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Under the water: flood impacts and economic dynamics in northern Peru

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Abstract

This paper assesses the effects of devastating flooding on household welfare in northern Peru. Remote sensing data are used to construct a novel damage index as a proxy for the local economic impact caused by the 2017 coastal El Niño floods. Using 5-year panel data from the Peruvian National Household Survey (ENAHO), we observe that affected households experience a decrease in income and expenditure compared to those in unaffected areas during the period 2015–2019. Additionally, poverty increases as a result of this natural hazard, especially among households in urban areas. Although there is a recovery in income and expenditure in the aftermath of the floods, households mitigate their consumption through donations of food and clothing. We suggest that, in a context where the occurrence of flooding affects the most vulnerable groups, the development of formal risk-coping strategies such as insurance is crucial for boosting their ability to reduce, mitigate, or adapt to future disaster risk.

Key words: floods, damage index, remote sensing, SWAT model, Event Study, Peru

JEL Code: C23, O12; Q54

1. Introduction

Climate change increases the frequency and intensity of extreme weather-related events globally. These events are sudden and sudden and unexpected, resulting from deviations in climate patterns from normal environmental conditions across large regions. Among the most common and damaging natural hazards, floods have caused more economic and property damage, and loss of life, than any other natural hazard in the 21st century (CRED, 2018). The “El Niño” phenomenon exacerbates flood risks and the likelihood of long-lasting and devastating effects on people’s livelihoods, particularly in developing countries where vulnerability is often linked to poverty. One of the countries most affected is Peru (Tyndall Centre, 2004), with approximately 1.51 million people living in inundation zones or areas susceptible to floods (Smith et al., 2021).

In early 2017, Peru experienced severe floods due to the coastal El Niño – a variant of the “El Niño” phenomenon, causing deaths and infrastructure damage (OCHA, 2017). The National Meteorology and Hydrology Service reported 107 fatalities (Sardon et al., 2022), while the Ministry of Economy and Finance noted a 1.5 percentage points[1] decline in Peru's Gross Domestic Product (GDP), estimated at US$ 3.1 billion as at 28 March 2017 (Leon et al., 2017). The floods affected the northern region, including the departments of Cajamarca, La Libertad, Lambayeque, Piura, and Tumbes. Residents faced recurring floods triggered by heavy rainfall in February and March of 2017, with the most extreme episodes occurring between 26 and 27 March 2017. Subsequent events in 2018 and 2019 sporadically affected a few districts within the same region, but with lesser impact and damage compared to the 2017 floods.

An investigation into the impact of extreme natural events on households in northern Peru is therefore crucial. It aids in understanding household disaster recovery and assesses the risk of poverty trap if there is limited external support. This study examines the economic effects of flood shocks on household welfare and poverty status by using 5–year panel data from 2015 to 2019 and employing a diff-in-diff event study model. The identification strategy relies on the causal effect of flood variation on household income and expenditure per capita, and poverty status in areas affected by this natural hazard relative to households in unaffected areas. Using a novel damage index as a proxy for the local impact of floods, treated households are defined as those located in

[1] According to the Central Bank's Annual Report Memory 2017, there were no transitory shocks or other economic disruptions apart from the 2017 coastal El Niño, which negatively impacted the entire economy of the northern region of Peru. This report can be accessed from the following link: https://www.bcrp.gob.pe/docs/Publicaciones/Memoria/2017/memoria-bcrp-2017.pdf

affected districts, and control households are those that lived in unaffected districts – discrete specification. Additionally, we use the index as a continuous measure of treatment as treated households were exposed to different levels of flood damage. We then compare treatment and control groups to estimate the effects of such disaster on household welfare (income and expenditure) and poverty status at the district level.

We construct the damage index as a measure of local economic impact for districts affected by floods, using several publicly available remote sensing data such as watershed shapefile, Digital Elevation Model and Land Use/Land Cover rasters, Digital Soil Map of the World, weather and night-time lights (VIIRS). The estimates of the associated damage may be useful for policy making prior to the realisation of a potential extreme weather event such as flooding. We also consider the possibility that households have relocated to areas with lower or non-flood risk after the occurrence of flooding, which may lead to inaccurate estimations of flood impacts. To address these endogeneity concerns due to the sorting of flood risk areas[2], we conduct propensity score matching in the pre-estimation step to create counterfactual observations of households in non-flooded areas. This ensures a more accurate analysis of the relationship between floods and household welfare in northern Peru.

The econometric results suggest that, in response to an average flood shock, household income and expenditure fall by 29% and 26.5%, respectively. We also find that poverty in urban areas increases by 41% because of job loss and deterioration of local economic activity. We observe signs of recovery in household income and expenditure but estimates are lower than those in the year prior to the flood occurrence.

The contribution to the literature is threefold. First, to the best of my knowledge, this study is one of the few research efforts to propose an index for measuring economic damage and estimating the causal impacts of the 2017 floods on districts within the northern region of Peru. The index not only serves as a proxy for local economic impacts but also ranks districts from most to least economically affected. This approach can provide central and local governments, emergency services, and aid workers with a practical tool to estimate the damages and intensity of the disaster—either ex ante or ex post—and allocate resources to areas most in need. Furthermore, previous empirical studies

[2] This is noted by Bakkensen and Ma, 2020 in the context of individuals sorting across levels of flood risk (low and high) by race, ethnicity, and income for South Florida, USA.

have usually relied on precipitation data as a proxy for floods, rather than capturing this weather-related event at the surface level.

Second, recent contributions in econometrics have highlighted the pitfalls of time-within-fixed effects models in study settings with multiple groups and time periods, variation in treatment timing, and a continuous treatment (Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2022; Goodman-Bacon, 2021; Sun and Abraham, 2021). In the study design, due to the nature of the variable of interest, we evaluate the causal effect of flood events on household welfare using the heterogeneity robust estimator proposed by de Chaisemartin and D'Haultfœuille (2022). This approach strictly compares districts switching to treatment in a time period with groups not-yet-treated during the same period and specifically considers dynamic effects.

Third, we provide additional evidence on the short- to medium-term impacts of floods on household income and expenditure per capita, poverty status, number of income earners, wage income, savings and disaster relief (food and clothing) by using 5-year household survey and remote sensing data, as well as Peruvian government reports of the districts' exposure to 2017 flood impacts.

The paper proceeds as follows. Section 2 reviews relevant literature, focusing on flood events that have occurred in developing countries and their impacts on household welfare. In Section 3, we describe the coastal El Niño floods that occurred in northern Peru in 2017. Section 4 explains the empirical strategy, including the classification of districts as treated and control groups, and the empirical modelling. Section 5 provides information on the datasets and the construction of the damage index, while Section 6 presents the pre-estimation process to address potential endogeneity resulting from sorting across households. Sections 7 presents the main results and extended analysis. Lastly, Sections 8 and 9 provide policy recommendation and concluding statements, respectively.

2. Related literature

The effect of weather-related shocks has been documented in several studies. However, there is little assessment of the impact of sudden-onset events on household incomes and expenditures in middle-income countries. The evaluation that does exist is focused either on households in high-income countries (e.g., earthquakes in Japan, and hurricanes in the United States) or on rural households in low-income countries (e.g., droughts in sub-Saharan Africa, and hurricanes in Central America).

The literature on flood impacts finds that these natural events negatively affect the income and expenditure of households. For instance, Noy et al. (2020) analyses the economic impact of the Thailand 2011 floods on household-level welfare. Using household self-reported shock and satellite images, they show that business and wage incomes drive the negative impacts on flooded households relative to the control group. Similarly, flood-unaffected households located in flood areas (called households spillover) experience income loss as much as the directly impacted households. In terms of spending, floods led to increased housing expenditure but reduced consumption on luxuries, particularly among higher-wealth households.

In a similar paper, Chantarat et al. (2016) examine the impacts of the 2011 Thailand flood on rice-farming households' preferences, subjective expectations, and behavioural choices. A flood inundation map was used to identify villages heavily affected by floods and those nearby not-so-heavily flooded. Using a specially designed survey, they find that households experiencing the flood event are more risk averse, more impatient, and more altruistic, and that asset-poor farming households were more likely to be affected by the flood than better-off households. The flood also made households adjust upward their subjective expectations of future severe floods.

Work by Del Ninno et al. (2001) studies the 1998 Bangladesh floods and their impact on rural household welfare. They find that more than half of those affected by the floods experienced a loss in assets, employment, and days worked in the agricultural sector. The authors highlight the coping mechanisms used by households, such as reducing expenditure, selling assets, and borrowing, with borrowing being the most common strategy. Government relief efforts, including food and cash transfers, were targeted to flood-exposed and poor households, however, were insufficient to meet all household needs.

A study undertaken by Mueller and Quisumbing (2011) finds short- and long-term impacts of floods on household wages by using 5-year household panel data for the case of the 1998 Bangladesh floods. They create a flood shock variable that shows the flood depth deviated from normal conditions. Their results show a short-term decline in wages of salaried workers in the non-agricultural sector (from 8.4 to 13.8%) and agricultural sector (from 34.3 to 45.6%). In that context, agricultural workers who moved towards non-agricultural employment to cope benefitted from a lower percentage reduction in short-term wages.

Another branch of literature explores the effects of floods on human health. For example, Yonson et al. (2018) employ three flood variables – height in meters, duration in hours, and exposure – to estimate the probability of urban households suffering from diseases in the Philippines between 2011 and 2014. They find that flood height is positively associated with bronchitis, influenza, and leptospirosis, while flood duration is associated with bronchitis, influenza, and typhoid fever. Parida et al. (2018) study the impact of floods on farmer suicides using state-level panel data from 17 Indian states for the period 1995 to 2011. Flood maps are used to identify the states affected by floods, indicating that floods have no direct impact on farmer suicides.

In addition to this, there are several papers that analyse the effects of excessive rainfall (as proxy for floods events) rather than one-off natural shocks. Maccini and Yang (2009) argue that rainfall shocks, even if experienced well before schooling age – around the time of birth, can have persistent, long-term impacts on adult outcomes such as health, education, and socioeconomic status. The exogenous variation of rainfall is defined as the percentage deviation of birth year rainfall from the long-run average annual rainfall in a given municipality. These impacts operate through effects on infant health and educational attainment. They demonstrate that higher early-life rainfall correlates with improved health indicators, taller stature, increased educational attainment, and higher socioeconomic status, especially among women. This positive association is attributed to the beneficial effects of rainfall on agricultural output and household income.

Among the studies focusing on the impact of disasters on poverty, Karim and Noy (2016a, 2016b) find that poorer households are generally more vulnerable to the effects of natural events. Using a meta-regression analysis of the existing literature on the impact of disasters on households, they observe that poor households smooth their food consumption by reducing the consumption of non-food items, especially health and education, suggesting long-term adverse consequences and thereby sustaining poverty. Moreover, Rodriguez-Oreggia et al. (2013) show that natural hazards, in general, increase poverty, however floods and droughts have more significant adverse effects compared to other disaster events, including frost and rainfall.

A study undertaken by Janzen and Carter (2013) combines the literature on post-disaster poverty traps, assets, and microinsurance. Focusing on households affected by a drought in northern Kenya, they evaluate the asset dynamics of those who received insurance payouts compared to those who did not. Using instrumental variables technique to address selection bias, they found that households receiving insurance payments were 22–36 percentage points less likely to deplete their assets. Households with asset holdings above a certain level are more likely to smooth consumption, whereas those below the threshold display asset-smoothing behaviour.

Overall, understanding the economic impact of floods largely depends on household ability to cope after the climate-related shock, as well as their level of exposure and vulnerability to the event before it occurs. Most of the aforementioned research uses external meteorological measures such as rainfall data (Lertamphainont and Sparrow, 2016; Kocornik-Mina et al., 2020) or inundation maps to identify flooded areas (e.g., satellite images), which are then combined with household surveys to assess the impact. However, this approach has limitations due to its infrequency and imprecision (Noy et al., 2020). As noted by Guiteras et al. (2015), flooding in a specific area can be influenced by a broad and complex set of hydrological conditions[3]. This is crucial when trying to estimate the resulting economic consequences.

The analysis therefore considers these hydrological conditions as we construct a damage index, following the approach of Skoufias et al. (2020). The damage is defined as the local economic impact caused by the flood within a district. By using open-source remote sensing data, typically employed for natural hazard modelling, combined with night-time lights data as a proxy for economic activity, this approach calculates river discharge values within a basin. This provides a more accurate representation of the flood impact in northern Peru. The construction of the damage index is elaborated on in Section 5.

3. The 2017 'coastal' El Niño in Peru

The coastal El Niño (El Niño costero in Spanish) is one of the El Niño variants and occurs specifically in northern Peru. Unlike the traditional El Niño/Southern Oscillation – ENSO[4], that involves warming of ocean waters in the central and eastern Tropical Pacific (Niño3.4 region), the coastal El Niño events are localised and characterised by warmer-than-average sea surface temperatures (SSTs) along the coast of the departments of Tumbes, Piura, Lambayeque, and La Libertad (Niño1+2 region). These events predominantly occur between February and April when SSTs are typically at their warmest. A notable feature of coastal El Niño is the rapid and abrupt increase in SSTs, often rising by 7–9°C over a period of 1-2 weeks (Takahashi et al., 2017). This signals the beginning of heavy rainfall, usually occurring when surface temperatures exceed approximately 28˚C (Barnston, 2017).

3 Their findings show a positive but modest correlation (0.09) between monthly rainfall and flood extent measured at the district level in Bangladesh over the 2002 to 2011 period.

4 Peruvian fishermen were the first to coin the term "El Niño" in the late 1800s after noting unusual oceanic warmth near their coast.

In February to March 2017, the floods in northern Peru came as a surprise. Unfortunately, El Niño researchers, including those in the United States and Peru, the United States National Oceanic and Atmospheric Administration (NOAA), and the regional and Peruvian meteorological agencies did not expect this extreme weather shock despite a basin–wide monitoring system across the Pacific[5]. Thus, government agencies, socioeconomic sectors, public health officials, and citizens were not forewarned of the potential extreme weather and environmental-related hazards such as floods, flash floods and landslides. In addition, there was confusion over whether conditions in 2017 represented an El Niño phenomenon – as experienced in 1982 to 1983 and 1997 to 1998 – that provoked a hydrometeorological debate and stifled decision making (Ramirez et al., 2017).

Based on the January 2017 update blog from the NOAA ENSO alert system, La Niña conditions (a cooling pattern in the eastern Tropical Pacific) were anticipated for December 2016, after the monthly SST Niño 3.4 Index values dropped below the threshold of –0.5°C (Becker, 2017). However, on 31 January 2017, the SST abruptly increased reaching values above 26°C at various points along the northern coast in the Niño1+2 region (Multisectoral Committee for the Study of El Niño – ENFEN, 2017). These SST anomalies informed the Peruvian government that they were dealing with El Niño-like rainfall conditions. Only a few days later, on 6 February 2017, rainfall brought floods to the departments of Tumbes, Piura, Lambayeque, La Libertad, and Cajamarca.

On 23 February 2017, the government declared a state of emergency in many affected areas in northern Peru, and international aid efforts were mobilised to assist those impacted by floods. The worst flooding occurred between 26 and 27 March 2017 when heavy rainfall combined with already high river flows. These adverse effects associated with the SST anomalies can be seen in Figure 1, which displays the significant difference between the long-term average SST in March from 1980 to 2010 and the SST registered in March 2017 (highlighted in dark red) along the northern coast of Peru. By May 2017, the coastal El Niño finally subsided, leaving behind losses estimated at US$ 3.1 billion, as at 28 March 2017 (Leon et al., 2017), with close to 1.1 million people affected and approximately 46.7 thousand destroyed houses, as at 10 May 2017 (OCHA, 2017).

[5] The Niño 3.4 region is important for predicting and monitoring basin-wide El Niños; however, it may not always be the best area for observing other types of El Niño events that have extreme weather impacts concentrated along the coasts of northern Peru and southern Ecuador.

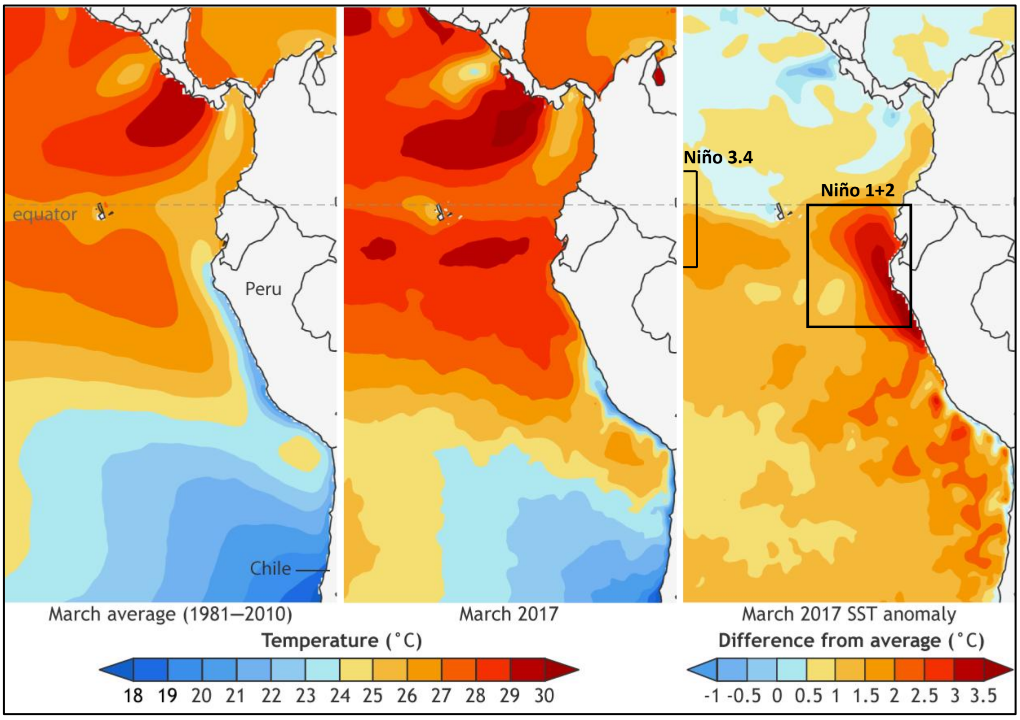

Figure 1 SST anomaly in March 2017 along the northern coast of Peru

The left panel displays the long-run average of sea surface temperatures (SST) in the eastern Tropical Pacific for March from 1981 to 2010. In the middle panel, SST for March 2017 is shown. The right panel illustrates the difference between the left and middle panels, indicating the SST anomaly for March 2017 along the northern coast of Peru.

Source: NOAA Climate.gov – April 2017 ENSO Update.

4. Empirical strategy

Treatment variable

The treatment variable represents the local economic impact (i.e., at the district level) resulting from floods. It is defined as a binary variable that takes a value of one if the district was affected in 2017, switches to zero if the district became unaffected, and reverts to one if it was affected again, or remains one if the district was continuously affected between 2018 and 2019 (see Figure A.1 in the Appendix). For districts that were never affected, the treatment variable remains zero throughout. The binary treatment is based on an index associated with the damage to buildings and infrastructure calculated using remote sensing data at the district level[6]. Due to floods being very localised, the damage index appears to determine the financial and property losses suffered by affected districts relative to unaffected districts in northern Peru.

The decline in household welfare and the increase in poverty were plausibly exogenously determined by flood events. However, this approach may be confounded by residential sorting. As households relocate across areas with varying flood risk within a district, the magnitude of the flood impacts may become biased. It is problematic to take the observations of these affected households; therefore, in Section 6.1, we conduct the Propensity Score Matching (PSM) technique and drop these observations from the analysis. The newly matched data, adjusted with both PSM and household weights, will be used for the rest of the study.

Definition of treatment and control groups

To efficiently capture variation in the impact of flooding, we define two groups: one with affected districts, and one with unaffected districts. First, we define a measure of treatment, which is the damage index used as a proxy for the local economic impact in flooded districts. Second, the group with impacted districts is identified if the damage index is greater than zero (**treatment**) and the group with free-impacted districts if the damage index is equal to zero (**control**).

$$FD_{d,T} = \begin{cases} 1 \quad if \;\; damage\ index > 0 \\ 0 \quad if \;\; damage\ index = 0 \end{cases}$$

Estimating treatment effects

[6] The index includes the flood and night-time light intensities to take into account the local physical characteristics of this natural hazard, and the local economic activity exposed to it.

In this study, the key identification assumption is that the 2017 coastal El Niño floods occur unexpectedly regardless of household behaviour. This allows us to compare households in affected districts to those in unaffected districts. We causally estimate the economic impact of these weather-related events on their income and expenditure per capita, and poverty status using a standard diff-in-diff/event study model. The estimating equation is written as:

$$y_{h,T} = \beta_0 + \delta_{-2}.FD_{d,T}^{-2} + \sum_{e=0}^{L=2} \boldsymbol{\tau_e}.FD_{d,T}^{e} + \mu_d + \lambda_T + X_{h,T}.\gamma_h + \varepsilon_{h,T} \quad (1)$$

Subscripts h, T and d denote the household, year, and district respectively; $y_{h,t}$ is the household welfare and poverty status outcomes; $FD_{d,T}$ is a dummy variable indicating whether the district was affected by floods at year T (=1) or not (=0); μ_d and λ_T are the district and year fixed effects, respectively; $X_{h,T}$ is a vector of covariates, including dwelling information, such as dummy indicators for access to sewage, water, electricity, and a concrete roof; household head characteristics, such as dummy variables for female status and public health insurance coverage, years of education, and age in years; household-level variables, such as household size, the number of income earners, and a dummy variable indicating whether the household owns their own house or not; and geographic characteristics, such as distance to the near river, terrain slope and altitude. For household welfare and poverty status outcomes, $e = -2$ specifies the year 2015 before the 2017 coastal El Niño floods, while $e = -1$ is the (dropped) base year against which all estimated effects are compared; $e = 0$ signifies the year of the 2017 coastal El Niño floods; and values of $e > 0$ and $\leq L$ indicate the years after the 2017 coastal El Niño floods. β_0, δ_{-2}, and τ_e are coefficients to be estimated.

In the standard diff-in-diff/event study model defined in equation (1), estimated δ_{-2} indicates pre-treatment impacts and estimated $\boldsymbol{\tau_e}$ denote average treatment effects. The latter can be taken as causal under the supposition that both the "parallel trends" and "no anticipation" assumptions are satisfied. The parallel trends assumption implies that the outcome trend of the treated group would have evolved in parallel to the outcome trend of the control group, in both pre- and post-treatment periods, given no treatment. The no anticipation assumption requires that no treatment effects exist before treatment begins. A more detailed discussion of these two assumptions is found in Section 6.2.

Given that the panel data includes only one lead (i.e., year 2015) and it is not possible to directly test the parallel trends assumption[7], we ensure that households' characteristics between treated and control groups are balanced during the pre-treatment period (2015–2016). To achieve more balanced conditions, we use PSM in Section 6, which allows me to create counterfactuals for the treated group and exclude observations without a counterfactual pair (off-support) from the panel dataset. If the estimated δ_{-2} is statistically insignificant, this is generally considered supportive evidence for the parallel trends assumption (Sun and Abraham, 2021). Additionally, balancing household characteristics between the treated and control groups during the pre-treatment period using PSM increases the likelihood that the parallel trends assumption holds.

Equation 1 defines the conventional diff-in-diff/event study model. One challenge of this framework is the issue of the "forbidden comparisons" or "negative weights." This approach estimates treatment effects by comparing treated units to control units, which may include "never treated" units, "not-yet treated" units, and "already treated" units. While "never treated" and "not-yet treated" are valid controls, "already treated" controls are potentially problematic because they may receive negative weights in estimation. These negative weights are likely to bias the estimated effects in both the pre- and post-treatment periods (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

The identification strategy in this study assumes that the treatment variable is quasi-random after controlling for distance of the surveyed house to the nearest river. In the Appendix (see Tables A.1 and A.2)[8], we provide empirical evidence supporting this assumption. Note that the quasi-random treatment variable assumes that it is orthogonal to both potential outcome levels and trends, whereas the parallel trends assumption relies on the independence of potential outcomes trends only (Roth and Sant'Anna, 2023). While the treatment variable is plausibly exogenous, the data contains only one pre-treatment year and lacks time trends. As a result, it cannot be argued that the quasi-random treatment assumption is stronger than the parallel trends assumption. To address this

[7] Roth (2022) and Rambachan and Roth (2023) developed two test procedures to support the claim that the parallel trends assumption holds. However, it is not possible to apply these procedures in this study due to the availability of only one year of data (i.e., year 2015) before the flood shocks in 2017.

[8] We take two distinct approaches. First, we regress the binary (switching) and non-binary (damage index) treatment variables, on the main outcomes and covariates, controlling for the log of the distance of a house to the nearest river and year fixed effects, using data from 2015 to 2019. Second, we apply the same procedure to the subsample of untreated districts (i.e., districts that never experienced flood shocks) for the period following the coastal El Niño floods (2017–2019).

limitation, we include covariates to help ensure that the parallel trends assumption holds. Further details are discussed in Section 6.2.

In addition, negative weights may still be problematic, however, even when treatment is plausibly exogenous and, as a result, the standard diff-in-diff/event study estimation remains ill-advised (Roth and Sant'Anna, 2023). To circumvent the forbidden comparisons and negative weights problems, as well as accommodate the treatment that switches on and off over time, we employ an estimator developed by de Chaisemartin and D'Haultfuille (2023). This modern event study estimator starts by aggregating units into cohorts of "switchers" and "non-switchers" based on the year in which they received treatment. Note that the non-switchers include two groups: (i) those whose treatment status stays the same between periods; and (ii) those with no treatment status between periods. The estimator then compares the evolution in mean outcomes among cohorts that switched into treatment between periods $t-1$ to t to the evolution in mean outcomes among groups that were untreated in both periods $t-1$ to t[9]. It then averages these diff-in-diff estimands across all groups to derive the average treatment effect on the treated (ATT) [10]. Therefore, the estimator is robust to heterogeneous effects across groups of all treatments, and ensures that it is robust to heterogeneous effects over time of all treatments. We test the robustness of the main results in this paper using the Dynamic Two–Way Fixed Effects (TWFE) approach, which we discuss more in detail in Section 7.2.

This paper uses the Stata package 'did_multiplegt' developed by de Chaisemartin and D'Haultfuille (2023)[11] to estimate the main treatment effects. The analysis includes control variables, 200 bootstrap replications, and clusters standard errors at the district level. Since the estimator does not restrict treatment to binary form (i.e., it allows for continuous treatment), we use the flood damage index based on remote sensing data as a proxy for the local economic impact to demonstrate that the results are consistent with those from the switching treatment dummy specification.

[9] Switchers can only switch from untreated to treated between periods $t-1$ to t, and this may occur at different points in time. This likely aligns with the definition of a staggered design; however, it extends the definition of a staggered design to include non-binary treatments as it is in this study.

[10] The Average Treatment Effect on the Treated (ATT) is accurately identified when additionally, the parallel trends and no anticipation assumptions already hold.

[11] This study uses the older version of the did_multiplegt Stata package instead of the newer did_multiplegt_dyn version, as the latter does not account for some control variables in groups (therefore, less observations used to estimate the Average Treatment on the Treated) where the baseline treatment is equal to 0. This issue may arise because some control variables in the dataset lack sufficient variation over time and across groups, particularly those related to geographic characteristics.

5. Data

The analysis is based on a district-level dataset covering demographic, socio-economic, geographic, and weather variables over the period 2015 to 2019 from multiple sources. In addition, we utilise Peru's government reports on flood events registered between 2017 and 2019 to identify the districts typically affected. This also includes information on government support, international aid, infrastructure affected by floods, and the number of affected households and people displacement.

5.1 Household data

The panel data comes from the Peruvian National Household Survey (ENAHO) collated by the National Institute of Statistics and Informatics of Peru. A total of 308 households has been tracking over five years, from 2015 to 2019, across 57 districts in northern Peru. The survey includes detailed information on socioeconomic characteristics over time for each household, as well as demographic information such as gender, age, marital status, and educational attainment.

An advantage of using ENAHO is that it provides information on household coordinates (longitude and latitude), and individual places of residence at the time of the survey. This is contrary to previous studies that use coordinates of each district centre where the households live as a proxy for location. A potential concern with attrition is that it can distort sample representativeness and compromise causal inferences when using panel data. However, the ENAHO's overall attrition rate is relatively low, with a re-contact rate of 99.44% among all original households. In addition, the rate of household survey completion is, on average, 89.56% between 2015 and 2019.

5.2 Remotely sensed data

The inputs needed to model the river discharge (m^3/s) for basins are watershed, Land Use and Land Cover (LULC), soil data, and Digital Soil Map of the World (DSMW). The details of each geospatial data are explained below.

Watershed

The watershed is a shapefile that delineates the boundaries of the watershed area. In this area, all surface water flows into a common outlet, such as a river, stream, lake, or ocean. Watershed shapefiles typically contain polygons that delineate the boundaries of these drainage basins. The shapefile is obtained from the website GEO GPS PERU[12]. The watershed shapefile is essential for setting up the spatial extent of the SWAT model simulation and for accurately representing the hydrological processes within the watershed.

Digital Elevation Model (DEM)

A DEM is a form of geographic data known as a raster. A raster is a grid of digital, uniform, square cells covering an area on the earth's surface with each cell containing information about elevation (in meters above sea level) and slope (in degrees). We employ ASTER GDEM V3 to model the surface water runoff within the watershed since it offers relatively high-resolution data of land areas on earth of 1 arc second (approximately 30 meters horizontal posting at the equator). These data are downloaded from the National Aeronautics and Space Administration (NASA) [13].

Land Use and Land Cover (LULC)

The LULC is also a raster where each cell corresponds to a specific geographic location and contains information about the land use or land cover type present in that location. Each cell is assigned a discrete value or code representing a particular land use or land cover category[14]. This information is crucial as it provides information about the characteristics of the land surface that influence hydrological processes. For example, impermeable surfaces such as urban areas generate more surface runoff compared to vegetated or forested areas where infiltration rates are higher. By incorporating LULC data into hydrological models, we estimate how much precipitation will directly contribute to runoff, affecting river discharge. The data are downloaded from the Esri website that provides Sentinel–2 10m LULC timeseries from 2017 to 2021[15].

Digital Soil Map of the World (DSMW)

The DSMW is a vector data that provide soil type classification and characterisation of soil parameters. The soil moisture capacity information, that is the soil type and depth, plays a crucial role in regulating runoff generation and river discharge. For instance, wet soils contribute more to runoff generation, whereas dry soils promote infiltration and reduce surface runoff. Hydrological

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12 Data can be downloaded from the following link: https://www.geogpsperu.com/2014/02/descargar-cuencas-hidrograficas-del.html.

13 Data can be downloaded from the following link: https://search.earthdata.nasa.gov/search.

14 We use the following class definitions: water, forest, agriculture land, urban area, and barren areas.

15 Data can be downloaded from the following link: https://www.arcgis.com/apps/instant/media/index.html?appid=fc92d38533d440078f17678ebc20e8e2.

models that integrate DSMW data can simulate soil moisture dynamics over time, helping predict changes in river discharge during wet and dry periods.

In addition, soil properties influence the partitioning of rainfall into surface runoff and infiltration. Soils with low infiltration rates and high runoff coefficients generate more surface runoff, leading to increased river discharge during storm events. The DSMW data allow modelers to characterise soil properties such as porosity, hydraulic conductivity, and bulk density, which are essential for estimating runoff generation processes and simulating river discharge accurately. The data are downloaded from the Food and Agriculture Organisation of the United Nations (FAO) [16].

Weather data

Weather data are obtained from the NASA – Prediction of Worldwide Energy Resources (NASA-POWER)[17]. This website provides geo-referenced information on global daily terrestrial temperature (maximum and minimum), precipitation (in mm), humidity, wind, and solar radiation at a spatial resolution of 0.5 × 0.5 degrees. Relative humidity, wind speed, solar radiation, and the minimum and maximum air temperatures were obtained from the Climate Forecast System Reanalysis (CFSR), which was designed based on the forecast system of the National Centres for Atmospheric Prediction (NCEP) to provide estimation for a set of climate variability from 1979 to the present day.

VIIRS night-time lights

Floods are idiosyncratic local shocks, occurring generally near a body of water (mostly rivers). This means that flooding affects only small geographic units within a given region, and within the flooded areas, the impact is spatially unequal. Even further, the local population and their assets are also exposed and impacted differently to this natural event. As proxy for a local impact of floods, we use the Visible Infrared Imaging Radiometer Suite (VIIRS) night-time lights to capture the economic downturn following the natural event.

Night-time lights have found widespread use to estimate the impact of weather anomalies. For instance, a study undertaken by Felbermayr et al. (2022) uses night-time emission to investigate the impact of weather anomalies on economic activity. Other studies such as Bertinelli and Strobl, 2013; Elliott, Strobl, and Sun, 2015; and Kocornik-Mina et al., 2020 have studied hurricane, typhoon, and

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[16] Data can be downloaded from the following link: https://power.larc.nasa.gov/data-access-viewer/.

[17] Data can be downloaded from the following link: https://data.apps.fao.org/map/catalog/srv/eng/catalog.search;jsessionid=1F80A9CA383A4FCDACE7702E1AF73195?node=srv#/metadata/446ed430-8383-11db-b9b2-000d939bc5d8.

flood impacts on night-time light emissions, respectively. Their findings strengthen the case for assessing impacts of weather anomalies using night-light emissions at the local level.

We extract district level night-time lights data from the VIIRS-Day Night Band (DNB) Cloud Free Monthly Composites (version 1 and tiled) provided by the Earth Observation Group at the Colorado School of Mines[18]. The VIIRS-DNB are spatially and temporally detailed data for night-time lights. In terms of coverage, each VIIRS-DNB image consists of 15 arcseconds grids (463 meters at the equator) and span from 00N latitude to 180W around the entire globe, meaning that the whole of Peru is included. Following Skoufias et al. 2020, to count for months with no radiance value, we have interpolated between the month before and after (in this case, only three months have no light values).

5.3 Government reports: Identifying flooded districts

We use government data to identify the districts in northern Peru affected by floods in 2017. Reports compiled by the National Civil Defence Institute (INDECI)[19] contain information on flood-induced damage at the district level, including the extent of destruction to infrastructure, homes, agricultural land, and the number of affected and displaced individuals. This data enables us to identify the subset of districts impacted by the 2017 floods, forming the treatment group. Among the 57 districts examined, 40 are included in the treatment group, while the remaining 17 constitute the control group.

5.4 Construction of the damage index

Empirical economics literature often uses rainfall (e.g., number of days of extreme precipitation) as a source of exogenous variation in explaining the impact of floods on household welfare. More recent studies have used satellite imagery and geocoding, or a combination of both, to create binary measures to identify areas unaffected and affected by flood events that occurred in the past. Less attention has been given to finding a proxy that estimates the (economic) damage caused by flooding due to the data limitations at the local level and its multidimensional nature.

In this paper, the damage associated with flood events is defined as an overall economic impact in the administrative unit (i.e., at the district level) after the occurrence of the disaster. The

[18] Data can be downloaded from the following link: https://eogdata.mines.edu/nighttime_light/monthly/v10/.

[19] The Peru's government disaster reports are available freely from the National Institute of Civil Defence (INDECI) of Peru website: https://portal.indeci.gob.pe/informe/informe-de-emergencia/.

construction of the damage index involves three stages. First, we use the Soil and Water Assessment Tool (SWAT) [20] to predict daily river discharge within a river basin, using remote sensing data. This provides the volume of water passing specific points along the river. The second and third stages follow the approach of Skoufias et al. (2020), which uses the time series of streamflow data to calculate the flood intensity[21] in a watershed. Flood intensity is defined as the number of days with high floodwaters exceeding the normal level in the affected area. This intensity measure is then combined with disaggregated local economic activity, obtained from night-time lights data, to estimate an index for flood damage at the district level.

SWAT – input data and model application

The procedures applied from the initial stage to the hydrologic simulation in ArcSWAT – ArcGIS 10.4 are illustrated in Figure A.2 in the Appendix (left panel). The first step of the simulation model involves delineating the basin where the stream or discharge flows and obtain the morphometric parameters[22] of that basin. This is achieved by combining the Watershed shapefile, which contains polygons delineating each river basin in the northern region of Peru, with the Digital Elevation Model (DEM).

Following the delineation step, the process of creating the Hydrologic Response Units (HRUs) begins. The SWAT model allows the delineation of subbasins within a watershed, which are spatially correlated to one another. In each subbasin, we create HRUs which possess unique land use and land cover, and soil attributes. To achieve this, we use an LULC map for the year 2017, derived from Sentinel-2 images Esri, and a global digital map of soil types developed by the Food and Agriculture Organization (FAO). Slope classes ranging from 0% to 20%, 20% to 40%, and steeper than 40% are employed. After defining the input data of this step, it is possible to create the HRUs for each subbasin within a watershed.

The next step involves the creation of tables containing climate variable values such as temperature, precipitation, relative humidity, solar radiation, and wind speed. This is achieved using NASA-POWER

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[20] Developed by the USDA Agricultural Research Service in collaboration with Texas A&M University and Esri, the SWAT model provides a user-friendly interface for setting up, running, and analysing event-based floods within the ArcGIS software environment. This model has been used to obtain hydrological measures such as evapotranspiration, precipitation, surface runoff, finding that the model captures the daily variability of stream flows across large areas, making it useful for flood simulation.

[21] For a given level of damage, areas with higher concentration of assets contribute more to the overall losses, as indicated by the level of nocturnal illumination. Consequently, such areas are expected to display significant changes in night-time lights values.

[22] Measurements related to the shape and configuration of river basins, watersheds, and other hydrological features to understand the behaviour of water flow, runoff, and sediment transport in river systems.

data, which provides near real-time weather information at a resolution of 0.5 x 0.5 degrees for the period of 2012 to 2019. Finally, the SWAT model is prepared to simulate variables such as streamflow, evapotranspiration, sediment production and transportation, and nutrient concentration. For this study, daily values of streamflow (river discharge) are simulated for the period between 2015 and 2019, excluding the initial three years of model warm-up (January 2012–December 2014).

The SWAT simulation of streamflow in ArcGIS can be observed in Figure A.3 in the Appendix. As an example, we present the SWAT simulation for the Tumbes River in ArcGIS (left) and the daily river discharge in m^3/s for that river basin (right), which is used to calculate the flood intensity (Equations 2 and 3).

Flood day

Using the daily river discharge (m^3/s) calculated for both each river basin and sub-basin within the period of analysis, we estimate a threshold to define a riverine flood[23] in a day:

$$Flood\ day = 1 \quad if \quad Q > P_{95} + \sigma \tag{2}$$

where P_{95} is the 95th percentile value, and σ is the standard deviation of the river discharge (Q).

Flood intensity

When a flood day is computed, the next step involves calculating the flood intensity. We use the river stream flow as a proxy for intensity, employing the following equation:

$$I_{b,t} = \begin{cases} 0 & : Flood\ day = 0 \\ \dfrac{Q_{b,t} - \bar{Q}_b}{\sigma_b} & : Flood\ day = 1 \end{cases} \tag{3}$$

where $I_{b,t}$ denotes the intensity of a flood event that occurred in the river basin b at date t. $Q_{b,t}$ represents the river discharge in the same basin and time (basin b at date t), while Q_b and σ_b are the mean and standard deviation of river discharge in basin b. The flood intensity is zero if the flood

[23] This natural hazard is characterised by the overflow of river water exceeding its normal and expected levels, leading to the inundation of typically dry land in urban and rural areas.

threshold – 95th percentile value plus 1 standard deviation above the average – remains unexceeded[24].

In the context of the flood intensity, normalising the stream flow values within each river basin ensures that the intensity values are on a standardised scale and are independent of the absolute river flows, allowing for more meaningful comparisons and analyses across different basins and time periods. When normalising we constructed two proxies: 1) A simple count variable for the number of flood days within the river basin; and 2) The river discharge in m^3/s registered above the flood threshold[25].

For each month m, we sum the normalised values of flood days to obtain a cumulative value in that month. The cumulative value is a proxy for the total damage inside the river basin.

$$I_{b,m} = \sum_{t=1}^{30} I_{b,t} \ , \quad b = 1, \dots, B; \quad m = 1, \dots, 12 \tag{4}$$

VIIRS night-time lights and flood impact

The monthly average VIIRS night-time lights are used to calculate the weights that aid in finding the locations where flooding had the greatest economic impact and capture the effects of changes in local economic activity. The weights are estimated based on the night-time light cell values within the river basin and those within the district boundaries[26]. They are determined by the following equation:

$$W_{b,d,m,T-1} = \frac{\bar{L}_{b,m,T-1}}{\bar{L}_{d,m,T-1}} \ , \quad T-1 = 2014, \dots, 2018 \tag{5}$$

where $\bar{L}_{b,m,T-1}$ and $\bar{L}_{j,m,T-1}$ are the mean of VIIRS night-time lights in basin b and in district d, respectively, in month m, and year $T-1$. A one-year lag ($T-1$), preceding the flood impact, is applied to address concerns regarding endogeneity, specifically reverse causality, between the outcome variables – household income and expenditure per capita – and VIIRS night-time lights. As a

[24] The key assumption consists of two points: i) residents who live close to rivers are prepared for the fluctuations in river water levels, and ii) individuals residing near rivers present a higher level of readiness for variations in river stream flows compared to those living in closer proximity to more stable rivers.

[25] The methodology used to measure the flood intensity is relatively simple and cannot be used to predict local exposure or vulnerability within the river basin.

[26] The study area includes 22 river basins and 57 districts located in the northern region of Peru.

robustness test, we also use VIIRS night-time lights data from the year 2013 to validate the main results.

Then, the weight $W_{b,d,m,T-1}$ is multiplied with the flood intensity ($I_{b,m}$) to obtain the monthly flood impact, $FI_{b,d,m}$, in the river basin b, district d, in month m, and year T. The equation is as follows:

$$FI_{b,d,m} = W_{b,d,m,T-1} * I_{b,m} \tag{6}$$

Due to its size, watershed may include more than a single district, and it is assumed that the flood intensity remains consistent across all districts within the river basin.

Flood damage index

As a final step, the flood damage index ($FD_{d,T}$) is calculated by adding all monthly flood impact values ($FI_{b,d,m}$) in river basin b, district d and month m:

$$FD_{d,T} = \sum_{m}^{T} \sum_{b}^{B} FI_{b,d,m}\,, \quad d = 1, \dots, D; \quad T = 2015, \dots, 2019 \tag{7}$$

where T is the sum of all monthly flood impact values in the year and B is the sum of all basins b in district d, and $FI_{b,d,m}$ is the proxy for flood impact from Equation 6. Figure A.2 in the Appendix displays the steps involved in constructing the flood damage index outlined above.

We calculate damage estimates for the period 2017 to 2019 associated with flood events and approximate the economic impact at the district level. In the Appendix, Tables A.3 to A.5 present three groups: 1) the “switcher” districts, 2) the “non-switcher” treated districts, and 3) the “non-switchers” control districts. All groups are ordered from the most to the least damaged districts in 2017.

In addition, Figure 2 displays the districts in the northern region of Peru that were most (darker purple) and least affected by floods, based on damage index values. It also shows the sampled households in the panel dataset and the rivers that cross the region.

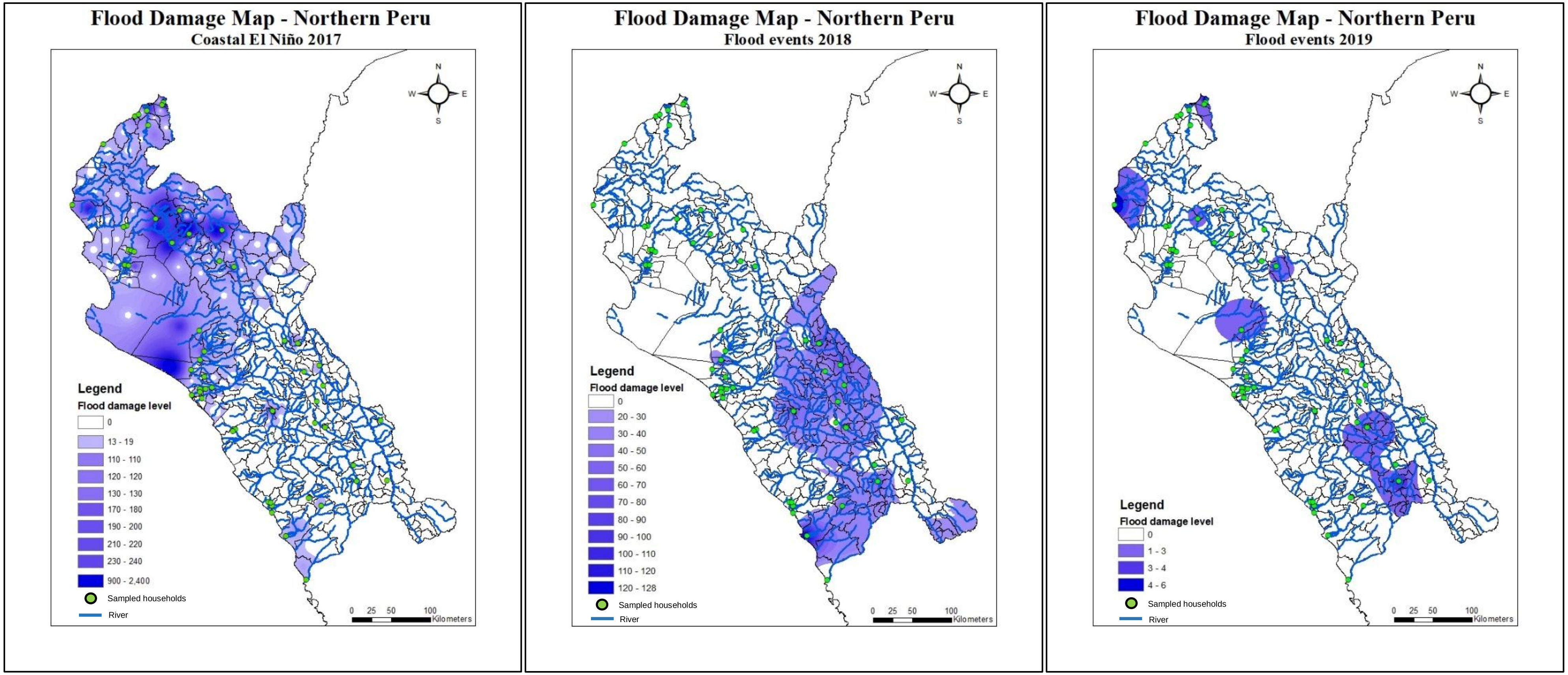


Figure 2 Maps of flood damage zones at the district level in northern Peru

Note: The Inverse Distance Weighting (IDW) interpolation method in ArcGIS was used to create the flood maps. These maps illustrate the spatial extent of flood damage hotspots in the northern region of Peru. The continuous smooth surface is classified into categories based on geometric intervals according to the damage level for each year. Flood-affected zones are depicted in deep purple, indicating the highest level of damage, while flood-free areas are shown in white. In addition, green dots denote the sampled households, and the blue line represents the river flowing through the area.

Source: Author’s illustration, 2024.

Descriptive statistics

Table 1 provides the summary statistics for all variables used in the analysis below. Note that all continuous variables are measured in logarithmic form, except for age and years of schooling of the household head, and the flood damage index.

A set of main outcome variables described in Panel A includes annual household income and expenditure per capita, and poverty status. We employ fourteen control variables in the regression analysis, which are presented in Panels B and C. For the potential channels analysis, we use income earners, wage income, household savings, and disaster relief in Panels A and B.

Table 1 Summary statistics

	All				
	N	Mean	Sd	Min	Max
Panel A: Income, expenditure and related variables					
Annual net household income per capita (in logs)	1,527	8.21	1.04	1.39	12.08
Annual net household expenditure per capita (in logs)	1,530	8.15	0.81	3.40	11.27
Poverty (1,0)	1,530	0.25	0.43	0	1
Urban (1,0)	1,530	0.59	0.49	0	1
Wage income (1,0)	1,293	0.22	0.41	0	1
Household savings (1,0)	1,530	0.44	0.50	0	1
Disaster relief - food and clothing (in logs)	1,530	3.97	2.77	0	9.51
Panel B: Dwelling and household characteristics	1,530	0.57	0.50	0	1
Sewage (1,0)	1,530	0.84	0.36	0	1
Water (1,0)	1,530	0.95	0.21	0	1
Electricity (1,0)	1,525	0.34	0.47	0	1
Concrete roof (1,0)	1,530	0.24	0.43	0	1
Female household head (1,0)	1,530	1.24	0.58	0	2.64
Household size (in logs)	1,530	55.23	15.38	21	97
Age household head (in years)	1,530	7.15	5.05	0	19
Years of schooling household head (in years)	1,526	0.74	0.49	0	2.08
Income earners (in logs)	1,530	0.79	0.41	0	1
Own house (1,0)	1,530	0.57	0.50	0	1

Public health insurance (1,0)					
	1,530	46.25	223	0	2,472.90
Panel C: Damage and geographic characteristics	1,530	0.28	0.45	0	1
Flood damage index	1,530	7.22	1.20	2.87	9.62
Flood dummy (1,0)	1,530	1.76	0.84	0.00	3.48
Distance to near river (in logs)	1,530	4.97	2.05	0.69	8
Terrain slope (in logs)	1,527	8.21	1.04	1.39	12.08
Elevation (in logs)	1,530	8.15	0.81	3.40	11.27

This table presents the summary statistics for the outcome variables and covariates. The household sample is obtained by dropping off-support observations following the application of the PSM approach.

Source: ENAHO, 2015–2019.

Figure 3 shows the districts in northern Peru (a total of 34) that switch from the treatment group to the non-treatment group during the period of 2017 to 2019. First, a group of 18 districts moves from the treatment group in 2017 to the non-treatment group in 2018. Then, a group of 16 districts moves from the treatment group in 2018 to the non-treatment group in 2019. Only 6 districts remain in the always-treatment group between 2017 and 2019.

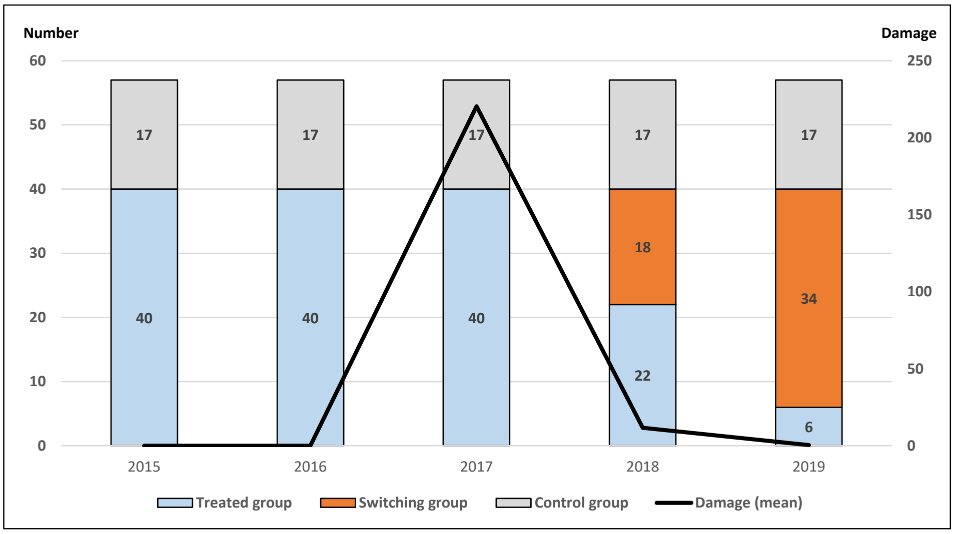


Figure 3 Switcher and non-switcher districts from 2015 to 2019

Note: The number of switchers from treated to untreated status was 18 districts in 2018 and 16 districts in 2019. The total number of switchers from 2017 to 2019 was 34 districts.

Source: Author's illustration.

6. Pre-estimation

6.1 Sample balance analysis

This study addresses the potential endogeneity (as a form of measurement error) arising from selectivity or sorting issues. In the context of floods, selection or sorting bias occurs when households may intentionally choose to reside in unaffected districts, thereby influencing the likelihood of experiencing flood impacts. For instance, in response to this natural event, a household might choose to relocate or rebuild in low- or non-risk areas to mitigate or avoid the negative effects on their income, consumption, wealth and work. Therefore, estimates relative to the impact of floods on the household welfare could be understated. If this issue is not appropriately addressed, it can lead to biased estimates.

To identify any potential selection bias in the dataset, we perform two tests. First, we evaluate whether areas unaffected and affected by floods differed in terms of socioeconomic characteristics ex-ante. Specifically, the test indicates whether the two groups differ systematically on observable characteristics. Second, we use a multiple linear regression (OLS) of the treatment dummy on pre-determined covariates to detect the possibility of systematic sorting.

In Table 2, column 3 shows single differences in means of key variables between affected and unaffected areas using the first two years of the panel data (2015 and 2016). Three of these differences are statistically significant at 1% and 10% (electricity, years of schooling of household head, and public health insurance), suggesting the presence of unbalanced household characteristics between the two groups. In addition, in Table 3, column 6, the OLS regression presents one variable is associated with the treatment dummy with a 5% significance level, from which we draw the conclusion that there is a sorting issue in the dataset.

Table 2 Balance tests between affected and unaffected areas – before PSM

	Control Group	Treatment Group	Single difference	N	p-value
Years: 2015/2016 Dependent variable	(1)	(2)	(3)	(4)	(5)
Sewage (1,0)	0.564	0.542	0.022	629	0.637
Water (1,0)	0.826	0.806	0.019	629	0.601

Electricity (1,0)	0.987	0.906	0.080	629	0.001	***
Concrete roof (1,0)	0.383	0.326	0.056	627	0.207	
Female household head (1,0)	0.221	0.258	-0.037	629	0.365	
Household size (in logs)	1.272	1.232	0.041	629	0.459	
Age of household head (in years)	54.409	53.788	0.622	629	0.670	
Years of schooling of household head (in years)	6.383	7.254	-0.872	629	0.067	*
Income earners (in logs)	0.734	0.706	0.028	629	0.545	
Ownership of house (1,0)	0.772	0.783	-0.012	629	0.767	
Public health insurance (1,0)	0.664	0.531	0.133	629	0.004	***

Note: Columns 1 and 2 report the sample mean for the unaffected (control) and affected (treatment) groups, respectively. The data is restricted to 2015 and 2016 household survey. Column 3 shows single difference in means between non-affected and districts affected by floods. Column 4 displays the number of observations, while column 5 presents the p-value on each balance test. ∗∗∗p < 0.01, ∗∗ p < 0.05, ∗ p < 0.1.

Source: ENAHO, 2015–2019.

By applying propensity score matching to the dataset, we find observations without a counterfactual pair (off-support) as shown in Figure 4. These observations are dropped, and after several iterations, the matching method of kernel with uniform distribution is chosen to obtain a balanced dataset.

To address the endogeneity, we employ propensity score matching during the pre-estimation step. This technique enables us to create counterfactuals for households living in flooded districts within the control group of the dataset. The aim is to achieve a balanced condition where the characteristics of observations in flooded areas are similar to those in non-flooded areas.

Table 3 Balance tests: OLS regressions – before PSM

	OLS	N	p-value	
Years: 2015/2016 Dependent variable	(1)	(2)	(3)	
Sewage (1,0)	-0.022	629	0.865	
Water (1,0)	-0.019	629	0.889	
Electricity (1,0)	-0.080	629	0.040	**
Concrete roof (1,0)	-0.056	627	0.519	
Female household head (1,0)	0.037	629	0.567	
Household size (in logs)	-0.041	629	0.688	
Age of household head (in years)	-0.622	629	0.757	
Years of schooling HH head (in years)	0.872	629	0.330	
Income earners (in logs)	-0.028	629	0.713	
Ownership of house (1,0)	0.012	629	0.874	
Public health insurance (1,0)	-0.133	629	0.139	

Note: This table displays the correlation between the dummy variable for affected and unaffected areas and a set of covariates. Each row represents a separate OLS regression of the dependent variable (covariate) on the dummy variable (equal to 1 if treated, 0 otherwise). All OLS regressions include district fixed effects. Columns 1 and 2 display the coefficient related to the covariate and the number of observations, while column 3 displays the p-value. Data are restricted to 2015 and 2016 household survey. $***p < 0.01$, $** p < 0.05$, $* p < 0.1$.

Source: ENAHO, 2015–2019.

We also display kernel density plots to see how covariates overlap before and after matching. In Figure 5, there is strong overlap in the distribution of propensity scores between the treated and untreated groups.

As a result, matching based on propensity scores effectively balance the two groups on observed covariates, leading to unbiased estimates of the treatment effect.

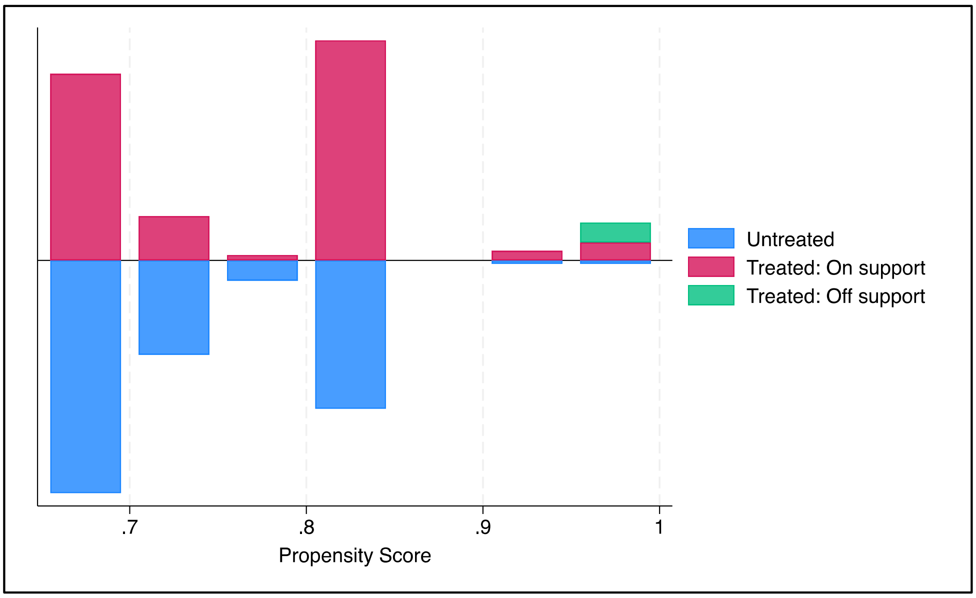


Figure 4 Propensity score matching

Note: The figure displays the distribution of propensity scores for the treated and control groups after matching, using the kernel matching method with a uniform distribution. Blue and red bars represent the matched pairs, where covariates are balanced across treated and control groups. Observations without a counterfactual pair (off-support), which are excluded from the analysis, are shown in green.

Source: ENAHO, 2015–2019.

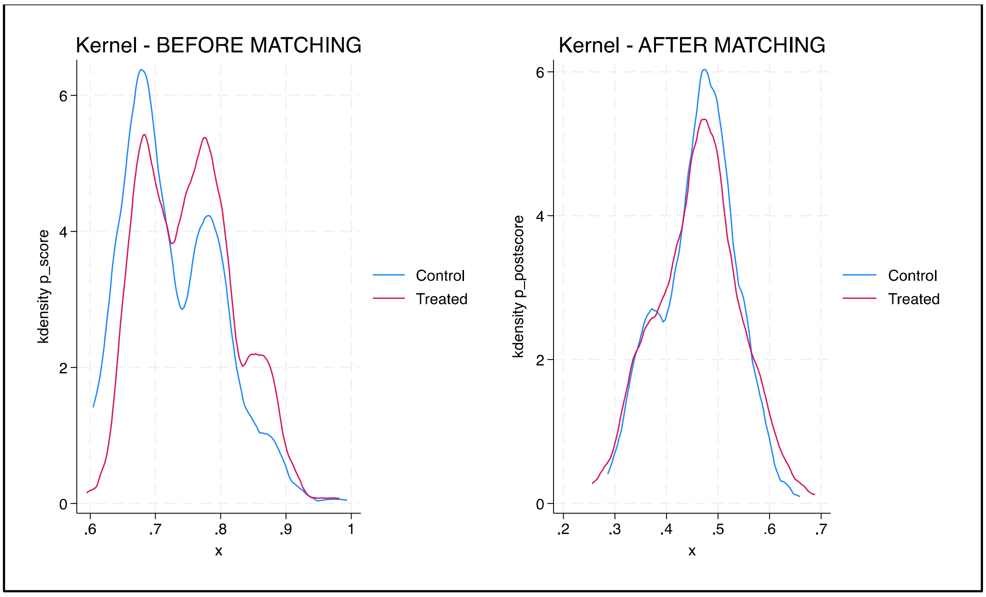


Figure 5 Kernel density before and after matching

Note: The figure illustrates the improved balance of propensity scores between the treated and control groups after matching. The kernel density distribution for the control group is shown in blue, while that of the treated group is in red.

Source: ENAHO, 2015–2019.

Next, we re-evaluate the association between the treatment dummy and these four variables using matched data and incorporating weights obtained from propensity score matching[27]. The new weights used in this estimation are calculated by multiplying the sample weights and the propensity score matching weights. The results show that the associations of the three variables (electricity, years of schooling household head, and public health insurance) are no longer significant; however, the household size variable still has a significant association albeit weaker significance (see Table 4, column 6).

Table 4 Balance exogeneity tests between unaffected and affected groups – after PSM

	Control Group	Treatment Group	Single difference	p-value	OLS	p-value	N
Years: 2015/2016 Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sewage (1,0)	0.717	0.688	0.029	0.623	-0.029	0.787	610

[27] The Propensity Score Matching technique calculates weights (propensity scores) for each observation in the control group to match with observations in the treatment group, based on their observed characteristics (covariates). In this study, the weights assigned to observations in the control group present different values within the pre-treatment period (2015 and 2016). Then, we use the weights for the control group calculated in 2016 and duplicate them for the years 2017, 2018, and 2019. We follow this procedure since the event study assumes parallel trends in both the pre- and post-treatment periods.

Water (1,0)	0.870	0.858	0.012	0.800		-0.012	0.842	610
Electricity (1,0)	0.953	0.949	0.004	0.917		-0.004	0.926	610
Concrete roof (1,0)	0.416	0.371	0.045	0.546		-0.045	0.618	608
Female household head (1,0)	0.198	0.280	-0.083	0.199		0.083	0.317	610
Household size (in logs)	1.400	1.234	0.166	0.055	*	-0.166	0.126	610
Age of household head (in years)	54.235	55.755	-1.520	0.480		1.520	0.467	610
Years of schooling household head (in years)	7.193	7.715	-0.522	0.562		0.522	0.666	610
Income earners (in logs)	0.839	0.747	0.092	0.239		-0.092	0.271	610
Ownership of house (1,0)	0.756	0.807	-0.051	0.361		0.051	0.574	610
Public health insurance (1,0)	0.447	0.509	-0.062	0.384		0.062	0.523	610

Note: Columns 1 and 2 report the weighted mean for the control and treatment groups, respectively. Column 3 shows the weighted single difference in means between districts unaffected and affected by floods. Column 5 displays the estimates of the treatment dummy on household characteristics using an OLS regression with weights. ***p < 0.01, **p < 0.05, *p < 0.1.

Source: ENAHO, 2015–2019.

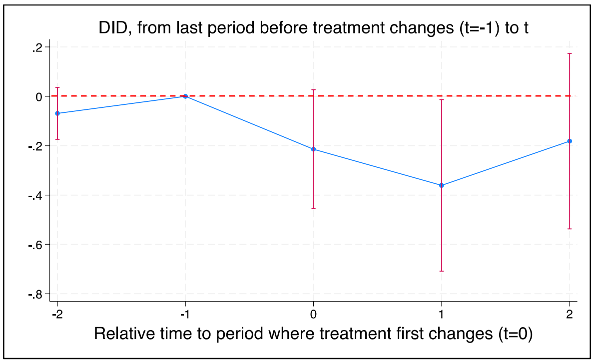
The matching process results in the discarding of several observations, leaving a final sample of 1530 observations (from a total of 1614 observations). We now expand the dataset based on the new weights constructed by sample weights and matching results, as most of the covariates are no longer significantly associated with the treatment variable (balanced conditions achieved).

6.2 Modern event study assumptions analysis

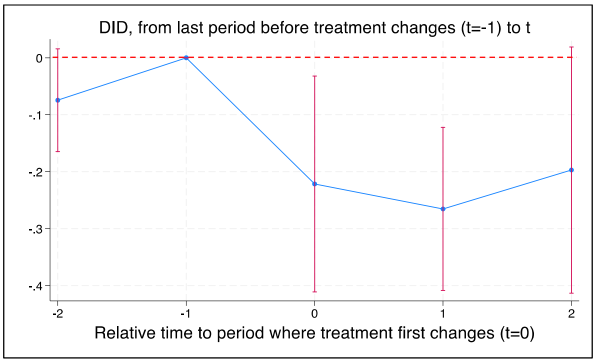
In this section, we test the parallel trends and no anticipation assumptions using the balanced panel data obtained from the pre-estimation analysis. On one hand, statistical tests for pre-treatment trends cannot be employed in this study, as the matched data only includes one year (i.e., 2015) prior to the treatment year (i.e., 2017). However, it is assumed that if the differences in pre-trends between the treated and control groups (also referred to as placebo effects) are not statistically significant in the regression, and if the confidence interval for the pre-treatment mean effect crosses zero in the event study plot, we can expect that the trends would have continued in the treated group had it not received the treatment. On the other hand, the difference in outcomes between the treated and control groups is not significantly different before the treatment year, suggesting that there were no pre-existing household responses indicating anticipation of the treatment.

Parallel trends

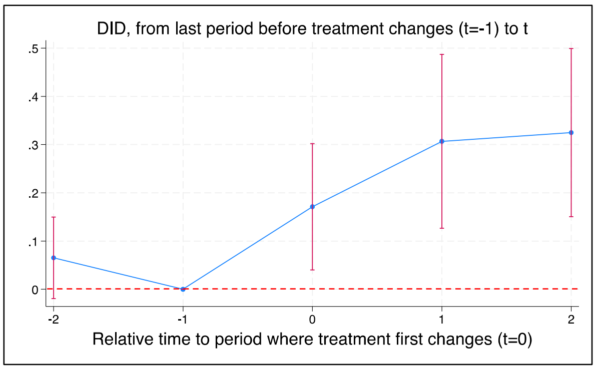
The diff-in-diff design in this study involves two pre-treatment years (2015–2016) and another three years post-treatment (2017–2019). As the floods occurred in 2017, year 2016 is dropped and serves as the base period against which all effects are compared. This reduces to only one lead with respect to the pre-treatment period (i.e., year 2015). We include a set of covariates in the model because they are important and strongly affect the outcomes to help ensure the parallel trends assumption holds. As stated by Caetano and Callaway (2024), adjusting for observable characteristics increases the likelihood that the parallel trends assumption holds, leading to more accurate and reliable ATT estimates. This requires that the covariates strongly influence the outcomes and evolve in a non-parallel fashion across treatment and control groups. The covariates included in the current analysis have been used in previous studies (i.e., dwelling and demographic characteristics), and display a non-parallel trend, as can been seen in Figure A.4.



Income per capita (in logs)



Expenditure per capita (in logs)



Poverty (1,0)

Figure 6 Event study plots for impact of floods on household welfare and poverty

Note: Estimation results based on de Chaisemartin et al. (2023) estimator, clustered standard errors, 95% CI. Negative numbers indicate the years before the coastal El Niño in 2017, and non-negative numbers represent years after the coastal El Niño in 2017.

Source: ENAHO, 2015–2019.

Figure 6 illustrates the parallel trends in the pre-treatment (Effect –2, year 2015). The coefficients are not statistically significant for household income and expenditure per capita, and poverty status, indicating that the assumption holds.

No anticipation

The presence of no anticipation effects implies that households located in flooded districts do not alter their behaviour in anticipation of the impact of floods. When anticipation effects are present, households may adjust their behaviour before the floods occur, expecting their effects to manifest. To test for anticipation effects, we examine if the pre-existing differences prior to the occurrence of the flood events (years 2015 and 2016) changed over time. The double differences in Table 5 are not statistically significant, implying that households were unlikely to anticipate and act on the shock ex-ante, at least at the district level.

Table 5 Double differences between treated and control groups

Years: 2015/2016 Dependent variable	Control Group (1)	Treatment Group (2)	Double difference (3)	N (4)	p-value (5)
Sewage (1,0)	0.717	0.688	-0.013	610	0.785
Water (1,0)	0.870	0.858	-0.027	610	0.650
Electricity (1,0)	0.953	0.949	0.040	610	0.563
Concrete roof (1,0)	0.416	0.371	-0.011	608	0.865
Female household head (1,0)	0.198	0.280	0.032	610	0.336
Household size (in logs)	1.400	1.234	-0.071	610	0.154
Age of household head (in years)	54.235	55.755	1.358	610	0.277
Years of schooling HH head (in years)	7.193	7.715	-0.010	610	0.972
Income earners (in logs)	0.839	0.747	0.002	610	0.985
Ownership of house (1,0)	0.756	0.807	0.171	610	0.107
Public health insurance (1,0)	0.447	0.509	-0.008	610	0.930

Note: Column 1 and column 2 report the sample mean for the control and treatment groups, respectively. The data are restricted to the 2015 and 2016 household surveys. Column 3 displays the estimate of the interaction term between the treatment dummy and the year 2016, using a Difference-in-Difference regression of each variable on interaction with weights. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: ENAHO, 2015–2019.

Another indicator supporting the assumption of no anticipation is that residents failed to relocate to safer areas after the flood events in 2017. Table 6 shows that the number of household members born in the same district remained unchanged after the flood occurrence. Moreover, the percentage of households owning a second house remained low, accounting for 7.1% of the total surveyed over the analysis period.

Table 6 District of birth and households owing a second house – number of households

District of birth	2015	2016	2017	2018	2019
Same	177	182	185	183	185
Different	125	126	122	124	121
Number of observations	302	308	307	307	306

Household owns 2nd house	2015	2016	2017	2018	2019
Yes	17	28	27	15	24
No	285	280	280	292	282
Number of observations	302	308	307	307	306

Source: ENAHO, 2015–2019.

The above results, therefore, produce supporting evidence of the causal impact of flood shocks on households in the districts affected.

7 Results

7.1 Main results

We begin by estimating equation (1) for net annual household income and expenditure, measured in log per capita terms, and poverty status as a binary variable. The ENAHO determines whether a household is poor based on a comparison of their income or expenditure per capita to the national poverty line. Table 7 presents the results of the estimations. When analysing the local economic impact of floods, we find that they reduced household income and expenditure per capita and increased the poverty level among the households located in northern Peru.

In column (1) of Table 7, the coefficient on the binary switching treatment is estimated to be –0.393. This implies that the treated group's income decreased by 32.5% relative to the average income of non-flooded households in the same region. Similarly, in column (2), the coefficient is –0.356, which translates to a 29.9% average decline in expenditure among the treated group relative to those outside the flooded areas. These findings are also confirmed by using the continuous switching treatment – the coefficients are also negative (higher in magnitude than using continuous variable) and translate to a 15.9% and 14.5% decline in income and expenditure per capita, respectively, relative to the unflooded control group[28].

In monetary terms, the loss of income and expenditure per capita is PEN 1,514.31 (USD 464.41) and PEN 1,154.12 (USD 353.94), respectively, following the flood events.

On the other hand, the poor are usually the most vulnerable to the effects of floods (Richie et al., 2020), resulting in a decrease in income and assets and further entrenching their poverty (Carter et al., 2007; World Bank, 2013; Hallegatte et al., 2016). As presented in column (3) of Table 7, we find a similar pattern in the northern region of Peru, where households in flooded areas were 41.74 percentage points more likely to fall below the poverty line relative to those outside the affected areas. Using the flood damage index, poverty levels rose by 19 percentage points in areas impacted by floods[29].

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[28] These percentage changes are calculated based on the average of the flood damage index, which is 46.47. The %change = exp ($\boldsymbol{\tau_e}$*46.47) − 1.

[29] Using the average damage index of 46.47, the expected impact on the probability of falling below the poverty line is calculated as: Pr = ($\boldsymbol{\tau_e}$*46.47) *100.

Table 7 Impact of flood shocks on household welfare and poverty

Dependent variable:	Income per capita (in logs)		Expenditure per capita (in logs)		Poverty (1,0)	
A: Binary treatment						
Effect -2 (year 2015)	-0.069		-0.075		0.065	
	(0.054)		(0.046)		(0.043)	
Effect 0 (year 2017)	-0.214	*	-0.222	**	0.171	**
	(0.123)		(0.097)		(0.067)	
Effect 1 (year 2018)	-0.361	**	-0.265	***	0.307	***
	(0.177)		(0.073)		(0.092)	
Effect 2 (year 2019)	-0.182		-0.197	*	0.325	***
	(0.181)		(0.110)		(0.089)	
ATT (flooded district=1)	**-0.393**	*	**-0.356**	***	**0.417**	***
	(0.220)		**(0.111)**		**(0.111)**	
B: Flood damage level						
ATT (flooded district=index)	**-0.004**	*	**-0.003**	***	**0.004**	***
	(0.002)		**(0.001)**		**(0.001)**	
District FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Cluster (district)	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
N	913		913		913	

The dependent variables are listed across the top row. Income and expenditure per capita are measured as the log of net annual household income and expenditure per member, respectively. Poverty is a binary variable that takes on a value of one if the household is below the poverty line, else zero. Estimation results are based on the de Chaisemartin et al. (2023) estimator, controlling for dwelling, household and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level.

$***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.1$.

Source: ENAHO, 2015–2019.

In addition, there are dynamic treatment effects in the aftermath of the coastal El Niño floods. Significant economic impacts on income and expenditure per capita can be observed between 2017 and 2019 (mostly at the 5% significance level), but they dissipate for income per capita in the following year. In the case of poor households, the treatment effects persist for up to three years (at the 1% and 5% significance level).

7.2 Robustness test

In this section, we apply the Dynamic TWFE regression using equation (1). Unlike the estimator proposed by de Chaisemartin et al. (2023), which can model a treatment variable that switches on and off, this technique considers that once the treatment (flood shocks) begins for a group (affected households), it continues throughout the remaining time periods (2017–2019). Due to sporadic and low effects of flooding in the subsequent years of the coastal El Niño floods, we assume the economic impacts that started in 2017 follow a similar downward trend for 2018 and 2019.

Table 8 presents the Dynamic TWFE regression using a binary treatment (flooded district=1). As can be seen, coefficients are relatively the same in magnitude and sign as those in the result section. However, we observe a higher significance level on estimates under the dynamic TWFE specification. Therefore, the effects of floods on household welfare and poor conditions are validated.

Table 8 Impact of flood shocks on household welfare and poverty, Dynamic (TWFE)

Dependent variable:	Income per capita (in logs)		Expenditure per capita (in logs)		Poverty (1,0)	
A: Binary treatment						
Effect -2 (year 2015)	-0.066		-0.051		0.145	***
	(0.099)		(0.073)		(0.051)	
Effect 0 (year 2017)	-0.143		-0.227	***	0.225	***
	(0.096)		(0.072)		(0.053)	
Effect 1 (year 2018)	-0.294	**	-0.273	***	0.329	***
	(0.128)		(0.072)		(0.084)	
Effect 2 (year 2019)	-0.056		-0.165	*	0.294	***
	(0.133)		(0.090)		(0.064)	
ATE (flooded district=1)	**-0.165**	*	**-0.222**	***	**0.283**	***
	(0.090)		**(0.055)**		**(0.056)**	
District FE	Yes		Yes		Yes	

Year FE	Yes	Yes	Yes
Cluster (district)	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	1,521	1,521	1,521

The dependent variables are listed across the top row. Income and expenditure per capita are measured as the log of net annual household income and expenditure per member, respectively. Poverty is a binary variable that takes on a value of one if the household is below the poverty line, else zero. Estimation results are based on the Dynamic TWFE estimator, controlling for dwelling, household and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level.

$***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.1$.

Source: ENAHO, 2015–2019.

The average effect of floods on net household income and expenditure per capita is –0.165 and –0.222, which translate to a 15.2% and 19.9% decline, respectively. For poverty, the average effect is 0.283, indicating a 28.3 percentage points increase in its incidence among households.

In addition, Figure 7 plots the coefficients from the separate regression of household income and expenditure per capita. The coefficients prior to 2016 are statistically insignificant (except for poor households), implying that the parallel trends assumption holds. Graphically, the results using the heterogeneity robust estimator are basically identical and follow the same dynamic treatment effects as the main results using the traditional TWFE specification.

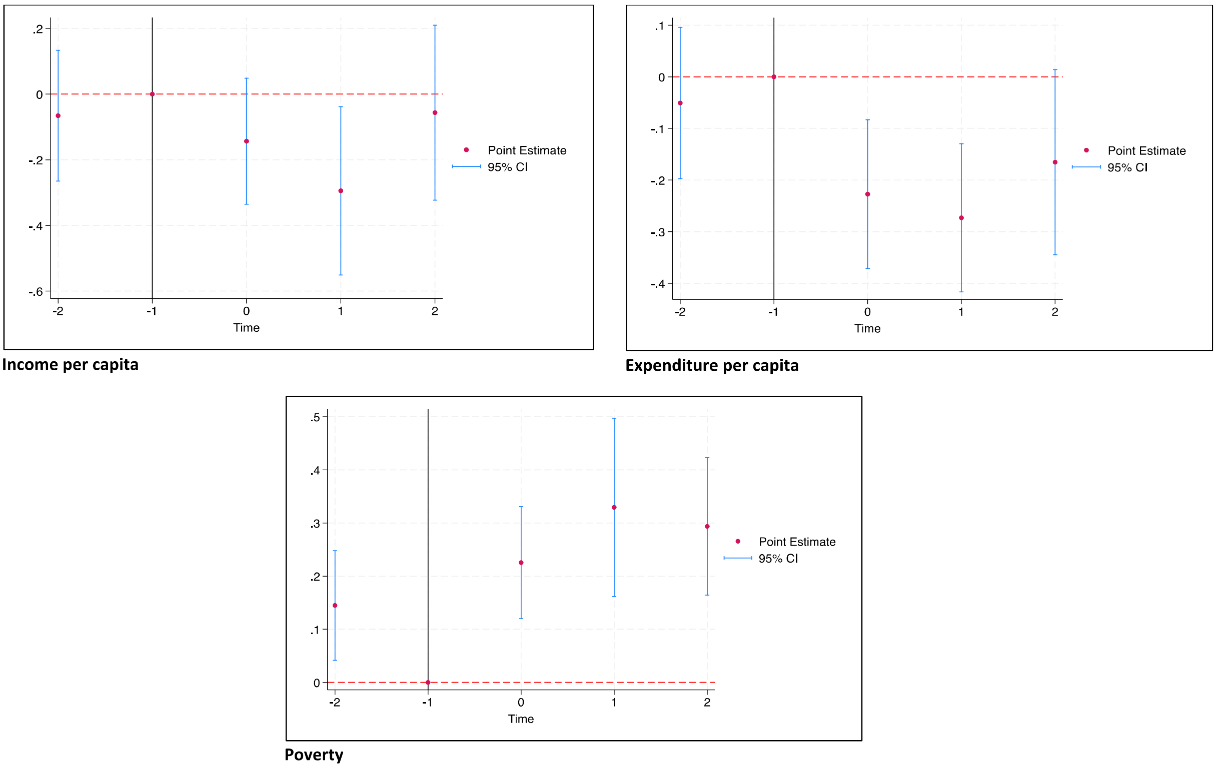

Figure 7 Event study plot for impact of floods on household welfare and poverty

Note: Estimation results based on Dynamic TWFE, clustered standard errors, 95% CI. Negative numbers indicate the years before the coastal El Niño in 2017, and non-negative numbers represent years after the coastal El Niño in 2017.

Source: ENAHO, 2015–2019.

Results using weights based on 2013 VIIRS night-time lights

As noted above, the flood damage index is employed to validate the findings under the binary switching treatment. However, concerns about reverse causality might arise, as VIIRS night-time lights weights are included as an input into the explanatory variable of flood intensity, even though they are also an outcome that could be correlated with the main dependent variables such as household welfare and poverty status. To examine the extent to which the empirical results may be affected by this choice, we construct an alternative flood damage index using weights based on 2013 VIIRS night-time lights and re-estimate equation (1). Note that the construction of the index follows the same procedure outlined in Section 5.4, but exclusively uses VIIRS night-time lights data from 2013 instead of the 2014–2018 data.

Table A.6 in the Appendix presents the results, which are similar in both sign and significance levels but show larger magnitudes compared to those in Table 7. Specifically, income and expenditure per capita declined by 28.5% (against 15.9%) and 26.2% (14.5%), respectively, while households in affected areas experienced an increase in poverty status of 36.8% (19%).

7.3 Extended analysis

In this section, we expand the empirical investigation by examining the heterogeneity of the main results related to household income and expenditure per capita to the extent of urban and rural contexts. We conduct this analysis using sub-samples of data that cover populations in both areas. In columns (1) and (2) of Table 9, floods did not affect household income in urban and rural areas. The absence of a significant effect may be attributed to the region's commencement of recovery from the flood effects through job creation in affected areas. On the other hand, only households located in urban areas experienced a decrease in expenditure due to the flood disasters (29.2%). This may be explained by an increase in spending on housing repair and furniture for flooded households.

Table 9 Heterogeneity impacts

Dependent variable:	Income per capita (in logs)		Expenditure per capita (in logs)			Socioeconomic Status (in logs)	
	Urban	**Rural**	**Urban**		**Rural**	**Quartile 1 Poorest**	**Quartile 4 Richest**
A: Binary treatment							
ATT (flooded district=1)	-0.110	-0.541	-0.345	**	-0.268	-0.580	0.033
	(0.324)	(4.973)	(0.137)		(4.233)	(0.929)	(0.547)
B: Flood damage level							
ATT (flooded district=index)	-0.001	-0.003	-0.005	**	-0.001	-0.003	0.000
	(0.004)	(0.027)	(0.002)		(0.023)	(0.004)	(0.010)
N	539	374	539		374	177	216
District FE	Yes		Yes			Yes	
Year FE	Yes		Yes			Yes	
Cluster (district)	Yes		Yes			Yes	
Controls	Yes		Yes			Yes	

The dependent variables are listed in the top row. Income and expenditure per capita are dummy variables equal to one for urban households and zero for rural households. Socioeconomic status ranges from one (poorest) to four (richest). Estimation results are based on the de Chaisemartin et al. (2023) estimator, controlling for dwelling, household and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level. ∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, ∗ $p < 0.1$.

Source: ENAHO, 2015–2019.

Using household net income, we create quartiles to assist in determining whether we observe heterogenous impacts of flooding across different socioeconomic status. We divide households using their corresponding income into quartiles representing poor (Q1), and rich (Q4) households. Then, we estimate the causal impact of floods on income per capita. provides a summary of results for the coefficient of interest separately for each group. We report only the coefficient on the flood impact. Results are presented in Columns (5) and (6) of Table 9. Although we see no significant difference in incomes across the two extreme quartiles, the results are still instructive. We observe that poor households experience a decline in their income per capita, while richer households face an increase in their income.

Table 10 Impacts of floods on poverty

Dependent variable:	**Poverty (1,0)**		
	Urban		**Rural**
A: Binary treatment			
Effect -2 (year 2015)	0.051		0.133
	(0.034)		(0.095)
Effect 0 (year 2017)	0.116		0.218
	(0.093)		(4.182)
Effect 1 (year 2018)	0.315	***	0.179
	(0.120)		(4.226)
Effect 2 (year 2019)	0.311	***	0.308
	(0.111)		(2.537)
ATT (flooded district=1)	**0.394**	***	**0.348**
	(0.147)		**(5.173)**
B: Flood damage level			
ATT (flooded district=index)	**0.005**	***	**0.002**
	(0.002)		**(0.029)**
District FE	Yes		Yes
Year FE	Yes		Yes
Cluster (district)	Yes		Yes

Controls	Yes	Yes
N	539	374

The dependent variable is in the top row. Poverty is a dummy variable equal to one for households below the poverty line in urban areas and zero for households below the poverty line in rural areas. Estimation results are based on the de Chaisemartin et al. (2023) estimator, controlling for dwelling, household and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level. ∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, ∗ $p < 0.1$.

Source: ENAHO, 2015–2019.

In general, poverty increases in the affected areas, however, it is concentrated more in urban areas compared to rural areas (see Table 10). This may be explained by the slow process of economic recovery after the flood event, especially in promoting job recovery, which can be challenging due to damaged infrastructure, displaced people, and heavy casualties and property loss.

In addition, Figure 8 displays the dynamic treatment effects in urban areas after the occurrence of flood events. There are short- and long-run causal effects on poverty that remain higher compared to the years prior to the floods occurring.

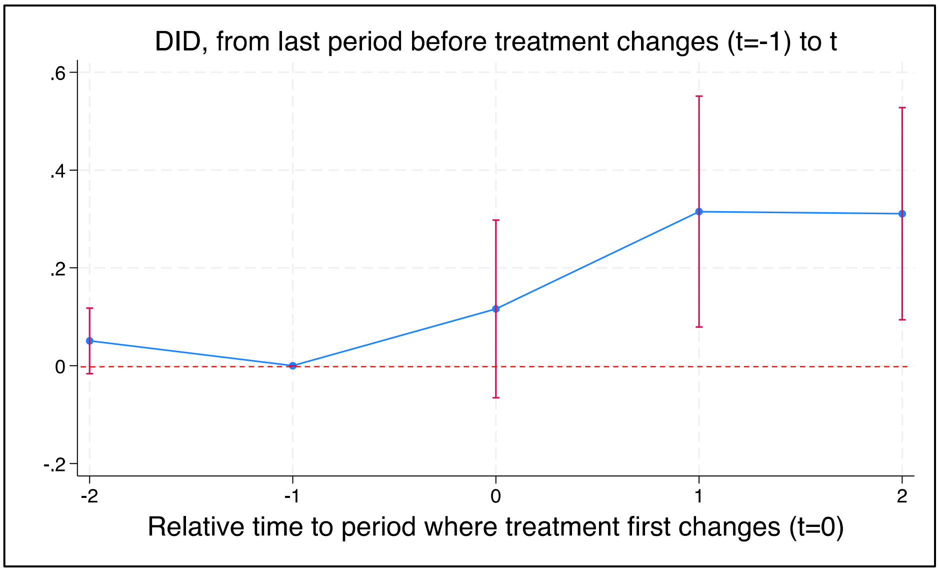

Figure 8 Economic dynamics after the disaster on poverty in urban areas

Note: Estimation results based on de Chaisemartin et al. (2023) estimator, clustered standard errors, 95% CI. Negative numbers indicate the years before the coastal El Niño in 2017, and non-negative numbers represent years after the coastal El Niño in 2017.

Source: ENAHO, 2015–2019.

7.4 Potential channels

Previous estimation results show a decline in income and expenditure of the treatment group relative to the control due to flooding. Here, we consider the potential channels behind these observed impacts. We first characterise the potential pathways with reference to the above empirical findings and test each possible path using the event study regression analysis.

Flooding may drive a decline in income by (i) reducing the number of income earners within the household, and (i) deteriorating wage income. Nevertheless, households could engage in consumption smoothing through (iii) depleting household savings, and (iv) donations or disaster relief to support their recovery from disasters. Table 11 displays that floods have a negative impact on household income earners, wage income and savings, while showing positive effects on disaster relief – such as food and clothing – provided to households.

Table 11 Income earners, wage income and disaster relief

Dependent variable:	Number income earners (in logs)		Wage income (1,0)		Household savings (1,0)		Disaster relief - food and clothing (in logs)	
A: Binary treatment								
Effect -2 (year 2015)	-0.121	**	0.048		-0.145	***	0.446	
	(0.056)		(0.165)		(0.045)		(0.363)	
Effect 0 (year 2017)	-0.183	**	-0.281		0.006		1.214	**
	(0.073)		(0.205)		(0.130)		(0.509)	
Effect 1 (year 2018)	-0.144	*	-0.516	**	-0.255	*	0.939	
	(0.074)		(0.224)		(0.145)		(0.620)	
Effect 2 (year 2019)	-0.093		-0.312		-0.425	***	0.885	
	(0.072)		(0.226)		(0.132)		(0.726)	
ATT (flooded district=1)	**-0.218**	**	**-0.602**	**	**-0.351**	*	**1.579**	**
	(0.098)		**(0.269)**		**(0.191)**		**(0.789)**	
B: Flood damage level								
ATT (flooded district=index)	**-0.002**	**	**-0.005**	**	**-0.003**	***	**0.015**	**
	(0.001)		**(0.002)**		**(0.002)**		**(0.006)**	
District FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
Cluster (district)	Yes		Yes		Yes		Yes	
Controls	Yes		Yes		Yes		Yes	
N	913		436		913		171	

The dependent variables are listed across the top row. The number of income earners is measured as the log of household members who earn income. Wage income is a dummy that takes on a value of one if the household head earns a wage as an independent contractor, else zero. Household savings is a dummy that takes on a value of one if the household head has a bank account, else zero. Disaster relief is measured as the log of the monetary value of food and clothing donations. Estimation results are based on the de Chaisemartin et al. (2023) estimator, controlling for dwelling, household, and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: ENAHO, 2015–2019.

We find that household workers are more likely to lose their jobs following a natural shock. This could be explained by the disruption of local economic activity. For instance, if one family member experiences income loss, their revenue may decline by 19.6% due to the flood. Additionally, households that experienced larger and longer floods during the period 2017 to 2019 may have seen much larger decreases in wage income and household savings compared to floods of shorter duration. Figure 9 illustrates the dynamic treatment effects of floods on both income earners and wage income.

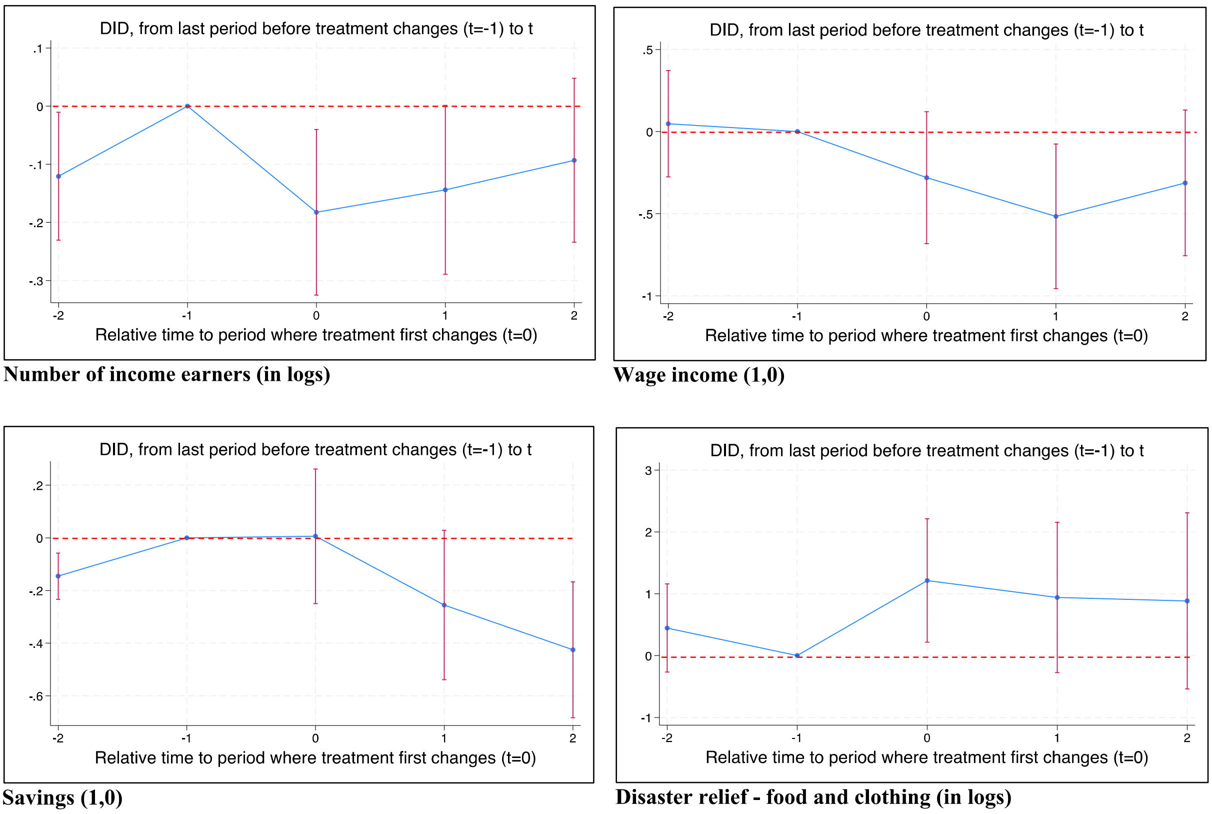

Figure 9 Dynamics of income earners, wage income, savings and disaster relief

Note: Estimation results based on de Chaisemartin et al. (2023) estimator, clustered standard errors, 95% CI. Negative numbers indicate the years before the coastal El Niño in 2017, and non-negative numbers represent years after the coastal El Niño in 2017.

Source: ENAHO, 2015–2019.

In addition, we observe that support from government and private sectors increased by 385.1% after a flood disaster of this magnitude. This increase was high relative to the average amount of lost income (32.5%) and expenditure (29.9%) these households experienced.

In monetary terms, the disaster relief in the aftermath of the 2017 floods reached PEN 335.61 (USD 102.93). However, this amount is significantly lower than the income and expenditure losses faced by households between 2017 and 2019. The disaster relief only covered 22.16% of the income loss and 29.08% of the expenditure loss per capita, indicating a substantial gap between the aid provided and the actual financial impact on affected households. The limited disaster relief may hinder recovery efforts, forcing households to rely on their own savings, which exacerbates their vulnerability in the long term.

8. Policy recommendation

The findings highlight the significant economic impact of flooding on household incomes and expenditures per capita, as evidenced by the 2017 coastal El Niño event in northern Peru. As discussed above, support in the form of food and clothing donations falls short of fully addressing the financial strain on affected households. To enhance resilience, it is recommended that disaster insurance be introduced with coverage levels at least equivalent to the difference between the value of post-disaster donations and the expenditure loss amount (PEN 818.51 or USD 251.02), thereby ensuring a baseline of financial security.

Moreover, the damage index, which identifies districts with a higher probability of vulnerability to flood events, could be utilized by central and local governments to guide budget reallocation for post-disaster financing. This index offers an empirical foundation for understanding how local governments adjust their spending in response to natural shocks, ensuring that resources are effectively allocated to the most vulnerable areas.

9. Conclusions

This paper estimates the causal impact of floods on household welfare outcomes and poverty, with the coastal El Niño serving as a treatment. This phenomenon caused destructive flooding in many districts in northern Peru in 2017. Isolated extreme weather also brought flood events with less damaging effects in 2018 and 2019 within the same area. As a proxy for the local economic impact, a novel damage index is constructed using remote sensing, and combined it with 5-year household panel data. We employ a diff-in-diff event study estimation strategy with heterogeneous treatment effects across groups and over time, accounting for treatments that switch on and off.

The results in this article reveal that households affected by floods experience lower income and expenditure per capita compared to households located in unaffected areas between 2015 and 2019. In addition, the findings confirm the presence of dynamic effects following the floods in 2017. There is evidence of a slow recovery process of income and expenditure, yet levels remain below those prior to the flood event. There has also been an increase in poverty, particularly among those located in urban areas, pushing more people below the poverty line.

Another key finding is that the decrease in the number of income earners within the household and the reduction in wage income are potential factors influencing the decline in income and expenditure between 2017 and 2019. Conversely, household financial assets, such as savings, and disaster relief served as ex-post coping strategies to smooth consumption expenditure among affected households. The loss of jobs, particularly in urban areas, may have resulted in fewer working members, leading to reduced income and expenditure. However, household savings and donations of food and clothing provided to affected households alleviated the adverse impact of floods and contributed to the slight economic recovery of the affected regions.

A key lesson from this study is the importance of recognising that family savings as well as both private donations channelled through NGOs and public sector resources (from foreign and/or domestic sources) available in the aftermath of flood events, act as support measures for ex-post coping mechanisms among affected households. However, it seems that household recovery primarily depends on donations since the level of support has remained unchanged in the post-disaster period (2018–2019). This can create a cycle of dependency that hinders the development of local resilience and self-reliance. It may discourage households and communities from investing in long-term solutions to mitigate the impact of future flood events. Disaster insurance could be introduced with coverage equal to or greater than the gap between post-disaster donations and expenditure losses (PEN 818.51 or USD 251.02) to make households in affected districts more resilient when flooding of this magnitude, such as the coastal El Niño, happens again.

Finally, it is clear that affected households have not fully recovered in the aftermath of the floods. The risk of a possible post-disaster poverty trap is especially acute if households depend exclusively on external support and lack access to formal risk-coping strategies, such as microinsurance. The empirical literature has already discussed the links between disasters and poverty traps (Janzen and Carter, 2013; Hallegatte et al., 2016), suggesting that insurance payments help stabilise consumption for poor households and help protect assets for those who are relatively well-off. In that context, it is crucial to explore opportunities for developing an insurance product to cover losses caused by floods among households located in areas with high risk of such events.

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Appendix

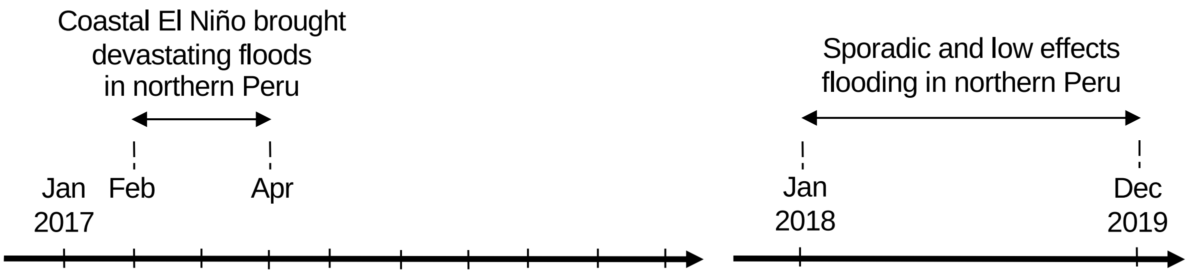


Figure A.1 Timeline of the 2017 coastal El Niño and subsequent flood events

Source: Author's illustration

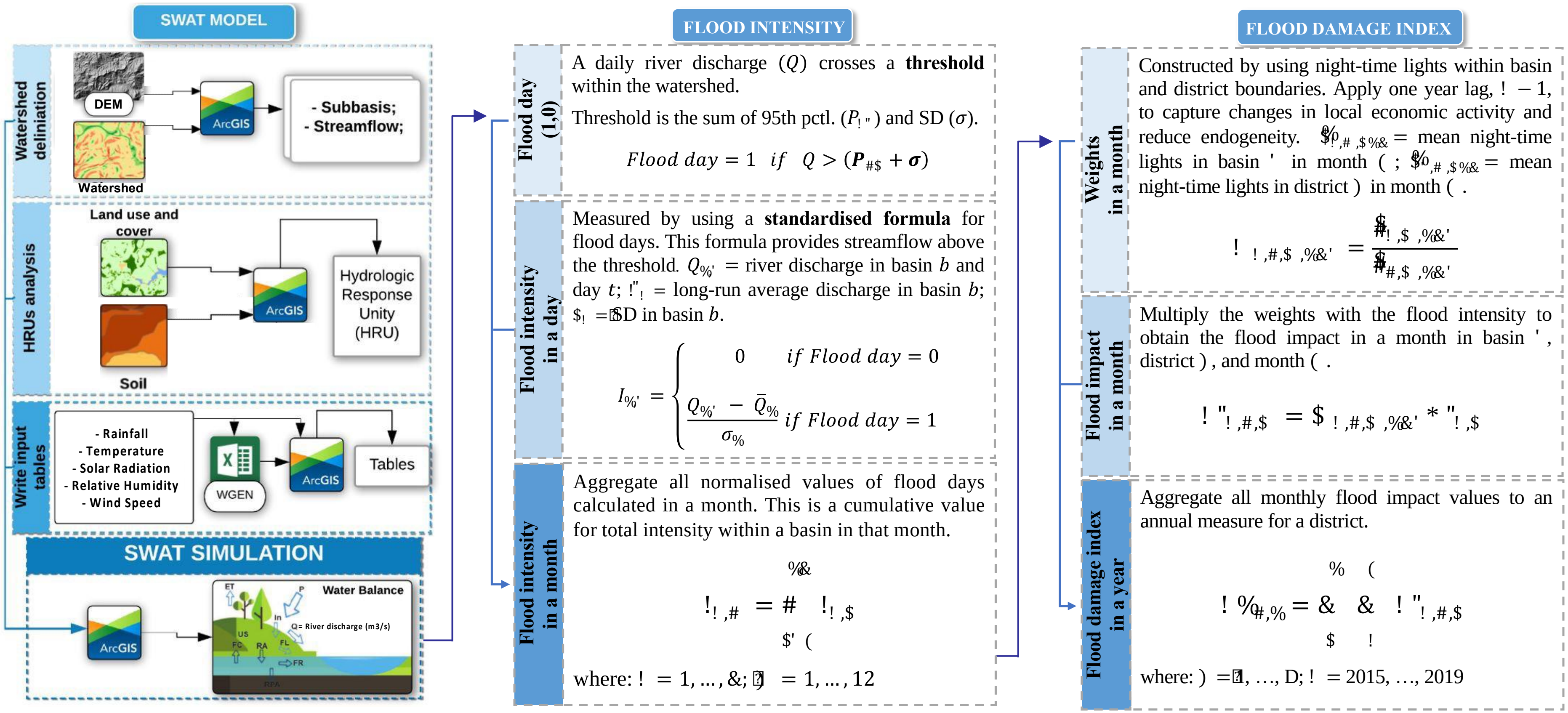


Figure A.2 Flowchart of the procedure used in the hydrological simulation by ArcSWAT, and construction of the flood damage index

Source: Author's illustration

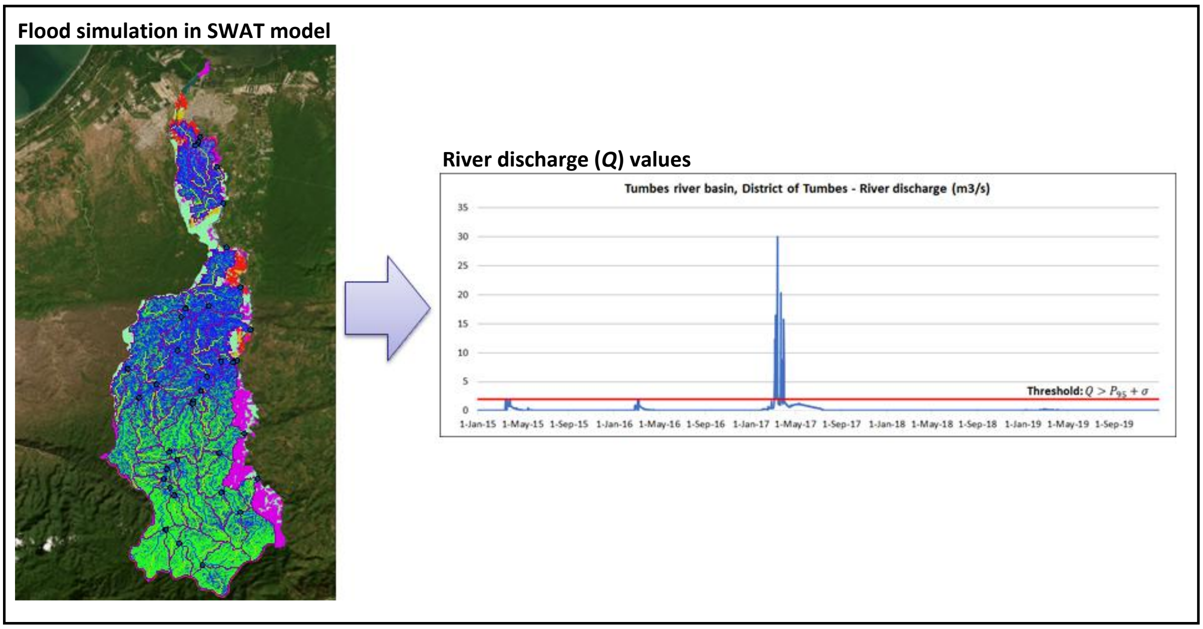


Figure A.3 Watershed study design for Tumbes river basin

Note: Watershed characteristics are shown including DEM, Watershed, LULC, DSMW, weather data.

Source: Author’s illustration

Table A.1 Exogeneity of the binary switching variable and flood damage index 2015–2019

Dependent variable:	Binary switching treatment		Flood damage index		N
Annual net HH income per capita (in logs)	-0.002		-9.340	*	1527
	(0.020)		(4.895)		
Annual net HH expenditure per capita (in logs)	-0.003		-9.439		1530
	(0.030)		(5.786)		
Poverty (1,0)	-0.003		5.367		1530
	(0.039)		(7.964)		
Urban (1,0)	-0.040		-23.822		1530
	(0.071)		(15.858)		
Wage income (1,0)	0.025		10.103		1293
	(0.035)		(9.266)		
Household savings (1,0)	0.043		1.212		1530
	(0.035)		(6.855)		
Disaster relief - food and clothing (in logs)	0.001		2.813	**	1530
	(0.007)		(1.354)		
Sewage (1,0)	-0.007		-24.420	*	1530
	(0.052)		(12.424)		
Water (1,0)	0.022		-2.417		1530
	(0.067)		(11.336)		
Electricity (1,0)	0.060		-25.983		1530
	(0.101)		(33.662)		
Concrete roof (1,0)	0.025		-11.334		1525
	(0.042)		(7.717)		
Female household head (1,0)	0.056		-5.364		1530
	(0.045)		(5.375)		
Household size (in logs)	-0.087	***	4.619		1530
	(0.031)		(6.401)		
Age household head (in years)	0.002		-0.219		1530
	(0.001)		(0.211)		

Years of schooling household head (in years)	0.001		-0.670	1530
	(0.004)		(0.590)	
Income earners (in logs)	-0.109	***	-3.111	1526
	(0.024)		(5.119)	
Own house (1,0)	-0.005		5.641	1530
	(0.032)		(5.685)	
Public health insurance (1,0)	-0.017		5.096	1530
	(0.042)		(5.658)	

Columns 1 and 2 present the results of regressions on outcomes and exogenous variables for the binary switching treatment and flood damage index, using data from 2015 to 2019. OLS estimations are employed with PSM and household weights, controlling for distance to the nearest river (in logs) and year fixed effects. Standard errors are clustered at the district level.

$***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Source: ENAHO, 2015–2019.

Table A.2 Exogeneity of the binary switching variable and flood damage index 2017–2019

	Period 2017–2019		
Dependent variable:	Binary switching treatment	Flood damage index	N
Annual net HH income per capita (in logs)	0.002	0.022	226
	(0.003)	(0.025)	
Annual net HH expenditure per capita (in logs)	0.004	0.042	226
	(0.005)	(0.046)	
Poverty (1,0)	-0.003	-0.025	226
	(0.003)	(0.028)	
Urban (1,0)	0.003	0.029	226
	(0.003)	(0.033)	
Wage income (1,0)	-0.004	-0.039	196
	(0.004)	(0.043)	
Household savings (1,0)	-0.005	-0.045	226
	(0.005)	(0.049)	
Disaster relief - food and clothing (in logs)	0.000	0.003	226
	(0.000)	(0.003)	
Sewage (1,0)	0.003	0.029	226
	(0.003)	(0.032)	
Water (1,0)	0.002	0.023	226
	(0.003)	(0.025)	
Electricity (1,0)	0.002	0.024	226
	(0.003)	(0.026)	
Concrete roof (1,0)	0.006	0.056	226
	(0.006)	(0.061)	
Female household head (1,0)	0.011	0.113	226
	(0.013)	(0.124)	
Household size (in logs)	-0.002	-0.024	226
	(0.003)	(0.027)	
Age household head (in years)	0.000	0.000	226

	(0.000)	(0.000)	
Years of schooling household head (in years)	0.000	0.001	226
	(0.000)	(0.002)	
Income earners (in logs)	0.002	0.019	226
	(0.002)	(0.022)	
Own house (1,0)	-0.011	-0.113	226
	(0.013)	(0.124)	
Public health insurance (1,0)	-0.005	-0.050	226
	(0.006)	(0.055)	

Columns 1 and 2 show the results of regressing against outcomes and exogenous variables for the subsample of untreated districts (i.e., for those districts that have not experienced flooding) in the period 2017–2019. OLS estimations are employed with PSM and household weights, controlling for distance to the nearest river (in logs) and year fixed effects. Standard errors clustered at the district level. ∗∗∗$p < 0.01$, ∗∗$p < 0.05$, ∗$p < 0.1$.

Source: ENAHO, 2015–2019.

Table A.3 "Switchers" districts in northern Peru

SWITCHING UNITS Districts:	Year				
	2015	2016	2017	2018	2019
Morrope	0	0	2,472.90	10.86	0
Frias	0	0	1,761.32	0	0
Pacaipampa	0	0	1,092.62	0	0
Chulucanas	0	0	828.01	0	0
Tambo Grande	0	0	744.54	0	1.77
Las Lomas	0	0	679.90	0	0
La Brea	0	0	497.23	0	4.87
Olmos	0	0	343.36	0	3.17
Tumbes	0	0	325.37	0	0
El Prado	0	0	252.53	53.90	0
Cura Mori	0	0	205.83	0	0
Jayanca	0	0	187.86	10.06	0
Sondorillo	0	0	174.23	0	1.62
Pomalca	0	0	158.19	11.50	0
San Andres de Cutervo	0	0	130.93	65.79	0
Pampas de Hospital	0	0	112.89	0	0
La Cruz	0	0	91.64	0	0
Viru	0	0	68.44	128.92	0
Pacora	0	0	64.30	49.57	0
Julcan	0	0	52.27	49.33	0
Castilla	0	0	50.25	0	0
Guadalupito	0	0	44.71	0	0
Chalamarca	0	0	36.66	63.25	0
Chota	0	0	26.17	24.41	0
Sullana	0	0	21.58	0	0
Pimentel	0	0	18.64	0	0
Piura	0	0	12.06	0	0.34
Guadalupe	0	0	11.77	12.34	0
Bambamarca	0	0	11.44	46.45	0

Tuman	0	0	10.60	17.82	0
Encañada	0	0	8.42	41.36	0
Trujillo	0	0	5.91	9.86	0
Veintiseis de Octubre	0	0	4.64	0	0.11
Reque	0	0	1.38	9.06	0

Note: The table shows the switching units (districts) as treatment (flooding) switches on and off over time (2017–2019) and across units (districts), with treated units (districts) receiving treatment (floods) in the same year (2017). The devastating coastal El Niño floods in 2017 affected all districts, while sporadic and less severe floods in 2018 impacted 16 districts, and only six districts experienced flood events in 2019.

Source: ENAHO, 2015–2019.

Table A.4 "Always treated" districts in northern Peru

TREATED UNITS Districts:	Year				
	2015	2016	2017	2018	2019
Aguas Verdes	0	0	561.46	3.67	6.65
La Victoria	0	0	39.73	5.18	0.48
Llacanora	0	0	21.84	44.65	3.02
Huamachuco	0	0	14.60	55.24	4.34
Chiclayo	0	0	11.30	1.55	0.14
Cajamarca	0	0	4.29	12.75	0.85

Note: The table shows the always units (districts) as treatment (floods) happened over time (2017–2019) and across units (districts), with treated units (districts) receiving treatment (floods) in the same year (2017). The devastating coastal El Niño floods in 2017 affected all districts, while sporadic and less severe floods in 2018 impacted 16 districts, and only six districts experienced flood events in 2019.

Source: ENAHO, 2015–2019.

Table A.5 “Never treated” districts in northern Peru

CONTROL UNITS Districts:	Year				
	2015	2016	2017	2018	2019
Bellavista	0	0	0	0	0
Bolivar	0	0	0	0	0
Cajabamba	0	0	0	0	0
Canchaque	0	0	0	0	0
Canoas de Punta Sal	0	0	0	0	0
Chepen	0	0	0	0	0
Cochorco	0	0	0	0	0
Corrales	0	0	0	0	0
Domingo de la Capilla	0	0	0	0	0
El Porvenir	0	0	0	0	0
Ferreñafe	0	0	0	0	0
Jose Leonardo Ortiz	0	0	0	0	0
La Arena	0	0	0	0	0
La Esperanza	0	0	0	0	0
Moche	0	0	0	0	0
Salpo	0	0	0	0	0
Zarumilla	0	0	0	0	0

Note: The table shows the control units (districts). These units are never treated during the analysis period. They serve as the comparison group to assess the impact of the treatment.

Source: ENAHO, 2015–2019.

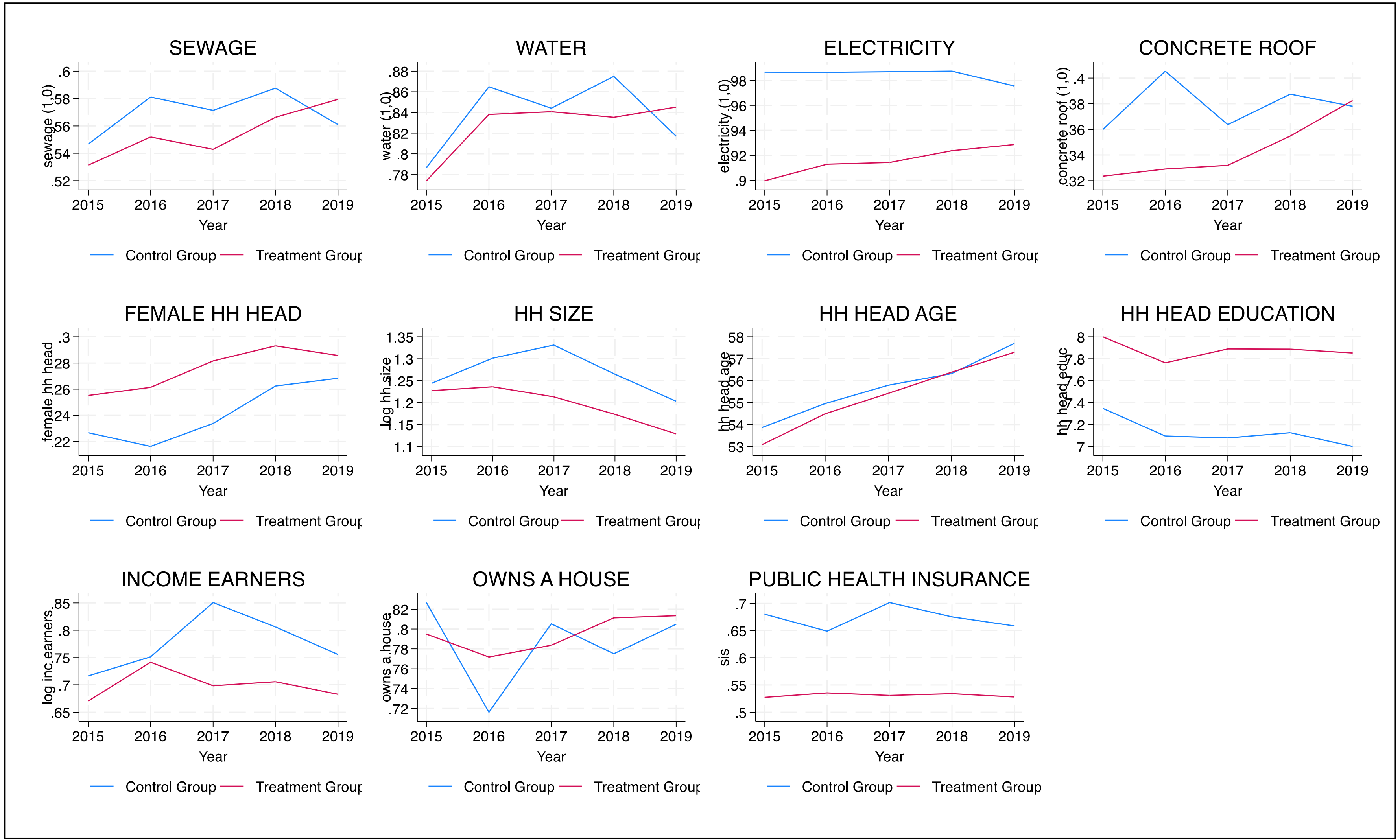


Figure A.4 Average covariates over time for treated and control groups

Note: Plots for average covariates that are included in the model, which evolve in a non-parallel fashion across the treatment and control groups.

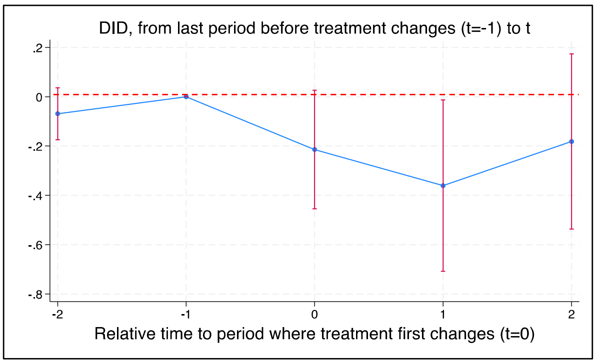
Source: Author’s illustration.

Table A.6 Impact of floods on household welfare and poverty using weights based on 2013 VIIRS night-time lights

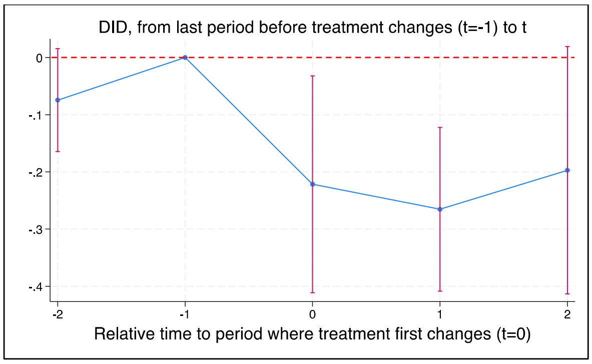
Dependent variable:	Income per capita (in logs)		Expenditure per capita (in logs)		Poverty (1,0)	
A: Flood damage level						
Effect -1 (year 2015)	-0.069		-0.075		0.065	
	(0.054)		(0.046)		(0.043)	
Effect 0 (year 2017)	-0.214	*	-0.222	**	0.186	**
	(0.123)		(0.097)		(0.067)	
Effect 1 (year 2018)	-0.361	**	-0.265	***	0.315	***
	(0.177)		(0.073)		(0.092)	
Effect 2 (year 2019)	-0.182		-0.197	*	0.327	***
	(0.181)		(0.110)		(0.089)	
ATT (flooded district=index)	**-0.007**	*	**-0.007**	***	**0.008**	***
	(0.004)		**(0.002)**		**(0.002)**	
District FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Cluster (district)	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
N	913		913		913	

The dependent variables are listed across the top row. Income and expenditure per capita are measured as the log of net annual household income and expenditure per member, respectively. Poverty is a binary variable that takes on a value of one if the households is below the poverty line, else zero. Estimation results are based on the de Chaisemartin et al. (2023) estimator, using a flood damage index constructed from 2013 VIIRS night-time lights data. The model controls for dwelling, household, and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

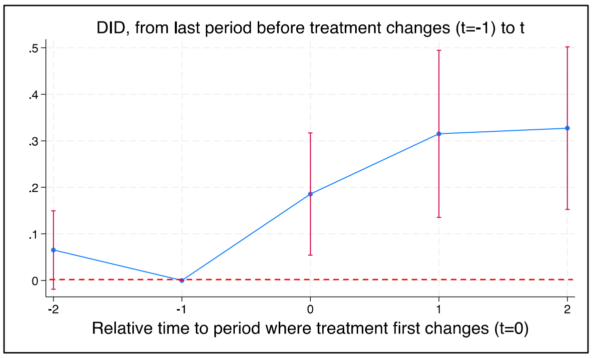
Source: ENAHO, 2015–2019.



Income per capita (in logs)



Expenditure per capita (in logs)



Poverty (1,0)

Figure A.5 Event study plots for impact of floods on household welfare and poverty using weights based on 2013 night-time lights

Note: Estimation results based on de Chaisemartin et al. (2022) estimator, clustered standard errors, 95% CI. Negative numbers indicate the years before the coastal El Niño in 2017, and non-negative numbers represent years after the coastal El Niño in 2017.

Source: ENAHO, 2015–2019.

Table A.7 Impact of floods on household savings

Dependent variable:	Household savings (1,0)		
	Urban		**Rural**
A: Binary treatment			
ATT (flooded district=1)	-0.551	**	-0.127
	(0.274)		(7.095)
B: Flood damage level			
ATT (flooded district=index)	-0.007	**	-0.001
	(0.004)		(0.039)
District FE	Yes		Yes
Year FE	Yes		Yes
Cluster (district)	Yes		Yes
Controls	Yes		Yes
N	539		374

The dependent variable is listed in the top row. Savings in urban areas equals one if the household head has a bank account. Savings in rural areas equals zero if the household head has a bank account in the rural area. Estimation results are based on the de Chaisemartin et al. (2023) estimator, controlling for dwelling, household and geographic characteristics, as well as district and year fixed effects. Standard errors are clustered at the district level. ∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, ∗ $p < 0.1$.

Source: ENAHO, 2015–2019.

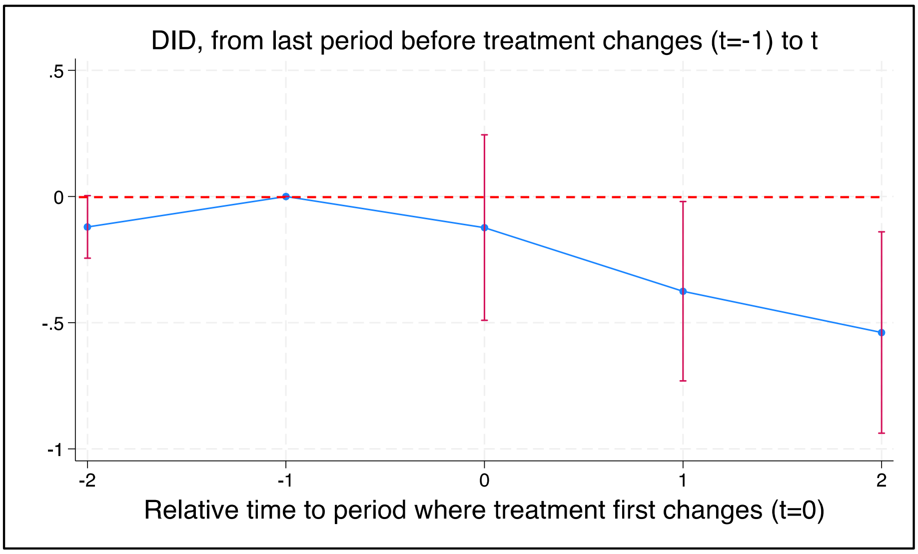


Figure A.6 Event study plot for impact of flood shocks on household savings (1,0) in urban areas

Note: Estimation results based on de Chaisemartin et al. (2023) estimator, clustered standard errors, 95% CI. Negative numbers indicate the years before the coastal El Niño in 2017, and non-negative numbers represent years after the coastal El Niño in 2017.

Source: ENAHO, 2015–2019.