Early Warnings for Floods Reduce Health and Economic Damage: Experimental Evidence from India

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PRELIMINARY: DO NOT CITE OR CIRCULATE

Abstract

Climate change is escalating flood risks globally, affecting one in four people. Flood risks exacerbate health and economic crises, increasing morbidity and poverty among vulnerable populations. This paper uses a multi-year randomized controlled trial in Bihar, India, covering 3.6 million people across 319 flood prone communities, to provide causal estimates of how an early warning system (EWS) for floods can mitigate these impacts. During the 2022 and 2023 flood seasons, a last-mile intervention improved EWS implementation: treatment households were 7.30 and 15.21 percentage points more likely to receive an alert in 2022 and 2023, respectively. This, in turn, increased household trust in warnings, and reduced the incidence of unannounced floods in treatment communities. Within the set of high-flood communities, households in treated communities scored 0.16 standard deviations on an ex ante adaptation index, 0.18 standard deviations higher on a physical health index and 0.12 standard deviations higher on an economic well-being index. Underlying these aggregate impacts, are marked changes in household behavior and outcomes: treated households in high-flood areas are more likely to store supplies, protect livestock, and safeguard important documents. They experience fewer waterborne diseases and slip-related accidents, cutting health expenditures. Finally, they were less likely to reduce essential consumption or mortgage assets during the floods. We estimate that for every $1 spent, treatment households saved up to $273 on just medical expenses during severe floods.

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1 Introduction

Climate change is escalating flood risks globally, affecting one in four people (IPCC, 2023). Floods have increased over 50% since 2010, and fourfold since 1980 (EASAC, 2018). Flood risks compound health and economic crises, elevating morbidity and poverty in vulnerable populations. In South Asia, 576 million people are exposed to significant flood risk, about 30.4% of the population (Rentschler et al., 2022). Within South Asia the Ganges-Brahmaputra basin, with 600 million residents and 200 million poor, is especially vulnerable; minor floods here can impact millions, as seen from 2000-2010, with over 16,000 deaths, 200 million displaced, and 20 billion dollars in economic damages (Priya et al., 2017).

Early warning systems (EWS) may present a cost-effective solution for protecting people and assets from natural hazards like floods. Countries with substantial to comprehensive early warning coverage experience disaster mortality rates that are six times lower than those with minimal coverage (United Nations Office for Disaster Risk Reduction and World Meteorological Organization, 2024). According to the United Nations, providing just 24 hours' notice of an impending hazardous event can reduce damage by 30%. Moreover, simple estimates suggest an investment of only $800 million in these systems in developing countries could prevent annual losses ranging from $3 to $16 billion (Global Commission on Adaptation, 2019). Recognizing the potentially critical role of EWS, the United Nations Secretary-General in 2022 issued a global call to action, aiming to ensure that by 2027, every person on Earth is protected by EWS. The "Early Warning For All" initiative requires targeted investments of $3.1 billion between 2023 and 2027 to enhance monitoring, forecasting, and the dissemination of warnings (United Nations Office for Disaster Risk Reduction and World Meteorological Organization, 2024).

However, despite these optimistic projections and anticipated investments, there are currently no causal estimates available that quantify the exact impact of these systems. It is not guaranteed that EWS will have protective effects on lives and livelihoods. For instance, mere access to early warnings may not be the primary constraint; the real limitations could include financial resources, a lack of knowledge about appropriate actions during a disaster, or access to in-kind disaster aid and essential supplies.

Estimating the causal effects of EWS is also difficult. The deployment of EWS is closely tied to anticipated need, which complicates the use of quasi-experimental methods that rely on variations in timing and placement for causal inferences. Moreover, data on outcomes before and after events in disaster-affected areas, crucial for implementing these quasi-experimental designs, is often unavailable.

In this paper, we report on a field experiment that randomizes access to a community-based alert dissemination system that is overlayed on top of an existing EWS available to both the treat-

ment and control communities.[1] Our alert dissemination system enhances the reach and trust in early warnings in treatment communities, generating differences in access to alerts issued by the EWS between treatment and control groups. This setup allows us to causally evaluate impacts of improved EWS access on ex-ante adaptations, health, and economic outcomes.

We conduct an experimental evaluation of a flood EWS in India, where floods are the most prevalent natural disaster, affecting approximately 390 million people who face significant flood risk (Rentschler et al., 2022).[2]

Our evaluation covers roughly 3.6 million people in Bihar—one of India's poorest and most flood-affected states—during the 2022 and 2023 flood cycles.[3] The intervention spanned 319 communities across 12 flood-prone districts. All communities had access to a flood forecasting and alerting system. However, we randomized access to a community-based flood alert dissemination system among 160 selected treatment communities. In each treatment community, two to three paid volunteers were trained to access, understand, and effectively communicate flood alerts. These volunteers disseminated alerts within the community using both traditional methods (loudspeakers and flag planting) and modern methods (WhatsApp groups).

In 2022 and 2023, our flood EWS greatly improved how households accessed and trusted flood alerts. Families in treatment communities received more and earlier warnings, along with more detailed information on water depth and timing. Even though they had more false alarms, they had fewer situations where flooding occurred but no warning was issued, resulting in a net improvement in overall accuracy compared to the baseline system. These benefits reached households across different caste groups, landownership sizes, and smartphone access levels, although families with more educated heads enjoyed somewhat larger gains.

Because they were better informed, households in severely flooded treatment communities took more precautions ahead of time, such as storing supplies, protecting livestock, and securing important documents. They also suffered fewer health problems—particularly waterborne illnesses—and spent less on medical treatments. Finally, they were less likely to reduce essential consumption, draw on savings, or take out large loans during the floods, suggesting that the EWS helped them recover more quickly and maintain their financial stability. We estimate that for every $1 spent, treatment households saved up to $273 on just medical expenses during severe floods.

[1] Even if we were to randomize access to the EWS, both treatment and control communities would retain access to some form of baseline, perhaps informal, EWS. Consequently, even in that scenario, we would not compare treatment outcomes directly against control outcomes without *any* EWS access.

[2] In the last six decades, floods in the country have claimed over a hundred thousand lives and inflicted an economic toll of 4.69 trillion INR (Mahapatra, 2020).

[3] 68.2 million Biharis, or 53.2% of Bihar's total population, face significant flood risks (Rentschler et al., 2022).

2 Background

2.1 Floods

Flooding stands as the most common and one of the most devastating natural disasters, hitting low-income countries particularly hard. Driven by climate change, the frequency of floods and extreme rainfall events has quadrupled since 1980, with a surge of over 50% since 2010 (European Academies' Science Advisory Council, 2018). Currently, floods threaten 1.8 billion people worldwide—about one in four individuals—with average annual reported losses and fatalities between 1980 and 2012 exceeding $23 billion and 5,900 people, respectively (IPCC, 2023). A staggering 89% of individuals threatened by flooding live in low- and middle-income countries (Rentschler et al., 2022). Consequently, 73% of all flood-related fatalities occur in poorer nations (Guha-Sapir, 2020).

In South Asia alone, 576 million people, or 30.4% of the population, face significant flood risks (Rentschler et al., 2022). The Ganges-Brahmaputra river basin—which is home to more than 600 million people, of which 200 million live in poverty— plays a central role in South Asia's vulnerability to flood disasters. For a relatively minor flood, the affected Lower Ganges population is estimated at approximately 8,000 Nepalis, 717,000 Bangladeshis, and 9,573,000 Indians. Put differently, a relatively mild flood is estimated to impact approximately one-tenth of the population living in the Nepalese portion, one-fifth of the population in the Indian portion, and nearly a third of the population occupying the portion in Bangladesh. Between 2000-10, floods in this basin were responsible for over 16,000 deaths, displacement of over 200 million people, and roughly $20 billion in economic damages (Priya et al., 2017).

2.2 Flood Early Warning Systems

Flood early warning systems (EWS) have significant potential to reduce flood-related morbidities and economic losses. For instance, back-of-the-envelope estimates suggest that the benefits of EWS for South Asia could exceed the costs by more than 500 times over a decade of normal floods (Teisberg and Weiher, 2009).

Flood EWS primarily consist of two critical components: monitoring and forecasting, and warning dissemination and communication. Continuous detection and monitoring gather hydroclimatic data within critical watersheds to identify early indicators of potential flooding. This data is analyzed using advanced hydrological and atmospheric models to forecast the likely progression of floods, including river discharges and extents (Perera et al., 2020).

However, significant challenges persist, especially in developing countries where limited technological resources hinder effective data collection and transmission. A comprehensive survey

of forecasters from 47 developing countries underscores these shortcomings: 75% of forecasters reported insufficient gauging stations, and 50% faced outdated technology in data transmission, complicating the accurate and timely analysis of data (Perera et al., 2019). Despite the use of sophisticated numerical weather predictions, many countries struggle to downscale global forecasts to actionable local scales, which can lead to missed or false flood warnings. The survey highlighted that nearly half of the forecasters considered their models to be inadequately advanced for reliable flood predictions across different climatic regions.

Effective communication of flood warnings also remains a formidable challenge. The survey revealed that despite timely dissemination, warnings often do not reach or are ignored by those at highest risk, particularly in remote or economically disadvantaged areas. Challenges include limited access to conventional media, insufficient coverage of communication networks, and a lack of tailored warning messages that resonate with local needs and understanding. Overcoming these barriers requires adapting warnings to local contexts and employing both traditional and innovative communication methods to ensure that they prompt necessary actions to safeguard lives and property (Perera et al., 2020).

2.3 Floods and EWS in Bihar

Bihar, one of India's poorest and most flood-affected states in the Ganges-Brahmaputra river basin, embodies the challenges faced by rural communities in South Asia. Annually, floods impact 6.87 million hectares out of Bihar's total area of 9.42 million hectares, making it home to 17.2% of India's flood-prone areas. Three-quarters of the population in north Bihar (approximately 50 million people) live with the constant threat of flood devastation (NSRC and ISRO, 2020). Our formative research reveals the severe disruption floods cause to lives and livelihoods in Bihar: following the 2019 flood season, 65% of households saw a decrease in agricultural income, 54% reported sickness, and over 20% experienced damage to livestock, homes, and personal belongings.

Despite the high risk, only 20% of Bihar's flood forecasting stations are operational, and just 38% of people in flood-prone areas are aware of active EWS (Tripathi et al., 2022). Our pilot survey underscores these gaps: during the 2019 flood season, while over 95% of households were affected by floods, only 45% received any alert. Moreover, although 60% of households desired information on forecast timing and 40% on water depth, only 15% of those who received alerts were provided this information.

3 Research Design

Our evaluation includes 319 panchayats (communities) with >3.6 million people in 12 flood-prone districts of Bihar (Figure A.1a).[4] 160 of these 319 communities form the treatment group, while the rest are in the control. The evaluation so far encompasses two flood seasons: 2022 and 2023. Our current funding supports the ongoing 2024 evaluation round. USAID DIV funding will finance an additional 2025 evaluation round and cover the costs of assessing a comprehensive range of health biomarkers after the intervention.

3.1 Intervention

In both seasons, we integrated a pre-existing forecasting and alerting system, accessible to both treatment and control communities, with a community-based alert dissemination system, available to only the treatment communities. In 2022, our intervention combined the Indian Central Water Commission's (CWC) forecasting and alerting system with a network of incentivized grassroots volunteers trained in community outreach activities for the flood EWS intervention.[5] In 2023, we merged Google's advanced forecasting and Android-based alerting system—which relies on real-time hydrological data from the CWC—with similarly trained and incentivized grassroots volunteers. In both years, our intervention addressed both flash and prolonged riverine (freshwater) floods in rural areas.

CWC's flood forecasting and alerting system. India's CWC operates an extensive flood forecasting network with 338 forecasting stations spanning the entire country, covering major river systems like the Ganges, Brahmaputra, and Indus. A crucial component of this system is data collection and transmission: CWC measures water levels hourly at over a thousand stream gauges across all of India. This data is transmitted in real-time via wireless, telephone, mobile, satellite-based telemetry systems, and VSAT (a two-way satellite ground station) directly to CWC's forecasting Stations, which are equipped with state-of-the-art telemetry and modeling systems.

The forecasting function of the CWC uses a basin-wise flood forecasting model that leverages rainfall-runoff mathematical modeling to provide a two-to-five-day advance advisory. This model incorporates data from the Global Forecast System (GFS) and Weather Research and Forecasting (WRF) models supplied by the Indian Meteorological Department (IMD).

The CWC categorizes flood situations into three levels—normal, above normal, and severe—based on river water levels in relation to pre-defined warning and danger flood levels. This clas-

[4]Panchayats are the lowest level of administrative division in rural India. Each panchayat typically oversees the administration of 2 to 5 villages, forming the grassroots level of India's political system.

[5]Google's flood forecasting and alerting system was not operational during the 2022 flood season.

sification assists in issuing targeted yellow and red alerts, respectively, at forecasting stations. Flood alerts are disseminated through various channels including traditional and social media, with the CWC issuing over 7,000 flood forecasts annually at an accuracy rate exceeding 90%.

For every flood event, several alerts are disseminated: initially, yellow alerts providing projected water levels are sent a few days before the anticipated event; these are then escalated to red alerts as the situation intensifies, and subsequently revert to yellow alerts as flood waters begin to subside.[6]

Google's flood forecasting and android-based alerting system. In 2023, the CWC teamed up with Google to enhance flood prediction through cutting-edge applications of artificial intelligence and geospatial mapping.

Google's flood forecasting system employs artificial intelligence to operate a hydraulic model that uses two key inputs: it integrates real-time water level measurements and forecasts provided by the CWC, with high-resolution digital elevation models (DEMs) developed by Google from a vast array of satellite imagery. Their hydraulic model efficiently processes these inputs, translating river conditions into highly accurate spatial risk maps and pinpointing which areas are likely to flood and which will remain dry.[7] Such capabilities enable the rapid issuance and continuous updates of flood predictions.[8]

Google incorporates these predictions into its Public Alerts service, providing flood forecasts two to five days in advance. That is, when a flood alert is issued, Google notifies Android smartphones with location services turned on in the areas likely to be impacted by the flood.

Like CWC forecasts, flood situations are categorized into three levels—normal, above normal, and severe—based on river water levels relative to warning and danger levels predefined by the CWC. This classification system aids in issuing targeted alerts: warning (yellow) for above normal and severe (red) for severe situations. Finally, again like the CWC's system, for every flood event, several alerts are disseminated: initial warning (yellow) alerts provide early notices with projected water levels, escalating to severe (red) alerts as the threat intensifies, and scaling back to warnings as conditions improve.

[6]For further information, see `https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1849954` and `https://indiawris.gov.in/wiki/doku.php?id=cwc_national_flood_forecasting_network`.

[7]To address areas where the hydraulic model's accuracy is compromised by factors such as inaccuracies in the DEMs, breaches in embankments, or unexpected water sources, Google employs a second predictive inundation model. This model utilizes historical data from the European Space Agency's Sentinel-1 satellite constellation, which is equipped with C-band Synthetic-Aperture Radar (SAR) instruments. SAR imagery is highly effective at detecting inundation under all weather conditions, including through clouds. By correlating historical water level measurements with past inundations captured by SAR, Google can make precise adjustments to the hydraulic model. This approach helps distinguish between errors caused by actual changes in ground conditions and those resulting from model inaccuracies, thus enabling more reliable flood predictions.

[8]For further information, see `https://research.google/blog/an-inside-look-at-flood-forecasting/`.

Community-based alert dissemination. We started planning for our intervention in 2021. First, we initiated a collaboration with the local NGO Yuganter to recruit and train community-based volunteers to effectively communicate flood alerts. This training would prepare volunteers to disseminate CWC's flood alerts in 2022 and Google's flood alerts in 2023 within each treatment community. Second, together with our NGO partner and Google, we selected 319 communities that were identified as flood-prone and covered by CWC's forecasting stations. Third, we mapped all villages in each of the 319 communities in our study to one of 26 CWC stations (Figure A.1b). This mapping was based on discussions with both the Bihar State Disaster Management Authority and engineers at Google's Flood Forecasting Initiative.

In both 2022 and 2023, multiple android-phone owning volunteers were recruited in each treatment community for a period of five months, from June to October, during which they receive a monthly stipend. Before the start of each flood season, in May, these volunteers were trained to understand and disseminate flood alerts from the CWC in 2022 and from Google in 2023.

Their daily task was consistent: whenever the CWC or Google forecasted water levels at a station associated with a sample to be above normal and issued a warning or yellow alert, community volunteers in all communities linked to that station were tasked with disseminating the alert. Similarly, when water levels were forecasted to be above the danger mark, triggering a severe or red alert, the same procedure was followed by the volunteers to alert their respective communities. They were required to use both traditional (e.g., loudspeakers) and modern (e.g., WhatsApp groups) communication methods to disseminate flood alerts (Figure A.3). No volunteers were recruited in the control communities. Finally, all volunteers were required to fill out a short Google form at the end of each day. The form collected information on whether they received any alerts that day, and if so, their activities in response to these alerts.

There were several differences between the 2022 and 2023 interventions. In 2023, we recruited only two community volunteers per treatment panchayat, compared to three in 2022. Additionally, unlike in 2022, we directly messaged treatment households about any flood alerts using WhatsApp groups and SMS in 2023. Another significant change in 2023 was that community volunteers not only communicated forecasted water levels at the station but also shared Google's flood maps. These maps, associated with each issued alert, clearly delineated areas likely to flood and those expected to remain dry. Volunteers were required to disseminate these flood maps via SMS and WhatsApp groups established for each treatment community.

3.2 Data Collection

Each year, we have a set approach (Figure A.4): from June to October, we implement our community-based alert dissemination system in treatment communities. Then, during the flood season, in late August or early September, we conduct a telephonic midline survey. This survey evaluates the accessibility of the intervention and the extent of protective actions undertaken by households. After the flood season, between November to February, we carry out an in-person endline survey. This survey aims to assess the effects of the flood on physical health and economic well-being. Additionally, it collects information on accessibility and proactive adaptations from households that we couldn't reach during the midline survey. Our data collection is structured around the following key questions:

1. *Accessibility. How effectively did our flood EWS deliver warnings to households?* We assess this by gathering data during the flood season on the sources, methods, number, accuracy, trustworthiness, and timing of the flood alerts received.

2. *Ex ante adaptation. Did households take preemptive actions to mitigate flood impacts after receiving flood alerts?* During the flood season, we survey households to see how they protected family members, crops, livestock, personal items, and property.

3. *Physical health. Has the EWS contributed to better health outcomes during the flood season?* After the flood season, we inquire about instances of illness, injury, or death in the household, including the duration, medical costs, symptoms, and causes. This helps us understand the health impact of the floods and the effectiveness of the EWS in mitigating these impacts.

4. *Economic well-being. Did the EWS improve households' economic conditions during and after the floods?* We track household income from various sources like agriculture, non-farm businesses, wage employment, and livestock after the flood season. Additionally, we track work and school absences and school dropouts, to gauge the broader impact of EWS on daily life. Finally, after flood season, we collect information on household expenses and coping strategies from flood season and the past year.

Due to budgetary and risk management considerations, and given the uncertain trajectory of the ongoing COVID pandemic, we chose not to conduct a baseline survey (Muralidharan, 2017). Consequently, the households surveyed during the 2022 endline survey represent the central element of our midline and endline data collection activities, as well as our empirical analysis.

Indeed, following the 2022 flood season, between December 2022 and March 2023, we conducted an extensive in-person survey, reaching out to 5,582 households spread across 591 villages in 319 communities in our study. To select these households, we first randomly chose two villages

from each community. Within each village, we selected every third household starting from the center until we reached a total of 10 households. Of these, we ensured that at least eight households owned a smartphone and that there was representation from the lower caste proportionate to their population in the village. Since 64% of households in rural Bihar own a smartphone (Pandey, 2023),[9] we intentionally oversampled households with smartphones. This approach was based on the assumption that such households are more likely to receive flood alerts directly from the CWC and Google. Our goal was to evaluate the effectiveness of our community-based EWS in comparison to the standard CWC or Google EWS systems.

It is important to note that since we the study's sample had not been finalized during the 2022 flood season, the 2022 midline survey was unique. For this survey, we gathered the sample of respondents through phone calls to local leaders. Furthermore, its primary focus was to assess how accessible our intervention was to households, rather than evaluating the range of protective actions that households may have taken, which was instead assessed in the 2022 endline survey.

3.2.1 Floods

Measurement. To generate a measure of flood severity at the community-flood-season level, we leverage the mapping of all the villages in 319 communities in our study to one of 26 CWC stations, alongside daily water levels observed at these stations from June to October.

We start by defining three variables to characterize flooding: the number of flood events, the duration of flood events, and the intensity of flood events. A flood event is defined as a period that starts when observed water levels rise above the danger level and ends when they remain below the warning level for 5 consecutive days. That is, we allow for periods of up to 5 consecutive days where the water levels may temporarily dip below the warning level; if the gap between periods above the danger level does not exceed 5 days during which the water levels dip below the warning level, these periods are considered part of the same flood event. The duration of a flood event is measured by counting the days it persists. The intensity of a flood event is defined as the sum of the differences between the observed water level on days above the danger mark and the danger threshold, divided by the number of days the water levels were above the danger threshold. We then create a flood severity index at the station-flood-season level, which is an unweighted average of the z-scores for the number of flood events, the duration of the average flood event, and the intensity of the average flood event. Finally, we use the station-village mapping to generate a flood severity index for each of the 591 villages across 319 communities in our study in each flood season.

[9] Interestingly, Bihar has 9.3% of all the 5G-capable smartphones in the country, just behind Andhra Pradesh, which holds the maximum share of 5G-capable smartphones at 14% (Gupta, 2022)

Flooding statistics. Flood severity was greater in 2022 than in 2023. Figure 1 shows the distribution of flooding during the 2022 and 2023 flood seasons. Specifically, it displays the average difference between the observed water height and the severe threshold across all sample stations for both years.

Table 1 presents detailed flood statistics for our sample over the two flood cycles. The average number of flood events in 2022 was 1.33, compared to 0.93 in 2023. The mean duration of flooding in 2022 was 29.3 days, versus 14.7 days in 2023. Furthermore, the average flood intensity in 2022 measured 0.33 meters, compared to 0.21 meters in 2023.

3.2.2 Econometric Specification and Balance

To estimate impacts, we will estimate the following reduced-form regression specification:

$$Y_{hvpdt} = \gamma_0 + \gamma_1 \mathbf{1}(Treat_{pd}) + \mu_d + \alpha_t + v_{pd} \tag{1}$$

$Treat_{pd}$ takes the value 1 if community p in district d is in the treatment group, 0 otherwise. Y_{hvpd} is outcome of interest for household h in village v in community p in district d for flood season t. Because random assignment of the 319 community between the treatment and control group was stratified at the district level, we include district fixed effects (μ_d). We also include flood season fixed effects (α_t). v_{pd} is an error term, clustered at the community level.

We anticipate that the effects on proactive adaptation (ex ante), physical health, and economic conditions will be influenced by the severity of the floods.[10] Therefore, our second stage findings will take into account the severity of actual flooding. Specifically, we will apply Equation 1 to four mutually exclusive groups: communities that did not experience any flood events, and communities where flood severity fell into the first, second, and third terciles (estimated based on observations during the first year of our intervention, 2022). As we will detail below, flood severity is measured at the community-flood-season-level, assessed using an index that includes the number of flood events, the duration of each event, and the intensity of each event. As expected from the randomized design of our study, fixed observable characteristics that are unlikely to be influenced by our intervention are balanced between the treatment and control groups within our sample (Tables A.1 and 2).

[10]The effects on ex ante adaptation will be influenced by the severity of forecasted flooding, which is highly correlated with realized flooding; the correlation between forecasted water levels and observed water levels exceeded 0.92 in both 2022 and 2023 (Figure A.2).

4 Results

4.1 Accessibility

Our flood EWS effectively delivered warnings to households in both 2022 and 2023 (Figure 2). Households in treatment communities were more likely to receive flood alerts, with a greater number of alerts received compared to those in control communities. These communities also benefited from more timely alerts; treatment communities were also more inclined to trust flood alerts.

During the 2022 flood season, households in treatment communities received 2.40 more alerts (a 294% increase, Figure A.5) on average during the 2022 flood season (June-October), were 26% more likely to receive any alerts, 45% more likely to receive alerts before water reached their area, and 56% more likely to say they trust the alerts completely (Figure 2). In 2023, treatment communities received 3.52 more alerts on average (a 503% increase), were 71% more likely to receive any alert, 83% more likely to receive an alert before water reached their panchayat, and 91% more likely to say they trust alerts completely.[11]

Moreover, unlike in 2022, households in the treatment group during 2023 received more accurate alerts than those in the control group. The treatment group experienced more false positives, 8.92%, compared to the control group at 4.33% (Figure 2). Despite the increase in false positives, the reduction in false negatives (situations with flooding but no alerts) led to an improvement in overall alert accuracy. The control group experienced a higher rate of false negatives at 42.08%, significantly more than the treatment group's 31.92%. Overall, the treatment group had a lower incidence of forecast errors at 40.83% compared to the control group at 46.41%. This suggests that Google's flood forecasting system is more precise than the one employed by the CWC.

Lastly, households in treatment communities were more likely to receive the specific information they desired in our 2019 pilot survey, such as water depth and flood timing (Figure 5). Specifically, in both 2022 and 2023, these households were over 70% more likely to receive information about forecasted water depth and over 190% more likely to receive information about the timing of flooding compared to households in control communities.

- Across the two flood cycles, the intervention's impact was equitable across social strata, enhancing access for households regardless of their caste status, traditionally lower or upper (Table 3). This indicates that the measures taken effectively bridged customary social

[11] Treatment households were more likely to receive alerts from our NGO volunteers and from other villagers—neighbors, family, and friends within the same village (Figure 3). This suggests that communication among villagers further amplifies flood warnings in treatment communities. In terms of alert modes, treatment households were more likely to receive messages via SMS or WhatsApp, as well as through flags, loudspeakers, and phone calls (Figure 4).

divides, ensuring inclusive reach of the benefits.

- The intervention's impact on accessibility was consistent across landownership size, a measure of economic status. Similarly, we find that the intervention's impact on access was statistically similar irrespective of whether they owned a smartphone at baseline (May 2022). However, treatment households with more educated heads were more likely to receive alerts and received a higher number of alerts. That is, though the magnitude of the treatment effect among households with less educated heads is large and statistically significant, it was smaller compared to those with higher education. This disparity may be due to households with more educated heads being more proactive in seeking out information and better able to understand alerts provided. Educated household heads might have higher literacy levels, enabling them to comprehend written messages more easily. They may also recognize the importance of the alerts and engage more actively with the dissemination channels.

4.2 Household outcomes

4.2.1 Ex ante adaptation

Households in the treatment group who faced the most severe flooding (top tercile) were more likely to engage in precautionary actions against flooding (Table 4). Quantitatively, these households in the top tercile for flood severity had a score that was 0.16 standard deviations higher on indices measuring proactive adaptation compared to control households that were similarly affected by flooding. Specifically, treatment households were more likely than control households to take steps such as stocking supplies, safeguarding their animals, securing important documents needed for welfare programs, and protecting food and crops (Table 5).

4.2.2 Physical health.

Households in the treatment group who faced the most severe flooding (top tercile) experienced fewer health issues (Table 4). Quantitatively, these households in the top tercile for flood severity had a score that was 0.18 standard deviations higher on indices measuring physical health compared to control households that were similarly affected by flooding. The most heavily impacted treatment households showed a decrease in sickness and injury (Table 6), mainly due to fewer cases of waterborne diseases and slip-related accidents. As a result, households in treatment areas incurred roughly INR 6,890 less on illness treatment (a 35.51% decrease) and INR 1,730 less on injury treatment (a 8.92% decrease) (Table A.3).

4.2.3 Economic well-being.

With better preparation and improved health outcomes, households in the treatment group who faced the most severe flooding (top tercile) were also less economically affected (Table 4). Quantitatively, these households in the top tercile for flood severity had a score that was 0.12 standard deviations higher on indices measuring economic well-being compared to control households that were similarly affected by flooding. Specifically, treatment households in severely flooded areas were 8.2 percentage points (pp) less likely to reduce consumption of essential items, 6.9pp less likely to take money out of savings, 8.1pp less likely to mortgage assets and took 17,500 INR less in loans (Tables 7 and A.4).

4.3 Cost Effectiveness

Based on our updated estimates from 2022-23, we show that for every $1 spent, treatment households saved $12 to $273 on medical expenses during severe floods (Figure 6). Comparing our program to cost-effective malaria prevention bed nets, which yield $200 in benefits per dollar spent (Shepard et al., 2020), our intervention's upper estimate for medical cost savings alone, under a scenario where 50% of communities were severely affected and a conservative 50% of household could access the EWS, is over half the total benefits provided by access to bed nets.[12] We anticipate that incorporating longer-run impacts, as discussed above, into our analysis will significantly enhance our flood intervention's cost-effectiveness.

Our cost-effectiveness analysis excludes the expenses associated with maintaining Google's flood forecasting system. However, it's important to note that the flood forecasting system provided by India's Central Water Commission (CWC) is available at no cost to the public. NGOs can effectively utilize this system and implement a community-based alert dissemination system to achieve similar benefits. Both Google and CWC's flood forecasting models depend on real-time water level measurements recorded hourly by CWC at over a thousand stream gauges across India. In fact, our 2022 intervention utilized alerts from the CWC, and we only began incorporating Google's system into our interventions starting in 2023.

[12]While benefits are only realized in the most flood-affected areas, our estimates take into account the cost of dissemination in communities that were not severely affected.

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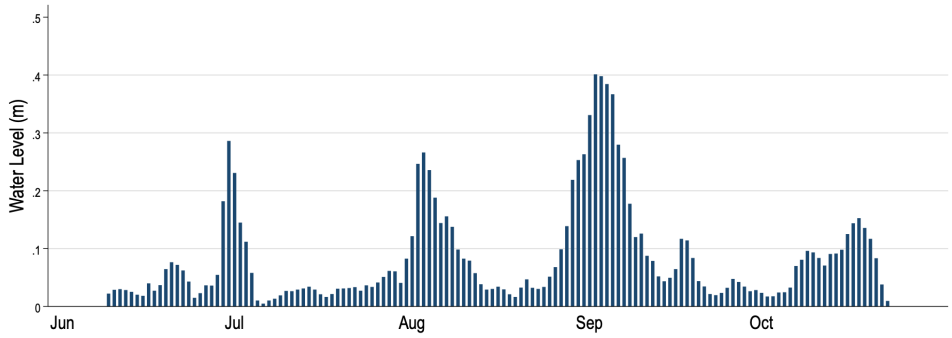
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5 Tables and Figures

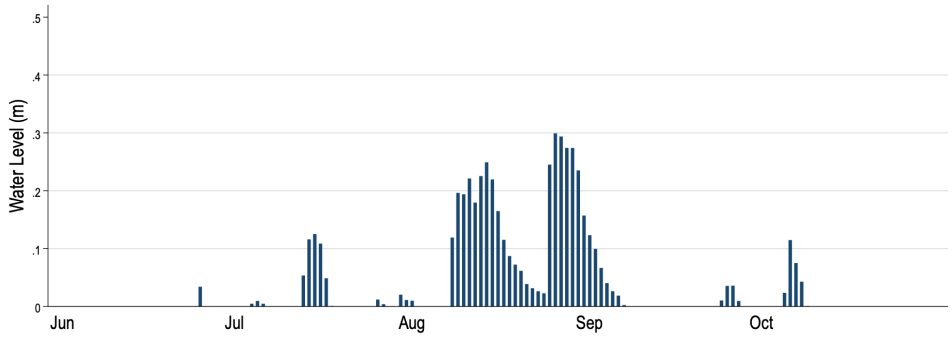
5.1 Figures

Figure 1: Average Water Levels, June to October

(a) 2022, Height Above Severe Threshold



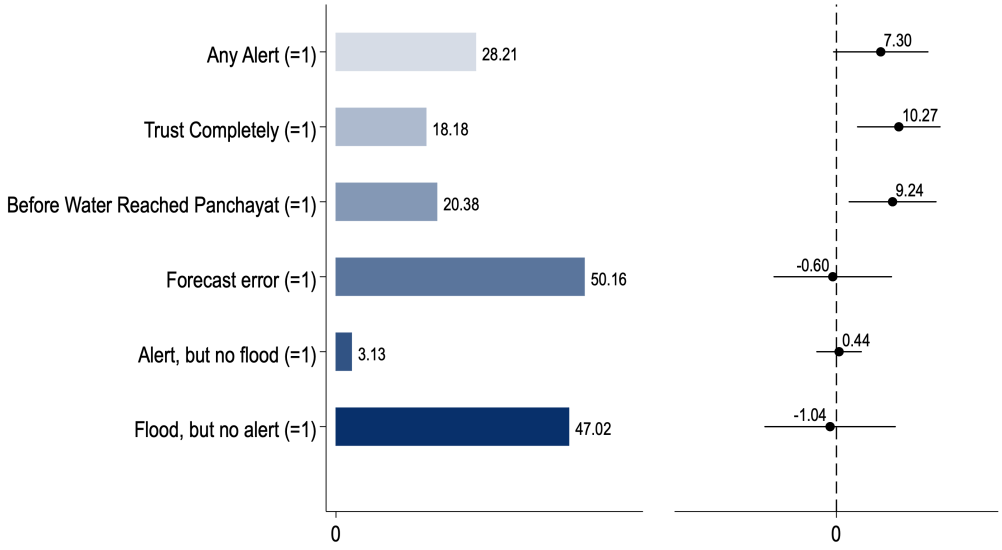
(b) 2023, Height Above Severe Threshold



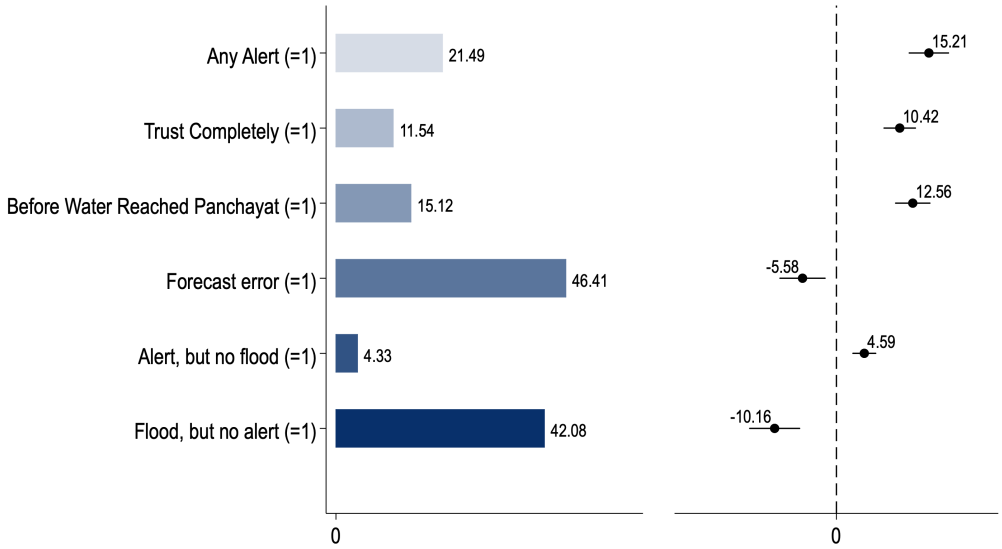
Notes. The figure plots the average difference between the height of the water and the severe threshold, across all 26 sample stations in 2022 and 25 sample stations in 2023. *Source: CWC J-O 2022, Google Flood Hub J-O 2023.*

Figure 2: Treatment Households Were More Likely to Receive an Alert

(a) 2022



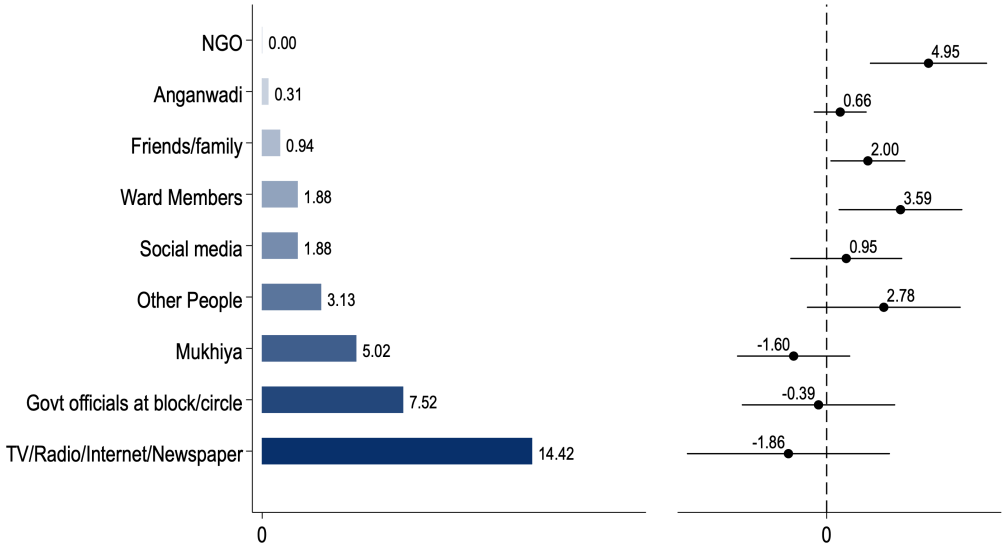
(b) 2023



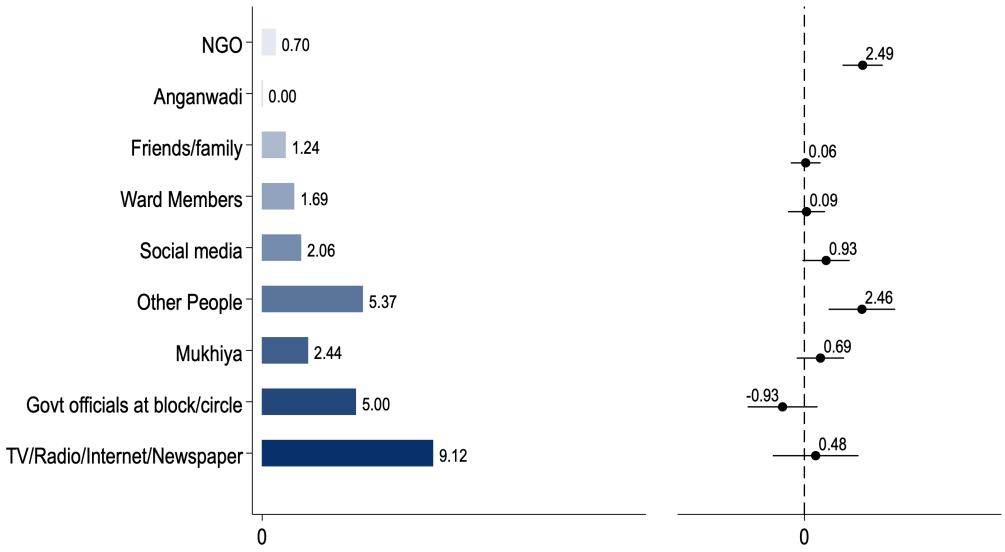
Notes. The left panels present the percentage of control households who received an alert, trusted a source of alerts completely, typically received alerts from any source before water reached the panchayat and experienced forecast error. The right panels present treatment effects. Regression includes midline and district fixed effects. Whiskers denote 95% confidence intervals. Standard errors are clustered at the panchayat level. Responses are taken from the 2022 midline and 2023 midline and endline surveys. In 2022, the sample consists of 634 households across 119 panchayats. In 2023, the sample consists of 4919 households across 319 panchayats.

Figure 3: Treatment households were more likely to receive an alert from our volunteers, an NGO and other people in the same panchayat

(a) 2022



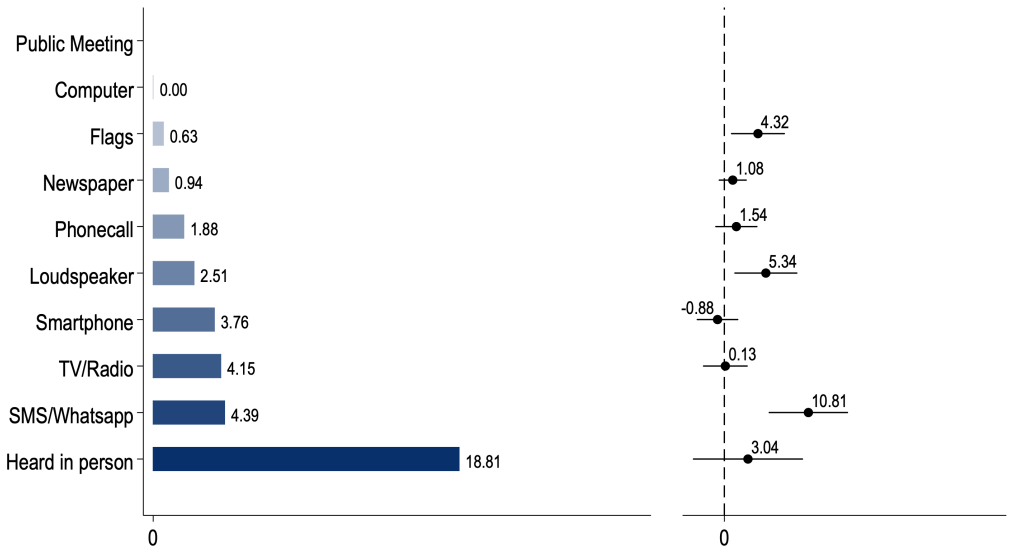
(b) 2023



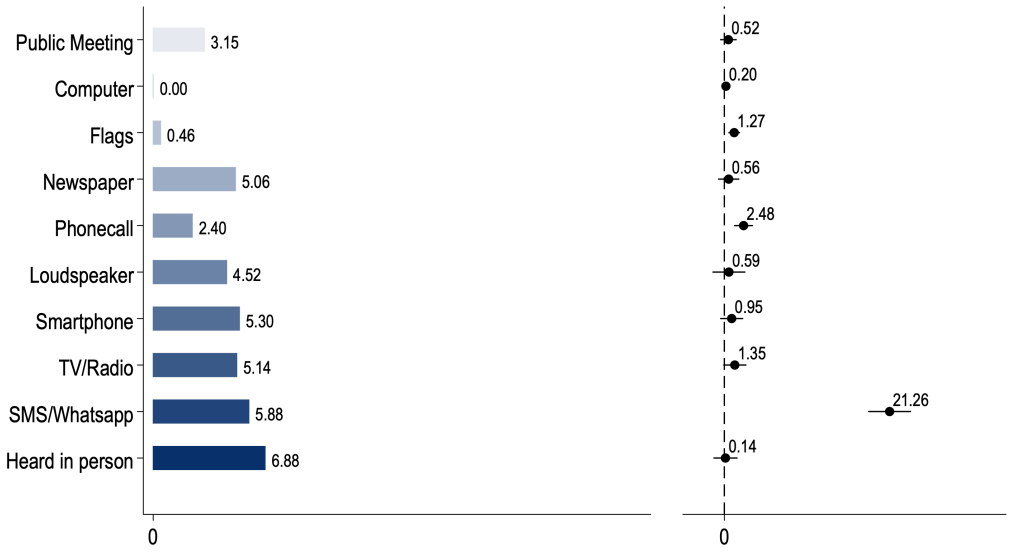
Notes. The left panels present the percentage of control households who received alerts from each source. The right panels present treatment effects. Regression includes midline and district fixed effects. Whiskers denote 95% confidence intervals. Standard errors are clustered at the panchayat level. Responses are taken from the 2022 midline and 2023 midline and endline surveys. In 2022, the sample consists of 634 households across 119 panchayats. In 2023, the sample consists of 4919 households across 319 panchayats.

Figure 4: Treatment Households Were More Likely to Receive an Alert via Flags and SMS/Whatsapp

(a) 2022



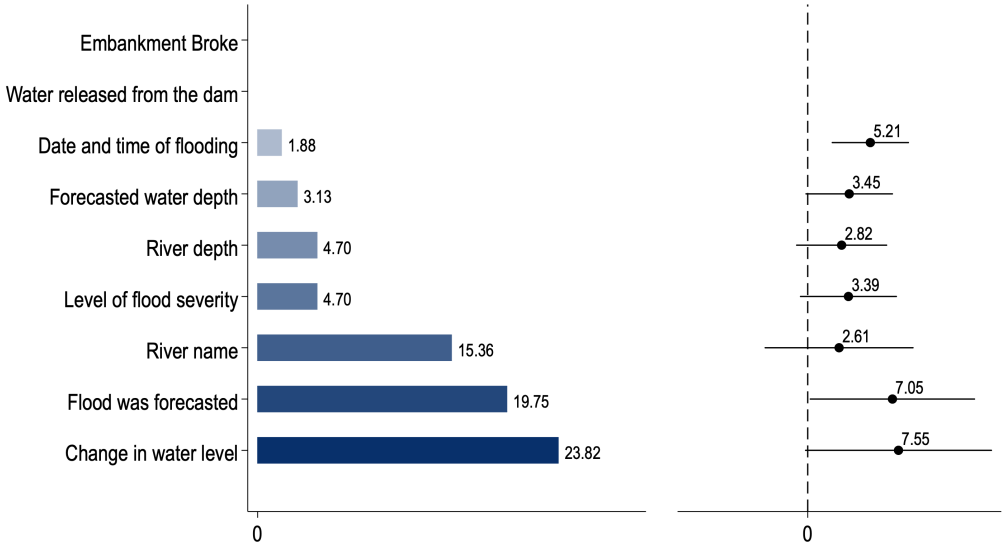
(b) 2023



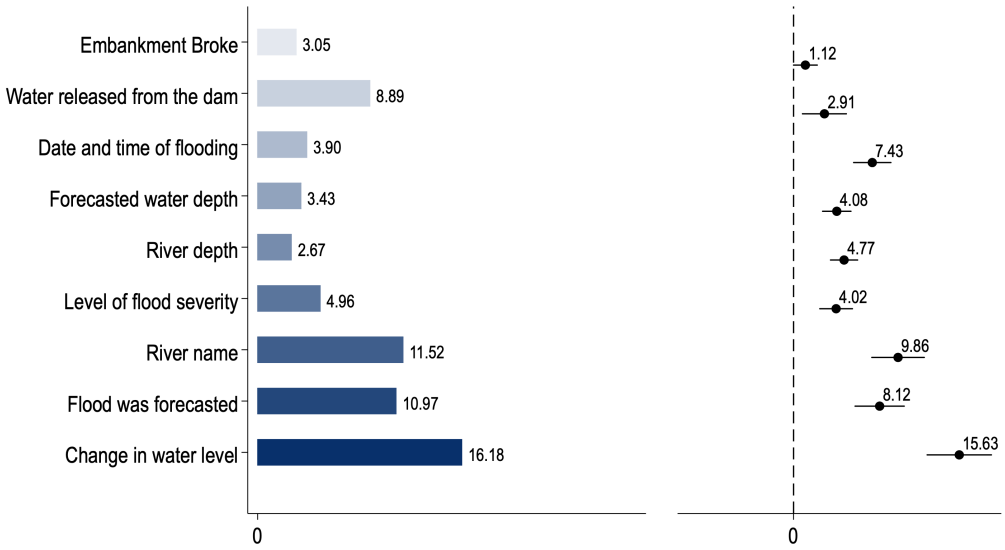
Notes. The left panels present the percentage of control households who received alerts from each mode. The right panels present treatment effects. Regression includes midline and district fixed effects. Whiskers denote 95% confidence intervals. Standard errors are clustered at the panchayat level. Responses are taken from the 2022 midline and 2023 midline and endline surveys. In 2022, the sample consists of 634 households across 119 panchayats. In 2023, the sample consists of 4919 households across 319 panchayats.

Figure 5: Treatment households receive more information from alerts.

(a) 2022

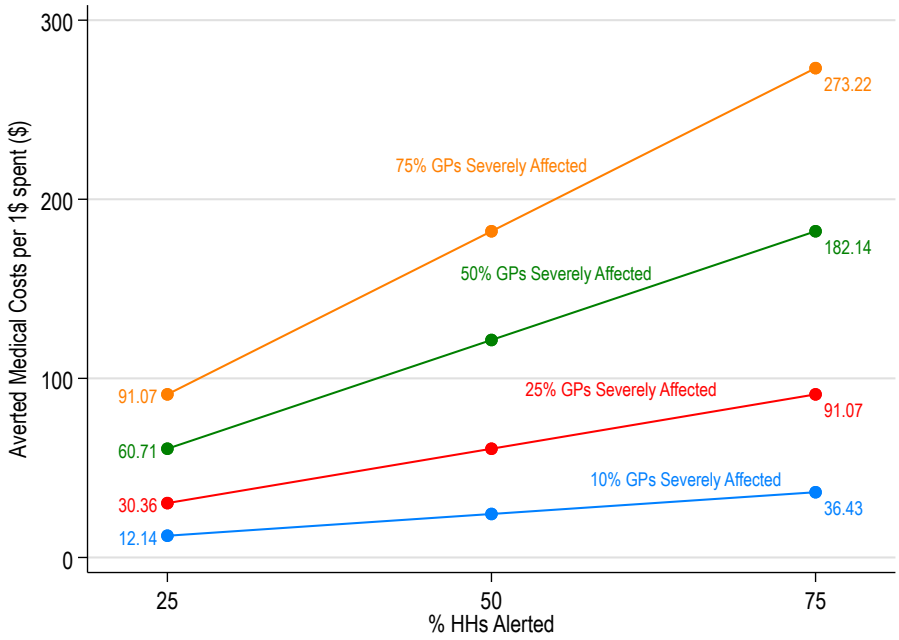


(b) 2023



Notes. The left panels present the percentage of control households who received each type of information. The right panels present treatment effects. Regression includes midline and district fixed effects. Whiskers denote 95% confidence intervals. Standard errors are clustered at the panchayat level. Responses are taken from the 2022 midline and 2023 midline and endline surveys. In 2022, the sample consists of 634 households across 119 panchayats. In 2023, the sample consists of 4919 households across 319 panchayats.

Figure 6: Cost Effectiveness



Notes. The figure presents cost ratios under different assumptions of how many households are reached by flood alerts, and how many GPs (communities) are severely effected by flooding. Each line represents a different proportion of GPs severely affected by flooding (equivalent to our third tercile of flood severity) and the x-axis represents the proportion of households within these GPs who were reached by flood alerts. Benefits are based on a treatment effect of -$119.10 on medical expenditure for households in the top tercile of flood severity. Total program costs in 2023 were $78,464.22 split across 160 treatment panchayats in 2023. We assume there are 2000 households per panchayat.

5.2 Tables

Table 1: Village-Level Flooding Characteristics

	(1) Mean	(2) Std. Dev.	(3) Min.	(4) Max.	(5) Villages (N)
Panel A: 2022					
Number of Flood Events					
No Flooding	0	0	0	0	177
Tercile 1	1.68	0.47	1	2	141
Tercile 2	2.29	0.95	1	4	207
Tercile 3	1.09	0.52	1	4	66
Aggregate	1.33	1.14	0	4	591
Mean Flood Duration (days)					
No Flooding	0	0	0	0	177
Tercile 1	13.3	3.89	6	18	141
Tercile 2	34.5	19.1	9.75	65	207
Tercile 3	125.2	24.1	15.8	145	66
Aggregate	29.3	39.4	0	145	591
Mean Flood Intensity (meters)					
No Flooding	0	0	0	0	177
Tercile 1	0.34	0.100	0.19	0.45	141
Tercile 2	0.51	0.036	0.39	0.54	207
Tercile 3	0.61	0.13	0.43	0.77	66
Aggregate	0.33	0.24	0	0.77	591
Panel B: 2023					
Number of Flood Events					
No Flooding	0	0	0	0	229
Tercile 1	1.26	0.68	1	3	199
Tercile 2	1.81	0.39	1	2	123
Tercile 3	1.85	1.08	1	4	40
Aggregate	0.93	0.92	0	4	591
Mean Flood Duration (days)					
No Flooding	0	0	0	0	229
Tercile 1	20.6	9.69	7	30	199
Tercile 2	22.0	14.9	4	78	123
Tercile 3	46.3	22.7	8.50	64	40
Aggregate	14.7	16.9	0	78	591
Mean Flood Intensity (meters)					
No Flooding	0	0	0	0	229
Tercile 1	0.16	0.10	0.020	0.29	199
Tercile 2	0.51	0.12	0.33	0.80	123
Tercile 3	0.69	0.11	0.50	0.77	40
Aggregate	0.21	0.24	0	0.80	591
Panel C: 2024					
Number of Flood Events					
No Flooding	0	0	0	0	52
Tercile 1	1.05	0.21	1	2	172
Tercile 2	1.46	0.65	1	3	184
Tercile 3	2.18	0.94	1	3	183
Aggregate	1.43	0.90	0	3	591
Mean Flood Duration (days)					
No Flooding	0	0	0	0	52
Tercile 1	16.8	16.0	5	59	172
Tercile 2	48.9	23.3	8	67	184
Tercile 3	54.4	29.1	22.5	111	183
Aggregate	37.0	29.7	0	111	591
Mean Flood Intensity (meters)					
No Flooding	0	0	0	0	52
Tercile 1	0.31	0.19	0.0067	0.49	172
Tercile 2	0.56	0.064	0.46	0.63	184
Tercile 3	0.68	0.086	0.48	1.01	183
Aggregate	0.48	0.24	0	1.01	591

Notes. The table presents summary statistics for components of our flood severity index. Flood information is sourced from stations, which are mapped to villages, not panchayats, so some panchayats contain villages that are mapped to different panchayats. In 2022, 303 panchayats were mapped to only one station and 16 were mapped to two stations. In 2023, 310 panchayats were mapped to only one station and 9 were mapped to two stations.

Table 2: Treatment-Control Balance Within Flooding Bins

Variables	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Household size	-0.189	3,615	0.117	2,970	-0.060	2,991	0.025	925	10,501
	(0.145)		(0.119)		(0.142)		(0.284)		
# Males	-0.093	3,615	0.009	2,970	-0.032	2,991	0.009	925	10,501
	(0.075)		(0.070)		(0.080)		(0.153)		
# Females	-0.094	3,615	0.112	2,970	-0.031	2,991	0.014	925	10,501
	(0.087)		(0.078)		(0.082)		(0.153)		
# Under 18s	-0.115	3,615	0.069	2,970	0.002	2,991	-0.078	925	10,501
	(0.088)		(0.094)		(0.114)		(0.215)		
HoH Age	-0.193	3,615	-0.015	2,970	-0.035	2,991	2.013	925	10,501
	(0.832)		(0.762)		(0.810)		(1.385)		
Mean Age	0.615	3,615	-0.525	2,970	1.030	2,991	1.557	925	10,501
	(0.683)		(0.678)		(0.770)		(1.222)		
HoH Years of Education	-0.008	3,613	-0.008	2,970	0.024	2,991	0.215	925	10,499
	(0.190)		(0.203)		(0.242)		(0.402)		
Muslim (=1)	-0.051*	3,595	0.007	2,952	-0.003	2,974	0.002	922	10,443
	(0.028)		(0.032)		(0.030)		(0.047)		
SC/ST (=1)	-0.031	3,553	-0.042	2,899	0.006	2,909	-0.038	889	10,250
	(0.028)		(0.029)		(0.039)		(0.036)		
OBC/EBC (=1)	0.070*	3,553	0.010	2,899	-0.024	2,909	-0.046	889	10,250
	(0.041)		(0.042)		(0.044)		(0.060)		
Smartphone (=1)	-0.023	3,615	-0.098**	2,970	-0.041	2,991	-0.123	925	10,501
	(0.044)		(0.040)		(0.038)		(0.083)		
Roof/Terrace (=1)	0.019	3,547	0.003	2,909	-0.037	2,900	-0.097	903	10,259
	(0.031)		(0.030)		(0.035)		(0.061)		
Land Owned (acres)	-0.077	3,614	-0.007	2,969	0.028	2,989	-0.004	924	10,496
	(0.089)		(0.105)		(0.088)		(0.190)		
Distance to Nearest River (km)	-0.445	3,615	0.405	2,970	-0.353	2,991	-0.583	925	10,501
	(0.342)		(0.330)		(0.366)		(0.456)		
Flood Severity Index	0.000	3,615	0.031	2,970	-0.000	2,991	0.041	925	10,501
	(0.000)		(0.027)		(0.006)		(0.045)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table presents estimates for treatment-control differences for all surveyed households in 2022 and 2023. Regression includes round and district fixed effects. Regression for each variable is fully interacted with the flooding bin. Standard errors are in parentheses and clustered at the panchayat level. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 3: First stage treatment effects by caste, smartphone ownership, years of education and land ownership.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: By Caste Category	*General*	*N1*	*OBC/EBC*	*N2*	*SC/ST*	*N3*	*N*
Any Alert (=1)	0.15***	1062	0.16***	3340	0.12***	1018	5420
	(0.03)		(0.02)		(0.03)		
Number of Alerts	3.19***	1060	3.75***	3329	2.82***	1018	5407
	(0.51)		(0.36)		(0.49)		
Clusters	238		314		282		319
Panel B: By Smartphone Ownership	*No Smartphone*	*N1*	*Smartphone*	*N2*			*N*
Any Alert (=1)	0.16***	2773	0.13***	2767			5540
	(0.02)		(0.02)				
Number of Alerts	3.85***	2770	2.84***	2757			5527
	(0.39)		(0.34)				
Clusters	314		279				319
Panel C: By HoH Years of Education	*≤ Median*	*N1*	*> Median*	*N2*			*N*
Any Alert (=1)	0.12***	3673	0.20***	1862			5535
	(0.02)		(0.02)				
Number of Alerts	2.43***	3668	5.41***	1854			5522
	(0.26)		(0.55)				
Clusters	319		314				319
Panel D: By Land Owned	*≤ Median*	*N1*	*> Median*	*N2*			*N*
Any Alert (=1)	0.17***	2497	0.14***	2410			4907
	(0.02)		(0.02)				
Number of Alerts	3.26***	2497	3.85***	2410			4907
	(0.40)		(0.40)				
Clusters	317		316				319

Notes. The table presents treatment effects on first stage outcomes. Sample is midline 2022 and midline and endline 2023. Regression includes district, round and midline fixed effects. The treatment indicator and fixed effects are fully interacted with the heterogeneity variable. Standard errors clustered at the panchayat level are in parentheses. The median number of years of education obtained by the head of household is 10. The median amount of land owned is 0.31 acres.

Table 4: Summary Indices, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Ex Ante Adaptation	0.013	3,610	-0.010	2,969	0.011	2,991	0.158**	924	10,494
	(0.039)		(0.048)		(0.048)		(0.067)		
Physical Health	0.052	3,449	-0.049	2,807	-0.009	2,892	0.177***	892	10,040
	(0.038)		(0.047)		(0.048)		(0.064)		
Economic Wellbeing	0.042	3,449	-0.008	2,807	-0.016	2,892	0.121**	892	10,040
	(0.050)		(0.056)		(0.050)		(0.055)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects on KLK indices, which are all oriented such that a larger number reflects a more positive outcome. Regression includes round and district fixed effects for all outcomes. The Ex Ante Adaptation index is composed of responses from midline and endline surveys in 2023, so the regression includes midline and endline fixed effects. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 5: Ex Ante Adaptations, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Any step to stock supplies (=1)	-0.008	3,610	-0.008	2,969	0.001	2,991	0.046*	924	10,494
	(0.017)		(0.016)		(0.014)		(0.025)		
Any step to protect land (=1)	0.013	3,610	0.004	2,969	0.013	2,991	0.014	924	10,494
	(0.017)		(0.016)		(0.015)		(0.028)		
Any precaution to keep animals safe (=1)	0.016	3,609	0.003	2,967	-0.002	2,989	0.092***††	924	10,489
	(0.017)		(0.020)		(0.022)		(0.032)		
Any step to relocate assets (=1)	-0.008	3,609	-0.007	2,967	-0.013	2,989	0.060**	924	10,489
	(0.014)		(0.018)		(0.018)		(0.029)		
Any agricultural protective step (=1)	0.007	3,609	0.003	2,967	0.018	2,989	0.049	924	10,489
	(0.011)		(0.012)		(0.016)		(0.032)		
Any step to relocate HH members (=1)	0.000	3,609	-0.007	2,967	-0.000	2,989	-0.007	924	10,489
	(0.009)		(0.014)		(0.013)		(0.021)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects on groups of ex ante adaptation. Regression includes endline, midline, round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by †, ††, †††.

Table 6: Physical Health Indices, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Sickness	0.065	3,449	-0.025	2,807	-0.010	2,892	$0.200^{***}_{\dagger\dagger\dagger}$	892	10,040
	(0.040)		(0.042)		(0.049)		(0.066)		
Injury	0.008	3,449	-0.047	2,807	0.017	2,892	$0.110^{*}_{\dagger}$	892	10,040
	(0.037)		(0.047)		(0.037)		(0.056)		
Death	0.026	3,449	-0.021	2,807	-0.024	2,892	0.029	892	10,040
	(0.034)		(0.036)		(0.046)		(0.061)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects on KLK indices of health-related outcomes, which are oriented such that a larger number reflects a more positive outcome (less illness, injury and death). Regression includes round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by †, ††, †††.

Table 7: Economic Wellbeing Indices, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Income	-0.016	3,449	0.016	2,807	0.022	2,892	-0.015	892	10,040
	(0.039)		(0.037)		(0.054)		(0.068)		
Assets	-0.012	3,443	0.009	2,803	0.004	2,889	-0.060	892	10,027
	(0.056)		(0.060)		(0.055)		(0.090)		
Flood Damages	0.044	3,449	0.109**	2,807	-0.020	2,892	-0.060	892	10,040
	(0.041)		(0.054)		(0.057)		(0.090)		
Food & Nutrition	0.007	3,449	-0.010	2,807	-0.045	2,892	-0.053	892	10,040
	(0.041)		(0.051)		(0.048)		(0.059)		
Migration	-0.030	3,449	0.013	2,807	0.067	2,892	0.106	892	10,040
	(0.050)		(0.057)		(0.045)		(0.066)		
Absence from Work	0.075	3,448	-0.040	2,799	-0.001	2,889	0.084	892	10,028
	(0.051)		(0.050)		(0.046)		(0.080)		
Absence from School	0.079*	1,970	-0.047	1,614	-0.029	1,676	0.086	505	5,765
	(0.045)		(0.058)		(0.055)		(0.079)		
Coping Measures	-0.002	3,449	-0.034	2,807	-0.057	2,892	$0.274^{***}_{\dagger\dagger\dagger}$	892	10,040
	(0.041)		(0.042)		(0.046)		(0.057)		
Expenditures	0.023	3,449	-0.078	2,807	-0.019	2,892	0.097	892	10,040
	(0.049)		(0.054)		(0.037)		(0.064)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

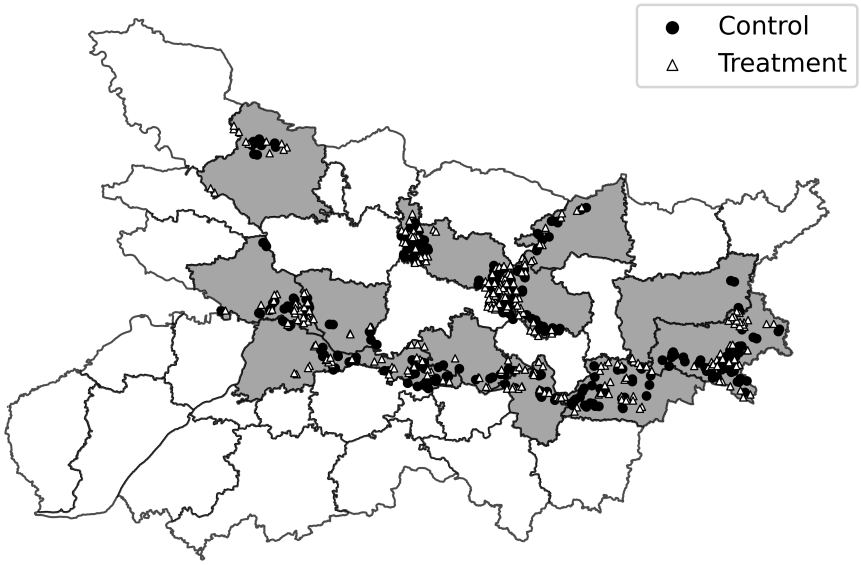
Notes. The table shows treatment effects on KLK indices, which are oriented such that a larger number reflects a more positive outcome (damage and absence are flipped). Regression includes round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by $\dagger, \dagger\dagger, \dagger\dagger\dagger$.

A Appendix

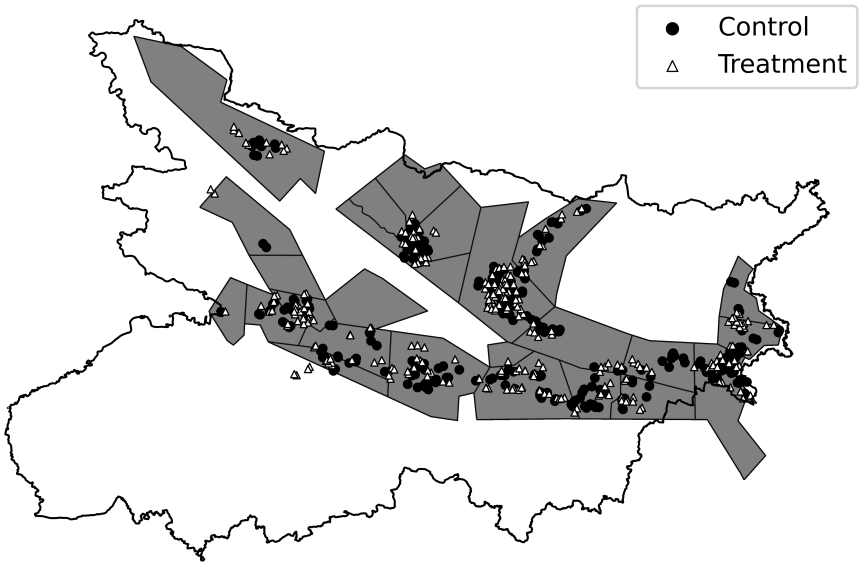
A.1 Figures

Figure A.1: Sample Villages in Bihar

(a) Treatment Assignment



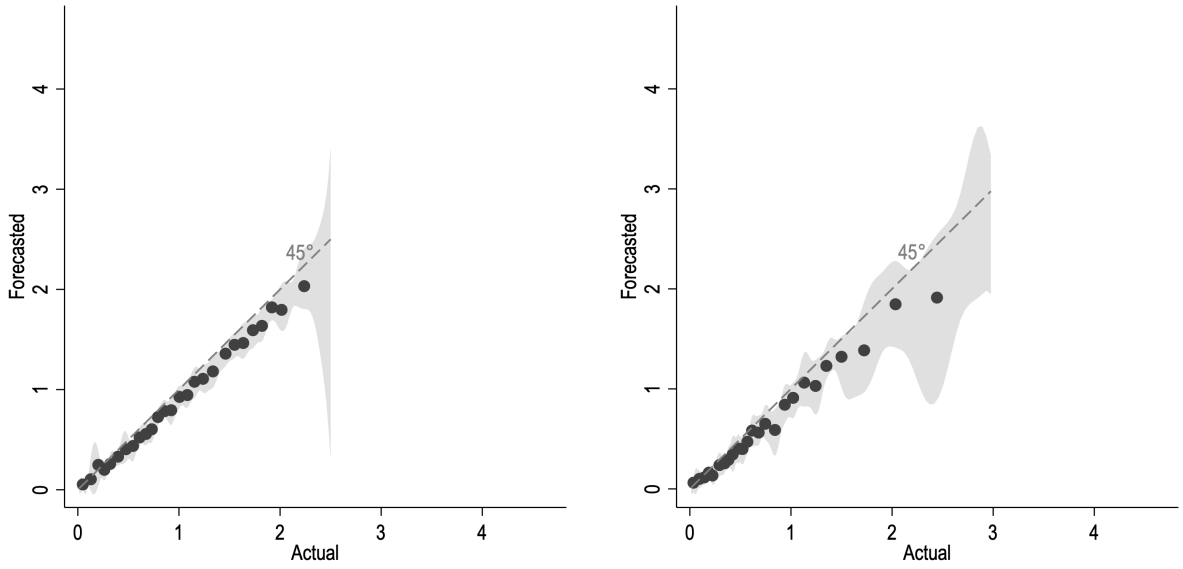
(b) Sample Villages and Water Gauge Forecast Areas



Notes. Panels A and B depict Bihar, a northern state of India. Our sample consists of 159 control panchayats covering 291 villages and 160 treatment panchayats covering 300 villages in 12 districts. Sample districts are colored gray. Panel B depicts assignment of villages to water gauges, which are used to forecast flooding. Each gray polygon reflects a station's 'area of interest' within which all the villages are forecasted by this station (with a small number of exceptions).

Figure A.2: Forecasted vs Actual Water Levels, Binned Scatter

(a) 2022 (b) 2023



Notes. The figure presents binscatters following Cattaneo et al. (2024), with a 95% confidence band in gray. The x-axis plots the difference between water levels and station warning thresholds and the y-axis plots the forecasted difference. The binscatter is run only when the actual difference was greater than 0. *Source: CWC J-O 2022, Google Flood Hub J-O 2023.*

Figure A.3: Traditional and Modern Methods of Alert Dissemination

(a) A Yuganter volunteer placing a flag in a high place in the village.



(b) Example Alert Sent by Volunteers to WhatsApp Group

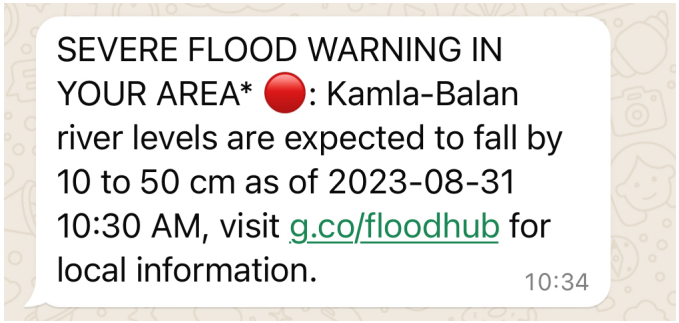


Figure A.4: Intervention Timeline

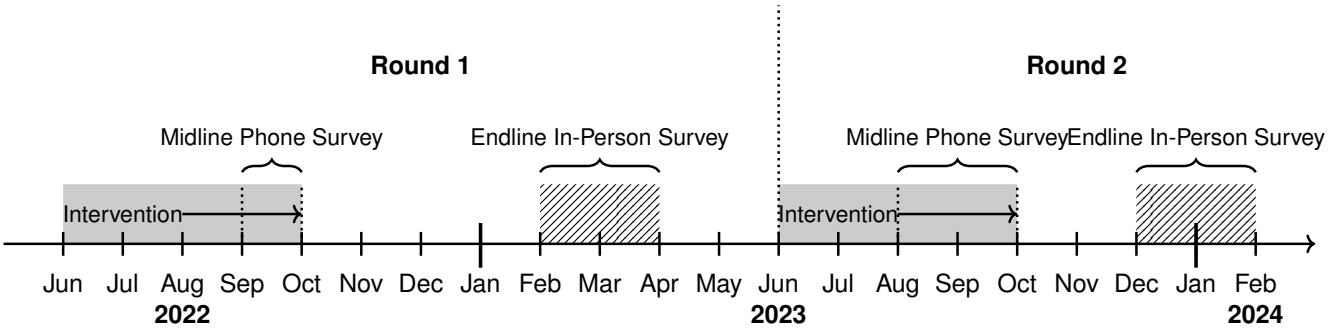
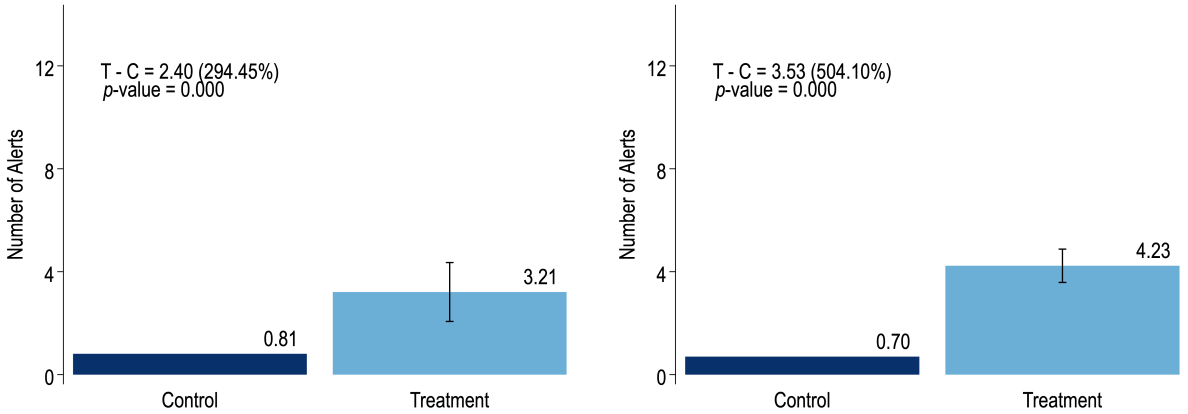


Figure A.5: Treatment Households Received More Alerts

(a) 2022 (b) 2023



Notes. The figure presents the control mean and control mean $+\beta$ for number of alerts received. Regression includes district and midline fixed effects. Whiskers denote 95% confidence intervals. Standard errors are clustered at the panchayat level. Responses are taken from 2022 midline and 2023 midline and endline surveys. In 2022, the sample consists of 634 households across 119 panchayats. In 2023, the sample consists of 4919 households across 319 panchayats.

A.2 Tables

Table A.1: Treatment-Control Balance for Sample Households

Variable	(1) Control	(2) N	(3) Treatment	(4) N	(5) Estimate	(6) N
Household size	5.48	2743	5.43	2839	-0.05	5582
	[2.39]		[2.54]		(0.08)	
# Males	2.68	2743	2.64	2839	-0.03	5582
	[1.53]		[1.59]		(0.05)	
# Females	2.80	2743	2.79	2839	-0.01	5582
	[1.41]		[1.48]		(0.05)	
# Under 18s	2.20	2743	2.18	2839	-0.02	5582
	[1.78]		[1.85]		(0.06)	
HoH Age	44.68	2743	44.87	2839	0.15	5582
	[14.92]		[15.37]		(0.48)	
Mean Age	30.26	2743	30.73	2839	0.43	5582
	[12.11]		[12.57]		(0.43)	
HoH Years of Education	8.80	2743	8.81	2838	-0.00	5581
	[3.50]		[3.44]		(0.13)	
Muslim (=1)	0.10	2726	0.08	2822	-0.02	5548
	[0.30]		[0.26]		(0.02)	
SC/ST (=1)	0.21	2680	0.19	2766	-0.03	5446
	[0.41]		[0.39]		(0.02)	
OBC/EBC (=1)	0.59	2680	0.61	2766	0.02	5446
	[0.49]		[0.49]		(0.03)	
Smartphone (=1)	0.48	2743	0.44	2839	-0.05*	5582
	[0.50]		[0.50]		(0.03)	
Roof/Terrace (=1)	0.54	2651	0.53	2759	-0.02	5410
	[0.50]		[0.50]		(0.02)	
Land Owned (acres)	0.98	2741	0.96	2836	-0.02	5577
	[1.63]		[1.51]		(0.06)	
Distance to Nearest River (km)	2.76	2743	2.65	2839	-0.15	5582
	[2.16]		[2.02]		(0.21)	
Flood Severity Index	0.33	2743	0.28	2839	-0.02	5582
	[0.99]		[1.01]		(0.08)	
Attrition:						
Completed Survey: Endline 2022 (=1)	0.88	3114	0.87	3281	-0.016	6395
	[0.32]		[0.34]		(0.011)	
Attrition: Midline 2023 (=1)	0.38	2743	0.39	2839	0.003	5582
	[0.49]		[0.49]		(0.014)	
Attrition: Endline 2023 (=1)	0.19	2743	0.21	2839	0.014	5582
	[0.40]		[0.41]		(0.013)	
Clusters	159		160		319	

Notes. The table presents mean values for control and treatment households. Standard deviations are presented in square brackets and standard errors in parentheses are clustered at the panchayat level. Regression includes district fixed effects. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table A.2: Ex Ante Adaptation Outcomes, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Panel A: Protecting Agriculture									
Moved food/crops to higher ground (=1)	0.018	1,683	-0.000	1,317	0.017	1,970	0.053	607	5,577
	(0.019)		(0.020)		(0.021)		(0.039)		
Harvested crops/fruits/vegetables (=1)	0.004	1,683	0.015	1,317	0.004	1,970	0.016	607	5,577
	(0.006)		(0.014)		(0.011)		(0.014)		
Took agriculture related precautionary measures (=1)	0.000	1,926	0.010	1,650	0.014	1,019	0.018	317	4,912
	(0.009)		(0.012)		(0.019)		(0.031)		
Panel B: Keeping Animals Safe									
Vaccinate livestock (=1)	0.009	1,683	0.019*	1,317	0.003	1,970	0.008	607	5,577
	(0.009)		(0.010)		(0.008)		(0.013)		
Took precautions to keep animals safe (=1)	0.018	3,609	0.001	2,967	-0.004	2,989	0.109***†††	924	10,489
	(0.017)		(0.020)		(0.021)		(0.030)		
Moved animal fodder (=1)	0.001	1,683	-0.003	1,317	-0.002	1,970	-0.004	607	5,577
	(0.012)		(0.014)		(0.014)		(0.023)		
Panel C: Stocking Supplies									
Stored drinking water (=1)	0.011	3,609	0.003	2,967	0.007	2,989	0.021	924	10,489
	(0.009)		(0.012)		(0.011)		(0.015)		
Stocked food (=1)	0.022	1,926	0.018	1,650	-0.028	1,019	0.065	317	4,912
	(0.024)		(0.027)		(0.039)		(0.062)		
Bought supplies (=1)	0.006	1,926	-0.003	1,650	-0.036	1,019	0.099**	317	4,912
	(0.018)		(0.026)		(0.035)		(0.044)		
Stocked medicines (=1)	-0.011	1,751	-0.007	1,483	0.089***	918	-0.010	284	4,436
	(0.029)		(0.029)		(0.032)		(0.081)		
Stocked equipments to protect yourself from insects, etc (=1)	-0.049	1,751	-0.032	1,483	-0.003	918	-0.046	284	4,436
	(0.033)		(0.028)		(0.046)		(0.100)		
Ensured clean water for drinking or sanitation purposes (=1)	0.031	1,751	0.021	1,483	0.031	918	-0.053	284	4,436
	(0.023)		(0.024)		(0.026)		(0.049)		
Stocked supplies for sanitary purposes (=1)	0.003	1,751	0.017	1,483	0.035	918	-0.104*	284	4,436
	(0.024)		(0.025)		(0.034)		(0.060)		
Purchased firewood/coal (=1)	-0.004	1,751	0.011	1,483	0.003	918	-0.090	284	4,436
	(0.031)		(0.036)		(0.040)		(0.095)		
Panel D: Protecting Land									
Got a motor to drain water (=1)	0.004	3,609	0.009	2,967	-0.002	2,989	0.001	924	10,489
	(0.006)		(0.006)		(0.007)		(0.008)		
Secured land (=1)	0.013	1,683	0.004	1,317	0.001	1,970	0.014	607	5,577
	(0.011)		(0.012)		(0.009)		(0.018)		
Secured house (=1)	0.002	1,926	-0.011	1,650	0.017	1,019	0.029	317	4,912
	(0.014)		(0.019)		(0.029)		(0.038)		
Secured land (not including agricultural land) (=1)	0.006	1,926	0.003	1,650	0.021	1,019	0.061	317	4,912
	(0.014)		(0.015)		(0.026)		(0.040)		
Took measures to prevent water collecting (=1)	0.010	1,751	-0.025	1,483	0.029	918	-0.102***†	284	4,436
	(0.016)		(0.017)		(0.021)		(0.039)		
Cleaned around the house (=1)	0.022	1,751	0.029	1,483	0.068	918	-0.126	284	4,436
	(0.034)		(0.035)		(0.047)		(0.108)		
Dug a drainage canal (=1)	0.027	1,751	-0.006	1,483	0.039	918	-0.027	284	4,436
	(0.020)		(0.021)		(0.025)		(0.062)		
Panel E: Relocating Assets									
Moved household items (=1)	-0.008	3,609	-0.007	2,967	-0.011	2,989	0.030	924	10,489
	(0.012)		(0.016)		(0.016)		(0.025)		
Moved documents to a safe place (=1)	-0.001	3,609	0.005	2,967	-0.005	2,989	0.054**	924	10,489
	(0.012)		(0.015)		(0.015)		(0.027)		
Panel F: Relocating Members									
Household members moved (=1)	0.005	3,609	-0.006	2,967	-0.005	2,989	-0.004	924	10,489
	(0.007)		(0.010)		(0.009)		(0.014)		
Bought/arranged a boat (=1)	-0.002	1,926	0.008	1,650	0.006	1,019	-0.043	317	4,912
	(0.010)		(0.020)		(0.031)		(0.048)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects. Regression includes midline, round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are computed within each panel and significance levels are denoted by †, ††, †††.

Table A.3: Physical Health Outcomes, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Panel A: Sickness									
Any member sick (=1)	-0.001	3,449	0.004	2,807	-0.002	2,892	-0.039$_{\dagger\dagger}$	892	10,040
	(0.019)		(0.019)		(0.020)		(0.032)		
# members sick	-0.069	3,449	0.063	2,807	-0.008	2,892	-0.282$^{**}_{\dagger\dagger}$	892	10,040
	(0.071)		(0.080)		(0.099)		(0.131)		
Avg # days sick	-0.657	3,448	0.383	2,807	0.403	2,892	-1.804$^{**}_{\dagger\dagger}$	892	10,039
	(0.453)		(0.673)		(0.530)		(0.857)		
Number of Illness Symptoms	-0.120	3,449	0.008	2,806	0.023	2,891	-0.354$^{***}_{\dagger\dagger}$	891	10,037
	(0.081)		(0.078)		(0.093)		(0.132)		
Number of Illness Causes	-0.084$^{**}_{\dagger}$	3,369	-0.032	2,727	0.010	2,853	-0.142$^{**}_{\dagger\dagger}$	870	9,819
	(0.034)		(0.045)		(0.042)		(0.065)		
Illness treatment (1K Rs)	-1.972	3,449	2.511	2,807	0.016	2,892	-6.890$^{***}_{\dagger\dagger}$	892	10,040
	(1.318)		(1.590)		(1.464)		(2.182)		
Panel B: Injury									
Any member injured (=1)	0.000	3,449	0.020	2,807	0.003	2,892	-0.035	892	10,040
	(0.017)		(0.021)		(0.018)		(0.029)		
# members injured	-0.009	3,449	0.042	2,807	-0.019	2,892	-0.061	892	10,040
	(0.032)		(0.036)		(0.033)		(0.041)		
Avg # days injured	-0.154	3,449	0.063	2,807	-0.719**	2,892	-0.982*	891	10,039
	(0.338)		(0.406)		(0.304)		(0.552)		
Number of Injury Symptoms	-0.027	3,449	0.019	2,807	0.016	2,892	-0.034	892	10,040
	(0.026)		(0.036)		(0.026)		(0.039)		
Number of Injury Causes	0.004	3,449	0.022	2,807	0.003	2,892	-0.047	892	10,040
	(0.022)		(0.026)		(0.021)		(0.031)		
Injury treatment (1K Rs)	0.175	3,449	0.768*	2,805	-0.178	2,892	-1.731$^{***}_{\dagger}$	892	10,038
	(0.370)		(0.442)		(0.348)		(0.660)		
Panel C: Death									
Death in the household, A-A (=1)	-0.006	3,449	0.005	2,807	0.005	2,892	-0.004	892	10,040
	(0.007)		(0.007)		(0.009)		(0.012)		
Number of deaths in the household, A-A	-0.004	3,449	0.005	2,807	0.001	2,892	-0.009	892	10,040
	(0.007)		(0.008)		(0.012)		(0.015)		
Number of death causes	-0.007	3,449	0.004	2,807	0.009	2,891	-0.006	892	10,039
	(0.007)		(0.008)		(0.010)		(0.013)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects. Regression includes round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by $_{\dagger}$, $_{\dagger\dagger}$, $_{\dagger\dagger\dagger}$.

Table A.4: Economic Wellbeing Outcomes, by Severity of Flooding

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Panel A: Income									
Total household income (1K Rs), A-A	0.948	3,414	-0.073	2,762	-1.325	2,866	0.776	884	9,926
	(1.850)		(2.087)		(2.367)		(3.995)		
Remittances in (1K Rs), A-A	-0.098	3,430	-0.292	2,790	0.627	2,879	1.221	889	9,988
	(0.487)		(0.533)		(0.574)		(0.880)		
Total Kharif Harvest Sales (1K Rs)	-0.029	3,383	0.037*	2,756	0.011	2,877	-0.102$^{**}_{\dagger\dagger}$	881	9,897
	(0.024)		(0.021)		(0.036)		(0.041)		
Panel B: Assets									
Item: Pressure Cooker (=1)	0.014	3,449	0.032	2,807	-0.003	2,891	0.009	892	10,039
	(0.029)		(0.034)		(0.033)		(0.043)		
Item: Chair (=1)	0.011	3,449	0.023	2,807	-0.020	2,891	-0.018	892	10,039
	(0.015)		(0.015)		(0.017)		(0.027)		
Item: Cot/Bed (=1)	-0.005	3,449	0.004	2,807	0.005	2,891	-0.006	892	10,039
	(0.008)		(0.009)		(0.010)		(0.008)		
Item: Table (=1)	0.014	3,449	0.039	2,807	0.018	2,891	-0.010	892	10,039
	(0.025)		(0.027)		(0.025)		(0.049)		
Item: Electric Fan (=1)	-0.004	3,449	-0.013	2,807	-0.001	2,891	-0.039	892	10,039
	(0.013)		(0.014)		(0.013)		(0.032)		
Item: Radio/Transistor (=1)	-0.003	3,449	-0.001	2,807	-0.002	2,891	0.006	892	10,039
	(0.009)		(0.008)		(0.009)		(0.018)		
Item: Black and White Television (=1)	0.018**	3,449	-0.008	2,807	0.004	2,891	0.004	892	10,039
	(0.008)		(0.009)		(0.006)		(0.015)		
Item: Color Television (=1)	0.033	3,449	0.009	2,807	-0.005	2,891	-0.007	892	10,039
	(0.023)		(0.023)		(0.024)		(0.026)		
Item: Sewing Machine (=1)	-0.021	3,449	-0.020	2,807	0.000	2,891	0.012	892	10,039
	(0.022)		(0.018)		(0.014)		(0.029)		
Item: Mobile Telephone (=1)	0.001	3,449	-0.003	2,807	0.002	2,891	0.009	892	10,039
	(0.005)		(0.007)		(0.004)		(0.008)		
Item: Landline Telephone (=1)	-0.001	3,449	0.002	2,807	0.000	2,891	0.004	892	10,039
	(0.003)		(0.003)		(0.002)		(0.004)		
Item: Internet (=1)	-0.011	3,449	-0.011	2,807	0.025	2,891	0.006	892	10,039
	(0.024)		(0.024)		(0.019)		(0.026)		
Item: Computer (=1)	-0.005	3,449	-0.011	2,807	0.010	2,891	-0.013	892	10,039
	(0.007)		(0.008)		(0.008)		(0.013)		
Item: Refrigerator (=1)	-0.032**	3,449	0.014	2,807	-0.003	2,891	-0.013	892	10,039
	(0.016)		(0.018)		(0.014)		(0.024)		
Item: Air Conditioner/Cooler (=1)	-0.010*	3,449	-0.010*	2,807	0.001	2,891	0.004	892	10,039
	(0.006)		(0.005)		(0.004)		(0.007)		
Item: Washing Machine (=1)	-0.004	3,449	-0.003	2,807	0.010	2,891	-0.007	892	10,039
	(0.010)		(0.007)		(0.007)		(0.014)		
Item: Watch/Clock (=1)	0.052**	3,449	0.002	2,807	-0.009	2,891	-0.021	892	10,039
	(0.023)		(0.027)		(0.028)		(0.040)		
Item: Bicycle (=1)	0.024	3,449	-0.016	2,807	-0.022	2,891	0.016	892	10,039
	(0.024)		(0.027)		(0.026)		(0.039)		
Item: Motorcycle/Scooter (=1)	-0.003	3,449	-0.014	2,807	-0.018	2,891	-0.069	892	10,039
	(0.023)		(0.026)		(0.023)		(0.047)		
Item: Animal-drawn Cart (=1)	-0.004	3,449	0.002	2,807	-0.001	2,891	0.015*	892	10,039
	(0.003)		(0.003)		(0.002)		(0.008)		
Item: Car (=1)	-0.012***	3,449	0.001	2,807	-0.007**	2,891	-0.004	892	10,039
	(0.004)		(0.005)		(0.003)		(0.007)		
Item: Water Pump (=1)	-0.019	3,449	0.004	2,807	0.004	2,891	-0.013	892	10,039
	(0.019)		(0.019)		(0.018)		(0.032)		
Item: Thresher (=1)	-0.006	3,449	-0.002	2,807	-0.007	2,891	0.008	892	10,039
	(0.005)		(0.007)		(0.005)		(0.018)		
Item: Tractor (=1)	-0.008	3,449	-0.001	2,807	0.001	2,891	-0.006	892	10,039
	(0.009)		(0.008)		(0.008)		(0.019)		
Item: Other (=1)	-0.005**	3,449	0.003	2,807	0.001	2,891	0.004	892	10,039
	(0.002)		(0.003)		(0.002)		(0.006)		
Number of animals owned	0.009	3,443	-0.109	2,803	0.037	2,890	0.163	892	10,028
	(0.182)		(0.217)		(0.229)		(0.384)		
Number of animals rented	-0.010	3,443	-0.007	2,803	-0.043	2,890	-0.015	892	10,028
	(0.016)		(0.017)		(0.026)		(0.034)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects on economic outcomes. Regression includes round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by $_{\dagger}$, $_{\dagger\dagger}$, $_{\dagger\dagger\dagger}$.

Table A.4: Economic Wellbeing Outcomes, by Severity of Flooding (continued)

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Panel C: Flood Damages									
Damage to the house, A-A (=1)	-0.003	3,449	-0.016	2,807	0.010	2,892	0.032	892	10,040
	(0.016)		(0.018)		(0.023)		(0.038)		
Damage to the house, A-A (1K Rs)	-0.600	3,446	-0.765	2,805	0.118	2,889	0.384	892	10,032
	(0.610)		(0.653)		(0.785)		(1.311)		
Damage to items, A-A (=1)	-0.003	3,449	-0.020	2,807	0.003	2,892	0.031	892	10,040
	(0.012)		(0.018)		(0.018)		(0.026)		
Damage to items, A-A (1K Rs)	0.114	3,448	-0.400	2,807	-0.030	2,891	0.559	892	10,038
	(0.212)		(0.277)		(0.316)		(0.504)		
Repair Costs (1K Rs)	-0.801**	3,448	-0.203	2,804	0.262	2,892	-0.867	892	10,036
	(0.383)		(0.453)		(0.343)		(0.758)		
Number of animals sick	-0.032	3,443	-0.093	2,803	0.030	2,890	0.046	892	10,028
	(0.056)		(0.080)		(0.084)		(0.125)		
Number of animals dead	-0.022	3,443	-0.095	2,803	0.029	2,890	0.030	892	10,028
	(0.054)		(0.080)		(0.085)		(0.113)		
Number of Docs. Damaged	-0.015	1,762	-0.090**	1,488	0.025	922	0.022	285	4,457
	(0.018)		(0.041)		(0.027)		(0.031)		
Panel D: Food & Nutrition									
Food Insecurity Index (flipped)	0.027	1,762	-0.184	1,489	-0.230	922	0.669**†	285	4,458
	(0.147)		(0.200)		(0.238)		(0.331)		
Sufficient food for all months of year (=1)	0.001	3,449	-0.000	2,807	-0.009	2,892	-0.026*†	892	10,040
	(0.010)		(0.011)		(0.011)		(0.016)		
Panel E: Migration									
Any HH Member Migrated (=1)	-0.015	3,449	0.015	2,807	0.019	2,892	0.079**†	892	10,040
	(0.024)		(0.030)		(0.023)		(0.031)		
Number of migrants in the household	-0.006	3,449	-0.002	2,807	0.106	2,892	0.047	892	10,040
	(0.094)		(0.091)		(0.080)		(0.118)		
Reason for Migration: Education (=1)	0.005	3,449	-0.007	2,807	-0.007	2,892	0.014	892	10,040
	(0.014)		(0.017)		(0.016)		(0.029)		
Reason for Migration: Employment (=1)	-0.002	3,449	0.008	2,807	0.038	2,892	0.035	892	10,040
	(0.023)		(0.028)		(0.024)		(0.037)		
Other Reason for Migration (=1)	-0.011**†	3,449	0.003	2,807	0.009*	2,892	0.008	892	10,040
	(0.005)		(0.006)		(0.005)		(0.008)		
Panel F: Absence from Work									
Any member absent from work, Aashadh-Ashwin (=1)	-0.035	3,448	0.007	2,799	0.004	2,889	-0.040	892	10,028
	(0.024)		(0.024)		(0.022)		(0.041)		
# members absent from work, Aashadh-Ashwin	-0.077*	3,448	0.058	2,799	-0.024	2,889	-0.071	892	10,028
	(0.046)		(0.044)		(0.045)		(0.078)		
Any Health Reason for Work Absence (=1)	-0.006	3,447	0.011	2,797	0.010	2,886	-0.032	889	10,019
	(0.019)		(0.021)		(0.019)		(0.028)		
Other Reason for Work Absence (=1)	-0.034	3,448	0.013	2,799	-0.002	2,889	-0.017	892	10,028
	(0.024)		(0.023)		(0.021)		(0.046)		
Panel G: Absence from School									
Any member absent from school, Aashadh-Ashwin (=1)	-0.036*	1,970	0.017	1,614	0.017	1,676	-0.009	505	5,765
	(0.021)		(0.029)		(0.027)		(0.040)		
# members absent from school, Aashadh-Ashwin	-0.108**	1,970	0.121*	1,614	0.046	1,676	-0.048	505	5,765
	(0.052)		(0.064)		(0.061)		(0.096)		
Any Health Reason for School Absence (=1)	-0.000	1,970	-0.031	1,611	-0.025	1,672	-0.063**	504	5,757
	(0.016)		(0.020)		(0.020)		(0.028)		
Other Reason for School Absence (=1)	-0.037*	1,970	0.041	1,614	0.039	1,676	-0.021	505	5,765
	(0.022)		(0.028)		(0.028)		(0.037)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects on economic outcomes. Regression includes round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by †, ††, †††.

Table A.4: Economic Wellbeing Outcomes, by Severity of Flooding (continued)

Outcomes	(1) No Floods	(2) N1	(3) Tercile 1	(4) N2	(5) Tercile 2	(6) N3	(7) Tercile 3	(8) N4	(9) N
Panel H: Coping Measures									
Coping: Postponed large purchases (=1)	-0.005	3,449	0.009	2,807	0.011	2,892	-0.045	892	10,040
	(0.024)		(0.022)		(0.022)		(0.039)		
Coping: Took out money from savings (=1)	0.007	3,449	-0.000	2,807	0.021	2,892	-0.069$^{*}_{\dagger}$	892	10,040
	(0.020)		(0.021)		(0.019)		(0.038)		
Coping: Mortgaged assets (=1)	-0.006	3,449	-0.014	2,807	0.024	2,892	-0.081$^{***}_{\dagger\dagger}$	892	10,040
	(0.015)		(0.017)		(0.018)		(0.027)		
Coping: Sold off other assets (=1)	-0.001	3,449	0.014	2,807	0.029**	2,892	-0.023	892	10,040
	(0.011)		(0.012)		(0.013)		(0.018)		
Coping: Reduced consumption of essential items (=1)	0.018	3,449	0.019	2,807	-0.007	2,892	-0.082$^{**}_{\dagger}$	892	10,040
	(0.023)		(0.024)		(0.020)		(0.036)		
Number of animals sold	-0.007	3,443	-0.034	2,803	0.010	2,890	-0.046	892	10,028
	(0.022)		(0.032)		(0.027)		(0.049)		
Loan Taken Since Aashadh (=1)	-0.007	3,449	0.044*	2,807	-0.011	2,892	-0.042	892	10,040
	(0.023)		(0.024)		(0.021)		(0.044)		
Loan Amount Since Aashadh (1K Rs.)	0.773	3,447	2.299	2,805	0.337	2,892	-17.463$^{**}_{\dagger}$	892	10,036
	(3.736)		(3.220)		(4.130)		(7.053)		
Panel I: Expenditures									
Medical Costs (1K Rs)	-1.819	3,448	2.729	2,801	0.476	2,891	-8.813$^{***}_{\dagger\dagger\dagger}$	891	10,031
	(1.586)		(1.999)		(1.813)		(2.823)		
Education Costs (1K Rs)	-0.290	3,441	0.033	2,800	0.053	2,883	-0.630	892	10,016
	(0.369)		(0.480)		(0.402)		(0.777)		
Livestock Costs (1K Rs)	0.183	3,449	0.380	2,805	0.389	2,889	0.492	891	10,034
	(0.425)		(0.450)		(0.275)		(0.619)		
Food Expenditure (1K Rs)	-0.112	3,422	0.900	2,773	-0.317	2,877	-0.213	885	9,957
	(0.583)		(0.645)		(0.358)		(0.590)		
2022 Clusters	99		83		115		37		319
2023 Clusters	123		114		66		22		319

Notes. The table shows treatment effects on economic outcomes. Regression includes round and district fixed effects for all outcomes. The regression is fully interacted with the categorical flood severity variable. Standard errors are in parentheses and clustered at the panchayat level. Flood severity is assigned at the village, not panchayat level, so some panchayats will fall in multiple bins. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level. Anderson's sharpened q-values are denoted by $_{\dagger}$, $_{\dagger\dagger}$, $_{\dagger\dagger\dagger}$.