Immediate Relief, Delayed Recovery: Labour Market Impacts of Natural Disasters

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Abstract: Disaster response policies often focus on immediate relief or long-term reconstruction, but what happens in between? We examine how the impacts of Pakistan's 2022 floods evolve over two years, by collecting panel data from 5,100 low-income households across six districts, and leveraging exogenous local variation in topography and rainfall to estimate causal effects. One year post-floods, a more severe flood shock depleted household assets and reduced labour demand, prompting households to sell assets, commute further for work, and turn to self-employment. They also received more formal and informal aid. As a result, they were able to sustain consumption levels on par with less affected households. However, by year two these patterns are reversed: more flooded households have returned to private employment, working similar hours as less flooded households, but doing so at lower wages. They are also more likely to report reducing consumption and health expenditure, taking new loans and drawing down savings to make ends meet. We also find that more intense floods have persistent negative impacts on physical and mental health - particularly women's. These findings reveal a medium-run assistance gap: after emergency relief but before long-run reconstruction, households face income risks that standard disaster response overlooks, allowing the effects of climate shocks to persist through labour markets.

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Introduction

Extreme weather events like floods destroy homes, inundate fields, and disrupt livelihoods. Disaster response typically focuses on two phases: immediate relief to meet basic needs, followed by longer-term rebuilding of damaged infrastructure. But what happens in the period in between emergency aid and reconstruction?

We study this question in the context of Pakistan's catastrophic 2022 floods, which were estimated to affect one in seven people (GoP et al., 2022) and left over 10% of the country underwater. Using newly collected panel data and an instrumental variables (IV) research design, we document a medium-run assistance gap where disaster-affected households face mounting economic pressures after emergency relief ends but before reconstruction begins. One year post-floods, heavily affected households maintain consumption levels despite employment declines, supported by aid, commuting and asset sales. By year two, these patterns reverse: employment recovers, wages fall, and households increasingly skip meals and forgo healthcare. They also experience worse health and mental health. This reveals how disaster impacts evolve over time.

To trace how natural disasters affect households over time, we combine several sources of new and existing data. We collect panel data on 5,100 rural households across six districts, one and two years post-flood, measuring employment, wages, migration, assets, and coping strategies. To avoid selection bias from convenience sampling (such as sampling displaced households in relief camps), we randomly sample from a 2017 baseline census of all poor households in our study areas, which also provides a brief pre-floods snapshot of household composition, employment and assets. To measure flood exposure, we use satellite data on flooding extent, rainfall, and topography. Finally, we draw on geo-located government administrative damage records covering nearly 2 million properties . The study is based in Sindh, one of Pakistan's five provinces, and the epicentre of flooding in 2022.

Using these data, we show that the 2022 floods were exceptional in both scale and nature. Satellite imagery reveals 10% of Pakistan underwater at the peak, affecting 33 million people. In Sindh, 21% of land was flooded, with over 10% remaining inundated for more than 2 months. Administrative data records 1.96 million homes partially or fully damaged and $14.9 billion in total damages. In our study areas, flooding was particularly severe - 49% of land was underwater at the peak, with households reporting average flood durations of 2.5 months and water depths of 3 feet.

Unlike typical seasonal flooding, these floods were driven by extreme rainfall - 531% above Sindh's 20-year average - concentrated in historically low-risk areas. Most strikingly, the meteorological department had declared the monsoon nearly over just two weeks before the deluge began.

Motivated by the wide variation in flood depth, duration and extent across affected areas, we measure flood intensity using a standardised (Anderson) index combining satellite and self-reported measures of these three dimensions (Anderson, 2008).

Our research design relies on an IV approach. This is because comparing outcomes across more versus less flooded areas will not reflect the causal impact of flooding, as flood-prone areas could differ systematically in both their exposure to flooding and their economic characteristics. For example, floodplains may have both higher flood risk and more productive agriculture, while wealthier areas might have better drainage infrastructure that reduces realised flooding. Our IV design is motivated by the fact that these floods were driven by unforeseen and unprecedented rainfall. We exploit the fact that extreme rainfall on flat terrain leads to more severe flooding, while rainfall in sloped areas drains more quickly. Importantly, Sindh is predominantly low-lying and flat, so we are exploiting very granular local variation in the slope of land rather than large topographical differences such as comparing mountains to valleys. Our instrument interacts 2022 rainfall with pre-flood land gradient within a 5 km radius around a households' pre-flood residence, controlling for historical rainfall patterns and historical flood risk in that radius, and district fixed effects. The first stage is strong (F=59), with the instrument significantly predicting all components of our flood index - extent, depth, and duration.

While this approach controls for systematic flood risk factors, our planned next step is to implement an extended analysis using recentered instruments following (Borusyak and Hull, 2023). This method addresses the "exposure problem" - that even with random rainfall, some areas systematically flood more due to their position in the hydrological network. By recentering the instrument to remove expected flood exposure based on simulated alternative rainfall realizations, this approach isolates only the quasi-random variation in flooding intensity conditional on systematic flood risk, providing cleaner identification of flood impacts.

This paper presents results using our preliminary IV research design. The 2022 floods caused severe damage and economic disruption. In the year following floods, more flooded households reported being 21 percentage points more likely to have homes fully destroyed and 24 percentage points more likely to experience livestock or land damage. Beyond physical destruction, flooding disrupted economic activity for months through evacuations and inaccessible trade routes, with agricultural output taking several months to recover.

In the face of this enormous shock we find, perhaps surprisingly, that one year post-flood heavily flooded households maintained average consumption levels at par with less flooded households. In fact, relative to less flooded households, they were 7.6 percentage points less likely to report skipping meals, 17.1 percentage points less likely to forgo healthcare, and 11.0 percentage points less likely to reduce non-food expenditure to make ends meet.

By year two, however, a different picture emerges. Whilst average consumption remains similar across more and less flooded households, those in flooded areas increasingly reported unmet needs - they were 9.9 percentage points more likely to skip meals, 20.7 percentage points more likely to forgo healthcare and 11.3 percentage points more likely to reduce non-food spending to make ends meet. They also experience worse physical and mental health outcomes, particularly among women who become 11 percentage points more likely to have severe mental distress, even as they spend more on healthcare.

To understand these dynamics, we explore three broad ways in which households may be smoothing consumption: labour supply, receipt of external assistance, and financial adjustments.

Turning to labour markets, we find evidence of deteriorating labour demand conditions between the first and second year after the floods. In the first year, individuals in more heavily flooded areas were 7 percentage points (13.6%) less likely to be employed and 3 percentage points (+43%) more likely to be self-employed. These effects are concentrated among agricultural workers, suggesting that the inundation of fields depressed demand for farm labour. Yet, somewhat surprisingly, those who remained employed reported higher monthly earnings.

By the second year, employment among the more flooded households recovered, while self-employment rates declined. This temporary substitution into self-employment during the period of inundation, followed by a return to wage employment once floodwaters receded, reflects the pattern of labour rationing documented by (Breza et al., 2021). and reinforces that the initial employment shock was likely to be demand-driven.

Yet, this recovery in employment masks a deterioration in earnings. In the second year, workers in more flooded areas earn 13% less per month than their counterparts in less flooded areas, despite working the same number of hours. Conditioning on a balanced panel of individuals employed in both waves shows that workers in more flooded areas experience wage declines between survey waves, suggesting that these results are not driven by negative worker selection but by changes in wages conditional on worker characteristics.

A further systematic shift between the two annual survey waves lies in the supply of external assistance available. In the first year after floods, more flooded households are 23 percentage points more likely to receive some form of formal flood relief, 11 percentage points more likely to receive formal food aid or informal gifts of food. By 2024, two years after the floods, almost all relief programmes have wrapped up, whilst very few households have received any payments from the major home reconstruction programme still being rolled out by the Government of Sindh.

Finally, households' financial resources appear to shift over time. In year one, households in more flooded areas were 5 percentage points more likely to sell household assets, though not productive assets like livestock or agricultural equipment, and we found no significant differences in the use of savings or loans to make ends meet. As a result of both asset sales and flood damages, more flooded households had more depleted asset stocks (0.13 standard deviations lower per SD of flooding) but were 19 percentage points more likely to have savings (from a very low base of 2%). By year two, we find no statistically significant differences in asset sales between more and less flooded areas - perhaps because households in the more flooded areas had already sold the assets they could afford to part with. However, households in flooded areas were now 24 percentage points more likely to draw down savings and 10 percentage points more likely to take on new loans to make ends meet. By the end of our study period, more flooded households are 13 percentage points less likely to have savings and 12 percentage points more likely to have debt.

These patterns reveal a medium-run assistance gap that standard disaster response overlooks. While more flooded households continue to maintain similar consumption levels to their less flooded counterparts two years post-flood, they do so under increasing strain - with depleted savings, more debt, deteriorating health, and worsening labour market conditions. This raises important questions about the interactions between these factors: does the withdrawal of support combined with depleted financial resources leave households with little choice but to accept lower wages (Jayachandran, 2006)? When they accept lower wages once, do labour markets settle at a new, worse equilibrium (Kaur, 2019)? In work in progress, we explore heterogeneity in these results by local land ownership and measures of worker outside options to understand how monopolistic competition in labour markets might amplify disaster impacts.

The rest of the paper proceeds as follows. Section 1 describes our data sources. Section 2 documents the scale and nature of the 2022 floods. Section 3 presents our research design. Section 4 reports results. Section 5 concludes.

1 Data

Given the data challenges inherent in studying disasters, we begin by describing our unique combination of sources that allow us to track households before, during, and after the floods. To trace how disasters affect labour markets over time we combine multiple data sources, as summarised in Table 1.1. First, we use satellite data on flooding extent, rainfall, and topography to construct measures of flood exposure and identify exogenous variation in flooding. Second, we randomly sample 5,100 rural households from 2017 baseline administrative data and track these same households through panel surveys conducted one and two years post-flood to measure employment, wages, migration, assets, and coping strategies. Finally, we match this panel data to administrative property damage records covering nearly 2 million properties.

Table 1.1: Data Sources and Coverage

Data Type	Source	Years	Freq.	Key Variables
Panel A: Flood Exposure Measurement				
Flood extent	NOAA VIIRS	2022-23	Daily	Inundation (375m)
Rainfall	NASA GPM	2000-22	Daily	Precipitation (10km)
Topography	GMTED2010	Static	–	Land gradient (1km)
Flood risk	Fathom	Static	–	Historical flood probability
Panel B: Household Panel Data				
Baseline census	NGO admin records	2017	Once	Demographics, assets
Follow-up surveys	Primary collection	2023-24	Annual	Employment, wages
Village census	Pakistan census	2020	Once	Infrastructure
Property damage	Sindh govt	2022-23	Once	1.96M properties

Treatment: flooding and its drivers

To measure flooding and its drivers, we rely on satellite data. We use the NOAA VIIRS 5 day composite maps at 375m resolution to measure daily flood extent over the second half of 2022 and into 2023. We obtain daily rainfall measures from NASA's Global Precipitation Measurement (GPM) database, which provides data at 0.1 degree resolution (approximately 10km) from 2000 to present. For topography, we use GMTED2010 land gradient data from EarthEnv, which is supported by NCEAS, NASA, NSF, and Yale University at 1 km resolution. Since flooding results from the interaction of rainfall with flat terrain where water cannot drain quickly, we combine these measures to construct our instrument for our flooding index (see section 3). We also incorporate historical flood risk measures from Fathom to account for the fact that households may sort based on known flood risk.

Household and individual-level outcomes

Our individual-level data comes from both baseline administrative records and follow-up surveys. For baseline data, we have access to a 2017 census of all households in 6 districts of Sindh. The data was collected by a local NGO to determine eligibility for various local development and poverty alleviation programmes. The six districts correspond to the areas of operation of our NGO partner. These administrative data contain the address of the household, a list of household members (including their age, sex, education and occupation), household asset holdings across 21 asset classes and a 'poverty score' constructed based on these asset holdings. We use these data as a sampling frame and for balance tests. Where possible, we also use these data to control for baseline characteristics of the household and its members. We sample only low-income households from these data - setting the cut-off such that approximately 50% of households are poor enough to be eligible for the main cash transfer programme in Pakistan (BISP), whilst the remaining 50% are ineligible.

We combine our household data with village ("Mouza") census data from 2020. The survey is at the village level and contains information about the presence of various infrastructure around the village (e.g. metalled road, market, primary school).

For follow-up data, we collect panel data on a random sample of 5,100 low-income, rural households across 6 districts of Sindh. These households are drawn based on pre-flood characteristics from the 2017 dataset described above. We surveyed these households one and two years after the 2022 floods. The first wave of surveys took place in July-September 2023, with the second wave in July-September 2024. With the assistance of local community members, we successfully located 92% of households in 2023 or 2024, of which almost all were in their 2017 village. Attrition between the 2017 and 2023 datasets is balanced on treatment, although we were more likely to interview more flooded households in 2024 (+9ppt, significant at 10% level, see table 6.1). This is the opposite of the usual concern that those most impacted by disasters migrate away from their original locations and therefore can't be tracked. In total we have 5,120 households and 33,202 people in 2023, 4,902 households and 33,645 people in 2024. Our main analysis is undertaken with the 4684 households (and their constituent members) that we survey in 2023 and 2024. This data contains 30,507 individuals in 2023 and 32,143 individuals in 2024.

We collect data on a vast range of outcomes including damages to assets, lost income, drawdown of savings, sale of assets, new loans, changes in labour supply and educational or nutritional investments, as well as migration and occupational change. Our surveys also capture flood exposure measures including duration of flooding, depth of flood waters, evacuation decisions, and damage to property and productive assets. Additionally, we are able to match 2103 households in our panel to government administrative data on property damage which recorded 1.96 million damaged properties (of which 1.37 million were 'fully damaged') across Sindh.

2 The 2022 Floods

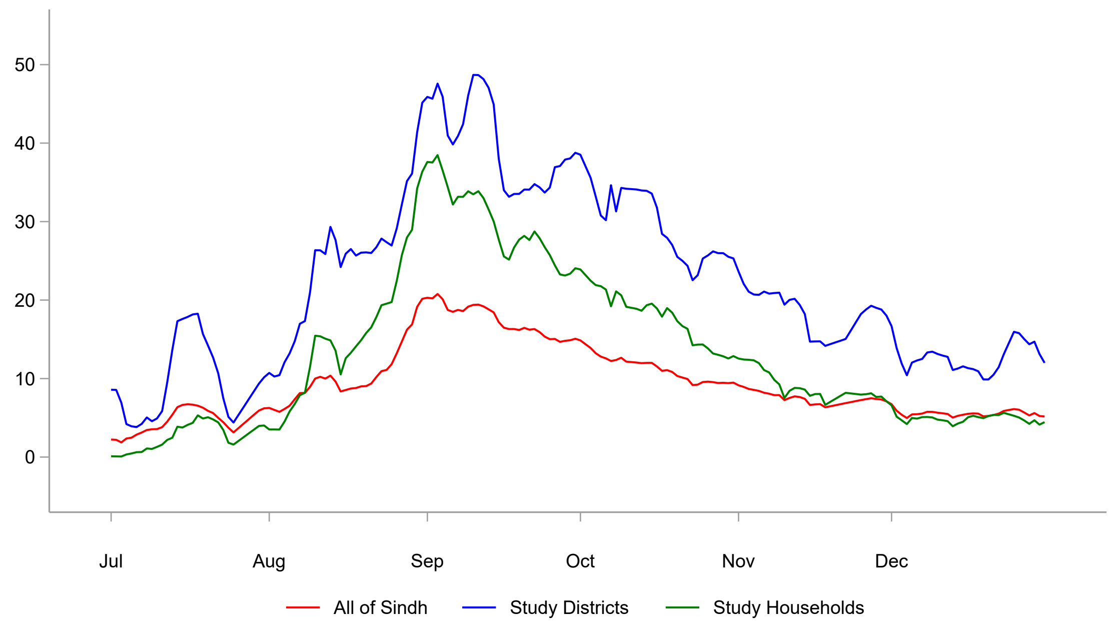
On July 27th 2022, the Pakistani Meteorological Department (PMD) declared the monsoon was almost over - weakening and moving northwards.[1] Two weeks later, an average 1200mm of rain fell within the span of one week across Sindh – one of the five provinces of Pakistan, located in the south of the country. As a consequence the province - which is predominantly low-lying and flat - faced widespread flooding.

Across the whole country these floods were of catastrophic proportions: the Government of Pakistan estimated the one in seven people were affected, and officially designated more than half of all districts impacted (**?**). Sindh was particularly affected: according to satellite data, flood extent in Sindh rose steadily throughout July and August, peaking at 21% of normally dry land being

[1] Express Tribune, Jul 27 2022

inundated at the start of September. The waters slowly receded over the next 4 months - with 15%, 9% and 7% still inundated at the start of October, November and December respectively.

Figure 1: Percentage of Land Flooded (Year 2022)

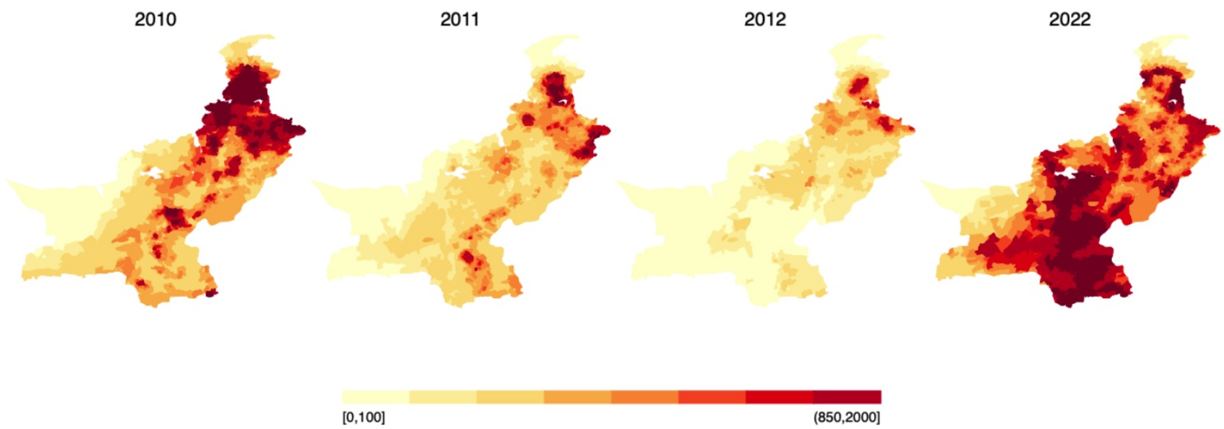


Notes: This figure plots the percentage of land flooded during 2022 for all of Sindh, for the six districts in our study sample, and for the households in our study sample. The y-axis shows the percentage of land area flooded, while the x-axis shows time from July to December 2022. The source of the data is NOAA NESDIS OSPO (2021), River and Surface Flood Map Products (RSVFM).

The areas of Sindh where we work - dictated by where our NGO partner operated - experienced more intense flooding on average - with 49% of land flooded at the peak in early September, dropping to 39%, 24% and 17% at the start of October, November and December respectively. This long duration is mirrored in self-reports in our survey data, where the average household reported flooding of 2.5 months, and for some the inundation lasted up to 7 months. The flooding was also deep - the average peak water depth reported by respondents was 3 feet.

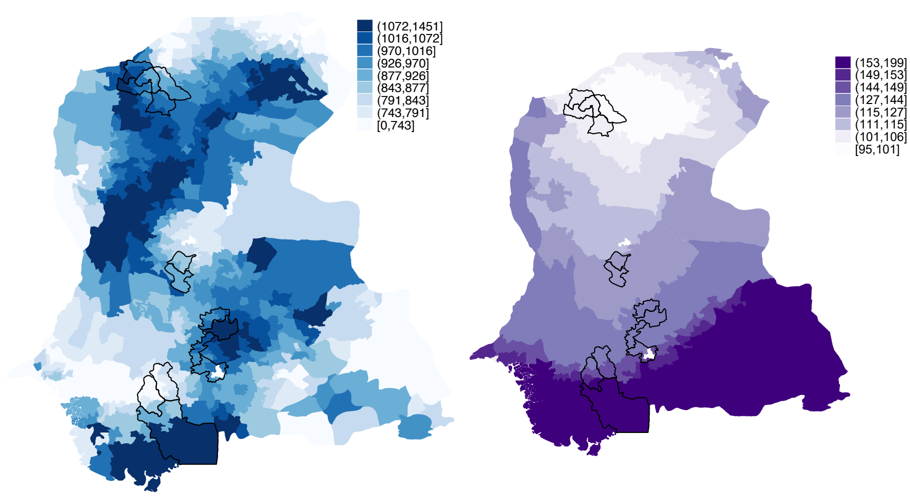
Although some areas of Pakistan regularly experience flooding, particularly those on the banks of the Indus river, this particular flood was unusual - driven by intense rains in places with low flood risk. Cumulatively that summer, Sindh received rain 531% above the 20-year average of rainfall for that time of year, and worse than the previous major flood years of 2010, 2011 and 2022 (Figure 2). Moreover, as Figure 3 the spatial pattern of rainfall varied vastly from historic patterns - heaviest in places which do not usually experience major flooding. Attribution studies have found that this rainfall was 75% more intense than it would have been without human-induced global warming.[2] Yet whilst the probability of such events is surely rising, only 11% of households in our sample thought unusually heavy rain was likely or very likely in the summer of 2022.

Figure 2: Cumulative monsoon rainfall during previous severe floods



Notes: NASA Global Precipitation Measurement (GPM)

Figure 3: 2022 monsoon rainfall (left) compared to historical average (right)



(a) Cumulative rainfall July - August 2022

(b) Average cumulative rainfall July-August, 2000-2022

Note: Tehsils included in our data collection are outlined in black polygons. Rainfall is measured in millimetres.
Source: NASA GPM.

[2]World Weather Attribution. 2022. "Climate Change Likely Increased Extreme Monsoon Rainfall, Flooding Highly Vulnerable Communities in Pakistan." https://www.worldweatherattribution.org/wp-content/uploads/Pakistan-floods-scientific-report.pdf

3 Research Design

3.1 Measuring Flood Intensity

To study the impact of flooding on outcomes, we must first measure flooding. Flooding can have multiple dimensions - extent, depth and duration. We therefore construct an index of flood intensity which captures all three. The index combines both satellite-derived measures and self-reported data from household surveys. From satellite data, we calculate: the maximum share of land flooded in a household's vicinity, and the number of days when various thresholds of surrounding land (>5%, >50%, >80%, >90%) were inundated. From self-reports we include: whether the village experienced flooding, whether rainfall was above average, peak flood water depth (in feet), and flood duration (in days). We combine these nine measures using the Anderson (2008) inverse variance-weighted index method.

The index shows substantial variation across our sample. The median household experienced flooding for 60 days with peak water depth of 3 feet. Table 3.1 shows how the components of the index differ by decile of the overall index value. Households in the bottom 10th percentile experienced 17 days of flooding with 1.5 feet of water, while those in the top decile faced 139 days with 4.7 feet of water.

Table 3.1: Average flooding by decile of flood index

Index Decile	Max Flooded	Flooded > 90 days	Flooded > 80 days	Flooded > 50 days	Flooded > 5 days	Flood Depth (Feet)	Flood Length (Days)
1	16.4	0.0	0.0	0.6	25.7	1.5	16.9
2	31.6	0.0	1.0	6.4	60.6	1.8	35.7
3	39.1	0.0	1.7	9.7	74.0	2.1	48.2
4	43.3	0.1	3.2	11.5	93.8	2.4	56.3
5	50.2	0.1	1.9	12.3	118.3	2.7	60.7
6	55.3	0.1	2.0	13.3	123.1	3.0	76.8
7	58.2	0.2	2.1	17.1	127.5	3.4	87.7
8	62.7	0.1	2.8	21.4	133.9	3.8	101.6
9	69.1	0.3	7.2	30.9	137.0	4.0	121.1
10	80.3	7.4	18.9	48.5	144.1	4.7	138.8

Notes: This table presents average values of flood index components across deciles of the overall flood index. Decile 1 represents areas with the lowest flood intensity, while decile 10 represents the most severely flooded areas. The flood index is a standardized composite measure combining seven indicators. Columns 2-6 report satellite-derived measures: maximum percentage of area flooded, and percentage of area flooded for various duration thresholds (>90 days, >80 days, >50 days, and >5 days). Columns 7-8 report household self-reported measures: flood depth in feet and flood duration in days.

Table 3.2 contains a Shapley decomposition of the index, showing which components drive most of the variation in our treatment. Self-reported flood duration is the largest contributor (26.1%), but the remaining variation is distributed fairly evenly across measures of flood extent, depth, and duration, with each measure explaining at least 8.7%. This indicates that our flood index is driven by all three dimensions of flood intensity—extent, depth, and duration—with relatively balanced contributions from each, though duration plays the strongest role.

Table 3.2: Shorrocks-Shapley Decomposition of R-Squared

Variable	Contribution (%)
Flood duration (days)	26.13
Max share of land flooded around HH	9.68
N days when > 5 pct surrounded land flooded	15.22
N days when > 50 pct surrounded land flooded	8.70
N days when > 80 pct surrounded land flooded	10.54
N days when > 90 pct surrounded land flooded	15.69
Peak flood water depth (feet)	14.03

In our analysis, we use this flood intensity index both as a continuous standardised variable. In robustness checks we examine heterogeneous effects across flood intensity quintiles to capture potential non-linearities.

3.2 Identification Challenges

Estimating the causal effect of flooding on economic outcomes faces several identification challenges that could bias results in either direction. Areas with higher historical rainfall systematically may receive more precipitation in 2022 and therefore experience more flooding. These same areas often have higher agricultural productivity due to better water availability. In this case, we would underestimate flood impacts. Similarly, flatter areas are more prone to flooding but also tend to have higher agricultural productivity, again biasing estimates downward.

Conversely, other factors may lead us to overestimate flood impacts. Areas with high flood risk experience may experience more flooding in 2022 but may already be poorer due to past climate shocks or selective out-migration of wealthier households. Additionally, our results may be biased by adaptative investments: wealthier areas can afford flood protection infrastructure (or drainage), reducing their flood exposure while maintaining better economic outcomes, making floods appear more devastating than they actually are.

To address these concerns, we are in the process of implementing additional analysis using a re-centered instruments approach following (Borusyak and Hull, 2023). This paper, contains preliminary results using a simplified IV design that aims to approximate the (Borusyak and Hull, 2023) approach. Our current IV approach attempts to control for systematic flood risk factors (topography, historical rainfall patterns, baseline flood risk) while using their interaction with the 2022 rainfall shock to instrument for realised flooding—though this may not fully separate expected from unexpected flood exposure as cleanly as the full recentering procedure. We describe here both our eventual research design, and the current research design.

3.3 *In Progress*: Recentered Instrumental Variables Approach

Our identification concerns stem from the fundamental challenge that flooding is not randomly distributed across space. The flooding generation process can be approximated[3] as:

$$\text{FLOODING}_t = \sum_{l=0}^{\infty} F^l \tilde{R}_{t-l} + \varepsilon_t \tag{1}$$

Here R_{t-l} is the vector of rainfall that falls in each location at time $t-l$. Whilst F is the hydrological flow matrix - analogous to a Markov transition matrix in economic models. Each element F_{ij} captures the proportion of water that flows from location i to location j in each time period. The matrix is derived from digital elevation models: water flows from higher to lower elevations following the steepest gradient. F^l captures multi-period flow accumulation. Rain falling upstream affects downstream areas with a lag, and the infinite sum reflects how water accumulates as it moves through the watershed network. This spatial interdependence means that flooding at any location depends on the entire rainfall vector $\tilde{R}$ across all upstream areas, weighted by their position in the flow network.

Expressing flooding like this allows us to see that flooding is determined by a sort of 'formula', which combines some shifts (rainfall) with some shares (the flow matrix). This therefore suggests using a shift-share IV approach to instrument for flooding.

While rainfall R is stochastic, its realization at time t is not exogenous with respect to the drivers of economic outcomes. Rainfall in any given year is correlated with underlying local climate patterns, which have shaped long-run economic development, infrastructure investments, and adaptation strategies. To extract the exogenous component of rainfall we consider several approaches, each of which makes an assumption about how economic agents form and respond to rainfall expectations.

1. **Deviations from average rainfall**: $\widetilde{\text{RAIN}}_t = \text{RAIN}_t - \overline{\text{RAIN}}$, which assumes agents have adapted to long-run average conditions

[3]The true workings of a hydrological model are not linear, but the approach here can also be applied to non-linear shift-share instruments. We therefore work with a linear approximation here for simplicity

2. **standardised deviations**: $\widetilde{\text{RAIN}}_t = \frac{\text{RAIN}_t - \overline{\text{RAIN}}}{\sigma_{\text{RAIN}}}$, which accounts for the fact that a given deviation may be more surprising in areas with historically stable rainfall

3. **Residuals from a more flexible expectations model, e.g.**:

$$\widetilde{\text{RAIN}}_t = \hat{\varepsilon}_i = \text{RAIN}_t - \hat{\beta}_1 \overline{\text{RAIN}} - \hat{\beta}_2 \sum_{t=0}^{10} \text{RAIN}_{t-i} \tag{2}$$

Once we have extracted the surprise component of rainfall, we must address the 'exposure problem' discussed in (Borusyak and Hull, 2023). Given any rainfall realisation, some areas will systematically flood more than others due to their position in the flow network captured by F. An area at the bottom of a watershed will experience more flooding than one at the top, regardless of the rainfall shock realization.

The flow matrix F is inherently correlated with economic fundamentals: productive agricultural areas are often located in floodplains with specific topographical features, while drainage and waterway patterns both influence and are influenced by human settlement and economic activity. This creates a fundamental identification challenge—locations with high values in F (those receiving water from many upstream areas) may systematically differ in both their flood exposure and their economic potential. Even random rainfall shocks are transformed by F into non-random flooding patterns that correlate with pre-existing economic conditions.

To address this exposure problem, we implement a recentered instrumental variables approach. Our first stage becomes:

$$\text{FLOOD}_t = \sum_{l=0}^{\infty} F^l \cdot \tilde{R}_{t-l} - E\left[\sum_{l=0}^{\infty} F^l \cdot \tilde{R}_{t-l}\right] \tag{3}$$

where the expected exposure term is calculated by simulating flooding under alternative rainfall realizations. This recentering removes the systematic component of flood exposure that derives from position in the flow network, leaving only the variation due to the current year's rainfall shock. This approach ensures our instrumental variable exploits only the quasi-random variation in flooding intensity conditional on systematic flood risk.

3.4 *Current Approach*: IV with controls

Whilst our analysis using recentered instruments is underway, this paper contains preliminary results using a simplified IV design that aims to approximate the (Borusyak and Hull, 2023) approach.

As described above, our primary concern is that factors which lead to flooding (climate, topography and flood risk) are correlated with (unobserved) outcomes in the absence of flooding - for example through agricultural productivity.

Our initial estimates seek to address these concerns by controlling directly for proxies of these factors. For topography, we include the share of land within a 5km buffer that is flat (defined as having a gradient below 0.1 degrees). We control for historical rainfall patterns using average July-August rainfall from 2001 to 2021. We also include cumulative monsoon rainfall from 2022. To account for baseline flood risk, we incorporate both fluvial and pluvial flood risk measures from the Fathom flood risk model. All specifications include district fixed effects. For individual-level regressions, we additionally control for age and sex.

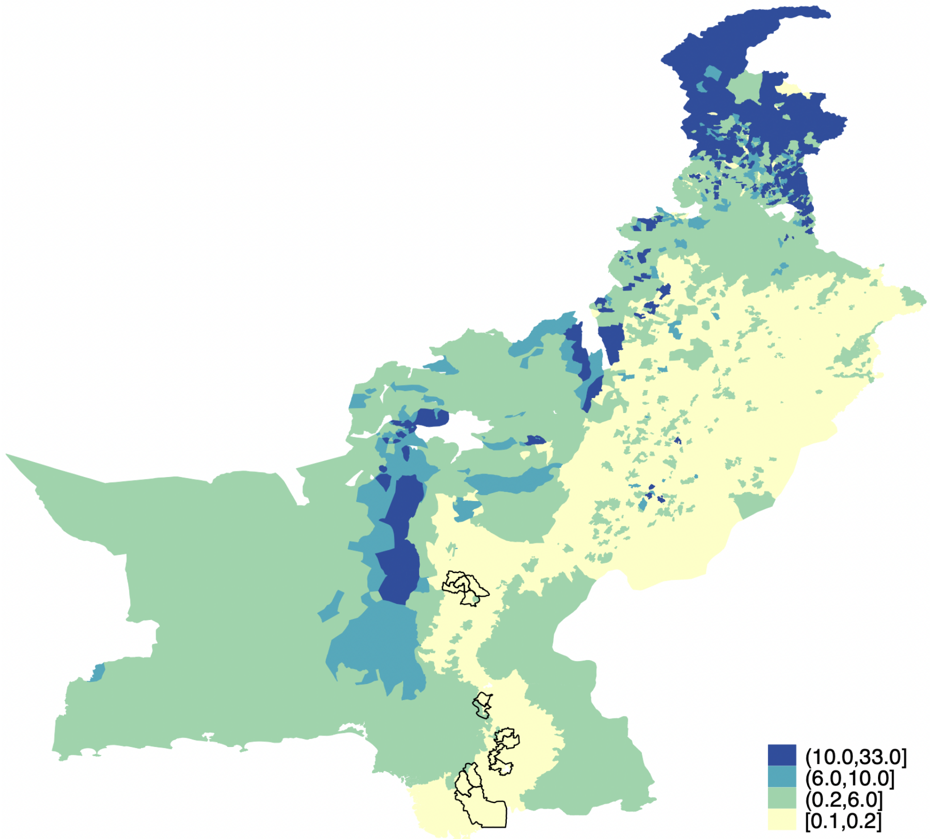
The controls included above leave one key concern unaddressed: adaptation. Wealthier areas may be able to afford better infrastructure which protects against floods (either intentionally or unintentionally, as in the case of irrigation canals and drainage), reducing their flood exposure while maintaining better economic outcomes, making floods appear more devastating than they actually are.

To address this, we would like to extract the component of realised flooding which is driven by 'natural' factors rather than human intervention. For our preliminary analysis, we therefore instrument for local flooding using the interaction of 2022 rainfall with pre-flood topography, controlling for historical rainfall patterns, topography, flood risk and district fixed effects. By 2022 rainfall, we mean the cumulative rain that fell in a 5km area around a household over the months July - August 2022, and by pre-flood topography we mean the share of land in that same buffer which is flat (has a gradient of less than 0.1°).

Intuitively, we exploit that that extreme rainfall on flat terrain leads to more severe flooding, while rainfall on sloped areas drains more quickly. This instrument can be thought of as a simplification of the predictions from a hydrological model, which would simulate rainfall flowing over the surface of the land, and would predict that water would accumulate in those areas which are flattest.

Importantly, Sindh is predominantly low-lying and flat. Figure 4 shows gradient across the entirety of Pakistan, with the boundaries of our study areas in black. The area enclosed by these polygons almost entirely very flat (coloured in yellow). As a result, we are exploiting very granular local variation in the slope of land rather than large topographical differences such as comparing mountains to valleys.

Figure 4: The land in our study areas (black outlines) is predominantly flat



Note: Tehsils included in our data collection are outlined in black polygons.
Source: Amatulli et al. (2018), A suite of global, cross-scale topographic variables for environmental and biodiversity modeling, Scientific Data, 5:180040.

Our first stage regression is:

$$\begin{aligned} \text{FLOOD}_{it} = \alpha + \beta_1(\text{RAIN2022}_i \times \text{FLAT}_i) + \beta_2\text{FLAT}_i + \beta_3\text{RAIN2022}_i \\ + \phi\text{RISK}_i + \theta\text{HISTRAIN}_{it} + \psi\text{DISTRICT}_i + \epsilon_{it} \end{aligned} \tag{4}$$

Where we regress $FLOOD_{it}$ (a standardised index combining satellite and self-reported flooding measures) on the instrument $RAIN2022_i \times FLAT_i$, where $RAIN2022_i$ is total July-August 2022 rainfall (mm) and $FLAT_i$ is the share of land with gradient less than 0.1°. We control for $RISK_i$ (fluvial flood risk quintiles and above/below median pluvial risk), $HISTRAIN_{it}$ (average July-August rainfall 2001-2021), plus district fixed effects. All variables use 5km buffers around households' 2017 coordinates. Standard errors are clustered at the settlement level.

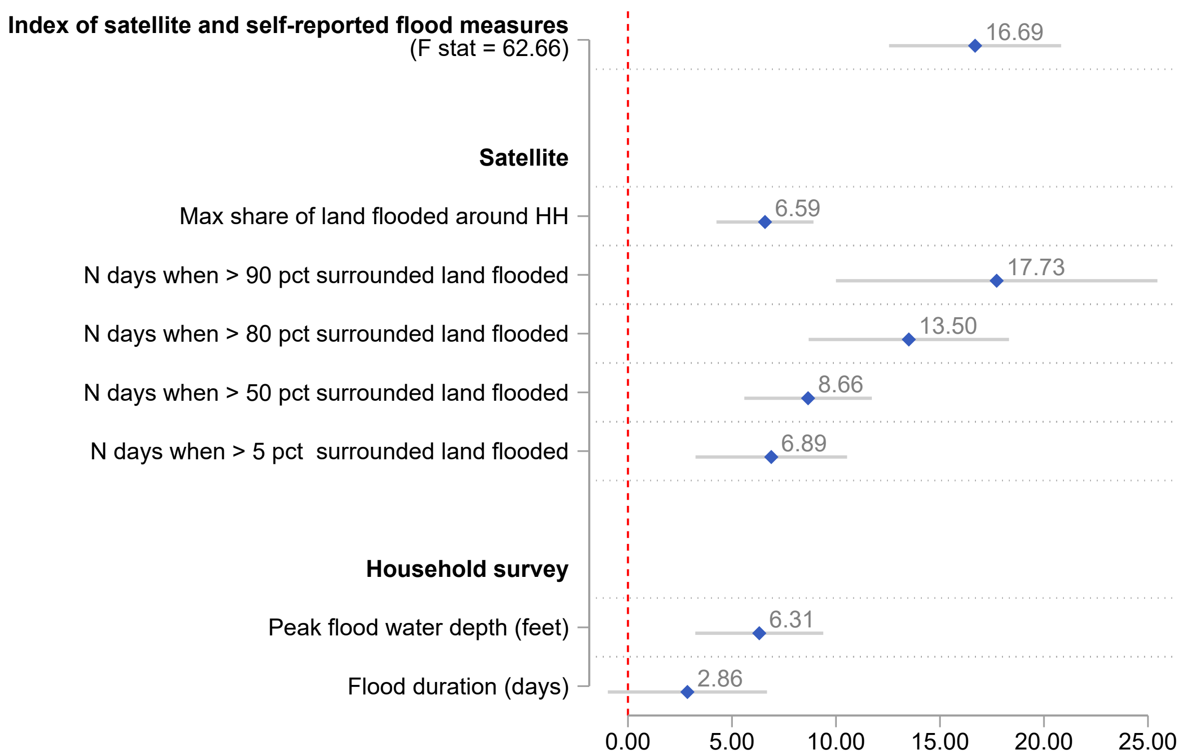
Our second stage is

$$Y_{it} = \mu + \gamma_1 \widehat{\text{FLOOD}}_{it} + \gamma_2 \text{FLAT}_i + \gamma_3 \text{RAIN2022}_i + \lambda \text{RISK}_i + \omega \text{HISTRAIN}_{it} + \kappa \text{DISTRICT}_i + \xi_{it} \tag{5}$$

Where Y_{it} is the outcome of interest and $\widehat{FLOOD}_{it}$, is the predicted flood index from the first stage. In these equations, i indexes either households or individuals depending on the outcome of interest, for example labour market outcomes are measured at the individual level, while asset ownership and consumption outcomes are measured for the household.

Our first stage is strong (F=59), with the rainfall × flat land interaction explaining substantial variation in flood exposure. Figure 5 shows that our instrument significantly predicts all components of the flood index, moving each in the expected direction. This confirms that our topography-rainfall interaction captures flooding across multiple dimensions of the disaster experience.

Figure 5: First stage from preliminary IV



F stat is Sanderson-Windmeijer F stat

4 Results

This section reports results from our preliminary research design - namely, difference-in-differences results where possible, and IV estimates where pre-flood data is unavailable. We are currently implementing a revised IV approach based on (Borusyak and Hull, 2023)'s recentered instruments, and results are subject to change. Despite these caveats, our preliminary findings reveal clear patterns in how flood impacts evolve over the medium term.

4.1 Physical Destruction

In section 2 we showed that the 2022 floods covered a very large area of land and lasted a very long time. This caused widespread destruction of the types we typically see after disasters - to housing, crops and infrastructure.

In simple terms, flood waters can damage physical structures through the force of water passing by at speed, or by saturation. Most (58%) households in our study had houses made from mud brick before the floods - making them particularly vulnerable. According to official administrative records, 43%[4] of our sample of 5,100 households experienced housing damage. Self-reported rates are higher - 95% reported some damage to their residential property, and 42% reported that their home was fully destroyed.

Flood waters also destroyed crops in the field - 35% of households reported crop destruction - and damaged livestock - 59% of those who owned livestock prior to the floods reported that their livestock was injured, fell sick, lost, killed or otherwise negatively impacted.

These patterns were mirrored nationwide: official assessments documented $14.9 billion in physical damage to housing, infrastructure and agriculture across Pakistan, with 61% occurring in Sindh (including 1.4 million homes completely destroyed).[5]

[4] This figure is based on the share of households that we were able to match to administrative data on damages. Only households with damage are recorded in the administrative data, so if we cannot match a household it means either that they did not experience damage, or that the ID number recorded in our survey does not match what was reported to the government. 43% is therefore a lower bound on the share of households in our sample who experienced officially recorded damages.

[5] Government of Pakistan. Pakistan Floods 2022: Post-Disaster Needs Assessment (PDNA) – Main Report. Islamabad: Ministry of Planning, Development & Special Initiatives, October 2022. Accessed 23 October 2025. https://thedocs.worldbank.org/en/doc/4a0114eb7d1cecbbbf2f65c5ce0789db-0310012022/original/Pakistan-Floods-2022-PDNA-Main-Report.pdf

Table 4.1: IV estimates: Damages to housing and livestock

	(1) House fully damaged	(2) Livestock or land damaged
Flood Index	0.213***	0.237***
	(0.066)	(0.070)
Observations	2026	2439
Control group mean	0.62	0.57
F stat	31.33	32.61

Notes: Column 1 of this table is based on households in our balanced panel that were matched with the government's housing damage admin records. It shows official records of households classified as having fully destroyed houses. Column 2 includes all households that reported owning livestock or land and having reported damages to these assets. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As shown in Table 4.1, our IV estimates find that more flooded households are more likely to experience physical damage. Among households in the bottom 10th percentile of flooding, 66% had their homes fully destroyed according to administrative records. Each standard deviation increase in flood intensity raises this probability by 21.3 percentage points (p<0.01). Similarly, 57% of the least flooded households experienced damage to either livestock or land (conditional on owning these assets pre-flood), increasing by 23.7 percentage points per standard deviation of flooding (p<0.01). These estimates confirm that our flood intensity measure captures meaningful variation in physical destruction, with more heavily flooded areas experiencing substantially greater damage to both housing and productive assets.

4.2 Economic disruption

Beyond destroying physical assets, flooding created a web of economic disruptions that affected people's ability to work and earn income. Understanding these multiple pathways is crucial for interpreting the labour market dynamics that followed.

Many workers were temporarily displaced from their normal place of residence. 40% of households evacuated away from their normal place of residence, for an average of 23 days[6], predom-

[6] The majority stayed, primarily to protect their land, property and livestock.

inantly to the nearest area of dry land (rather than to "official" camps). Among the least flooded households (bottom 10th percentile), 38% evacuated, increasing by 11.8 percentage points for each standard deviation of flood intensity (p<0.05).

Table 4.2: Displacement and disruption to trade

	(1) **Any member evacuated**	(2) **Any TP Inaccesible**	(3) **Length TPs Inaccesible**
Flood Index	0.118**	-0.196***	-16.635***
	(0.049)	(0.054)	(4.807)
Observations	4684	4684	4684
Control group mean	0.35	0.84	43.10
F stat	44.37	44.37	44.37

Notes: The sample consists of all households in our balanced panel data. Column 1 indicates whether any member of the household evacuated their house. TP refers to trade partners. Column 1 also reports whether any trade partners were inaccessible, while Column 2 shows the number of days at least one trade partner was inaccessible (0 if all trade partners remained accessible). The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Roads were inundated - impeding travel to work and markets. As a result, 81% of households were cut off from at least one trading partner - defined as somewhere that people from this village normally go to for buying and selling goods, work, education or healthcare. Amongst those who had at least one trade partner flooded, it took an average of 43 days for access to return to normal.

The spatial distribution of flooding was such that we find that a households own intensity of flooding is negatively correlated with flooding of trade partners (Table 4.2). Among households in the bottom 10th percentile of flood intensity, 86% had at least one trading partner that was inaccessible, falling by 19.6 percentage points per standard deviation increase in flooding (p<0.01). Similarly, it took an average of 45.5 days for normal trade to resume in the bottom 10th percentile, falling by 16.6 days for each standard deviation increase (p<0.01).

4.3 Household outcomes 1 year after flood onset

Despite the physical destruction documented above, we find little difference in consumption and well-being between more and less flooded households in the one year after the onset of the floods, when we fielded our first wave of surveys. As shown in Table 4.3 total household expenditure shows a modest difference between flooded and less flooded areas. Among households in the bottom 10th percentile of flooding, average monthly expenditure was 10,830PKR. Each standard deviation increase in flood intensity is associated with a 806PKR decrease in expenditure (p>0.10). However, Figure 6 shows that we do not find statistically significant differences in the CDF of consumption by flood intensity. We also find no statistically significant differences in households food expenditure over the last 7 days, or health expenditure in the last 12 months.

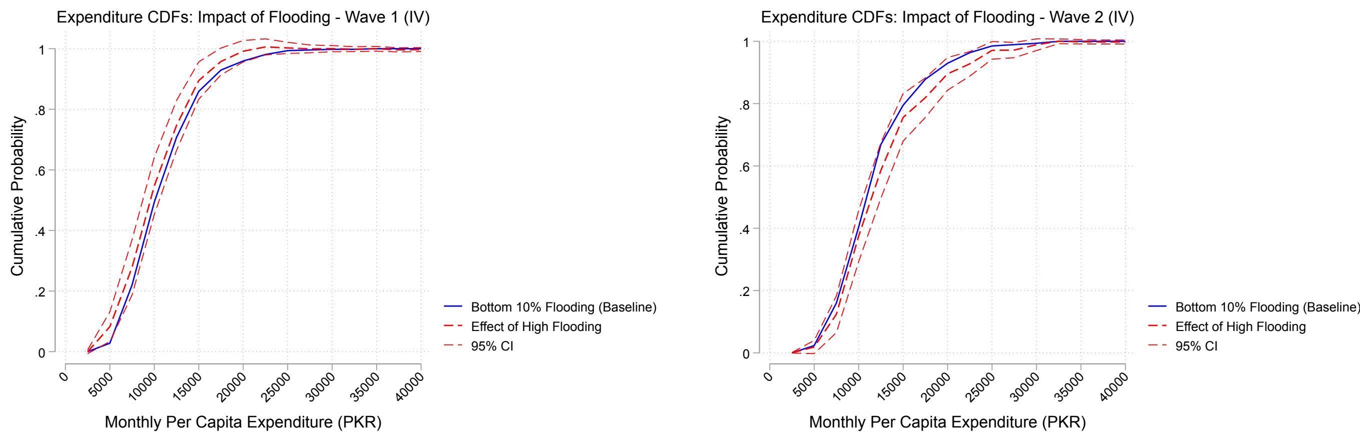
Table 4.3: Year 1: Consumption and unmet needs

	(1) Monthly expenditure	(2) Weekly food expenditure	(3) Annual health expenditure	(4) Reduced food spending	(5) Reduced non-food spending	(6) Skipped healthcare	(7) Health index	(8) Mental health score
Flood Index	-805.501*	-25.764	-877.435	-0.076**	-0.110***	-0.171***	0.082	-0.953
	(470.159)	(45.266)	(1641.744)	(0.034)	(0.038)	(0.058)	(0.100)	(0.680)
Observations	4684	4684	4684	4684	4684	4684	4684	2318
Control group mean	10829.23	482.58	14337.94	0.92	0.91	0.65	0.04	17.22
F stat	44.37	44.37	44.37	44.37	44.37	44.37	44.37	35.33

Notes: The sample consists of all households in our balanced panel data. Column 1 shows the household's monthly total expenditure. Column 2 shows weekly total household expenditure on food, while Column 3 shows annual total health expenditure. All expenditure variables are in PKR and are equivalised by the number of household members. Column 4 shows whether households reduced food spending by lowering food quality or quantity. Column 5 shows whether they reduced non-food spending to make ends meet. Column 6 shows whether households delayed, skipped, or were unable to complete healthcare visits. Column 7 shows a health index constructed using various types of diseases reported by households. Column 8 shows whether the respondent has severe mental distress as measured using the Kessler-6 mental health scale. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

More flooded households report lower rates of consumption-smoothing behaviors. Among the least flooded households, 91% reported reducing food spending to make ends meet in the year prior to survey. This rate falls by 7.6 percentage points for each standard deviation increase in flooding (p<0.01). We find similar patterns for other coping strategies: 63% of least flooded households skipped healthcare to save money, falling by 17.1 percentage points per SD of flooding (p<0.01), while 91% reduced non-food expenditure to afford essentials, declining by 11.0 percentage points per SD (p<0.01). Neither our standardised index of disease incidence nor the probability of experiencing severe mental distress (measured using Kessler-6) show significant differences by flood intensity.

Figure 6: Impact of Flooding on Equivalised Household Expenditure Distribution



These findings raise the question of how households were able to smooth consumption in the face of such a negative economic shock. We first examine labour supply.

More flooded areas experienced substantial declines in employment, as shown in Table 4.4. Among individuals in the least flooded areas (bottom 10th percentile), 51.6% were engaged in paid work. Each standard deviation increase in flooding reduces employment probability by 7.0 percentage points (p<0.01).[7] As shown in Panel C of Table 4.4 these effects are concentrated among agricultural workers, suggesting that the inundation of fields - visible in our satellite data - depressed demand for farm labour.

This employment effect is also concentrated among men. Male employment in the least flooded areas stands at 81.8%, falling by 9.0 percentage points per standard deviation of flooding (p<0.01). The decline in male employment is driven primarily by a reduction in casual labour, where employment falls by 15.0 percentage points per SD of flooding (p<0.01). This is partially offset by an increase in self-employment of 8.0 percentage points per SD (p<0.01).

[7]This is one of the few outcomes where we have pre-flood data available. Robustness checks show that our estimates are consistent across OLS and DiD specifications, with IV estimates being larger—consistent with these representing a local average treatment effect.

Table 4.4: Year 1: Individual Labour Outcomes

Panel A: *Men and Women*

	(1) Paid Work	(2) Casual Work	(3) Self Employed	(4) Total Wage	(5) Works Outside Village
Flood Index	-0.07***	-0.09***	0.03*	3,494.40***	0.03*
	(0.03)	(0.03)	(0.02)	(800.00)	(0.02)
Observations	14696	14696	14696	7304	14696
Control group mean	0.516	0.422	0.0697	10119.9	0.0861
F stat	46.54	46.54	46.54	46.34	46.54

Panel B: *Men Only*

	(1)	(2)	(3)	(4)	(5)
Flood Index	-0.09***	-0.15***	0.08***	3,653.68***	0.06*
	(0.03)	(0.04)	(0.03)	(863.12)	(0.03)
Observations	7823	7823	7823	6206	7823
Control group mean	0.818	0.707	0.0644	11439.4	0.153
F stat	43.32	43.32	43.32	41.34	43.32

Panel C: *Men and Women in paid agriculture work*

	(1)	(2)	(3)	(4)	(5)
Flood Index	-0.01	-0.21***	0.20***	3,624.83***	0.04
	(0.01)	(0.05)	(0.04)	(865.77)	(0.03)
Observations	4005	4005	4005	3907	4005
Control group mean	0.987	0.865	0.109	10397.3	0.0985
F stat	49.74	49.74	49.74	48.97	49.74

Panel D: *Men and Women in paid non-agriculture work*

	(1)	(2)	(3)	(4)	(5)
Flood Index	0.00	0.13*	-0.02	2,531.84*	0.05
	(0.03)	(0.08)	(0.05)	(1376.01)	(0.08)
Observations	3385	3385	3385	3205	3385
Control group mean	0.951	0.689	0.171	10200.9	0.255
F stat	16.67	16.67	16.67	16.94	16.67
Controls for age and sex	✓	✓	✓	✓	✓

Notes: For Panel A, the sample consists of all working-age adults in our balanced panel data. For Panel B, the sample consists of all working-age men in our balanced panel data. Panel C includes all working-age adults engaged in paid agricultural work, and Panel D includes all working-age adults engaged in paid non-agricultural work. Column 1 shows whether individuals are in paid work. Column 2 shows whether they are employed in casual work, while Column 3 shows whether they are self-employed. Column 4 shows total wages in PKR, conditional on being in paid work. Column 5 shows whether individuals work outside the village or take work trips outside the village. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for age, gender, and district fixed effects. Standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Those who remain employed in more flooded areas have higher monthly labour income but travel further to find work. Monthly wages among employed individuals in the least flooded areas average 10119 PKR. Each standard deviation increase in flooding is associated with 3494PKR higher wages (p<0.01). This wage premium comes with increased commuting: 9% of workers in the least flooded areas work outside their village, rising by 3 percentage points per SD of flooding (p<0.10). This effect is driven by men, of which 15% in the least flooded areas work outside the village, rising by 6ppts for each SD of flooding (p<0.10). At the household level, 21% of least flooded households report that members travelled further to find work in the past 12 months, increasing by 10 percentage points per SD of flooding (Table 4.5).

Table 4.5: Year 1: Household self-reported use of labour supply as a coping strategy

	(1) **Increase labour supply**	(2) **Travelled further for work**
Flood Index	-0.024	0.098*
	(0.057)	(0.050)
Observations	4684	4684
Control group mean	0.38	0.20
F stat	44.37	44.37

Notes: The sample consists of households in our balanced panel data. Column 1 shows whether households reported increasing work or business activities, including sending household members who were not working before to look for work. Column 2 shows whether households reported travelling further to find work outside their village. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These results suggest that labour earnings alone cannot explain how households maintained consumption levels following the floods. We therefore examine other potential mechanisms.

More flooded households had greater access to formal flood relief (Table 4.6). Among the least flooded households, 24% reported receiving any type of flood relief during the floods. This increases by 23 percentage points for each standard deviation increase in flooding (p<0.01). Food aid (both formal aid and gifts from others) reached 16% of the least flooded, rising by 10.6 percentage points per SD of flooding (p<0.01).

Table 4.6: Year 1: Aid

	(1) Received any flood relief	(2) Received food aid	(3) Received BISP ever	(4) Received other SP post-floods	(5) Received BISP or other SP post-floods
Flood Index	0.230***	0.106**	0.044	-0.056	0.043*
	(0.072)	(0.045)	(0.045)	(0.037)	(0.026)
Observations	4318	4684	4684	4684	4684
Control group mean	0.24	0.16	0.60	0.19	0.06
F stat	29.62	44.37	44.37	44.37	44.37

Notes: The sample consists of households in our balanced panel data. Column 1 shows whether households reported receiving any type of flood relief. Column 2 shows whether households reported receiving any type of food aid or food as gifts. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we examine financial coping strategies—selling assets, drawing down savings, and taking new loans. While these strategies are fairly common in our sample, we find no statistically significant differences by flood status in the probability that households spend savings, take new loans, or skip bill payments, as shown in Table 4.7. More flooded households were, however, more likely to sell household assets such as cooking equipment, fans, and other domestic items. Among the least flooded households, 4% report making such sales, rising by 5 percentage points per SD of flooding (p<0.10). We find no differential effect for sales of productive assets like livestock or agricultural equipment, perhaps because these were more likely to have been damaged in flooded areas, as shown in Table 4.1.

Table 4.7: Year 1: Financial Coping

	(1) **Spent savings**	(2) **Took new loans**	(3) **Non-payment of bills**	(4) **Sold any assets**	(5) **Sold productive assets**	(6) **Sold household assets**
Flood Index	-0.035	-0.065	-0.064	0.039	-0.011	0.053*
	(0.046)	(0.048)	(0.054)	(0.039)	(0.049)	(0.030)
Observations	4684	4684	4684	4684	3193	3762
Control group mean	0.61	0.49	0.19	0.18	0.15	0.08
F stat	44.37	44.37	44.37	44.37	39.23	38.17

Notes: The sample consists of households in our balanced panel data for Columns 1 to 4, and of households who owned the relevant category of assets in 2017 for Columns 5 and 6. Column 1 shows whether households reported spending their savings as a coping mechanism. Column 2 shows whether households reported taking new loans to cope with the floods. Column 3 shows whether households reported non-payment of bills as a coping strategy. Column 4 shows whether households reported selling any assets. Column 5 shows whether households sold productive assets, and Column 6 shows whether they sold household assets. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

More flooded households have depleted asset stocks—likely due to both damage and sales (Table 4.8). Using a standardized index of asset holdings across 21 categories, we find that a one standard deviation increase in flooding is associated with a 0.13 standard deviation reduction in asset holdings (p<0.10). However, the likelihood of having savings increases by 19 percentage points for each standard deviation of flooding (from a very low base of 2% among the least flooded). We find no statistically significant difference in debt prevalence, though debt is common across all households, with 76% of the least flooded reporting some debt.

Table 4.8: Year 1: Assets

	(1) **Asset index**	(2) **HH has debt**	(3) **HH has savings**
Flood Index	-0.132*	-0.007	0.192***
	(0.080)	(0.042)	(0.039)
Observations	4684	4684	4684
Control group mean	-0.08	0.76	0.02
F stat	44.37	44.37	44.37

Notes: The sample consists of households in our balanced panel data. Column 1 shows asset index which is constructed using 24 assets ownership. Column 2 shows whether household had any outstanding debt in the year. Column 3 shows whether household had any savings. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Household outcomes 2 years after flood onset

Two years after the floods, aggregate consumption measures remain similar between more and less flooded households (Table 4.9). While average total expenditure is higher among more flooded households (+977 PKR per SD of flooding on a base of 11,808 PKR per month), Figure 6 shows we cannot reject that the distribution of expenditure is the same across flood intensity levels. Food consumption shows no statistically significant difference between more and less flooded households.

Despite maintaining similar consumption levels, more flooded households increasingly report unmet needs. Among the least flooded, 92% report cutting food expenditure to make ends meet, rising by 9.9 percentage points per SD of flooding (p<0.01). Similarly, 91% report cutting non-food expenditure, increasing by 11.3 percentage points per SD (p<0.01). We can look in more detail at one category of non-food expenditure: healthcare. More flooded households report skipping healthcare to save money (60% of the least flooded, increasing by 20.7 percentage points per SD, p<0.01), yet simultaneously spend more on healthcare (20,386 PKR among the least flooded, rising by 11,010 PKR per SD, p<0.10).

Table 4.9: Year 2: Consumption and unmet needs

	(1) Monthly expenditure	(2) Weekly food expenditure	(3) Annual health expenditure	(4) Reduced food spending	(5) Reduced non-food spending	(6) Skipped healthcare	(7) Health index	(8) Mental health score
Flood Index	977.067**	-25.151	11009.195***	0.099***	0.113***	0.207***	0.082	-0.953
	(487.743)	(43.087)	(3168.549)	(0.029)	(0.029)	(0.059)	(0.100)	(0.680)
Observations	4684	4684	4684	4684	4684	4683	4684	2318
Control group mean	11807.65	508.62	20385.62	0.92	0.91	0.60	0.04	17.22
F stat	44.37	44.37	44.37	44.37	44.37	44.33	44.37	35.33

Notes: The sample consists of all households in our balanced panel data. Column 1 shows the household's monthly total expenditure. Column 2 shows weekly total household expenditure on food, while Column 3 shows annual total health expenditure. All expenditure variables are in PKR and are equivalised by the number of household members. Column 4 shows whether households reduced food spending by lowering food quality or quantity. Column 5 shows whether they reduced non-food spending to make ends meet. Column 6 shows whether households delayed, skipped, or were unable to complete healthcare visits. Column 7 shows a health index constructed using various types of diseases reported by households. Column 8 shows whether the female respondent has severe mental distress as measured using the Kessler-6 mental health scale. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These results suggest that while more flooded households appear to maintain similar consumption to their less flooded counterparts 2 years after the floods - they face higher needs they find difficult to meet within their budgets. Consistent with this interpretation, we find a growing gap in health and mental health by flood status. Self-reported health status declines by 0.4 standard deviations per SD of flooding (p<0.01). Mental health scores for men show no systematic differences between groups, the probability that the female respondent has severe mental distress increases by 11ppts for each SD of flooding, on a base of 20% in the least flooded households.

Why have these gaps opened up? While employment rates no longer differ significantly by flood intensity, two years after the floods working adults in more flooded areas earn lower wages (Table 4.10). Monthly wages averaged 12849 PKR in the least flooded areas, falling by 1,709 PKR per SD of flooding (p<0.01), contrasting with the wage premium observed in Wave 1. Figure 7 shows this is driven by workers in more flooded households being less likely to earn in the top of the wage distribution, whilst Figure 8 shows this pattern remains when looking at all individuals, regardless of whether or not they are in work. These estimates suggest this reflects lower hourly wages rather than fewer hours worked, though these estimates are imprecise.

Table 4.10: Year 2: Individual Labour Outcomes

Panel A: *Men and Women*

	(1) Paid Work	(2) Casual Work	(3) Self Employed	(4) Total Wage	(5) Works Outside Village	(6) Monthly Hours Worked	(7) Hourly Wage
Flood Index	0.03	0.03	-0.01	-1,709.31***	-0.02	-7.77	-7.16
	(0.02)	(0.03)	(0.01)	(597.50)	(0.04)	(7.82)	(5.45)
Observations	14271	14271	14271	6679	14271	7154	6676
Control group mean	0.473	0.371	0.0575	12848.6	0.188	180.4	77.99
F stat	44.11	44.11	44.11	38.86	44.11	41.12	38.74

Panel B: *Men Only*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Flood Index	0.02	0.05	-0.04*	-2,109.50***	-0.00	-10.93	-5.35
	(0.03)	(0.04)	(0.02)	(646.81)	(0.04)	(8.32)	(4.62)
Observations	7735	7735	7735	5610	7735	5971	5608
Control group mean	0.773	0.612	0.0836	13999.5	0.200	193.3	77.58
F stat	41.91	41.91	41.91	40.47	41.91	42.64	40.34

Panel C: *Men and Women in paid agriculture work*

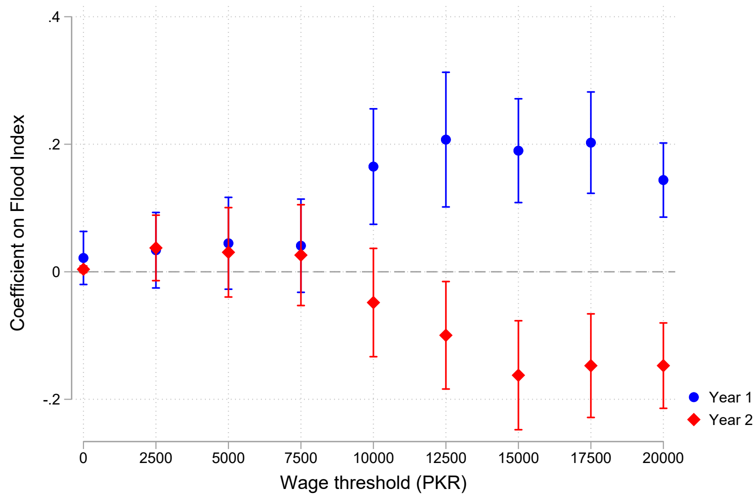
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Flood Index	0.03	0.02	-0.03	-2,848.47***	0.03	-17.49*	-6.81
	(0.03)	(0.05)	(0.02)	(799.89)	(0.05)	(9.59)	(5.08)
Observations	3661	3661	3661	2736	3661	2873	2735
Control group mean	0.783	0.631	0.0798	14102.9	0.162	188.4	78.43
F stat	39.39	39.39	39.39	35.38	39.39	38.55	35.41

Panel D: *Men and Women in paid non-agriculture work*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Flood Index	0.02	0.04	-0.03	-1,444.22	-0.10	-3.58	2.03
	(0.06)	(0.08)	(0.05)	(1296.78)	(0.08)	(19.02)	(10.72)
Observations	3129	3129	3129	2221	3129	2392	2219
Control group mean	0.723	0.559	0.0859	12813.9	0.238	183.0	75.55
F stat	17.62	17.62	17.62	14.78	17.62	14.65	14.56
Controls for age and sex	✓	✓	✓	✓	✓	✓	✓

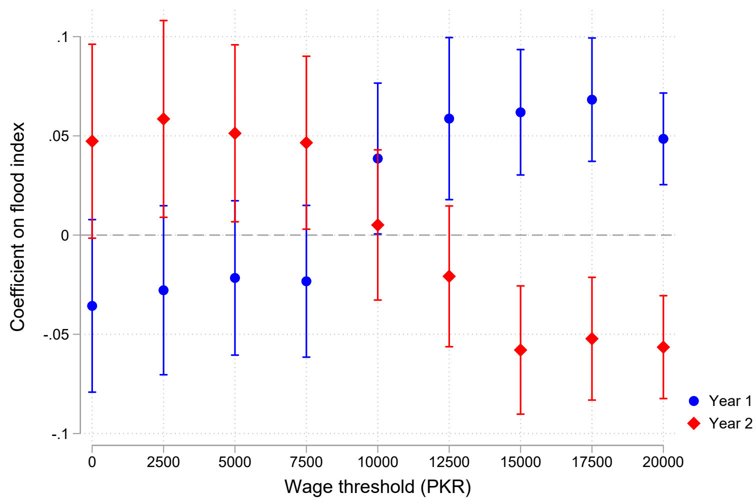
Notes: For Panel A, the sample consists of all working-age adults in our balanced panel data. For Panel B, the sample consists of all working-age men in our balanced panel data. Panel C includes all working-age adults engaged in paid agricultural work, and Panel D includes all working-age adults engaged in paid non-agricultural work. Column 1 shows whether individuals are in paid work. Column 2 shows whether they are employed in casual work, while Column 3 shows whether they are self-employed. Column 4 shows total wages in PKR, conditional on being in paid work. Column 5 shows whether individuals work outside the village or take work trips outside the village. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for age, gender, and district fixed effects. Standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 7: IV estimates: Flood exposure effect on exceeding wage thresholds



Notes: The sample consists of all working-age adults in paid work in our balanced panel data. The x-axis shows exceeding wage thresholds (in PKR) for Year 1 and Year 2, conditional on being in paid work. The y-axis shows the coefficients on the Flood Index, which is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level.

Figure 8: IV estimates: Flood exposure effect on exceeding wage thresholds (all working age adults)



Notes: The sample consists of all working-age adults in our balanced panel data. The x-axis shows exceeding wage thresholds (in PKR) for Year 1 and Year 2, conditional on being in paid work. The y-axis shows the coefficients on the Flood Index, which is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level.

To test whether this wage decline is driven by selection effects, in Table 4.11 we examine the change in wages between waves for workers who are in paid work in both years. For this selected sample we find that wages decline between waves in more flooded areas relative to less flooded areas, suggesting the wage penalty is not purely compositional. In the least flooded areas, monthly income *increased* by 906 PKR on average for those employed in both wages. For each SD increase in flooding this effect is reduced by 2,021 PKR, implying an overall decrease in wages.

Whilst wages are lower and hours no higher, households report that they increased labour supply - the probability that a household reports increasing labour supply to make ends meet increases by 24.8ppts per SD of flooding, from a base of 28% amongst least flooded households (Table 4.12). Reconciling this with the individual results, it may be that more households members were in work, or that these increases in labour supply happened earlier in the year. More flooded households also continue to report travelling further to find work - though the magnitude of the coefficient is smaller than one year after the floods.

Concurrent with worsening labour market conditions, aid flows to flooded households had declined substantially, with relief programmes across the country largely concluded. While a major housing reconstruction programme had begun to provide households with conditional cash transfers of around $1,200 to rebuild damaged houses - at the time of our surveys payouts from this scheme were very low. Only 6% of the least flooded households had received any housing programme payment, rising by 7.5ppts per SD of flooding (p<0.05), suggesting that the rollout of this programme had a long way to go (Table 4.13).

Table 4.11: Difference between W1 and W2 wages

	(1) Difference between W1 and W2 wages	(2) Difference between W1 and W2 log wages
Flood Index	-2,021.32**	-0.35***
	(884.02)	(0.13)
Observations	6096	4769
Control group mean	906.0	0.109
F stat	41.98	37.53
Controls for age and sex	✓	✓

Notes: The sample consists of working age adult in our balanced panel data who are in paid work in both waves of our survey. Column 1 is the difference between year 1 and year 2 wages (in PKR). Column 2 is the difference between year 1 and year 2 log wages. All regressions control for age, gender, and district fixed effects. Standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.12: Year 2: Household self-reported use of labour supply as a coping strategy

	(1) **Increase labour supply**	(2) **Travelled further for work**
Flood Index	0.248***	0.069*
	(0.053)	(0.042)
Observations	4682	4683
Control group mean	0.28	0.21
F stat	44.30	44.33

Notes: The sample consists of households in our balanced panel data. Column 1 shows whether households reported increasing work or business activities, including sending household members who were not working before to look for work. Column 2 shows whether households reported travelling further to find work outside their village. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.13: Year 2: Reconstruction

	(1) Aware of Programme	(2) Believe Eligible	(3) Received Any Payment
Flood Index	0.070***	0.089**	0.075**
	(0.023)	(0.036)	(0.035)
Observations	4431	4431	4431
Control group mean	0.93	0.75	0.06
F stat	43.60	43.60	43.60

Notes: The sample consists of households in our balanced panel data. Column 1 shows whether household reported they were aware of the housing reconstruction program. Column 2 shows whether household believed they were eligible for the program. Column 3 shows whether household reported having received any payment as part of the program. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Looking at financial coping strategies (Table 4.14) - we see very different behaviours compared to wave 1. Whilst more flooded households were more likely to have sold household assets one year after the floods, two years after we find no statistically significant differences in asset sales or non-payment of bills. However, more flooded households are now more likely to have taken new loans or spent the savings they were more likely to have a year ago. The probability that a household reports spending savings to make ends meet increases by 24ppts (p<0.01) per SD of flooding, on a base of 43% amongst the least flooded, whilst the probability of taking new loans increases by 9.7ppts per SD of flooding, compared to 62% in amongst the least flooded.

Perhaps unsurprisingly given these patterns, the financial positions of more and less flooded households diverged between survey waves (Table 4.15). While one year post-flood, more flooded households had lower physical assets but were more likely to have savings and similarly likely to have debt, these patterns reversed by year two. Asset holdings converged - we find no statistically significant differences - but financial buffers diverged sharply. Among the least flooded, 76% have debt, rising by 12 percentage points per SD of flooding. Meanwhile, only 13% have savings, falling by 13 percentage points per SD.

Table 4.14: Year 2: Financial Coping

	(1)	(2)	(3)	(4)	(5)	(6)
	Spent savings	**Took new loans**	**Non-payment of bills**	**Sold any assets**	**Sold productive assets**	**Sold household assets**
Flood Index	0.244***	0.097*	-0.011	-0.001	0.030	0.028
	(0.054)	(0.051)	(0.032)	(0.035)	(0.044)	(0.031)
Observations	4683	4683	4683	4684	3193	3762
Control group mean	0.43	0.62	0.10	0.13	0.11	0.04
F stat	44.33	44.33	44.33	44.37	39.23	38.17

Notes: The sample consists of households in our balanced panel data for Columns 1 to 4, and of households who owned the relevant category of assets in 2017 for Columns 5 and 6. Column 1 shows whether households reported spending their savings as a coping mechanism. Column 2 shows whether households reported taking new loans to cope with the floods. Column 3 shows whether households reported non-payment of bills as a coping strategy. Column 4 shows whether households reported selling any assets. Column 5 shows whether households sold productive assets, and Column 6 shows whether they sold household assets. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.15: Year 2: Assets

	(1) **Asset index**	(2) **HH has debt**	(3) **HH has savings**
Flood Index	0.143	0.120***	-0.132***
	(0.098)	(0.044)	(0.035)
Observations	4684	4684	4684
Control group mean	-0.13	0.76	0.13
F stat	44.37	44.37	44.37

Notes: The sample consists of households in our balanced panel data. Column 1 shows asset index which is constructed using 24 assets ownership. Column 2 shows whether household had any outstanding debt in the year. Column 3 shows whether household had any savings. The Flood Index is a household-level measure constructed from multiple satellite- and survey-based indicators of flooding. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means correspond to households in the bottom 10th percentile of the Flood Index. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These results indicate that while more flooded households maintain similar consumption levels to their less flooded counterparts two years post-flood, they do so with depleted savings and increased debt. Combined with higher reported unmet needs and deteriorating health outcomes, these patterns suggest reduced economic resilience among flood-affected households, with potential implications for their ability to cope with future shocks.

5 Summary and concluding remarks

In this paper, we examine how the impacts of natural disasters evolve over the medium term, using Pakistan's 2022 floods as a case study. Combining newly collected panel data on 5,100 households with satellite measures of flood exposure and an instrumental variables design, we document a critical medium-run assistance gap. One year post-flood, heavily affected households successfully maintain consumption despite lower employment. They report fewer unmet needs than less-flooded households - being less likely to cut meals or skip healthcare - and are more likely to have savings. This resilience seems to stems from substantial flood relief, higher wages for those who remain employed, and household asset sales, though workers must travel further for work.

By year two, the picture has changed completely. While consumption remains similar by flood status, flooded households now report significantly higher rates of unmet needs, worse physical and mental health (particularly for women), and higher healthcare expenditure. Labour market conditions have reversed - wages are now substantially lower in flooded areas despite employment recovery. Financial buffers have been worn down: flooded households are less likely to have savings and more likely to have debt, increasingly relying on loans rather than asset sales. Crucially, while emergency aid has ended, the promised housing reconstruction programme had reached very few eligible households at the time of our survey. These findings reveal a medium-run assistance gap: after emergency relief but before long-run reconstruction, households face persistent impacts of natural disasters that the standard policy response overlooks.

These findings highlight a fundamental challenge in the design of policies to adapt to climate change. Coordinating an effective response to extreme weather events requires co-operation of three (overlapping) groups of actors: providers of emergency relief (including governments, local community organisations and NGOs), social protection departments administering cash transfers, and infrastructure agencies (often with development bank partners) managing long-term reconstruction. Each operates on different timelines, with different budgets, and under different institutional constraints. The 'optimal' response from an economic perspective - such as reallocating resources from long-term infrastructure to medium-term income support - may be institutionally impossible when budgets are controlled by different actors with distinct mandates.

Despite these coordination challenges, our results suggest that gaps in the current approach may have important consequences. The period between emergency relief and reconstruction appears to coincide with increasing economic pressures for affected households, even though they may eventually receive reconstruction support. As climate-related disasters become more frequent and severe, understanding how relief, social protection, and reconstruction interventions interact will be crucial for preventing temporary climate shocks from becoming permanent poverty traps in low-income countries.

6 Supplementary tables

Table 6.1: Attrition

	Household Found			Household Interviewed		
	(1)	(2)	(3)	(4)	(5)	(6)
	2023	2024	Either	2023	2024	Either
Flood Index	0.053	0.099**	0.060*	0.049	0.124***	0.059*
	(0.036)	(0.046)	(0.032)	(0.036)	(0.048)	(0.032)
Rain 2022	-0.021*	-0.019	-0.014	-0.021*	-0.020	-0.014
	(0.013)	(0.014)	(0.011)	(0.013)	(0.014)	(0.011)
Flat Land	0.039***	0.032**	0.028***	0.038***	0.033**	0.029***
	(0.012)	(0.013)	(0.010)	(0.012)	(0.013)	(0.010)
Historical Rain	-0.028	-0.044	-0.011	-0.027	-0.055	-0.014
	(0.030)	(0.034)	(0.023)	(0.030)	(0.035)	(0.023)
Fluvial Flood Risk Quintile=2	0.045**	-0.001	0.025	0.046**	0.001	0.025
	(0.021)	(0.034)	(0.017)	(0.021)	(0.037)	(0.017)
Fluvial Flood Risk Quintile=3	-0.046***	-0.024	-0.039***	-0.048***	-0.018	-0.039***
	(0.016)	(0.021)	(0.014)	(0.017)	(0.022)	(0.014)
Fluvial Flood Risk Quintile=4	-0.069***	-0.082***	-0.062***	-0.067***	-0.089***	-0.064***
	(0.021)	(0.025)	(0.018)	(0.021)	(0.026)	(0.018)
Fluvial Flood Risk Quintile=5	-0.040	-0.041	-0.032	-0.042*	-0.036	-0.035
	(0.025)	(0.028)	(0.022)	(0.025)	(0.028)	(0.022)
Above Median Pluvial Flood Risk	-0.023	-0.075**	-0.025	-0.027	-0.082***	-0.029
	(0.025)	(0.031)	(0.023)	(0.026)	(0.032)	(0.023)
Observations	5100	5100	5100	5100	5100	5100
Control group mean	0.852	0.799	0.898	0.852	0.785	0.896
F stat	39.05	39.05	39.05	39.05	39.05	39.05

Note: This table reports household attrition from our original sample of 5,100 households. Columns (1)–(3) show the proportion of households where we successfully contacted a household member in the 2023, 2024, and either survey rounds, respectively, while Columns (4)–(6) show the proportion that were both contacted and successfully interviewed in the same rounds. *Flood Index* is a household-level index constructed from multiple satellite and survey-based measures of flooding, with higher values indicating greater flood exposure. *Rain 2022* is cumulative rainfall (in millimetres) during July–August 2022, and *Historical rain* is the 50-year average rainfall for the same period. The *Pluvial (above median)* variable is a binary indicator equal to 1 if the household is in an area with above-median risk of rain-induced surface flooding based on historical flood risk assessments. The *Fluvial (quintile)* variables classify historical river-induced flood risk into five exposure quintiles, with Q1 (omitted category) representing the lowest flood risk. All regressions control for district fixed effects, and standard errors are clustered at the settlement level. Control group means are reported for households in the bottom 10th percentile of flood exposure. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

References

Anderson, Michael L., "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American Statistical Association*, December 2008, *103* (484), 1481–1495. [Return to page **1**]

Borusyak, Kirill and Peter Hull, "Nonrandom Exposure to Exogenous Shocks," *Econometrica*, 2023, *91* (6), 2155–2185. [Referenced on pages **2, 10, 11, 12, and 16**]

Breza, Emily, Supreet Kaur, and Yogita Shamdasani, "Labor Rationing," *American Economic Review*, October 2021, *111* (10), 3184–3224. [Return to page **3**]

GoP, Asian Development Bank, European Union, United Nations Development Programme, and World Bank, "Pakistan Floods 2022 Post Disaster Needs Assessment," Technical Report 2022. [Return to page **1**]

Jayachandran, Seema, "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, June 2006, *114* (3), 538–575. [Return to page **4**]

Kaur, Supreet, "Nominal Wage Rigidity in Village Labor Markets," *American Economic Review*, October 2019, *109* (10), 3585–3616. [Return to page **4**]