the community level in an 'intent to

[17] As we consider many outcomes, we calculate Anderson (2008) adjusted q-values to correct for family-wise false discovery rates (FDR) with multiple hypothesis tests. These results are available upon request. In general, treatment effects that are significant at less than a 95% confidence level are no longer statistically significant after this adjustment, while other estimated effects remain statistically significant.

treat' specification will capture both direct effects from households that were themselves flooded as well as any indirect impacts from proximity to flooding, though we will not be able to distinguish between these types of effects.[18] On average, 40% of households report being affected by floods in communities with at least two household flood reports (of ten total sample households per community).

Post is an indicator for being observed in a survey round after 2011. The major flood events in 2012 largely occurred between August and November, at the same time as the 2012 GHSP post-planting survey.[19] As the primary outcomes we consider are reported in the post-harvest survey conducted in February-April 2013, we consider the 2012-13 round (along with the 2015-16 and 2018-19 rounds) to be post-flood. We use data from 2010-11 survey round to serve as a pre-flood comparison period and to test for baseline balance in household and community characteristics. In addition to the average effects over all post-2012 survey rounds estimated in the above specifications, we also estimate dynamic effects by interacting *Flood* with indicators of being observed in each survey round. These estimates allow us to evaluate how impacts of flood exposure evolve over time. As only a subset of panel households were included in the 2018-19 round, we have less power to detect whether effects persist that long suggesting any significant effects in this round are fairly strong.

We include household fixed effects (μ) to control for time-invariant household characteristics which might affect livelihood decisions and 2012 flood exposure, and state-by-round fixed effects (γ) to control for common changes over time across broad geographic areas. λ_{it} are household baseline characteristics-by-round controls, where we include characteristics that are unbalanced between flooded and non-flooded communities at baseline. We test the robustness of the results to varying the set of fixed effects and controls. We cluster standard errors at the level of the community of residence in 2012 since this is the level at which the flood treatment is assigned.

This is a 'canonical' difference-in-differences model where all units receive the treatment—being a resident in 2012 of a community that flooded—at the same time and the control group never receives this treatment. The key assumption of this model is the parallel trends assumption, that households that resided in communities which flooded in 2012 would have experienced similar trends over time as households that resided in communities which did not flood, if it had not been for the floods. If the occurrence of floods in 2012 were random over space, this assumption would hold in expectation, but while the timing of floods is exogenous their incidence in space is endogenous to local characteristics such as proximity to a river, elevation, slope, soil type, and other hydrological features. The household fixed effects will absorb these characteristics to the extent

[18] In particular, household poverty status and engagement in crop production in 2010 are significantly associated with the probability of reporting being affected by floods in 2012, both across all communities and within communities with any flood reports. Household outcomes may be affected by proximity to flooding even without direct physical losses through effects on local infrastructure or expectations of flood risk, for example. We therefore do not use community-level flooding to instrument for household-level flooding due to concerns about violations of the exclusion restriction.

[19] One-third of sample households in the 2012-13 post-planting round were surveyed in September and 60% were surveyed in October, with the few remaining households surveyed just before or after.

that they are largely time-invariant, but the analysis may still fail to recover the effects of the 2012 floods if trends in outcomes over time differ between areas at higher and lower risk of experiencing these floods.

We use two approaches to address this concern. First, we balance the sample on recent flood incidence and underlying flood hazard (from the JRC data). We count the number of years each community was exposed to floods from 2007-2011 using household recall data, and for each strata of years we trim the sample to only include communities within the common support of the distribution of underlying flood hazard by 2012 survey-reported flood incidence. This excludes from the sample communities for which there is no close 2012 flood counterfactual in terms of flood risk.

Second, we follow the Borusyak and Hull (2023) approach to dealing with non-random exposure to exogenous shocks by recentering our 2012 flood treatment variable around its expectation. For each flood measure, we predict 2012 community flood incidence as a function of geographic, weather, and mean household characteristics, using a Lasso regression for variable selection (Table A1 shows the results).[20] We set values outside the common support of the distribution of this prediction by 2012 flood incidence to missing and subtract this predicted flood exposure from the measured flood exposure to obtain the recentered treatment variable. This method directly controls for observable treatment correlates, isolating the effect of 2012 flood exposure.[21]

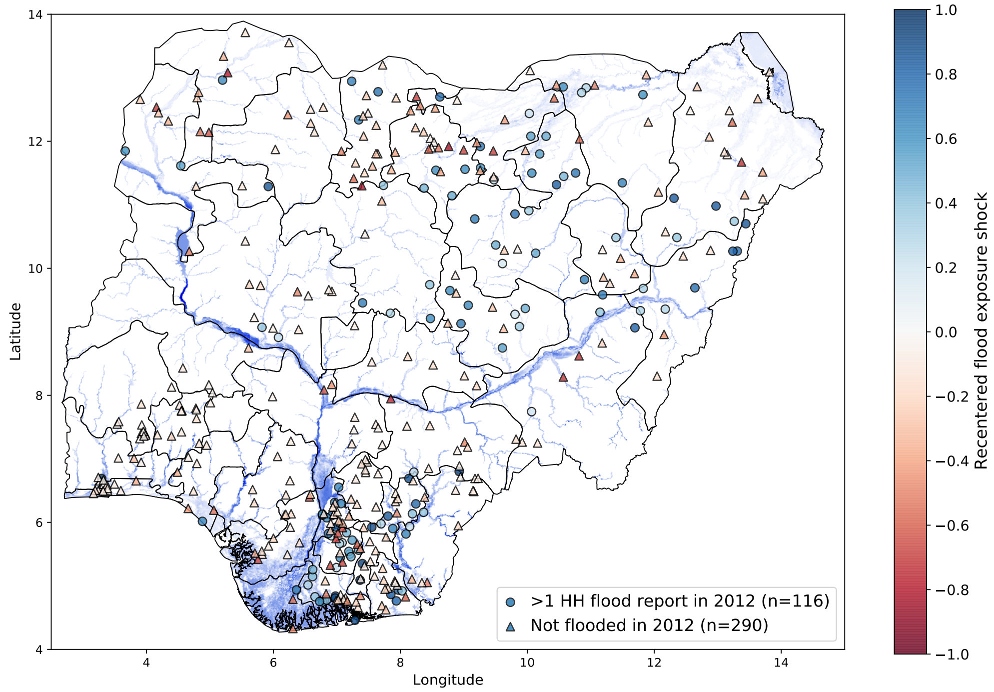
Figure 3 presents the communities in the analysis sample colored by the recentered 2012 flood shock variable. A comparison with Figure 2 shows which communities are dropped from the analysis sample from the balancing on recent flood history, underlying flood hazard, and predicted 2012 flood incidence. A value of 1 for the recentered flood exposure exposure indicates that a community was flooded in 2012 despite a predicted flood propensity of 0, while a value of -1 indicates that a community was not flooded despite a predicted flood propensity of 1. Under this approach, effects of the 2012 floods are identified from exogenous differences in flood incidence across communities in the same state with the same predicted flood incidence. We test the sensitivity of the results to different sample restrictions and approaches to controlling for correlates of 2012 flood incidence.

The parallel trends assumption cannot be tested but we assess its plausibility by testing for baseline balance in community and household characteristics by treatment status (Table A2). In line with the fact that flood incidence is not exogenous across space and with Table 1, we find that characteristics of communities flooded in 2012 differ from those not flooded along many margins. These differences largely disappear after recentering treatment around predicted flood incidence, and we cannot reject the joint hypothesis that all characteristics are the same ($p = 0.149$). Our main specifications include baseline characteristic-by-year controls for the few characteristics where we find significant differences. In addition to balance in baseline household and community characteristics, recentering the treatment variable also leads to balance in survey-reported flood incidence

[20] The most common selected predictors are distance to the nearest body of water, average 100-year flood depth, household flood reports in 2009, the share of households with any crop activity in 2010, and the share of agricultural land around the community centroid.

[21] The predicted 2012 flood likelihood does not come from a full hydrological model and may depend on the selection of predictors. We show in Subsection 5.5 that the results do not depend on this recentering procedure as long as we rebalance the sample and include the household fixed effects.

Figure 3: Recentered 2012 flood shock by survey-reported community flood incidence



Note: The figure plots the locations of GHSP communities in the analysis sample by 2012 flood incidence and recentered flood treatment. Flood incidence is defined as at least two survey households reporting being affected by floods within a community. The recentered flood treatment substract the estimated propensity of 2012 flood incidence from the binary incidence. A value of 1 indicates a flooded community with an estimated flood propensity of 0, and a value of -1 indicates a non-flooded community with an estimated flood propensity of 1. The blue shading in the background corresponds to the depth of 100-year fluvial floods.

across the full survey period, whereas the binary treatment variable is correlated with other flood events (Table A3). These results support the assumption that the recentered treatment variable identifies exogenous variation in 2012 flood incidence.

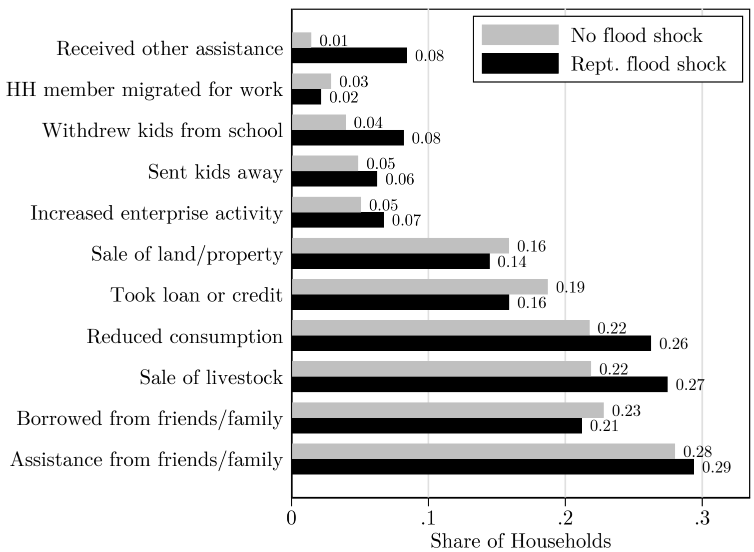
The final analysis sample after the above approaches to balance the sample of communities includes 3,821 unique households across 400 communities. We only include households that did not move prior to the 2012-13 survey round, as although movers were tracked in the GHSP community surveys we cannot confidently measure flood incidence for households outside the main sample communities in 2012. There is no significant difference in survey attrition either before or after the 2012-13 round by 2012 flood exposure. Of the analysis sample households, just 1,081 are observed in the 2018-19 round because of the partial GHSP sample refresh. The lower sample size for 2018-19 leads to larger standard errors for estimated dynamic effects in this period.

5 Results: Impacts of flood exposure

5.1 Immediate flood coping strategies

Before estimating impacts of 2012 flood exposure on household outcomes, we first explore households' reported coping strategies. Just 2.9% of sample households have any formal insurance of any kind in 2012, meaning they must use a variety of strategies to cope with shocks. Information on these strategies comes from the household survey shocks module in the 2013 post-harvest survey, where households are asked to report what adverse shocks they have faced and to list the coping strategies they have used. Death or disability of an adult household member is the most commonly declared shock, followed by floods (Figure A6). Figure 4 compares the strategies reported by households that declare a flood shock against those reported by households declaring only non-flood shocks. For both groups, we consider all the coping strategies households report across all shocks they face, as many shocks are interrelated.[22]

Figure 4: Household shock coping strategies, by reported flood exposure



Note: The figure shows the share of households reporting each type of coping strategy in 2012-2013, separately for households declaring experiencing a flood shock and for households declaring only non-flood shocks. Coping strategies are aggregated across all shocks faced by the household as many shocks are interrelated.

We find that the coping strategies reported by flooded and non-flooded households are broadly similar in terms of relative frequency.[23] Households declaring flood shocks are, however, significantly more likely to report receiving assistance from outside of family and friends, withdrawing children from school, and reducing their consumption, after controlling for state fixed effects. These suggest that flood shocks may be both more severe and attract more support than other types of household shocks, though even among flooded households just 8% report receiving assistance from outside their immediate network, such as government and non-profit relief. The most common coping strategies—borrowing and selling assets—may reduce household wealth in the long term and could drive persistent effects of flood exposure. We also observe that livelihood responses are not a

[22]For example, households declaring a flood shock are more likely to also declare non-flood harvest destruction, death of livestock to illness, and adverse price shocks than households declaring shocks other than floods, even after including state fixed effects (Table A4).

[23]We set aside responses of 'did nothing' which are the most common for both groups, at 40% and 36% of households, respectively.

frequent coping strategy. Few households increase enterprise activity and even fewer report any member migrating to find work in response to a shock. These results suggest long-term livelihood effects of flood exposure may be limited in this setting.

5.2 Household consumption and assets

We now consider impacts of 2012 community flood exposure on a series of household outcomes. Table 2 shows that households in communities with at least two household reports of floods in 2012 are 4 percentage points (pp) more likely to report experiencing any food insecurity over the last 12 months on average over the three post-flood survey rounds than households in non-flooded communities, a 22% increase. In line with this and with reported decreases in consumption in Figure 4, daily household consumption per capita falls by 0.72 USD (13%). This decrease is driven largely by decreased consumption on food items, which falls by 0.63 USD (14%), which can help explain the increase in food insecurity. The decrease in consumption per capita results in a 3pp increase in the probability that households are below the 1.90 USD PPP daily consumption per capita poverty line. Although sales of property and livestock are commonly-reported shock coping strategies, we find no significant effects of 2012 flood exposure on the total value of household assets or on livestock holdings.

Table 2: Impacts of 2012 community flood incidence on household consumption and assets

			Average impact	Dynamic impacts		
	N	Control Mean (SD)	2012 flood recentered × Post (SE)	2012 flood recentered × 2013 round (SE)	2012 flood recentered × 2016 round (SE)	2012 flood recentered × 2019 round (SE)
Any food insecurity in last 12 months	12218	0.18	0.04***	0.07***	0.01	0.02
		[0.38]	(0.02)	(0.02)	(0.02)	(0.04)
Daily HH consumption per capita (USD)	12218	5.42	-0.72***	-0.96***	-0.45*	-0.70**
		[4.30]	(0.24)	(0.33)	(0.27)	(0.32)
Daily HH food cons. per capita (USD)	12218	4.51	-0.63***	-0.52**	-0.79***	-0.40
		[4.47]	(0.20)	(0.25)	(0.21)	(0.28)
Daily HH non-food cons. per capita (USD)	12218	1.91	-0.20	-0.19	-0.21	-0.20
		[2.89]	(0.13)	(0.17)	(0.13)	(0.16)
HH under 1.90 USD PPP per capita daily poverty line	12184	0.36	0.03*	0.04	0.03	0.05
		[0.48]	(0.02)	(0.02)	(0.03)	(0.04)
Value of HH assets (USD)	12218	2066.20	-111.30	-299.25*	74.16	59.95
		[5282.98]	(140.38)	(173.25)	(173.01)	(289.09)
Livestock holdings (TLU)	12218	2.18	0.77	0.58	0.99	0.71
		[36.53]	(0.83)	(0.88)	(0.85)	(0.64)

Note: This table shows the results from separate regressions of household outcomes on recentered 2012 community flood exposure interacted with being observed after 2012. Control means are for communities with no flood exposure in the 2010-11 survey round. The first column of results shows average effects across all post-flood survey rounds. The next three columns show dynamic effects in each post-flood round. Flood exposure is defined as at least two households in the community reporting being affected by floods in 2012, and is recentered around predicted community incidence. Estimates therefore represent the effect of residing in a community that was exposed to floods 2012 for a given predicted propensity of incidence. All regressions include household and state-by-round fixed effects as well as controls for baseline characteristics-by-round for characteristics not balanced in Table A2. Standard errors are clustered at the community level. Each row represents an outcome. Daily household consumption outcomes are calculated on the basis of reported consumption across different goods and services, and are provided directly in the publicly-available GHSP data. Poverty is calculated based on aggregated consumption. The value of household assets is the sum of declared values across all assets owned. Livestock are measured in tropical livestock units (TLU) in order to aggregate across species. Monetary values are in 2016 PPP USD. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Turning to dynamic impacts, we find that the value of household assets does fall significantly in 2013 but recovers by 2016, indicating that households find ways to replenish their assets. Household food insecurity is also only significantly larger in 2013, though the point estimate remains positive in subsequent rounds. The decrease in daily consumption per capita, however, remains statistically significant in all post-flood survey rounds, though the magnitude of the effect is largest in 2013.

The results build on previous work on household flood impacts in African countries showing short-term decreases in food security and consumption (Amolegbe et al., 2023; Baez et al., 2020; Devereux, 2007; Reed et al., 2022), and similar results for an analysis of effects of natural disasters in Nigeria (Escalante et al., 2025). We show that community flood exposure makes households significantly and persistently worse off on average, even accounting for the fact that over half of households sampled in flooded communities do not report any direct adverse impacts of floods. These households may be indirectly affected by local flooding, or affected in ways not captured by the survey questions around flood damages. For example, Stein and Weisser (2022) find that households living in close proximity to a flood event have lower subjective well-being even if they do not report being directly affected by the flood.

5.3 Household composition and livelihood activities

Prior studies have found increases (Balboni et al., 2023; Patel, 2025; Pavel et al., 2023), decreases (Chen and Mueller, 2019; Chen et al., 2017), and null or mixed (Gray and Mueller, 2012b; Maystadt et al., 2016; Mueller et al., 2014) effects of flood exposure on short-term out-migration. Consistent with few households reporting migration as a shock coping strategy in this sample (Figure 4), Table 3 shows no average effects of 2012 flood exposure on the probability that the household moved or that any individual member left the household.[24] This aligns with a study of the impacts of temperature shocks on migration in Northern Nigeria (Dillon et al., 2011), which finds null average effects but that frequent heat shocks increase the probability of male migration, suggesting migration may be a response to particular types of shocks. A marginally significant decrease in the probability that any member left to join or start a new family is not significant after adjusting for multiple hypothesis test false discovery rates (FDR). We also find no effect on the likelihood any adult joined the household, in the count of household members, or in the count of household members ages 0-4, the latter of which implies no effects on household fertility decisions.

In terms of dynamic effects, households in communities exposed to the 2012 floods do not change their household composition in any round but we find some time-varying differences in the probability of households moving and members leaving or joining. Adults are less likely to leave households in flooded communities in the period immediately following the floods, and new adults are more likely to have joined these households by the time of the following survey round 3 years later. By the time of the 2018-19 survey round six years after the floods, however, households in exposed communities are 6 pp more likely to have moved and 10 pp more likely to have a member leave the household in search of work opportunities. These are strongly significant and large effects relative to the fact that just 15% of households retained in the panel by the 2018-19 round had

[24] Although initial displacement is a common consequence of flooding, fieldwork we conducted in Nigeria's Jigawa State after the 2022 floods showed that nearly all households return to the same community if not the same dwelling within 6 months of being displaced.

moved since the initial 2010-11 survey, and 12% had any member leave in search of work.

These results indicate that individual migration is not a common short-term response to floods in Nigeria, but the positive long term effects—also reported in Patel (2025)—suggest that this could be a result of individual and household migration constraints. In particular, the short-term decreases in household consumption and assets following flood exposure may reduce resources available to support migration.

Table 3: Impacts of 2012 community flood incidence on household migration, composition, and livelihood activities

			Average impact	Dynamic impacts		
	N	Control Mean (SD)	2012 flood recentered × Post (SE)	2012 flood recentered × 2013 round (SE)	2012 flood recentered × 2016 round (SE)	2012 flood recentered × 2019 round (SE)
HH moved since first survey round	12218	0.00	-0.00	-0.00*	-0.01	0.06***
		[0.00]	(0.00)	(0.00)	(0.01)	(0.02)
Any member left HH during/since last round	12218	0.08	-0.01	-0.04	0.02	0.01
		[0.27]	(0.02)	(0.02)	(0.02)	(0.04)
Any member left HH for work during/since last round	12218	0.02	-0.00	-0.02*	-0.00	0.10***
		[0.13]	(0.01)	(0.01)	(0.02)	(0.03)
Any member left HH for family during/since last round	12218	0.03	-0.03*	-0.04**	-0.02	-0.03
		[0.16]	(0.02)	(0.02)	(0.02)	(0.05)
Any adult member joined HH during/since last round	12218	0.07	0.01	0.00	0.03**	0.00
		[0.25]	(0.01)	(0.01)	(0.01)	(0.02)
Count of HH members	12218	5.53	-0.01	-0.07	0.05	-0.02
		[2.97]	(0.07)	(0.08)	(0.08)	(0.24)
Count of HH members ages 0-4	12218	0.90	-0.01	-0.01	-0.03	0.12
		[1.11]	(0.04)	(0.04)	(0.05)	(0.11)
Any HH farm activity	12218	0.74	0.03**	0.03**	0.03*	-0.00
		[0.44]	(0.01)	(0.01)	(0.02)	(0.03)
Any HH non-farm enterprise activity	12218	0.76	0.00	-0.01	0.01	0.01
		[0.43]	(0.02)	(0.02)	(0.02)	(0.04)
Any wage employment activity	12218	0.41	0.03	0.04*	0.01	0.01
		[0.49]	(0.02)	(0.02)	(0.02)	(0.04)
Count of HH members wkg. in HH farm	12218	1.89	0.14	-0.02	0.30***	0.30*
		[2.13]	(0.09)	(0.10)	(0.11)	(0.18)
Count of HH members wkg. in HH non-farm enterprise	12218	1.23	-0.03	0.00	-0.05	-0.08
		[1.36]	(0.05)	(0.05)	(0.06)	(0.20)
Count of HH members wkg. in wage employment	12218	0.79	0.14**	0.17**	0.10*	0.17*
		[1.41]	(0.06)	(0.07)	(0.06)	(0.09)
Count of HH members wkg. in any work	12218	2.73	0.07	-0.05	0.17	0.26
		[2.02]	(0.08)	(0.09)	(0.11)	(0.19)

Note: This table presents effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, following Table 2. Each row represents an outcome. Household moving is measured in reference to their location of residence during the initial survey in 2010, and includes moves both within and outside of the baseline community. Changes in household composition are measured in reference to the previous survey round, as the household roster is updated in each survey and respondents can indicate which members have left and if any new members have joined. Counts of household members working in different activities are based on the household labor and agricultural labor modules in the post-planting and post-harvest surveys where respondents indicate which members are engaged in different activities. We code each member as engaged in a given activity for a survey round if they were engaged in it during either the post-planting or post-harvest round, then take the sum of members in each activity for the household. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In contrast with short-term effects of floods on migration, prior studies consistently find that floods increase short-term engagement in non-farm labor (Akter, 2021; Chen et al., 2017; Gray and Mueller, 2012b; Maystadt et al., 2016; Mueller and Quisumbing, 2011; Patel, 2025; Vitellozzi and Giannelli, 2023), with the exception of Sajid (2023). We find no effect of 2012 flood exposure on household engagement in either household non-farm enterprise (NFE) or wage employment on the extensive margin, with the exception of marginally significant increase in wage employment activity in the period immediately after the floods. There is also no intensive margin effect on the count of household members working in household NFEs in any round (in line with Figure 4), but one in seven treated households have an additional member engaged in wage work post-flooding on average, a significant 18% increase. This increase in wage workers is persistent and fairly consistent in magnitude across all survey rounds, and is also reflected in an increase in total household hours in wage employment (Table A5).

There is no evidence of households exiting agriculture. If anything, households in flooded communities are 3 pp (4%) *more* likely to engage in crop or livestock production, an effect that persists to 2015-16. The average effect on the count of household members working in household farm activities is not statistically significant, but this masks a null effect in 2012-13 followed by significant increases in 2015-16 and 2018-19. Just under 1 in every 3 households has an additional member engaged in farm work over those later two survey rounds, a 16% increase. Null effects on the count of household members engaged in any work activity and no significant decrease in the count engaged in household NFE imply that increases in member engagement in farm and wage work are among members already engaged in other activities, indicating an intensification of household labor supply. This intensification implies a reduction in leisure time, another way in which flood exposure may decrease household well-being.

Table 4 further explores flood impacts on household crop production. In line with the increases in count of household members working in agriculture, total annual hours of household crop production labor increase by 237 (26%) for households in flooded communities in the survey rounds following the 2012 floods. The increase is persistent over the three post-flood survey rounds, though the individual coefficients are noisy and the significance does not survive FDR adjustment. The coefficient on household crop labor days is similarly positive but noisy. The increase in crop family labor inputs is not matched by increases in other inputs. Instead, total area planted falls by 0.36 ha (24%) and days of hired or exchange labor fall by 6.11 (59%). There is no significant effect on crop input expenditures per hectare, but the point estimate is also negative as is the estimated effect on use of inorganic fertilizer. The decrease in crop area planted persists over time and is largest in the 2018-19 survey round, when we also find larger effects on hired labor and inorganic fertilizer use.[25]

The implication of these results is that flood exposure appears to constrain household crop production, particularly in terms of purchased inputs, but leads to an intensification of family crop production labor. Despite the increase in family labor—which may in part represent an attempt to substitute for decreases in complementary inputs—the total annual value of crop production falls by 503 USD (33%) on average following community flood exposure. Crop sales also decrease by 177 USD (38%) annually on average after flood exposure, but the proportion of crop production value that is sold does not change, indicating households are not responding to their decreased production value by selling more or less of their output.

Large and significant decreases in crop production value after flooding are not surprising given that the community flood incidence measure is based in part on household reports of crop failure

[25]A negative point estimate for the effect in 2012-13 suggests some potential anticipation of floods or potentially non-reported of planted area lost to floods, as 2012 planting decisions would almost all have taken place before the floods occurred but were asked about around the same time as the floods.

Table 4: Impacts of 2012 community flood incidence on household crop production outcomes

	N	Control Mean (SD)	Average impact: 2012 flood recentered × Post (SE)	Dynamic impacts: 2012 flood recentered × 2013 round (SE)	2012 flood recentered × 2016 round (SE)	2012 flood recentered × 2019 round (SE)
Number of crops cultivated	12218	2.08	-0.07	0.03	-0.16	-0.20
		[1.97]	(0.09)	(0.10)	(0.10)	(0.23)
Household crop area planted HHI	6707	0.54	0.02	0.02	0.03	0.01
		[0.27]	(0.02)	(0.02)	(0.02)	(0.03)
Total area planted (ha)	12218	1.47	-0.36*	-0.33	-0.35*	-0.67***
		[3.03]	(0.19)	(0.20)	(0.19)	(0.23)
Total hired/exch. crop labor days in past year	12218	10.29	-6.11**	-5.04*	-3.71	-28.65***
		[34.21]	(2.68)	(3.02)	(3.37)	(10.56)
Total family crop labor days in past year	12218	118.25	38.77	35.86	40.92	45.99
		[333.75]	(28.22)	(37.90)	(27.02)	(29.77)
Total family crop labor hours in past year	12218	901.58	236.66*	169.95	305.15*	280.70
		[1817.94]	(135.81)	(172.55)	(168.82)	(187.46)
Any inorganic fertilizer use	12218	0.25	-0.02	-0.03	0.00	-0.09**
		[0.43]	(0.02)	(0.03)	(0.03)	(0.04)
Crop production costs per ha (USD)	12218	749.67	-222.61	-28.64	-352.55	-783.92
		[4256.87]	(277.58)	(271.43)	(353.32)	(627.86)
Total crop production value (USD 100s)	12218	15.30	-5.03***	-4.58***	-5.73***	-3.92
		[32.07]	(1.45)	(1.64)	(1.63)	(3.10)
Total crop sales (USD 100s)	12218	4.58	-1.77***	-1.43**	-2.16***	-1.66**
		[13.74]	(0.56)	(0.65)	(0.61)	(0.80)
Proportion of value of crop production sold	6707	0.27	-0.02	-0.03	-0.02	0.00
		[0.33]	(0.02)	(0.02)	(0.03)	(0.04)

Note: This table presents effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, following Table 2. Each row represents an outcome. All outcomes refer to the year including the most recent growing season. Outcomes for households not active in crop production (24% of the analysis sample) are assigned values of 0, except the crop area HHI and proportion of crop value sold are undefined for households with 0 area planted. The number of crops cultivated is across all household plots. The crop area Herfindahl-Hirschman-Index (HHI) is the sum of squared shares of total planted area allocated to different crops. Values closer to 1 indicate less diversification across crops. Total labor days and family labor hours are summed across all crop production activities reported in the post-planting and post-harvest surveys. Crop production costs are the sum of expenditures on purchased inputs such as seeds, fertilizer, labor, land, etc. These are divided by the total area planted. Crop sales are the sum across crops of quantity sold times sales price. Crop production value is the sum across crops of crop sales plus the value of unsold crops, measured as quantity harvested but not sold times the median sales price for that crop in the community. The proportion of value of crop production sold is the ratio of the two above variables. Monetary values are in 2016 PPP USD. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

or damages due to floods. Many studies report that floods can decrease agricultural output (e.g., Banerjee, 2010; Bangalore et al., 2025; Djoumessi Tiague, 2023; Kim et al., 2023), with a focus on direct damages. But the reduction in crop production value is not driven by immediate crop destruction by floods. The effect persists in subsequent survey rounds (though it is noisier in 2018-19) and the magnitude of the decrease in crop production value is in fact largest for the 2015-16 survey round.

To relate these results to prior studies of long-term effects of floods on labor supply, the persistent increases in wage work follow Patel (2025) who finds increased non-agricultural employment following flooding in Bangladesh, but contrast with Mueller and Quisumbing (2011) who find null effects in Bangladesh and Sajid (2023) who reports decreases in non-agricultural work following floods in rural areas of India. On the other hand, the increase in agricultural labor hours aligns with Sajid (2023) who shows increased engagement in agriculture in India, but not with Patel (2025) who finds that floods push employment out of agriculture in Bangladesh. In general, the results fall somewhat in between those of Patel (2025) and Sajid (2023), with some evidence of increased non-farm work and out-migration but also evidence of intensification of agricultural production.

5.4 Income sources and diversification

The central question of this paper is whether a weather-related natural disaster—in this case, floods—can promote sustained shifts of livelihood activities away from more vulnerable household agriculture. We find that community exposure to Nigeria's 2012 floods did not increase individual or household migration (at least in the short-term) but did persistently increase the number of members active in household farm production and in wage employment over the following 7 years (Table 3). This could represent diversification of household income sources and livelihood activities, but null effects of floods on the likelihood of any household wage activity suggests households are largely intensifying labor supply to existing activities. Although average crop area planted decreases (Table 4), family labor hours and the probability of any household farm activity increase, indicating there is no agricultural exit in this setting. As a result, we might expect limited changes in household livelihood diversification.

On the other hand, flood exposure significantly and persistently decreases the value of household crop production (Table 4). To the extent incomes from other sources are stable or increase this could change household income shares from different activities. In the context of overall lower incomes, however, this would not be seen as promoting resilience and adaptation. Household consumption per capita is persistently lower following flood exposure (Table 2), which suggests that households may not be able to make up for reduced crop production values.

Table 5 presents the results from directly testing the effects of community flood exposure in 2012 on household incomes or value of production from different sources and on relative income shares. We drop 817 sample observations with missing data for income or production value for all activities they are engaged in, though results are qualitatively similar if they are included.[26] Although flood exposure decreases household daily per capita consumption, we find no significant effect on total household income and production value in any survey round. This is largely because estimated effects on non-farm income are very noisy, though the point estimates are positive and offset part of the decrease in non-farm income. The total value of household farm—crop and livestock—production decreases significantly and persistently (though the effect in 2018-19 is imprecise). A comparison with impacts on crop production value in Table 4 indicates that small increases in livestock production value offset part of the decrease in crop production.

Looking at specific sources of non-farm income, income from non-wage and non-enterprises sources is typically a minor share of total income and does not change following flood exposure. Wage employment income is also unaffected despite the increases in household wage labor. The point estimate for 2013 is negative, suggesting potential flood-related disruptions preventing wage work from being a useful coping strategy, and though estimates for the following rounds are large and positive they are all very imprecise. Despite null effects of floods on household non-farm

[26] We describe our approach to calculating value of production for household farm activities and incomes from all other activities in Section 3.1. Across all survey rounds we find 817 sample household observations (6.7%) with zero total income and value of farm production, with no significant difference by 2012 flood exposure. These households do report being engaged in farm production (43%), NFE (51%), and wage employment (23%). Most these zeros are therefore likely the result of missing values from refusal to answer, inability to estimate, or coding errors.

Table 5: Impacts of 2012 community flood incidence on incomes and income shares by livelihood activity

			Average impact	Dynamic impacts		
	N	Control Mean (SD)	2012 flood recentered × Post (SE)	2012 flood recentered × 2013 round (SE)	2012 flood recentered × 2016 round (SE)	2012 flood recentered × 2019 round (SE)
Total HH income and production value (USD 100s)	11401	85.38 [180.85]	-3.06 (6.02)	-4.76 (6.88)	-3.60 (6.45)	10.85 (11.29)
Total value of HH farm production (USD 100s)	11401	19.24 [38.99]	-3.86** (1.65)	-3.96** (1.85)	-3.94** (1.89)	-2.80 (3.19)
Total income from non-farm activities (USD 100s)	11401	66.14 [179.25]	0.80 (5.71)	-0.80 (6.61)	0.34 (6.09)	13.66 (10.59)
Total non-farm HH enterprise income (USD 100s)	11401	27.90 [86.48]	0.76 (3.14)	2.53 (3.15)	-2.48 (3.57)	8.39* (4.86)
Total wage employment income (USD 100s)	11401	35.27 [155.50]	0.26 (4.72)	-3.61 (5.76)	3.52 (5.18)	5.86 (8.82)
Total HH income from other activities (USD 100s)	11401	2.98 [21.09]	-0.22 (0.97)	0.28 (1.02)	-0.70 (1.14)	-0.59 (1.96)
HH farm share of total HH income and prod value	11401	0.48 [0.43]	-0.02 (0.02)	-0.03* (0.02)	0.00 (0.02)	-0.04 (0.03)
NFE share of total HH income and prod value	11401	0.32 [0.39]	0.02 (0.02)	0.03 (0.02)	0.00 (0.02)	0.03 (0.03)
Wage share of total HH income and prod value	11401	0.17 [0.35]	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.02 (0.02)
Other share of total HH income and prod value	11401	0.03 [0.13]	-0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.02)
HH income Herfindahl-Hirschman Index	11401	0.84 [0.20]	-0.00 (0.01)	-0.00 (0.01)	0.01 (0.01)	-0.00 (0.02)

Note: This table presents effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, following Table 2. Each row represents an outcome. Section 3.1 describes how the income and value of production variables are constructed. Farm production includes crop and livestock activities. 'Other activities' includes income from pensions, remittances, investments, transfers, etc. Households not active in a given activity are assigned an income of zero for that activity. We drop households with zero total income and production value from the analysis as these likely represent missing data rather than true zeros. Table A8 shows the results including these households. The household income Herfindahl-Hirschman-Index (HHI) is the sum of squared shares of income from farm production, NFE, wage work, and other sources. Values closer to one indicate a greater concentration of income sources. Monetary values are in 2016 PPP USD. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

enterprise labor supply, we estimate a marginally significant but economically large increase in total NFE income in 2018-19. The significance does not survive FDR adjustment suggesting it is likely just noise.

If households who crop production value falls after flood exposure are active in other livelihood activities, this could lead to shifts in the income shares of different activities even if the households are not using other activities to cope with or adapt to flood exposure. On average, household income shares appear quite diversified, with 48% to farm production, 32% to NFEs, 17% to wage employment, and 3% to other sources. But the mean household Herfindahl-Hirschman Index value of 0.84—where 1 indicates all income is from a single activity—reveals much greater concentration of incomes at the household level. The mean of the maximum income share across all activities is 87% for sample households in 2010-11, and the median is 97% while even the 25th percentile is 77%. While income shares are diversified across households on average, individual households are highly specialized with very concentrated incomes even if engaging in multiple livelihood activities is common. The median and mean sample household is active in two out of farm production, NFE, and wage employment, and Table 3 indicates that this does not change following flood exposure.

Consistent with highly-concentrated household livelihoods, Table 5 shows no effects of the 2012 floods on household income shares or concentration in the following survey rounds. This could appear to contrast with a study of the impacts of harmful degree days in Nigeria using the same survey data, which finds that same-year decreases in agricultural productivity decrease the household crop income share and increase the share from livestock and wage employment (Amare and Balana, 2023). But that study only considers immediate impacts, and we also find a marginally significant decrease in the agricultural income share in the year the floods occurred. In addition, we combine crop and livestock income though results are similar when consider crop income separately. The farm share of income is not significantly lower in subsequent rounds even as the decrease in the value of households farm production remains persistent. This indicates that the most affected households are not offsetting these production decreases.

5.5 Robustness

The main results are robust to a variety of alternative specifications. We first consider changes to the controls and fixed effects and to the sample of included communities (Table A9). Dropping the baseline characteristic-by-round controls and shifting from state-by-round fixed effects to round or zone-by-round fixed effects does not qualitatively affect the results, though several effects of the 2012 floods are no longer significant if we use LGA-by-round fixed effects where the impacts are identified from a small number of LGAs with variation in flood incidence across communities. The main analysis sample stratifies communities by years of survey-reported flood incidence from 2007-2011 and drops communities outside the range of common support for average 100-year flood depth within 5 km. Results are nearly unchanged if we include all communities and if we instead drop communities more than 50 km from any community with a flood report. This is likely because the construction of the recentered flood shock variable already drops communities outside of the common support of estimated 2012 flood propensity by actual flood incidence, making the additional sample restrictions less meaningful. The results are robust to excluding control communities within 20 km of any community with a household flood report in 2012, which could potentially have been indirectly affected by flooding in nearby communities. Finally, estimated flood impacts are similar focusing just on the sample of households with any farm activity during the survey (78% of households); we test heterogeneity in effects by baseline farm activity below.

We next compare alternative approaches to controlling for differences in 2012 flood propensity besides recentering the flood incidence treatment variable while retaining the same analysis sample (Table A10). We observe no changes in the statistical significance of the main estimated impacts of flood exposure when including flood propensity-by-round or average flood hazard-by-round and local 2012 rainfall deviation-by-round fixed effects instead of recentering the treatment, with the exception that increases in the count of household members working in household agriculture become significant, and the magnitudes are all very similar. Importantly, we obtain very similar results if we do not directly control for the estimated 2012 flood propensity or even include baseline characteristic-by-round controls, relying instead on the sample restrictions and household fixed effects. The point estimates for impacts of floods on wage income are much larger in these specifications but the standard errors are similar and the estimates are not statistically significant. These tests show that the estimates do not depend on any one of the approaches to dealing with endogeneity of 2012 flood incidence.

Figure 1 and Figure A4 show that different approaches to measuring flood incidence identify different communities as being exposed to floods in 2012. Table 6 therefore presents the impacts of 2012 flood exposure using different flood incidence definitions but retaining the same sample restrictions and recentering approach after estimating definition-specific 2012 flood propensities. We do not include any baseline characteristic-by-round controls in these regressions.

Moving from requiring two household survey flood reports in a community (column 1) to any household report (column 2) to define a community as exposed does not meaningfully change the results. Point estimates for non-farm incomes become negative and point estimates for effects on crop area planted and family labor are smaller with the less restrictive definition, but we find similar magnitude significant effects on consumption per capita, value of farm production, engagement in farm production, and members working in wage employment. Additionally including communities with any community survey flood reported as exposed to floods (column 4) leads to similar results as the less restrictive household survey-based measure. Using only flood reports from the household shocks module—ignoring reports from the agriculture and food security modules—leads to some different conclusions (column 3). Effects of the 2012 floods on household consumption and on the value of farm production are no longer statistically significant and we find a marginally significant increase in the probability that any household member migrated. Impacts of flood exposure on household engagement in agriculture and wage employment are similar to the main results. These differences show that the choice of how survey respondents are asked about floods matters. Focusing just on a few specific ways that floods can affect households leads to different conclusions about the impacts of flood exposure when relying on survey reports to define flood incidence, even if many estimated effects are similar.

While there are some differences in results across different survey-based definitions, they also frequently align which is not surprising considering the strong correlations between these definitions. But survey- and satellite-based measures are poorly correlated, and Table 1 shows that these measures identify flood incidence in communities with different characteristics. In line with this, estimated effects of the 2012 floods as identified by MODIS satellite imagery (Table 6 columns 5 and 6) are considerably different from those using a survey-based definition. The estimates differ somewhat depending on whether a 5 km or 10 km buffer around communities is used to define satellite-based flood incidence, but in both cases the stark conclusion is that flood exposure has almost no significant effect on household outcomes over the following years. With a 5 km buffer we find only a marginally significant increase in NFE income and with a 10 km buffer we find a decrease in the probability of any individual migration and a large increase in crop area planted.

Focusing on the 5 km buffer, we strikingly find no significant impacts of being in a community with flooding identified within 5 km by MODIS imagery in 2012 on any of the main household outcomes in 2013, immediately after the floods (Table A11). This strongly indicates that this

Table 6: Sensitivity to alternative ways of measuring 2012 flood incidence

	(1) >1 HH flood report	(2) Any HH flood report	(3) Any HH flood shock	(4) Any HH or comm. flood report	(5) <5 km from MODIS flood	(6) <10 km from MODIS flood
Any food insecurity in last 12	0.01	-0.00	0.03	-0.02	0.03	-0.02
months	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Daily HH consumption per adult	-0.71**	-0.51*	-0.30	-0.39	0.34	-0.38
equiv (USD)	(0.31)	(0.28)	(0.37)	(0.24)	(0.40)	(0.27)
Total value of HH farm production	-3.68**	-3.51**	-0.88	-4.74***	-1.22	-1.61
(USD 100s)	(1.58)	(1.68)	(1.80)	(1.70)	(2.02)	(1.63)
Total non-farm HH enterprise	0.47	-4.67	1.80	-4.80*	7.96*	2.97
income (USD 100s)	(3.09)	(2.94)	(3.81)	(2.65)	(4.29)	(3.20)
Total wage employment income	0.43	-2.24	-3.15	0.17	-0.72	2.79
(USD 100s)	(4.75)	(4.58)	(5.14)	(4.79)	(7.10)	(5.07)
Any HH farm activity	0.05***	0.03**	0.04***	0.03**	-0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Any HH non-farm enterprise	0.00	0.01	-0.02	0.02	-0.00	-0.01
activity	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Any wage employment activity	0.03*	0.03	0.04*	0.01	0.02	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Count of HH members wkg. in HH	0.18**	0.06	0.14	0.08	0.05	-0.07
farm	(0.08)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)
Count of HH members wkg. in HH	-0.01	-0.00	-0.10	-0.01	0.03	-0.00
non-farm enterprise	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Count of HH members wkg. in	0.16***	0.14***	0.18***	0.11**	0.09	-0.08
wage employment	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)	(0.07)
Any member left HH for work	-0.01	-0.00	0.02*	-0.01	-0.01	-0.02*
during/since last round	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Total area planted (ha)	-0.29	-0.03	-0.16	0.09	0.27	0.46**
	(0.20)	(0.16)	(0.21)	(0.16)	(0.22)	(0.18)
Total family crop labor hours in	164.45	64.69	308.61*	127.30	138.16	153.24
past year	(144.15)	(117.30)	(173.67)	(118.70)	(157.62)	(117.90)

Note: This table shows the results from separate regressions of household outcomes on recentered 2012 community flood exposure interacted with being observed after 2012. Each row represents an outcome; see the main analysis tables for explanations of the variables. Monetary values are in 2016 PPP USD. Each column indicates how 2012 community flood incidence is defined, where column (1) presents the main definition of at least 2 household flood reports for 2012 within a community. For each 2012 flood measure, we estimate the 2012 flood propensity following the same approach as for the main flood definition and use this to recenter the community flood exposure treatment variable. All regressions include household and state-by-round fixed effects and the main analysis sample that is balanced on underlying flood hazard by 2007-2011 survey flood report strata, but do not include any baseline characteristic-by-round fixed effects. This explains differences between the results in column (1) and those in the preceding tables. In column (2) we only require 1 household flood report to define community flood incidence. In column (3) we only consider flood reports in the household shocks survey module, ignoring reports in the agriculture and food security modules. In column (4) we define a community as flooded if their is any household flood report in any module or any flood report in the community survey. Columns (5) and (6) use MODIS satellite imagery from the NASA NRT Global Flood Mapping product rather than survey reports to define flood incidence. Communities are considered flooded if there is any pixel classified as flooded at any point in 2012 within 5 and 10 km of the community centroid, respectively. Figure A4 panels A-E shows maps of flood incidence according the definitions in columns (1)-(5). Standard errors are clustered at the level of the community of residence in 2012. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

measure of flood incidence is not accurately identifying adverse flood events as experienced by survey households, and validates our focus on a survey-based measure.

6 Mechanisms and discussion

We find no evidence that Nigerian households respond to flood exposure by either exiting agriculture or diversifying their income sources. Households also are persistently worse off in terms of consumption per capita. In this section, we first explore why household increases in farm and wage labor do not increase incomes from these activities or affect household income shares. We then test whether impacts of flood exposure vary by flood risk and history and by access to markets or relief.

6.1 Explaining labor supply and income effects

The lack of income diversification despite the increased labor supply to different activities we find in Table 3 and Table 4 may imply that the returns to the increased labor supply are low. The decreases in value of agricultural production despite increased family labor and null effects on wage incomes despite a higher number of household members working for a wage suggest this is indeed true.

Table A5 shows persistent significant and economically meaningful increases in hours of wage work during both the post-planting and post-harvest periods following flood exposure. One possible reason for null effects of the floods on wage income is lower wages resulting from an increased supply of individuals looking for wage work.[27] We do not find significant effects of flood exposure on either community survey reports of average wages for agricultural labor or household reports of average wages paid to hired crop labor, but the point estimates are negative (Table A7). Low returns to wage labor may reflect limited local opportunities. In a study of the impacts of natural disasters in Nigeria, Escalante et al. (2025) report short-term reductions in employment opportunities. Table 3 shows that flood-exposed households are not more likely to have a member migrate or leave to find work. Local employment and migration constraints may thus prevent households from being able to increase wage income following exposure to a weather disaster.

We also find *decreases* in the value of farm production despite *increases* in household crop labor hours (Table 4). The persistent decrease in crop production value could have several explanations. First, households decrease area planted by 24% following flood exposure. There is no average effect on the crop mix, so if land productivity and crop prices are unchanged, this would suggest a 24% decrease in crop production value. We observe a somewhat larger decrease, suggesting changes in either land productivity or crop sales prices, and find evidence that both decrease following flood exposure.

Land productivity may fall due to direct persistent effects of floods or changes in the mix of production inputs. Floods can directly decrease productivity through soil erosion, siltation, or contamination, and increased salinity (in coastal areas), though they can also potentially increase productivity by depositing nutrients and sediments. Effects on crop input expenditures per ha and inorganic fertilizer use are not statistically significant, but the negative point estimates suggest some households are decreasing use of purchased inputs following flood exposure. This could be a rational response to changes in soil fertility or represent tighter budget constraints following flood exposure. Though we cannot identify the specific mechanism, we find suggestive evidence of decreased crop yields following flood exposure (Table A6). The estimated effects are noisy but an aggregate measure of cereal yields—weighted by area planted for households planting more than one of maize, sorghum, millet, and rice—falls by 679 kg/ha (31%) after flood exposure. The decreases in yields are largest in 2012 when the floods occurred, in line with direct flood damages. Decreased yields despite increases in family labor imply limited substitutability between labor and other crop

[27] Mueller and Osgood (2009b) find that droughts lead to persistent decreases in rural wages in areas more dependent on agriculture.

production inputs.

Another factor in valuing crop production is crop prices. We value crops produced by a given household using either the actual sales price for the quantity that is sold or the median of community sales prices for the quantity that is not sold at the time of the post-harvest survey.[28] Crop prices would generally be expected to rise in the short-term following flood exposure due to destruction of local output and potential supply disruptions. While effects on sales prices are not statistically significant for most of the most commonly cultivated crops in Nigeria, point estimates are nearly all negative and we find a highly significant decrease of 0.31 USD/kg (63%) for cereals on average (Table A6).

One possibility is that producers in areas not affected by floods benefit from being able to sell more of their crops at higher prices. Another is that food security and consumption needs of households in flood-exposed communities drive them to sell their crops soon after harvest when prices are generally lower, though we do not have data on the timing of crop sales to test this. Market price data collected in the community surveys suggests prices in the post-harvest period are not in general lower in communities after flood exposure (Table A7), suggesting timing of crop sales may be a factor. This mechanism would align with Kakpo et al. (2022)'s finding that weather shocks in Niger lead to reduced millet market prices immediately after harvest, but increases 6 months later.

The results in Table 5 show that households are not on average offsetting decreases in the value of farm production by diversifying income sources. The share of total household income from farm production only falls significantly in the year of the floods and the household income Herfindahl-Hirschman Index does not change significantly in any year after flood exposure. In addition to low returns to increased wage employment, this could indicate that households primarily respond to floods by intensifying labor supply in activities they are already engaged in. To test this possibility, we estimate heterogeneity in impacts of flood exposure by baseline (pre-flood) engagement in different livelihood activities.

Table 7 presents the results for heterogeneous effects of flood exposure on household engagement, count of active household members, and income or production value from household agriculture, household NFE, and wage work, and on whether any household member migrated in search of work since the last survey round. In each regression, we estimate a triple-differences model fully interacting a baseline household characteristic H with the Post and Flood dummies.[29] We calculate the average effect in the group with the given characteristic by taking the sum of the $Flood \times Post$ and $Flood \times Post \times H$ coefficients, and also report the p-value for the triple interaction term which tests for equality of effects between the two groups.

We find that only households engaged in agriculture at baseline are more likely to be active

[28] For crops with fewer than three sales observations within a community, we use the median price within the state.

[29] These heterogeneity models drop baseline characteristic by round controls except for food insecurity-by-round as the other controls are either included in or closely related to the characteristics for which we explore heterogeneity. We follow Feigenberg et al. (2025) inalso interacting the characteristic H with the state-by-round and insecurity-by-round fixed effects, though the results are similar if we do not.

Table 7: Impacts of 2012 community flood incidence on livelihood activities and incomes by baseline engagement

	HH agriculture			HH NFE			Wage work			
	(1) Any act.	(2) Count mems.	(3) Value prod.	(4) Any act.	(5) Count mems.	(6) Total inc.	(7) Any act.	(8) Count mems.	(9) Total inc.	(10) Work migr.
A. H = Any baseline HH agriculture										
Flood × Post, H=0	0.01	-0.11	-2.93	0.00	-0.05	-8.88	-0.05	-0.00	8.58	-0.02
	(0.05)	(0.08)	(1.85)	(0.03)	(0.07)	(9.22)	(0.05)	(0.08)	(27.07)	(0.04)
Flood × Post, H=1	0.03**	0.17*	-3.79**	-0.00	-0.05	3.76	0.04**	0.17***	2.30	-0.00
	(0.01)	(0.10)	(1.77)	(0.02)	(0.06)	(2.80)	(0.02)	(0.06)	(3.71)	(0.01)
p, equality of effects	0.63	0.03	0.73	0.90	0.98	0.20	0.07	0.09	0.82	0.70
B. H = Any baseline wage work										
Flood × Post, H=0	0.04***	-0.02	-1.54	-0.00	-0.10*	-1.05	0.01	-0.01	-1.01	-0.01
	(0.01)	(0.10)	(1.93)	(0.03)	(0.06)	(3.99)	(0.02)	(0.03)	(1.57)	(0.01)
Flood × Post, H=1	0.07***	0.44***	-7.17***	0.02	0.09	6.74	0.02	0.33***	8.76	-0.00
	(0.02)	(0.12)	(2.35)	(0.03)	(0.09)	(4.28)	(0.04)	(0.12)	(10.85)	(0.02)
p, equality of effects	0.09	0.00	0.07	0.49	0.06	0.20	0.71	0.00	0.37	0.67
C. H = Both HH agriculture *and* wage work at baseline										
Flood × Post, H=0	0.05***	0.02	-1.89	0.00	-0.05	-0.17	-0.01	0.01	1.70	-0.01
	(0.01)	(0.09)	(1.76)	(0.02)	(0.05)	(3.56)	(0.02)	(0.04)	(5.39)	(0.01)
Flood × Post, H=1	0.04*	0.46***	-8.31***	-0.01	0.02	5.55	0.02	0.34**	5.96	0.01
	(0.02)	(0.16)	(2.94)	(0.03)	(0.11)	(4.78)	(0.04)	(0.15)	(9.89)	(0.02)
p, equality of effects	0.99	0.01	0.07	0.80	0.52	0.34	0.56	0.03	0.70	0.42
Observations	12213	12213	12213	12213	12213	12213	12213	12213	12213	12213

Note: This table presents average effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, by baseline household characteristics as indicated in the panel headings. Each column represents an outcome. For each category of livelihood activities (HH agriculture, HH NFE, and wage work), we show effects on household engagement in that activity, count of active household members, and income or production value from. In addition, we show whether any household member migrated away from the household in search of work since the last survey round. See Table 5 and Table 3 for an explanation of the outcome variables. The results for each column in each panel are from a single triple-differences regression fully interacting the baseline household characteristic H with the Post and Flood dummies. We calculate the average effect in the group with $H = 1$ by taking the sum of the $Flood \times Post$ and $Flood \times Post \times H$ coefficients and estimate SEs using the *xlincom* function in Stata. We also report the p-value for the triple interaction term, which tests for equality of effects between the two groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

in farm production after flood exposure and to increase the count of members in household farm work, and the latter difference is statistically significant (Panel A). Similarly, only households engaged in wage employment at baseline increase the count of members engaged in wage work after flood exposure, and this difference is strongly significant (Panel B). But the table also shows that baseline agricultural households are significantly more likely to increase their engagement in wage work after flood exposure than households not engaged in agriculture, and that households with wage workers at baseline increase the count of members working in agriculture by significantly more than households without baseline wage activities. These results appear to conflict with each other, but the results in Panel C help to explain them. We find that only households active in *both* agriculture and wage work at baseline increase the count of members working in these activities after flood exposure, and that the differences are large and strongly statistically significant.

The results emphasize the finding that households are not responding to flood exposure by diversifying their livelihood strategies and engaging in new types of activities. Instead, households exclusively intensify their labor supply to their existing activities. This implies constraints to households potentially wishing to engage in different livelihood activities. In particular, households with no members engaged in wage work at baseline may live in locations with few wage opportunities or lack to the skills for available work, limiting their options following floods. We find no heterogeneity in household member migration by baseline work activities. In addition, in no cases are differences in household member engagement in a given activity in Table 7 associated with differences in household income from that activity. This further highlights the challenges to households in realizing returns from increasing their labor supply following flood exposure.

6.2 Heterogeneity in effects by community characteristics

Beyond differences by household engagement in livelihood activities at baseline, the conceptual framework suggests other factors that could affect the long-term impacts of flood exposure on households. First, increasing labor supply to non-farm activities is dependent on there being demand for either household NFE products or for wage labor. Both types of demand may fall following a flood shock in response to reduced household incomes in flood-affected areas. The results show evidence of constraints to households increasing labor supply to new non-farm activities. To the extent demand for non-farm labor and output is likely to be larger closer to major market towns, we might expect more of a labor response to flooding for households in these areas.

Table 8 Panel A shows no clear evidence that this is true. The count of household members engaged in wage work increases by 0.17 after flood exposure for households in communities below the median distance to the nearest major market, compared to no effect farther from markets, but this difference is not statistically significant. We also find no significant difference in the effect on income from wage work. Therefore, even where wage employment opportunities may be more available, households exposed to floods may struggle to increase their income from wage activities. Panel A also shows that adverse impacts of flood exposure on the value of household farm production are significantly larger and concentrated in communities that are farther from major markets, although households in both sets of communities are similarly likely to increase engagement in household agriculture. Part of this may reflect lower reliance on agricultural production in communities closer to markets.[30] Another factor could be more stable prices in more market-integrated communities, as we we find suggestive evidence of lower crop sale prices following flood exposure (Table A6).

Another important set of factors that could affect household livelihood responses to floods is their experience with and perceptions of flood risk. Changes in livelihood strategies following flood exposure could represent both efforts to cope with the shock and efforts to adapt to a perceived change in the risk of future exposure. Recent community flood exposure could increase the need for coping strategies to deal with repeated shocks and further emphasize the need for adaptation,

[30]Households in communities below the median distance to the nearest market are 12% less likely to be engaged in agriculture and cultivate 42% fewer hectares of crops at baseline.

Table 8: Impacts of 2012 community flood incidence on livelihood activities and incomes by community characteristics

	HH agriculture			HH NFE			Wage work			
	(1) Any act.	(2) Count mems.	(3) Value prod.	(4) Any act.	(5) Count mems.	(6) Total inc.	(7) Any act.	(8) Count mems.	(9) Total inc.	(10) Work migr.
A. H = Below median distance to nearest market										
Flood × Post, H=0	0.06***	0.17	-8.14***	0.00	0.03	4.25	-0.00	0.02	-4.17	-0.00
	(0.02)	(0.15)	(2.57)	(0.03)	(0.08)	(4.41)	(0.03)	(0.10)	(5.63)	(0.02)
Flood × Post, H=1	0.06***	0.17*	-1.27	0.01	-0.02	-1.34	0.04	0.17**	0.35	-0.02
	(0.02)	(0.10)	(1.87)	(0.03)	(0.07)	(3.83)	(0.03)	(0.07)	(6.92)	(0.02)
p, equality of effects	0.84	0.98	0.03	0.86	0.57	0.34	0.32	0.21	0.61	0.48
B. H = Any survey flood report in community from 2007-2011										
Flood × Post, H=0	0.06***	0.13	-1.61	0.00	0.02	-1.33	0.01	0.11*	0.91	-0.02
	(0.01)	(0.08)	(1.72)	(0.02)	(0.06)	(3.37)	(0.02)	(0.06)	(5.08)	(0.02)
Flood × Post, H=1	0.05***	0.32*	-11.52***	-0.03	-0.21**	10.54*	0.06*	0.30**	-2.24	0.01
	(0.02)	(0.19)	(3.36)	(0.03)	(0.10)	(6.38)	(0.03)	(0.14)	(8.79)	(0.02)
p, equality of effects	0.79	0.36	0.01	0.34	0.05	0.10	0.18	0.19	0.76	0.18
C. H = Non-zero fluvial flood risk										
Flood × Post, H=0	0.04***	0.26***	-1.26	-0.00	-0.06	2.46	0.05*	0.20***	5.06	-0.03*
	(0.01)	(0.09)	(1.83)	(0.02)	(0.06)	(3.75)	(0.02)	(0.07)	(5.40)	(0.02)
Flood × Post, H=1	0.07***	-0.02	-9.63***	0.03	0.03	-3.23	0.01	0.14	3.61	0.02
	(0.02)	(0.16)	(2.48)	(0.03)	(0.09)	(4.61)	(0.03)	(0.09)	(9.95)	(0.02)
p, equality of effects	0.34	0.12	0.01	0.45	0.40	0.34	0.32	0.59	0.90	0.06
Observations	12212	12212	12212	12212	12212	12212	12212	12212	12212	12212

Note: This table presents average effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, by baseline community characteristics as indicated in the panel headings. Community distances to the nearest main market are provided in the GHSP data based on actual (non-offset) community locations. Fluvial flood risk data are from the European Commission Joint Research Centre (JRC; Baugh et al., 2024). Each column represents an outcome. For each category of livelihood activities (HH agriculture, HH NFE, and wage work), we show effects on household engagement in that activity, count of active household members, and income or production value from. In addition, we show whether any household member migrated away from the household in search of work since the last survey round. See Table 5 and Table 3 for an explanation of the outcome variables. The results for each column in each panel are from a single triple-differences regression fully interacting the baseline household characteristic H with the Post and Flood dummies. We calculate the average effect in the group with $H = 1$ by taking the sum of the $Flood \times Post$ and $Flood \times Post \times H$ coefficients and estimate SEs using the *xlincom* function in Stata. We also report the p-value for the triple interaction term, which tests for equality of effects between the two groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

though some actions may have already been undertaken. Living in an area with higher underlying flood risk could similarly increase the probability of prior adaptation actions, but could also imply more severe flood shocks.

Panel B of Table 8 shows some significant differences in effects of 2012 flood exposure by whether the community also experienced floods over the previous five years. Decreases in the value of farm production are significantly larger in communities with prior flooding, indicating potential compounding effects on agricultural productivity. Household NFE income increases by significantly more in recently flooded communities, but this is accompanied by a decrease in the count of members engaged in NFE so this may just be statistical noise. The point estimates for effects on household wage work engagement are larger and more statistically significant for these communities, which is suggestive or larger livelihood responses to repeated shocks, but the differences are not significant. Overall, we do not find clear evidence that recent flood exposure is associated with different coping or adaptation responses to major floods.

Panel C also shows some significant differences in flood impacts by whether the community is in a location with non-zero estimated risk of fluvial flooding according to maps from the European Commission Joint Research Centre (Baugh et al., 2024), and some of the patterns are suggestive. The count of household members engaged in agricultural production only increases significantly after flood exposure in communities with no estimated risk of fluvial floods, and there is no significant decrease in farm production value in these communities. In contrast, households in communities with some underlying fluvial flood risk do not increase agricultural labor after flood exposure and see their production value decrease significantly. While the difference in effects on count of members engaged is not significant ($p = 0.12$), the difference for the value of production is significant ($p = 0.01$). Households in areas with no underlying fluvial flood hazard are also less likely to have any member leave the household to look for work ($p = 0.06$).

These patters could have several explanations. First, the nature of the 2012 flood shock may differ between these locations. Floods in communities with no fluvial risk are likely to be pluvial floods due to heavy local precipitation, which may have different effects than floods from overflowing rivers. In particular, there are likely different processes of sedimentation and land degradation. Second, the recentered flood shock variable measures reported flood exposure relative to expected exposure, of which fluvial flood risk is an important component (Table A1). Floods among communities with high expected exposure may have had particularly severe consequences on agricultural production. Third, households in higher flood risk areas may perceive lower expected returns from increasing agricultural labor. However, to the extent this is true, we do not find that households in these communities reallocate labor to other activities. If anything, it is also flooded communities with no fluvial flood risk that increase their engagement in wage work.

6.3 Heterogeneity in effects on consumption and assets

Figure 4 shows that households do not commonly report livelihood strategies as a main approach to coping with flood shocks. To the extent that livelihood responses to flood exposure vary by household or community characteristics, however, these might lead to different effects of floods on measures of household well-being over the following years. Any such heterogeneity could help inform policies to mitigate or respond to floods and flood risk.

We find no heterogeneous effects on household food insecurity, per capita consumption, value of assets, or total income by community proximity to market, recent flood experience, or fluvial flood risk (Table A13). This indicates that better market access does not necessarily help households cope with flood shocks, and that repeated flood exposure or higher risk neither aggravate nor attenuate household consumption effects. We similarly find no heterogeneity in these outcomes by baseline household engagement in agriculture or in wage work alone.

On the other hand, panel A of Table 9 shows significant differences in impacts of flood exposure on household consumption ($p = 0.02$) and assets ($p = 0.01$) by whether households were engaged in *both* types of activities prior to the floods. Households engaged in both activities at baseline experience no increase in the probability of reported food insecurity, no decrease in consumption per capita, and a marginally significant increase in asset value after flood exposure. Households engaged in only one or neither activity experience large and significant adverse effects of flood exposure. These differences indicate that baseline livelihood diversification can protect households against adverse impacts of floods. Table 7 Panel C suggests that larger labor supply responses in these diversified households are a potential mechanism allowing them to better cope with the flood shock, smoothing consumption while preserving assets.

Table 9: Heterogeneity in impacts of 2012 community flood incidence on household consumption, assets, and total income

	(1) Any food insec.	(2) Daily HH cons./cap.	(3) Value HH assets	(4) Total HH income
A. H = Both HH agriculture *and* wage work at baseline				
Flood × Post, H=0	0.04***	-1.02***	-274.32	1.21
	(0.02)	(0.28)	(172.77)	(6.61)
Flood × Post, H=1	0.03	-0.04	420.02*	0.95
	(0.02)	(0.34)	(234.58)	(12.00)
p, equality of effects	0.55	0.02	0.01	0.99
B. H = Community access to safety nets				
Flood × Post, H=0	0.03	-1.05***	-28.73	-2.88
	(0.02)	(0.32)	(160.84)	(5.59)
Flood × Post, H=1	0.05**	0.04	-175.18	11.04
	(0.02)	(0.32)	(272.03)	(13.15)
p, equality of effects	0.46	0.02	0.64	0.33
Observations	12215	12215	12215	12215

Note: This table presents average effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, by baseline household or community characteristics. Baseline agriculture and wage work is based on household reports for that same survey round. Access to safety nets is defined as whether any household in the community reported receiving assistance from social safety net programs in the 2010-11 survey round. Each column represents an outcome. See Table 2 and Table 5 for an explanation of the outcome variables. The results for each column in each panel are from a single triple-differences regression fully interacting the baseline household characteristic H with the Post and Flood dummies. We calculate the average effect in the group with $H = 1$ by taking the sum of the $Flood \times Post$ and $Flood \times Post \times H$ coefficients and estimate SEs using the *xlincom* function in Stata. We also report the p-value for the triple interaction term, which tests for equality of effects between the two groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From a policy perspective, another important question is whether social safety nets or relief programs help to protect households from adverse effects of floods. Figure 4 shows that eight percent of households that report experiencing a flood shock in 2012 report that they used some form of assistance from outside of friends and family other than a loan or credit as a shock coping strategy. Whether or not households receive such assistance may depend on a variety of factors which could be associated with household outcomes. To test whether impacts of floods vary by access to social safety nets, we consider community participation in general assistance programs. We define households as living in a community with access to safety nets at baseline before the floods if any household in the community reported receiving cash, food, or other aid from a government or non-profit social program in the 'safety nets' module of the 2010-11 household survey.

Few survey households report benefiting from any form of social safety nets, which include programs such as free food distribution, food or cash for work programs, school feeding programs, scholarships, or direct cash transfers from government or development organizations. Just 1.6% of households report receiving assistance from any such programs in 2010, a share that does not change much during the first three survey rounds but increases to 9% in the 2018-19 round. These recipient households are widely spread across communities, such that 32 percent of households live in a community with at least one household that reported safety net assistance in the 2010-11 survey. This measure of access to safety nets is strongly correlated with household reports of receiving assistance from outside of family and friends to help them cope with shocks. The vast majority (82%) of households reporting assistance to cope with shocks in the 2012-13 survey round reside in communities with access to safety net programs. We therefore consider this measure to potential capture where households may have been more supported in dealing with effects of the 2012 floods.

Table 9 Panel B shows that households in communities with access to social safety nets have significantly smaller reductions in household per capita consumption on average in the years following community flood exposure ($p = 0.02$). The persistent average decreases in consumption following flood exposure are concentrated exclusively in communities with no baseline safety net presence. This difference suggests official assistance programs may support flood relief and recovery, though we do not find different effects on the likelihood that households report any food insecurity, which increases significantly after floods in communities with safety net access.

There is no significant difference by access to safety nets in the effects of floods on the value of household assets or on total household income. The heterogeneity in impacts on consumption is not driven by differences in labor supply effects of floods across these communities, as we find no significant differences for these outcomes (Table A12). This is consistent with households more commonly reporting that they use external assistance than livelihood strategies to cope with flood shocks (Figure 4).

An important caveat is that these results do not represent causal impacts of social assistance on flood recovery, merely that households with better access to assistance experience less adverse impacts of floods. Community-level access to assistance may be correlated with other factors which could drive the estimated heterogenous effects, rather than the probability that households receive any post-flood assistance. In particular, Table A12 shows that floods in communities with access to safety nets have significant smaller negative effects on value of crop production ($p = 0.07$) and are more likely to lead individuals to leave their household in search of work ($p = 0.08$)

7 Conclusion

Floods are among the most common and destructive natural disasters, and climate change is increasing flood risk. This has implications for the well-being and livelihoods of households in areas at risk of flooding. Increased flood risk and damages in agricultural communities in developing countries may also affect household labor market decisions and broader structural transformation by affecting both expected returns to different livelihood strategies and resources available to invest in these activities.

We find that community-level exposure to floods during Nigeria's 2012 flood disaster persistently decreases agricultural productivity and household food consumption. To the extent that the average effects of community-level flood exposure are driven by effects on households experiencing direct damages, the direct effects of floods are likely to be much larger. We further show that farm households intensify their agricultural labor supply while decreasing complementary crop production inputs. This echoes studies of the long-term impacts of climate change and temperature increases, notably Nath (2025) who finds that climate change is likely to exacerbate the 'food problem' (Gollin et al., 2007) and trap workers in agriculture due to a need to meet consumption needs in areas with poorly integrated markets.

In line with this, the results indicate that flood exposure does not lead to agricultural exit or livelihood diversification either as a coping or adaptation strategy. Households already engaged in both agriculture and wage employment before the floods increase their labor supply in both activities and are more resilient in terms of consumption and food security. Other households either do not increase labor supply or only intensify engagement in existing activities at a cost of reduced leisure. Persistent decreases in agricultural productivity in flood-exposed communities imply that floods are more likely to constrain the process of structural transformation in the absence of any policy interventions.

Migration is highlighted as a key potential response in the literature on climate change and structural transformation or labor supply, but in many contexts migration decisions are constrained (Cruz, 2024; Ibáñez et al., forthcoming). We find that migration is not affected by the 2012 floods on average, but this masks differences over time. Flood-exposed households are less likely to move or have any members migrate in the short-term, but this reverses 7 years after flood exposure suggesting households need time to overcome migration constraints. A longer-term analysis would be needed to evaluate whether this eventual migration reverses the persistent consumption decreases following flood exposure.

We find that proximity to markets is not associated with a larger wage employment response to floods or with greater wage incomes. Access to social safety net programs attenuates adverse effects of flood exposure, but recent flooding experience and higher fluvial flood hazard drive larger losses in agricultural production value. Future work analyzing constraints to and drivers of household livelihood responses could help shed light on why and how households react to flood exposure. In particular, understanding on-farm adaptation responses would benefit from analyses of farm household beliefs about flood risk and expected returns from different crop production strategies.

Another important conclusion from this study is that decisions of how to measure flood incidence matter, echoing some previous work (Bangalore et al., 2025; Chen et al., 2017; Saunders et al., 2025). We show that the identification of flooded areas in Nigeria in 2012 differs depending on whether survey reports or MODIS satellite imagery is used, with limited overlap between the two measures. Measurement error in survey reports and limitations in satellite imagery and flood detection algorithms can explain some of the difference, but we argue that they also represent differences in definitions of floods and capture different phenomena. Floods reported in household surveys by definition affected households, and therefore represents cases where households were both vulnerable and floods were not expected, not prepared for, or more severe than expected. Satellite imagery on the other hand captures any fluctuation in surface water, including anticipated seasonal fluctuations and other cases that did not adversely affect households, but misses any short-duration floods masked by clouds. These measurement choices affect conclusions about the impacts of floods. In contrast to the effects we document for survey-reported floods in Nigeria in 2012, we find no consistent effects of floods detected by satellite imagery and included in the NASA NRT Global Flood Mapping database, indicating they do not capture key events affecting households.

We argue that despite their limitations, survey reports have great value as ground-truth measures of situations where floods caused damages, in contrast to previous work dismissing survey data (Guiteras et al., 2015). New methods incorporating satellite-based radar and cross-validating measures of flooding from multiple data sources (see e.g., Patel, 2025; Saunders et al., 2025) may help increase accuracy of flood detection but will still be subject to data limitations and to decisions of how to define what constitutes a 'flood.' Researchers must carefully consider both definition and measurement issues in empirical studies of the effects of flood exposure, as these affect how the effects should be interpreted. They should also test the sensitivity of estimated impacts of flood exposure to data and definition decisions, in line with recent calls to do so for other remotely-sensed data (e.g., Gibson et al., 2021; Josephson et al., 2026; Sun et al., 2018).

One limitation of the study is that we study a single flood event. If part of the mismatch in flood identification across data sources is due to adaptation of communities to floods in certain areas, this would imply that analyses of a single major flood event will fail to capture longer-run effects of changes in flood risk and resulting adaptation responses of households, unless prior floods were limited in frequency and severity. We find that impacts of exposure to the 2012 floods in Nigeria do not vary significantly by recent community flooding, potentially because our recentered flood treatment measure controls for such recent exposure. Future work on the long-term economic impacts of flood exposure should consider effects of changes in flood hazard and cumulative flood exposure over longer time frames, as in the recent working papers by Patel (2025) and Sajid (2023). Satellite-based measures are likely be the best source of flood incidence data for such analysis due to the lack of high-frequency survey data in vulnerable communities, but researchers should seek additional data sources of ground truth to test against what is detected by satellite.

The results are also relevant to policymakers in developing countries. The failure of satellite imagery to identify a large share of survey communities where flood damages are reported has implications for emerging recommendations to use satellite imagery for policy targeting. An understanding of the limitations of what satellites can detect can inform decisions about how to allocate monitoring resources. For floods in particular, monitoring resources should target more remote areas following periods of heavy rainfall, though advances in using machine learning to combine satellite radar data—which can see through clouds but is infrequent—with satellite imagery can also help fill this gap. Our analysis also shows that floods persistently decrease household consumption and food security, but that these effects are mitigated in communities where households have access to social safety nets. The results imply a need for targeted relief and support to help affected households to recover as well as interventions to help households protect themselves from floods. The findings indicate challenges for households attempting to cope with or adapt to flood exposure, which could motivate policies to provide support for adaptation such as agricultural extension and training, access to inputs, and support to access non-farm wage employment.

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A Additional Figures

Figure A1: GHSP data collection timeline

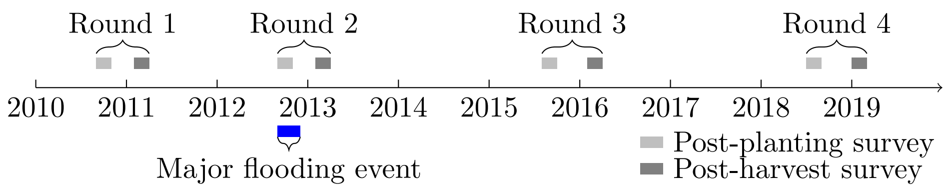
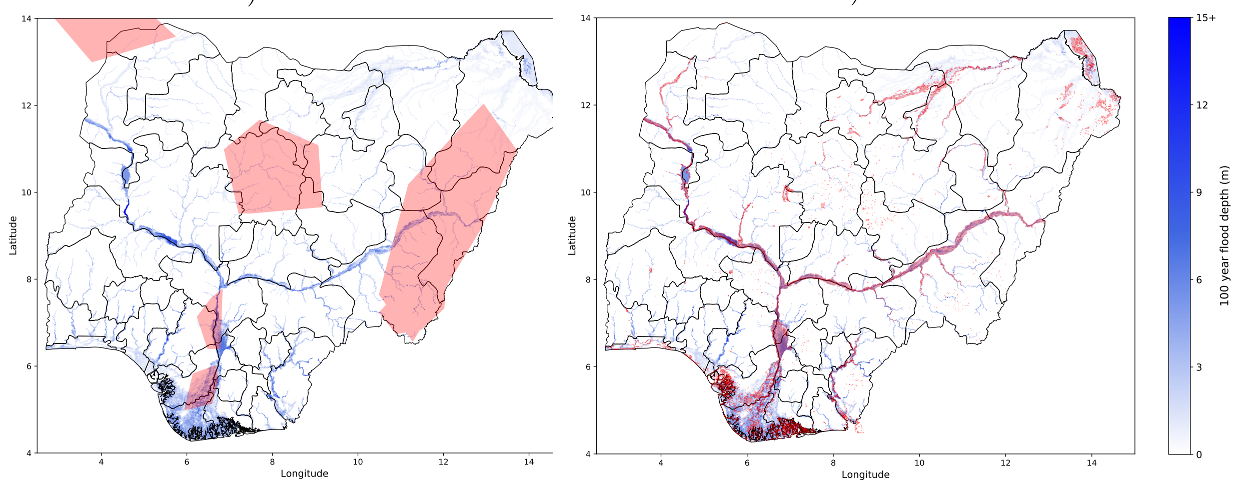


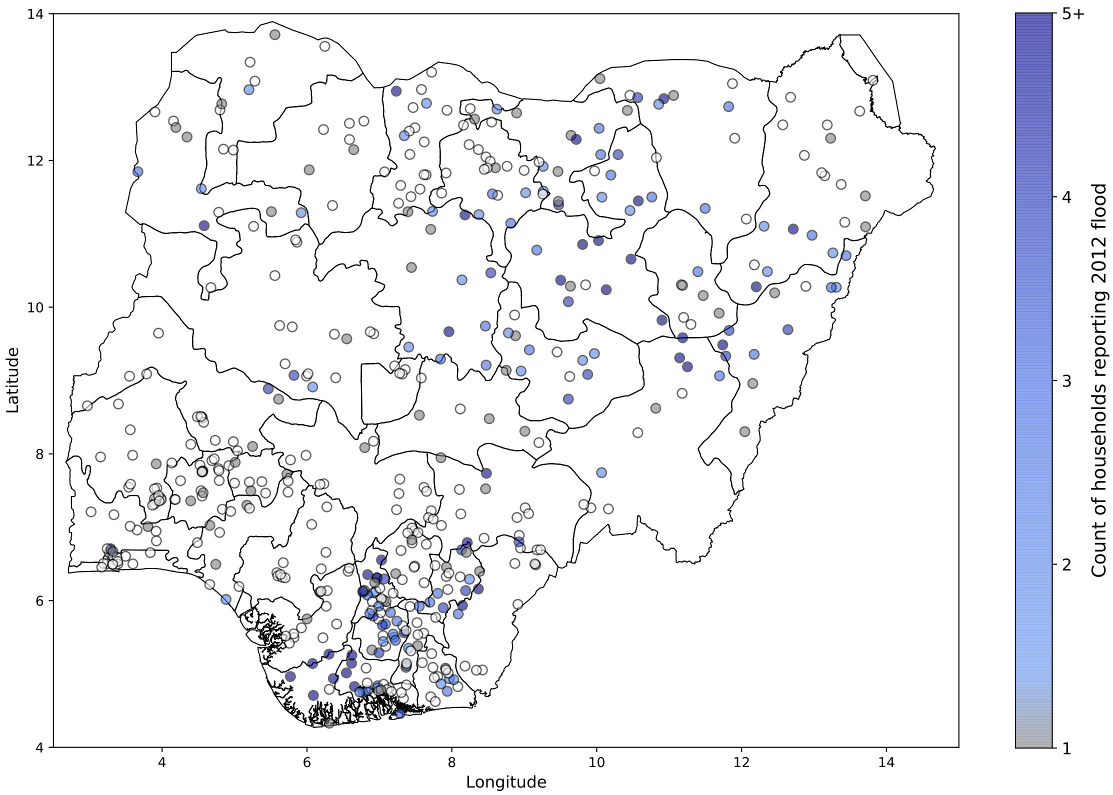
Figure A2: 2012 flood incidence according to DFO and MODIS

A) DFO B) MODIS



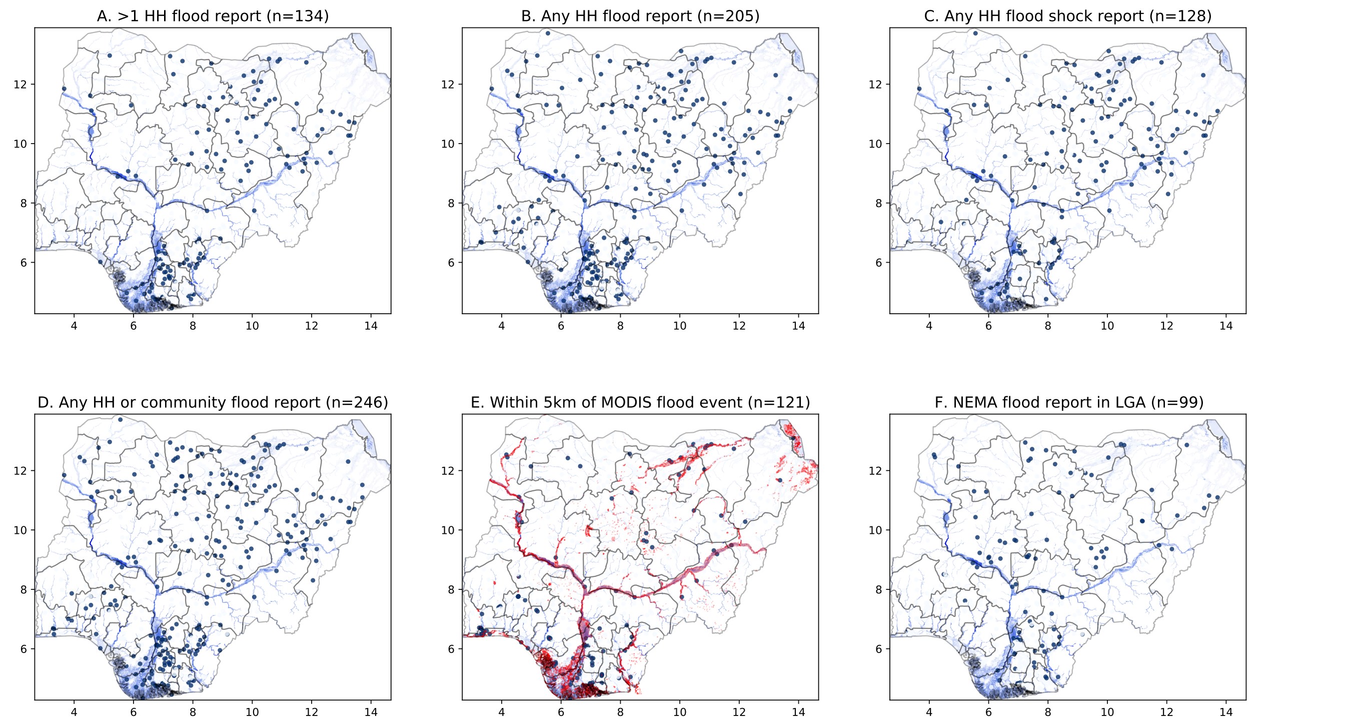
Note: The two panels show the areas where floods are identified in 2012 by different sources. The blue shading in the background of each panel corresponds to the depth of 100-year fluvial floods. Panel A shows the polygons affected by different flood events reported in the DFO archive, based on government and media reports. Panel B shows pixels where any flooding is detected by MODIS satellite imagery in the NASA NRT Global Flood Mapping product.

Figure A3: Counts of households reporting flood exposure in 2012 by community



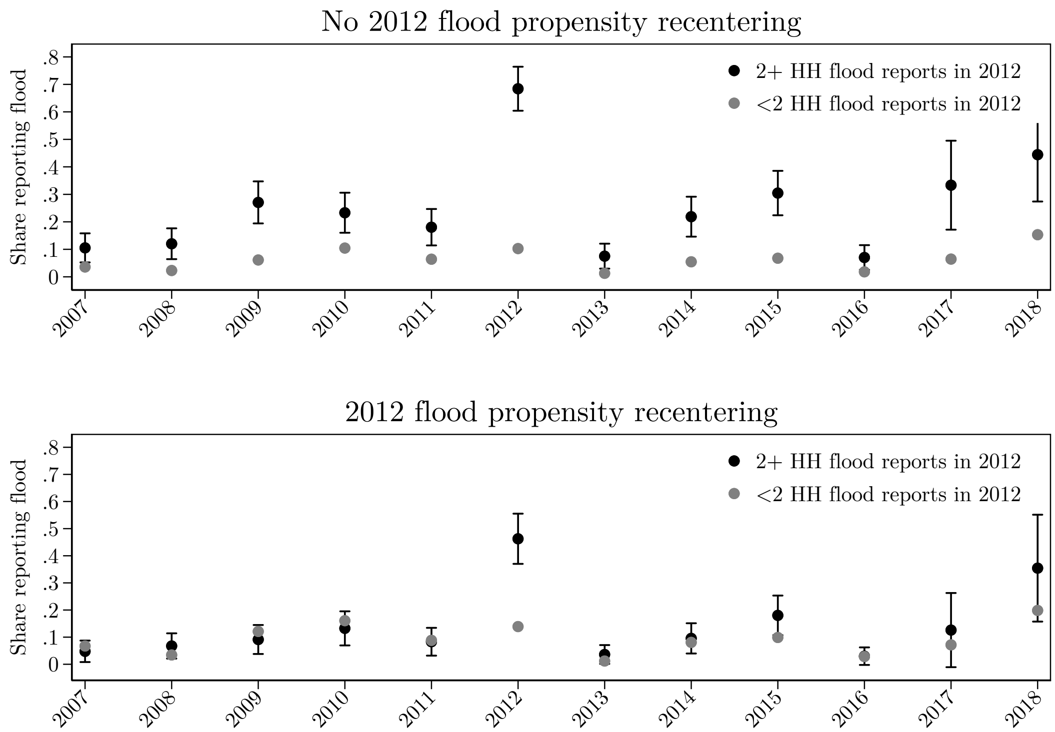
Note: Nigeria GHSP household flood reports are aggregated across questions from the household shocks, food security, and crop production modules. For each community, we calculate the number of households reporting being affected by floods in 2012 in one of these modules. White circles indicating communities with no household flood reports. Ten households are sampled for each survey community.

Figure A4: Community flood detection by flooding measure



Note: Each panel shows the set of GHSP communities identified as exposed to floods in 2012 according to a different definition of flood incidence. The blue shading in the background of each panel corresponds to the depth of 100-year fluvial floods. Panels A-D rely on survey reports of floods in 2012. Panel A shows communities with at least two household reports of floods in any module. Panel B shows communities with any such household reports. Panel C shows communities with any household reports of floods in the household shocks module only. Panel D shows communities with any household or community survey flood report. Panel E shows communities within 5 km of any pixel identified as flooded by MODIS satellite imagery at any point in 2012 in the NASA NRT Global Flood Mapping product. Panel F shows communities in local government areas (LGAs) where NEMA reports any floods in 2012.

Figure A5: Survey flood shock reports by year and 2012 community flood status



Note: Annual flood reports are from the Nigeria GHSP. In each survey round, households are asked to recall whether they experienced specific economic shocks over the last few years, including flooding that caused harvest failure and loss of property due to flood. These data were collected in the post-harvest survey waves in 2009, 2013, 2016, and 2019. This is a more restrictive measure of flood exposure than the main survey-based measured we use in this paper which incorporates reports of floods in the survey's food security and crop production modules, but there is no recall element for those questions. Both panels shows the share of communities with any household flood report in the shocks module by year separately for communities with at least two household flood reports in any module in 2012 and communities with fewer than two such reports. The share of communities with flood reports in 2012 shows how the measure using only the shocks module does not capture all household flood exposure. In the top panel we do not adjust for differences across communities in the estimated propensity of 2012 flood exposure. In the bottom panel we include inverse propensity weights based on those estimated propensities.

B Additional Tables

Table A1: Predictors of 2012 flood incidence

	(1) Any HH flood rept, shocks module	(2) Any HH flood rept, all modules	(3) > 1 HH flood rept, all modules	(4) Any HH or comm flood rept	(5) Any MODIS flood pixel w/in 5 km	(6) Any MODIS flood pixel w/in 10 km
Distance to nearest water area (km)	-0.010*	-0.016***	-0.018***	-0.011***	-0.024***	-0.026***
	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)
Avg 100-year flood depth within 5 km	0.797***	0.661***	0.746***	0.575***	1.561***	1.546***
	(0.177)	(0.164)	(0.176)	(0.166)	(0.416)	(0.417)
Max 100-year flood depth within 5 km					0.027	0.028
					(0.099)	(0.099)
Any HH reporting flood in 2008	1.025*		1.238**			
	(0.620)		(0.529)			
Any HH reporting flood in 2009	1.196***	1.313***	1.525***	1.390***		
	(0.378)	(0.364)	(0.353)	(0.387)		
Any HH reporting flood in 2011	0.431					
	(0.412)					
Distance to nearest MODIS flooded pixel (km)			-0.035**			
			(0.014)			
Deviation in wettest quarter rainfall					-0.001	-0.001
					(0.001)	(0.001)
Share of HHs w/ any crop activity	1.828***	2.015***	2.262***	1.017***	-1.060**	-0.941*
	(0.521)	(0.334)	(0.473)	(0.312)	(0.498)	(0.502)
Mean HH crop area planted	0.237***					
	(0.087)					
Percent ag land w/in approx 1 km	0.012**		0.012**	0.012***		-0.009
	(0.005)		(0.005)	(0.004)		(0.006)
Rural					-0.698*	-0.636*
					(0.376)	(0.378)
>50% artificial surfaces and associated urban areas					0.510	0.378
					(0.436)	(0.448)
Mosaic cropland (50-70%) /vegetation(20-50%)	1.149***					
	(0.313)					
Area equipped for irrigation in cell in 2005 (ha)	0.000					
	(0.000)					
Bauchi	2.394***					
	(0.761)					
Jigawa	2.320***					
	(0.852)					
Imo			1.969***			
			(0.531)			
Oyo				-2.200**		
				(1.045)		
Observations	497	486	497	497	497	497

Note: This table shows the results of logit regressions predicting 2012 flood incidence under different measurement approaches indicated in the column headings. See Figure A4 for a description of the different measures. The predictors are selected from a broader set of geographic, weather, and mean household characteristics in a first stage using a Lasso regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Balance in baseline characteristics by 2012 flood incidence

	No flood report Mean (SD)	Flood report difference (SE) No recentering	Flood report difference (SE) Recentering
Community characteristics			
Rural	0.62	0.10**	-0.03
	(0.49)	(0.05)	(0.05)
HH distance to nearest major road (km)	13.54	1.41	1.09
	(18.34)	(2.11)	(2.20)
HH distance to nearest market (km)	67.12	4.37	2.15
	(46.67)	(3.70)	(3.73)
HH distance to nearest pop. center w/	17.77	2.11	-0.69
>20k pop. (km)	(19.30)	(2.19)	(2.17)
Percent ag land w/in approx 1km	24.53	6.92***	-2.21
	(26.00)	(2.54)	(2.75)
Slope (percent)	3.32	-0.29	-0.04
	(2.65)	(0.25)	(0.26)
Elevation (m)	268.30	-33.96**	6.75
	(193.65)	(14.81)	(13.99)
Diff. in annual precipitation from hist.	-157.88	-17.04	7.53
avg. (mm)	(373.87)	(20.51)	(26.28)
Distance to nearest water area (km)	36.98	-4.94**	4.72**
	(31.74)	(2.39)	(2.31)
Avg 100-year flood depth within 5 km	0.23	0.28***	-0.05
	(0.53)	(0.08)	(0.07)
Any comm. HH flood report from 2007-2011	0.20	0.13***	-0.12**
	(0.40)	(0.05)	(0.05)
Household characteristics			
Female-headed HH	0.16	-0.02	-0.01
	(0.37)	(0.01)	(0.02)
Count of HH members	5.25	0.36**	0.11
	(2.95)	(0.15)	(0.17)
Any food insecurity in last 12 months	0.20	0.02	0.03*
	(0.40)	(0.02)	(0.02)
HH under 1.90 USD PPP per capita daily	0.32	0.05**	-0.00
poverty line	(0.47)	(0.02)	(0.03)
Household asset index	0.07	-0.20***	-0.07
	(1.07)	(0.06)	(0.06)
Any HH farm activity	0.64	0.09***	-0.05*
	(0.48)	(0.03)	(0.03)
Any non-farm HH enterprise activity	0.76	0.04**	0.03
	(0.43)	(0.02)	(0.02)
Any wage employment activity	0.42	-0.10***	-0.03
	(0.49)	(0.03)	(0.03)
Test of joint significance		F=8.51	F=1.35
		$p < 0.001$	$p = 0.151$
State FE		Yes	Yes

Note: This table shows the baseline (2010-11) control mean and difference by 2012 flood exposure status for selected community and household characteristics from a series of separate regressions. All regressions include state fixed effects, and standard errors are clustered at the 2012 community level ($N = 497$). 2012 flood incidence is defined as at least two households in a community reporting being affected by floods. The first column of differences uses the simple binary flood treatment measure while the second recenters the treatment around predicted flood incidence. The bottom of the table shows results for the test of the hypothesis that the relationship between a given 2012 flood exposure measure and all variables is jointly 0. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Balance in flood risk by 2012 flood incidence

	Any HH flood report in community-year (1)	(2)
2012 reported flood exposure	0.046***	
	(0.010)	
2012 recentered flood exposure		-0.007
		(0.012)
Observations	3921	3921
Mean, not flooded in 2012	0.059	0.059
State and Year FE	Yes	Yes

Note: This table shows the results from regressing a dummy for any community flood incidence in a given year according to the survey measure on dummies for flood exposure in 2012. The first row uses the simple binary flood treatment measure while the second recenters the treatment around predicted flood incidence. Observations are at the community-year level for 2007-2018, and 2012 is omitted. Fixed effects control for state and year. Standard errors are clustered by year. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Differences in probability of reporting a given shock in 2013 by household report of any flood shock

	No flood shock Mean (SD)	Any flood shock difference (SE)
Death/disability of adult member	0.15	-0.02
	(0.36)	(0.02)
Death of remittance sender	0.04	-0.00
	(0.20)	(0.01)
Departure of income earner	0.01	-0.00
	(0.10)	(0.01)
Non-farm business failure	0.05	0.02
	(0.21)	(0.02)
Theft of crops/cash/property	0.03	-0.00
	(0.16)	(0.01)
Other harv. failure/destruction	0.04	0.04**
	(0.19)	(0.02)
Dwelling damaged/demolished	0.02	0.01
	(0.14)	(0.01)
Death of livestock to illness	0.02	0.02*
	(0.13)	(0.01)
Input/output price shock	0.03	0.02*
	(0.17)	(0.01)
Increase of food prices	0.06	0.02
	(0.24)	(0.02)
Other shock	0.06	-0.04***
	(0.24)	(0.01)

Note: This table shows the results from separate regressions of indicators that households declare different shocks in the 2013 post-harvest survey on an indicator for whether they declare any flood shock. All regressions include state fixed effects. Standard errors are clustered by enumeration area. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Impacts of 2012 community flood incidence on household total hours of work by activity in the last 7 days

	N	Control Mean (SD)	Average impact: 2012 flood recentered × Post (SE)	Dynamic impacts: 2012 flood recentered × 2013 round (SE)	Dynamic impacts: 2012 flood recentered × 2016 round (SE)	Dynamic impacts: 2012 flood recentered × 2019 round (SE)
Total HH farm hours, last 7 days	12218	45.78	1.81	-1.15	4.45	6.28
PP		[59.53]	(2.92)	(3.29)	(3.62)	(5.80)
Total HH enterprise hours, last 7	12218	38.21	-2.41	-0.90	-4.05*	-2.79
days PP		[46.05]	(1.67)	(1.84)	(2.16)	(3.21)
Total HH wage hours, last 7 days	12218	22.09	3.04**	3.23*	2.51	5.01**
PP		[40.04]	(1.51)	(1.80)	(1.66)	(2.51)
Total HH farm hours, last 7 days	12218	34.07	-2.18	-6.74**	1.43	7.54
PH		[46.23]	(2.64)	(3.12)	(2.83)	(5.41)
Total HH enterprise hours, last 7	12218	34.53	0.30	0.13	0.17	2.42
days PH		[44.22]	(1.63)	(1.82)	(1.80)	(3.40)
Total HH wage hours, last 7 days	12218	24.10	2.35	2.97*	1.45	3.67*
PH		[39.96]	(1.54)	(1.71)	(1.58)	(2.07)

Note: This table presents effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, following Table 2. Each row represents an outcome. Outcomes are based on survey questions about hours of work by activity in the last 7 days for all household members over age 5. We calculate the sum of hours worked across all household members in the last 7 days for household agriculture, household non-farm enterprise, and wage employment in both the post-planting and post-harvest surveys. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Impacts of 2012 community flood incidence on crop yields and sales prices

	N	Control Mean (SD)	Average impact: 2012 flood recentered × Post (SE)	Dynamic impacts: 2012 flood recentered × 2013 round (SE)	Dynamic impacts: 2012 flood recentered × 2016 round (SE)	Dynamic impacts: 2012 flood recentered × 2019 round (SE)
Yield by area planted of cereals	4650	2158.89	-679.01*	-1039.78**	-218.89	-736.15
(kgs/ha) (household)		[4170.36]	(384.18)	(457.62)	(449.66)	(676.71)
Yield by area planted of maize	3304	1658.04	-460.83	-774.33*	-140.32	-736.73
(kgs/ha) (household)		[3904.93]	(397.70)	(460.51)	(468.83)	(618.17)
Yield by area planted of sorghum	3180	1560.91	11.79	-331.28	284.32	770.08*
(kgs/ha) (household)		[2607.84]	(302.43)	(450.27)	(421.87)	(431.94)
Yield by area planted of millet	2046	1250.57	-147.64	-216.07	-139.72	1072.03***
(kgs/ha) (household)		[1622.14]	(357.52)	(440.51)	(456.35)	(405.09)
Yield by area planted of cowpea	2253	607.34	106.21	-101.31	416.38	-66.08
(kgs/ha) (household)		[1268.03]	(181.02)	(182.61)	(278.02)	(424.31)
Yield by area planted of yam	2342	8357.64	-3852.06	-5303.91	-2871.29	697.03
(kgs/ha) (household)		[18380.24]	(2650.14)	(4446.44)	(2894.64)	(3983.14)
Yield by area planted of cassava	3392	1318.82	-1503.80**	-660.10	-2561.82***	-172.86
(kgs/ha) (household)		[3662.24]	(597.83)	(646.01)	(899.05)	(1227.95)
Average cereal price (USD/kg)	5410	0.49	-0.31***	-0.35**	-0.30***	-0.05
		[0.89]	(0.08)	(0.16)	(0.09)	(0.18)
Average maize price (USD/kg)	2780	0.26	-0.27	-0.43	-0.23	0.18
		[2.02]	(0.20)	(0.33)	(0.18)	(0.19)
Average sorghum price (USD/kg)	3110	0.94	-0.06	-0.01	-0.14	0.08
		[0.67]	(0.05)	(0.03)	(0.11)	(0.16)
Average millet price (USD/kg)	2008	0.12	-0.20**	-0.09	-0.34**	0.02
		[0.48]	(0.08)	(0.06)	(0.15)	(0.14)
Average cowpea price (USD/kg)	2130	1.77	-0.51	-0.60*	-0.37	-1.14
		[2.03]	(0.32)	(0.36)	(0.28)	(0.72)
Average yam price (USD/kg)	2198	0.70	0.01	0.02	0.03	-0.16
		[0.49]	(0.04)	(0.05)	(0.06)	(0.14)
Average cassava price (USD/kg)	988	0.67	-0.09	-0.31	0.10	-0.08
		[1.11]	(0.45)	(0.60)	(0.37)	(0.24)

Note: This table presents effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, following Table 2. Each row represents an outcome. We report results for the 6 crops with the highest average area planted in the sample. The results for cereals aggregate information for maize, sorghum, millet, and rice, weighted by the area planted to each crop for households growing multiple cereals. Yields are only defined for households with non-0 area planted for a particular crop. Prices are the average sales price reported by the household, or the median sales price in the community if they did not sell any output. Monetary values are in 2016 PPP USD. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Impacts of 2012 community flood incidence on market food prices and agricultural labor wages

	N	Control Mean (SD)	2012 flood recentered × Post (SE)
Comm. price shelled maize (USD/kg)	8475	0.03	-0.17
		[1.09]	(0.17)
Comm. price local rice (USD/kg)	8904	-0.01	-0.16
		[1.06]	(0.14)
Comm. price bread (USD/kg)	10433	0.04	-0.40***
		[1.02]	(0.14)
Comm. price yam roots (USD/kg)	9311	0.05	-0.25*
		[1.04]	(0.15)
Comm. price palm oil (USD/litre)	10429	-0.00	0.04
		[0.96]	(0.07)
Comm. price groundnut oil (USD/litre)	9921	-0.00	0.03
		[0.93]	(0.08)
Comm. price banana (USD/kg)	7974	-0.00	0.09
		[1.03]	(0.14)
Comm. price chicken (USD/kg)	8774	-0.03	0.01
		[0.99]	(0.11)
Comm. price sugar (USD/kg)	8698	0.00	0.34
		[1.02]	(0.22)
Comm. avg. daily wage for men's ag labor (USD)	9947	15.06	-1.14
		[9.09]	(1.05)
HH avg. daily wage for hired ag labor (USD)	4901	100.74	-3.48
		[278.68]	(20.85)

Note: This table presents effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, following Table 2. We do not present dynamic analyses of effects by survey round as the collection of community price data in 2018-19 followed a different format than in the previous rounds so we are constrained to the first three survey rounds. Each row represents an outcome. Data for all outcomes preceded by "Comm." are from the community survey. Market prices for commonly-reported food goods are from the post-harvest survey for the nearest market to the community. The units for goods are different in different rounds so we convert all prices to standard deviations relative to the non-flooded community mean in each survey round after converting values to USD and winsorizing. The average daily wage for men's agricultural labor is the mean wage across different types of reported activities from the post-planting survey. The household average daily wage is the average wage paid for hired labor across activities for households that hired any farm labor, weighted by amount of days provided. Monetary values are in 2016 PPP USD. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Impacts of 2012 community flood incidence on incomes, including households with zero estimated total income

			Average impact	Dynamic impacts		
	N	Control Mean (SD)	2012 flood recentered × Post (SE)	2012 flood recentered × 2013 round (SE)	2012 flood recentered × 2016 round (SE)	2012 flood recentered × 2019 round (SE)
Total HH income and production value (USD 100s)	12218	77.18	1.39	0.54	0.42	13.49
		[173.48]	(5.59)	(6.42)	(5.99)	(11.17)
Total value of HH farm production (USD 100s)	12218	17.42	-4.11***	-4.26**	-4.09**	-3.19
		[37.48]	(1.55)	(1.69)	(1.83)	(3.13)
Total income from non-farm activities (USD 100s)	12218	59.76	5.50	4.79	4.51	16.68
		[171.26]	(5.33)	(6.17)	(5.71)	(10.41)
Total non-farm HH enterprise income (USD 100s)	12218	25.29	2.03	4.89*	-2.29	8.78*
		[82.52]	(2.89)	(2.96)	(3.28)	(4.52)
Total wage employment income (USD 100s)	12218	31.78	3.07	-1.02	6.91	7.97
		[147.98]	(4.57)	(5.50)	(5.02)	(8.79)
Total HH income from other activities (USD 100s)	12218	2.70	0.40	0.92	-0.11	-0.08
		[20.05]	(1.03)	(1.10)	(1.18)	(1.92)

Note: This table reproduces the first rows of Table 5 but including households with zero total income and production value. The results for income shares are unchanged because the shares can only be calculated for households with non-zero income, and therefore are not shown. Monetary values are in 2016 PPP USD. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Sensitivity of estimated impacts of 2012 community flood incidence to alternative specifications and samples

	Main (1)	No controls (2)	LGA-round FE (3)	Zone-round FE (4)	Round FE (5)	All EAs (6)	W/in 50 km of any flood report (7)	Drop donut (8)	Ag HHs (9)
Any food insecurity in last 12	0.04***	0.01	0.03	0.08***	0.10***	0.04***	0.04***	0.03	0.03**
months	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Daily HH consumption per capita	-0.72***	-0.75***	-1.32**	-0.83***	-0.74***	-0.69***	-0.66***	-0.71***	-0.62***
(USD)	(0.24)	(0.23)	(0.64)	(0.25)	(0.24)	(0.24)	(0.24)	(0.26)	(0.24)
Total value of HH farm production	-3.86**	-3.68**	-0.10	-3.68**	-4.29***	-3.80**	-3.80**	-4.03**	-4.24**
(USD 100s)	(1.65)	(1.58)	(3.38)	(1.69)	(1.65)	(1.67)	(1.68)	(1.81)	(1.80)
Total non-farm HH enterprise	0.76	0.47	10.54	-0.43	0.58	1.40	1.74	1.27	4.10
income (USD 100s)	(3.14)	(3.09)	(7.87)	(2.90)	(2.97)	(3.08)	(3.05)	(3.29)	(3.11)
Total wage employment income (USD	0.26	0.43	15.51	-3.44	-2.76	0.95	1.01	-0.36	0.77
100s)	(4.72)	(4.75)	(16.27)	(4.50)	(4.12)	(4.74)	(4.76)	(4.83)	(4.19)
Any HH farm activity	0.03**	0.05***	0.10**	0.02*	0.03***	0.03*	0.03*	0.02	0.03**
	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Any HH non-farm enterprise	0.00	0.00	0.02	-0.00	-0.01	0.00	0.00	-0.00	-0.01
activity	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Any wage employment activity	0.03	0.03*	-0.02	0.04**	0.05**	0.02	0.02	0.04**	0.03
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Count of HH members wkg. in HH	0.14	0.18**	0.30*	0.15	0.17	0.12	0.12	0.14	0.13
farm	(0.09)	(0.08)	(0.17)	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)	(0.10)
Count of HH members wkg. in HH	-0.03	-0.01	-0.05	-0.04	-0.02	-0.04	-0.04	-0.02	-0.03
non-farm enterprise	(0.05)	(0.05)	(0.09)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
Count of HH members wkg. in wage	0.14**	0.16***	0.03	0.18***	0.21***	0.13**	0.13**	0.18***	0.15**
employment	(0.06)	(0.05)	(0.12)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
Any member left HH during/since	-0.01	-0.01	-0.03	-0.00	-0.01	-0.00	-0.00	-0.02	-0.01
last round	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Total area planted (ha)	-0.36*	-0.29	-0.06	-0.53**	-0.54**	-0.36*	-0.36*	-0.46**	-0.28
	(0.19)	(0.20)	(0.26)	(0.24)	(0.26)	(0.19)	(0.19)	(0.20)	(0.20)
Total family crop labor hours in	236.66*	164.45	340.85	268.00	551.57***	217.04	218.11	270.22**	238.10
past year	(135.81)	(144.15)	(207.96)	(196.81)	(212.44)	(134.07)	(134.89)	(135.29)	(147.68)

Note: This table shows the results from separate regressions of household outcomes on recentered 2012 community flood exposure interacted with being observed after 2012. Each row represents an outcome; see the main analysis tables for explanations of the variables. Monetary values are in 2016 PPP USD. The columns show average effects of flood exposure across all post-flood survey rounds. Flood exposure is defined as at least two households in the community reporting being affected by floods in 2012, and is recentered around predicted community incidence. Estimates therefore represent the effect of residing in a community that was exposed to floods 2012 for a given predicted propensity of incidence. Each column indicates how the specification or sample is changed relative to the main specification, presented in column (1), which includes household, state-by-round, and baseline characteristic-by-round fixed effects, and restricts the sample to communities within the common support of average 100-year flood depth within 5 km after stratifying by the number of years with any survey flood report from 2007-2011. In column (2) the baseline characteristic-by-round fixed effects are dropped. Columns (3)-(5) replace the state-by-round FE with different forms of round FE. In column (6) the community sample restrictions are removed. Column (7) replaces the main sample restriction with dropping any community more than 50 km from any community where floods were reported in 2012. Column (8) adds a sample restriction dropping communities less than 20 km from any community where a flood was reported in 2012. Column (9) reproduces the main specification but only includes households engaged in agricultural activity at some point during the four survey rounds. Standard errors are clustered at the level of the community of residence in 2012. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Sensitivity to alternative ways of controlling for non-random 2012 flood incidence

			(1)	(2)	(3)	(4)	(5)
			Recentering	No recentering			
	N	Control Mean (SD)	Main (SE)	Prediction-round controls (SE)	Risk/rain-round controls (SE)	No added controls (SE)	No baseline controls (SE)
Any food insecurity in last 12 months	12218	0.18	0.04***	0.04***	0.03**	0.04***	0.02
		[0.38]	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Daily HH consumption per capita (USD)	12218	5.42	-0.72***	-0.76***	-0.80***	-0.77***	-0.77***
		[4.30]	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Total value of HH farm production (USD 100s)	11401	19.24	-3.86**	-4.03**	-4.05**	-4.09**	-4.46**
		[38.99]	(1.65)	(1.70)	(1.71)	(1.74)	(1.75)
Total non-farm HH enterprise income (USD 100s)	11401	27.90	0.76	0.42	-0.28	-0.28	0.05
		[86.48]	(3.14)	(3.08)	(2.93)	(2.85)	(2.87)
Total wage employment income (USD 100s)	11401	35.27	0.26	1.71	2.48	4.84	4.15
		[155.50]	(4.72)	(4.88)	(5.51)	(5.31)	(5.33)
Any HH farm activity	12218	0.74	0.03**	0.04***	0.06***	0.06***	0.05***
		[0.44]	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Any HH non-farm enterprise activity	12218	0.76	0.00	0.00	0.00	0.00	-0.00
		[0.43]	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Any wage employment activity	12218	0.41	0.03	0.02	0.02	0.02	0.02
		[0.49]	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Count of HH members wkg. in HH farm	12218	1.89	0.14	0.16*	0.20**	0.20**	0.16*
		[2.13]	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Count of HH members wkg. in HH non-farm enterprise	12218	1.23	-0.03	-0.02	-0.00	-0.00	-0.01
		[1.36]	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Count of HH members wkg. in wage employment	12218	0.79	0.14**	0.14**	0.13**	0.13**	0.13**
		[1.41]	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Any member left HH during/since last round	12218	0.08	-0.01	-0.01	-0.01	-0.00	0.00
		[0.27]	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Total area planted (ha)	12218	1.47	-0.36*	-0.38**	-0.38**	-0.38**	-0.39**
		[3.03]	(0.19)	(0.19)	(0.18)	(0.17)	(0.19)
Total family crop labor hours in past year	12218	901.58	236.66*	294.70**	370.35***	391.27***	429.91***
		[1817.94]	(135.81)	(134.85)	(134.24)	(135.37)	(142.82)

Note: This table shows the results from separate regressions of household outcomes on recentered 2012 community flood exposure interacted with being observed after 2012. Control means are for communities with no flood exposure in the 2010-11 survey round. See Table A9 for additional details. Each column indicates how the specification is changed relative to the main specification, presented in column (1), where flood exposure is defined as at least two households in the community reporting being affected by floods in 2012, and is recentered around predicted community incidence. Columns (2)-(5) show effects of binary 2012 survey-reported flood incidence rather than the recentered variable and vary the set of included controls. Column (2) adds predicted 2012 community flood incidence-by-round fixed effects. Column (3) adds average 100-year flood depth within 5 km-by-round and community 2012 rainfall deviation-by-round fixed effects. Column (4) drops the recentering but does not include any additional controls to account for different 2012 flood propensities. Column (5) drops the recentering and also drops the baseline characteristics-by-round fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Impacts of satellite-detected 2012 community flood incidence

	N	Control Mean (SD)	Average impact: 2012 MODIS recentered × Post (SE)	Dynamic impacts: 2012 MODIS recentered × 2013 round (SE)	Dynamic impacts: 2012 MODIS recentered × 2016 round (SE)	Dynamic impacts: 2012 MODIS recentered × 2019 round (SE)
Any food insecurity in last 12 months	10122	0.17	0.03	0.04	0.02	0.09
		[0.38]	(0.03)	(0.03)	(0.03)	(0.08)
Daily HH consumption per adult equiv (USD)	10089	5.79	0.34	0.93	-0.31	0.35
		[4.46]	(0.40)	(0.60)	(0.35)	(0.50)
Total value of HH farm production (USD 100s)	9412	19.14	-1.22	-0.18	-2.71	1.92
		[35.99]	(2.02)	(2.37)	(2.13)	(3.66)
Total non-farm HH enterprise income (USD 100s)	9412	25.62	7.96*	4.59	11.24**	9.47
		[79.03]	(4.29)	(4.58)	(4.92)	(6.59)
Total wage employment income (USD 100s)	9412	27.20	-0.72	5.45	-6.45	-5.38
		[145.13]	(7.10)	(9.62)	(6.76)	(10.95)
Any HH farm activity	10122	0.82	-0.02	-0.02	-0.01	-0.04
		[0.38]	(0.02)	(0.02)	(0.02)	(0.07)
Any HH non-farm enterprise activity	10122	0.76	-0.00	-0.01	-0.00	0.10**
		[0.42]	(0.02)	(0.03)	(0.03)	(0.04)
Any wage employment activity	10122	0.39	0.02	0.02	0.02	-0.05
		[0.49]	(0.02)	(0.03)	(0.03)	(0.06)
Count of HH members wkg. in HH farm	10122	2.16	0.05	0.01	0.05	0.41*
		[2.20]	(0.10)	(0.12)	(0.12)	(0.22)
Count of HH members wkg. in HH non-farm enterprise	10122	1.33	0.03	0.01	0.01	0.43***
		[1.41]	(0.05)	(0.06)	(0.06)	(0.15)
Count of HH members wkg. in wage employment	10122	0.77	0.09	0.11	0.07	0.08
		[1.45]	(0.07)	(0.09)	(0.08)	(0.11)
Any member left HH for work during/since last round	10122	0.02	-0.01	0.00	-0.02	-0.12**
		[0.12]	(0.01)	(0.01)	(0.02)	(0.05)
Total area planted (ha)	10122	1.86	0.27	0.25	0.30	0.20
		[3.43]	(0.22)	(0.25)	(0.21)	(0.20)
Total family crop labor hours in past year	10122	1021.95	138.16	162.13	104.76	193.48
		[1929.58]	(157.62)	(197.07)	(175.60)	(180.38)

Note: This table shows the results from separate regressions of household outcomes on recentered 2012 community flood exposure interacted with being observed after 2012. Each row represents an outcome; see the main analysis tables for explanations of the variables. Monetary values are in 2016 PPP USD. Control means are for communities with no flood exposure in the 2010-11 survey round. The first column of results shows average effects across all post-flood survey rounds. The next three columns show dynamic effects in each post-flood round. The main difference between this table and the estimates in Table 2 and the other main results is in how flood exposure is defined. Instead of using survey reports, in this table flood exposure is defined as a community being within 5 km of any pixel identified as flooded at any point in 2012 by MODIS satellite imagery in the NASA NRT Global Flood Mapping product. As in the main analyses, 2012 flood incidence is recentered around predicted incidence. Estimates therefore represent the effect of residing in a community that was exposed to floods 2012 according to MODIS satellite imagery for a given predicted propensity of satellite-based incidence. All regressions include household and state-by-round fixed effects. Standard errors are clustered at the community level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Impacts of 2012 community flood incidence on livelihood activities and incomes by access to safety nets

	(1) Any act.	(2) Count mems.	(3) Value prod.	(4) Any act.	(5) Count mems.	(6) Total inc.	(7) Any act.	(8) Count mems.	(9) Total inc.	(10) Work migr.
Flood × Post, H=0	0.06***	0.21**	-5.41***	0.00	-0.01	-0.96	0.04*	0.15**	3.48	-0.02
	(0.01)	(0.10)	(1.73)	(0.02)	(0.06)	(3.13)	(0.02)	(0.06)	(4.41)	(0.02)
Flood × Post, H=1	0.05***	0.16	-0.11	-0.05	-0.09	7.59	-0.01	0.15	2.21	0.02
	(0.02)	(0.14)	(2.38)	(0.03)	(0.10)	(6.60)	(0.04)	(0.13)	(12.33)	(0.02)
Observations	12216	12216	12216	12216	12216	12216	12216	12216	12216	12216
p, equality of effects	0.82	0.76	0.07	0.23	0.47	0.24	0.28	0.96	0.92	0.08

Note: This table presents average effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, by whether any household in the community reported receiving assistance from social safety net programs in the 2010-11 survey round. Each column represents an outcome. See Table 5 and Table 3 for an explanation of the outcome variables. The results for each column in each panel are from a single triple-differences regression fully interacting the baseline household characteristic H with the Post and Flood dummies. We calculate the average effect in the group with $H = 1$ by taking the sum of the $Flood \times Post$ and $Flood \times Post \times H$ coefficients and estimate SEs using the *xlincom* function in Stata. We also report the p-value for the triple interaction term, which tests for equality of effects between the two groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Impacts of 2012 community flood incidence on household consumption, assets, and total income by community characteristics

	(1) Any food insec.	(2) Daily HH cons./cap.	(3) Value HH assets	(4) Total HH income
A. H = Below median distance to nearest market				
Flood × Post, H=0	0.06***	-0.87**	-142.92	-7.12
	(0.02)	(0.41)	(181.76)	(8.31)
Flood × Post, H=1	0.03	-0.87***	-173.35	-0.96
	(0.02)	(0.31)	(213.78)	(7.37)
p, equality of effects	0.32	0.99	0.91	0.58
B. H = Any survey flood report in community from 2007-2011				
Flood × Post, H=0	0.04*	-0.89***	-204.85	-0.92
	(0.02)	(0.27)	(193.36)	(6.41)
Flood × Post, H=1	0.04**	-0.58	-115.60	-4.61
	(0.02)	(0.42)	(224.48)	(10.57)
p, equality of effects	0.84	0.54	0.76	0.77
C. H = Non-zero fluvial flood risk				
Flood × Post, H=0	0.02	-0.51**	-204.11	5.81
	(0.02)	(0.20)	(169.17)	(6.38)
Flood × Post, H=1	0.06**	-0.90*	79.61	-6.68
	(0.02)	(0.50)	(221.77)	(10.99)
p, equality of effects	0.22	0.47	0.31	0.33
Observations	12212	12212	12212	12212

Note: This table presents average effects of 2012 community flood exposure on household outcomes in subsequent survey rounds, by baseline community characteristics as indicated in the panel headings. Community distances to the nearest main market are provided in the GHSP data based on actual (non-offset) community locations. Fluvial flood risk data are from the European Commission Joint Research Centre (JRC; Baugh et al., 2024). Each column represents an outcome. See Table 2 and Table 5 for an explanation of the outcome variables. The results for each column in each panel are from a single triple-differences regression fully interacting the baseline household characteristic H with the Post and Flood dummies. We calculate the average effect in the group with $H = 1$ by taking the sum of the $Flood \times Post$ and $Flood \times Post \times H$ coefficients and estimate SEs using the *xlincom* function in Stata. We also report the p-value for the triple interaction term, which tests for equality of effects between the two groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Survey Data

The main data source for the analysis is Nigeria's General Household Survey Panel (GHSP). The GHSP is a nationally-representative panel survey including 5,000 households conducted by the Nigeria National Bureau of Statistics, and is part of the World Bank's Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). Before the first survey round, 500 enumeration areas (communities) were randomly sampled after stratifying by state. Ten households were then randomly sampled in each enumeration area.

Four survey rounds were conducted between 2010 and 2019. Households are tracked over time, including if they move to a new location, but individual household members are not tracked. In 2018-19 the panel sample was partially refreshed, with 1,425 households from the original panel retained and 3,551 new panel households added to the sample. The GHSP data are publicly available from the World Bank's Microdata Catalog.

The main analysis sample includes 15,356 observations across the four survey rounds from 4,750 unique households. All households are observed in both the 2010-11 and 2012-13 rounds, 4,497 households are observed in the 205-16 round, and 1,430 households are observed in the 2018-19 round where we do not keep newly sampled households in the partially refreshed panel.

Each survey round includes both a post-planting and a post-harvest survey. Post-planting surveys took place in September-October 2010, September-October 2012, August-September 2015, and July-August 2018. Post-harvest surveys took place in February-April of 2011, 2013, and 2016 and in January-February 2019. Some information, such as individual labor supply, is recorded in each survey while other modules are only included in either the post-planting or post-harvest surveys.

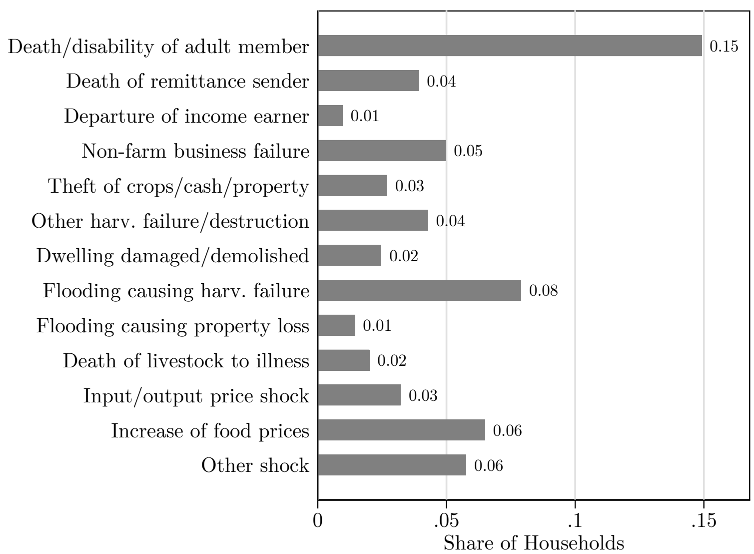
Basic cleaning decisions include replacing missing values with 0 where appropriate (i.e., for income in an activity the household was not engaged in) and replacing impossible values (such as more than 24 hours per day) with missing values. We winsorize continuous variables by replacing values above the 99th percentile with the value at the 99th percentile. All variables representing monetary values are converted to 2016 PPP USD.

For certain variables—notably the measures of total household income by activity—we modify code developed by the Evans School Policy Analysis & Research Group (EPAR) to construct variables in consistent ways accounting for differences in the survey instruments across rounds. The code is available on GitHub: https://github.com/EvansSchoolPolicyAnalysisAndResearch/LSMS-Agricultural-Indicators-Code.

Differences across survey flood measures

Several survey questions ask about flood exposure, each of which captures specific ways in which floods can affect households. In the post-planting agricultural survey, households can list flooding as the main cause of loss of stored crops since the beginning of the new year for each cultivated crop. Such losses are reported by 13% of households for 2012 but flood-related losses are only reported by 1% In the post-harvest agricultural survey, households can list flooding as a reason for not harvesting a particular crop. Failure to harvest is reported by 24% of households, but again floods are only listed as a reason by 3%. In both the post-planting and post-harvest household surveys, households can list flooding as a cause of household food insecurity in the past 12 months. Food insecurity is reported by 24% of households at post-planting and by 20% at post-harvest, and in both periods 3% list floods as a cause of food insecurity. Finally, in the post-harvest household survey shocks module, households are asked about various shocks they have been affected by over the past 5 years, the years in which they occurred, and the consequences of the shocks. Two shocks relate to floods: flooding that caused harvest failure is reported by 7% of households in 2012 and loss of property due to flood is reported by 1%. Floods are the second most commonly reported shock for 2012 (Figure A6).

Figure A6: Prevalence of shocks reported by households over the 12 months before the 2013 post-harvest survey round

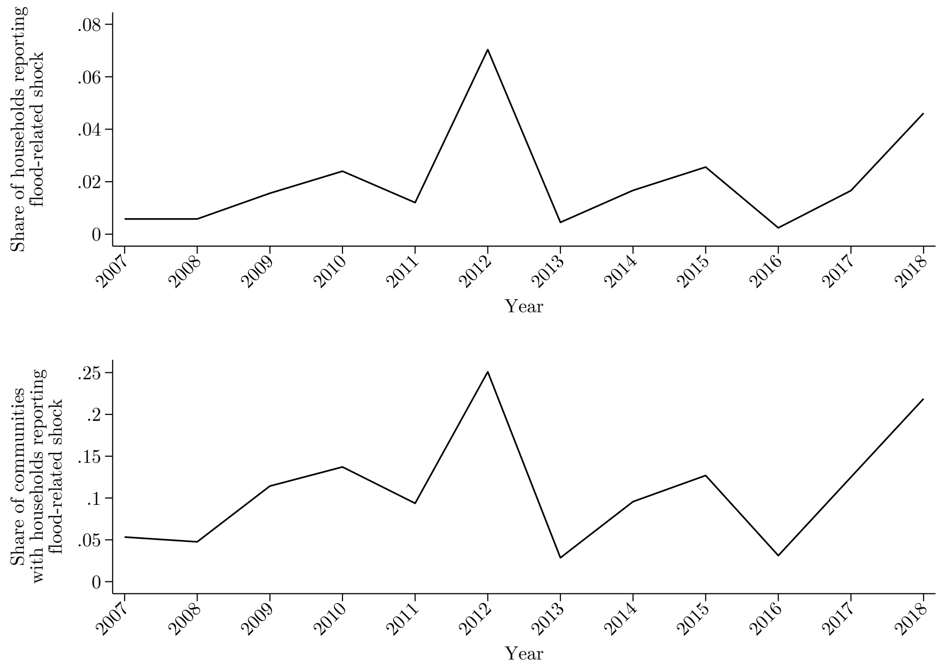


Note: Data are from the 2013 post-harvest household survey shocks module.

We can use the fact that household shocks are reported for multiple years to show how the prevalence of flood shocks was much greater in 2012 than in any other year from 2007-2018 (Figure A7). Other survey flood questions only relate to the year in which the surveys took place. The fact that the share of households reporting flood shocks is much lower than the share of communities where such shocks are reported highlights how not every household is affected in communities where flooding occurs. This result is supported by the community questionnaire, which asks informants to report important events that made people worse off in the community, including floods, and the year in which they occurred. Floods are reported in 20% of communities in 2012, and on average these are reported to have affected 48% of community households (the median is 50%).

Across all flood questions, 12.4% of households report being affected by floods in some way

Figure A7: Survey flood shock reports by year

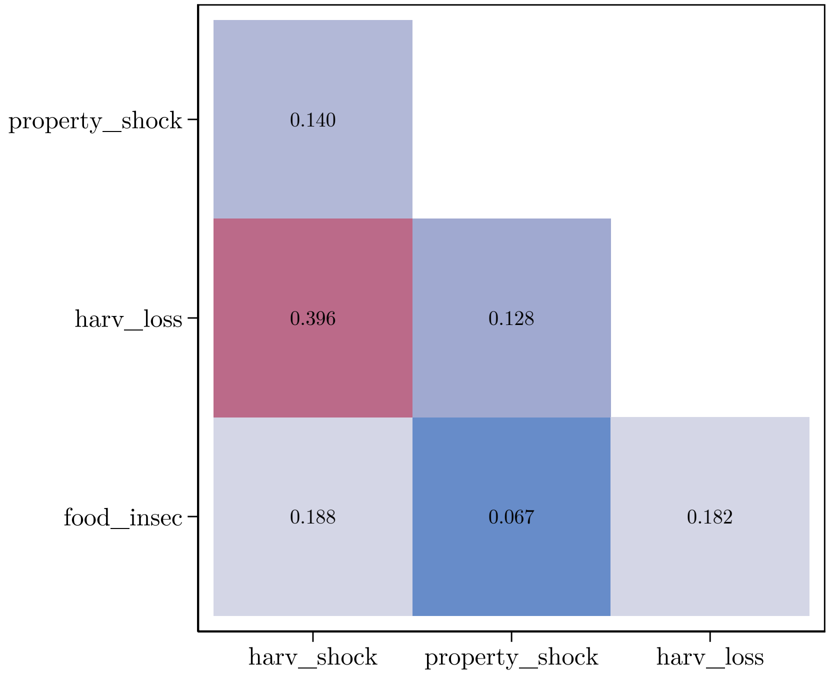


Note: Annual flood reports are from the Nigeria GHSP. In each survey round, households are asked to recall whether they experienced specific economic shocks over the last few years, including flooding that caused harvest failure and loss of property due to flood. These data were collected in the post-harvest survey waves in 2009, 2013, 2016, and 2019. This is a more restrictive measure of flood exposure than the main survey-based measured we use in this paper which incorporates reports of floods in the survey's food security and crop production modules, but there is no recall element for those questions. The top panel shows the share of households reporting any flood shock by year. The bottom panel shows the share of communities with any household flood shock report year

in 2012. Figure A8 shows a heatmap of correlations between these measures. We aggregate the agricultural survey questions as 'harv_loss' and the food insecurity questions as 'food_insec', in both cases coded as 1 if the household reports a flood in either the post-planting or post-harvest wave. We compare these against the two flood questions from the household shock module. While the two harvest-related measures are highly-correlated, correlations between the other measures are weak. This emphasizes that each measure is capturing different ways in which floods may affect households, and that they are primarily affecting different households rather than the same household being affected in multiple ways. The figure also indicates that household flooding reported in the shocks module—a common way survey-based flood measures are constructed—may miss some floods that did not cause the specific types of losses or damages that are asked about.

How do these household flood reports compare to what is reported in the GHSP community surveys? Twenty percent of households reside in communities where flooding was reported in 2012 in the community survey. Yet 41% of households reporting being affected by floods in 2012 reside in communities where no flooding was reported. In communities with a community survey flood report, 25% of households report a flood, compared to 7% in communities with no survey flood report. Households reporting floods not captured in the community survey may be driven by lack

Figure A8: Correlations between survey measures of household-level 2012 flood incidence



Note: This heatmap shows pairwise correlations between different measures of flood incidence in 2012 at the level of households in the Nigeria GHSP. 'harv_shock' indicates a report of a flood that caused harvest failure in the household shocks module. 'property_shock' indicates a report of a flood that caused property loss in the household shocks module. 'harv_loss' indicates a report of loss of stored crops or failure to harvest in the post-planting and post-harvest household crop production modules. 'food_insec' indicates a report of floods as a cause of household food insecurity in either the post-planting or post-harvest food security modules.

of complete information by the group of community survey informants, or by error in the household surveys. But even for the case where at least two separate sample households report flooding in the shocks module the correlation remains low. This suggests important measurement errors in the community survey and motivates the reliance on the household reports to define survey-based community flood exposure for the main analyses rather than the community reports. On the other hand, 25% of households are in communities with a community flood report but no survey flood report. A potential reason for this is floods affecting community households other than those included in the GHSP sample. We therefore test sensitivity of the results to including community reports in the survey flood definition.