Forecasting Fate: Experimental Evaluation of a Flood Early Warning System

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Abstract

Climate change is escalating global flood risks, affecting one in every four people. This increases health and economic challenges, particularly in South Asia where 576 million people face flood risks. Early warning systems (EWS) have the potential to reduce socioeconomic flood impacts, yet inadequate dissemination infrastructure, low literacy rates, and distrust in external agencies may hamper their effectiveness. We experimentally evaluate a flood EWS that pairs a cutting-edge flood forecasting system with community-based alert dissemination in Bihar, one of India's most flood-prone states. Household surveys indicate treatment communities received more flood alerts but also more false positives, yet with fewer missed floods, overall alert accuracy improved. This fostered greater trust in alerts and led to better preparedness and health outcomes, with treatment households exhibiting higher adaptation and health scores and a 30% reduction in medical costs compared to control communities.

Introduction. Climate change is escalating flood risks globally, impacting one in every four individuals (IPCC, 2023). Flood and extreme rainfall occurrences have increased by more than 50% since 2010, and fourfold since 1980 (EASAC, 2018). Between 2011 and 2020, floods killed 45,000 individuals, with 73% occurring in lower-income nations (Guha-Sapir, 2020). These disasters compound health and economic issues, elevating morbidity and poverty amongst vulnerable populations. In South Asia, 576 million people are exposed to significant flood risk, accounting for 30.4% of the population (Rentschler et al., 2022). The Ganges-Brahmaputra River basin, which has 600 million residents and 200 million poor, is especially vulnerable. Even minor floods can impact millions, as shown from 2000-2010, with over 16,000 deaths, 200 million displaced, and 20 billion dollars in economic damages (Priya et al., 2017).

Flood early warning systems (EWS) have the potential to reduce flood-related morbidities and economic losses in South Asia. Back-of-the-envelope estimates of potential EWS benefits over a decade of normal floods are more than 500 times the 10-year system cost (Teisberg and Weiher, 2009). In 2022, the UN Secretary-General launched "Early Warnings for All", proposing a US$ 3.1 billion investment over five years to strengthen observation and forecasting capabilities, as well as dissemination and communication of warnings. While recent advances in computation and machine learning have significantly improved the accuracy of 48-72 hour flood prediction (Nearing et al., 2024), we currently lack estimates of EWS effectiveness based on actual dissemination activities. A range of last-mile delivery difficulties, including communication infrastructure, state capacity,

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societal trust, and literacy levels, may have an impact on EWS systems' ability to affect household behavior.

In this paper, we report on the first experimental evaluation of a flood EWS covering roughly 3.6 million people in Bihar, India. Our evaluation spans three flood cycles over five years. We build on a partnership of Indian Central Water Commission with Google, wherein alerts based on Google's advanced flood-forecasting technology are disseminated as push notifications to location-services-enabled android smartphones. In 2019, via a pilot study, we evaluated the status quo flood EWS where the additional treatment simply amplified alert awareness to a single local leader. We found no treatment impacts. Specifically, despite widespread flooding, less than half the Bihari households received alerts and this was not differential by treatment status. Over the next two years we worked with Google to add localized features to the flood alert and with a local organization to develop a community-based alert dissemination system.

We experimentally assessed this approach over the two flood cycles in 2022 and 2023. Our intervention spans 319 village communities across 12 flood-prone districts. While all communities have access to Google's flood-forecasting system, the community-based outreach was randomized to selected 160 treatment communities, reaching over 1.8 million people. In each treatment community, two-to-three android-phone-owning volunteers were trained on understanding flood alerts. Flood alerts were disseminated by volunteers to the community via both traditional (loudspeakers and flag planting) and modern (WhatsApp groups) modes of communication.

Initial results from our household surveys show households in treatment communities more likely to receive flood alerts, with a greater number of alerts received compared to those in control communities. Importantly, while treatment communities received more alerts, they also experienced a higher rate of false positive alerts (alerts without subsequent floods). However, 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. Consequently, treatment communities were more likely to report trusting flood alerts compared to control communities.

These improvements in accessibility, accuracy, and trust translated into more proactive adaptive behavior, protecting treatment households' health from severe flooding. Quantitatively, treatment households in severely flooded areas had a score that was 0.18 standard deviations higher on indices measuring proactive adaptation and physical health compared to control households in similar areas. Overall, treatment households reported a 30% decrease in medical expenditures.

Context. 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 (Figure 1).

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 study underscores these gaps: during the 2019 flood season, while over 95% of households were affected by floods, only 45% received any alert (Figure 2). 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 (Figure 3).

Intervention. Our evaluation includes 319 panchayats (communities) with >3.6 million people in 12 flood-prone districts of Bihar (Figure 4).[1] 160 of these 319 communities form the treatment group, while the rest are in the control. Google's cutting-edge forecasting and android-based alerting system are combined with incentivized grassroots volunteers trained in community outreach activities for the flood EWS intervention.[2]

In 2019, via a pilot study, we evaluated the status quo flood EWS where the additional treatment simply amplified alert awareness to a single local leader. We found no treatment impacts. Specifically, as we mentioned above, despite widespread flooding, less than half the Bihari households received alerts and, crucially, this was not differential by treatment status. Following this pilot, in 2021, we partnered with a local NGO, Yuganter, to train community-based volunteers to use Google flood alerts in each treatment community. We further refined the effectiveness of this dissemination channel via volunteer incentives and launched our evaluation in 2022. Our evaluation is scheduled to run through the 2026 flood season.

Data collection. Each year, we have a set approach: from June to October, we implement our community-based intervention. 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, as well as to gauge post-flood adaptations. Additionally, it collects information on accessibility and proactive adaptations from households that we couldn't reach during the midline survey. Between December 2022 and March 2023, we conducted an extensive in-person survey, reaching out to 5,582 households spread across 319 communities in our study. These households represent the central element of our midline and endline data collection activities, and empirical analysis.[3]

Google's flood forecasting and android-based alerting system. Google's flood forecasting system uses two AI models with public data: a hydrologic model forecasting river water flow, and an inundation model identifying flood-prone areas and estimating water levels. As mentioned above, detailed alerts about forecasted timing and water depth, preferred by many, reach only a few households. This system predicts floods 2 to 4 days in advance, integrating forecasts into Google's Public Alerts service.

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. Both the treatment and control communities have access to this system. For every flood event, several alerts are disseminated: initially, warning alerts providing projected water levels are sent a few days before the anticipated event; these are then escalated to severe alerts as the situation intensifies, and subsequently revert to warning alerts as flood waters begin to subside.

[1] 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.

[2] Our intervention encompasses both flash and prolonged riverine (freshwater) floods in rural areas.

[3] Since the study's sample had not been finalized, 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.

However, our project identifies a crucial gap: these alerts often miss the most vulnerable, typically in rural areas, who might be illiterate or lack smartphone access. In rural Bihar, few households use location services, and even among smartphone users, only about 55% can correctly access Google's flood alerts on their phones. We aim to bridge this gap using a community volunteer model, enhancing villagers' access to this vital information.

Community-based alert dissemination. In each treatment community, three android-phone owning volunteers are trained at the start of the flood season to understand flood alerts from Google's forecasting and alerting system. Flood alerts are then disseminated by volunteers via both traditional (e.g., loudspeakers) and modern (e.g., WhatsApp groups) modes of communication. No volunteers are recruited in control communities. Our 2023-2026 interventions differ slightly in that we recruit two community volunteers per treatment panchayat instead of three. In addition, unlike in 2022, we also directly message (via WhatsApp groups and SMS) treatment households, who were enrolled in the 2022 endline survey, about any flood alerts.

Empirical Strategy. *Research questions.* Our research inquiry 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, usefulness, 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.

5. *Ex post adaptation. Did receiving alerts reduce the need for emergency actions or spending after the floods?* After flood season, we collect household expenses data from flood season and the past year. Additionally, we track work and school absences and school dropouts, to gauge the broader impact of EWS on daily life.

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

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

$Treat_{pd}$ takes the value 1 if community (panchayat) p in district d is in the treatment group, 0 otherwise. Y_{hvpd} is outcome of interest for household h in village v in panchayat p in district d. Because random assignment of the 319 panchayats between the treatment and control group was stratified at the district level, we also include district fixed effects (μ_d). v_{pd} is an error term, clustered at the panchayat level. We also plan to estimate Equation 3, factoring in the severity of flood alerts, which is indicated by the total number of alerts received. We anticipate that the effects on proactive adaptation (ex ante), physical health, economic conditions, and reactive adaptation (ex post) will be influenced by the severity of the floods.

In our study, which is based on a randomized design, an essential assumption for identifying cause-and-effect relationships is that the allocation of treatment is independent of any unobserved factors that might affect the outcomes. To test this assumption, we use the 2022 endline survey to examine and confirm that there is a balanced distribution across fixed observable characteristics that are unlikely to be affected by our intervention and might influence the primary outcomes of our study (Table 1).

Floods. In 2022 and 2023, roughly the same number of panchayats received alerts, with around 80% in both the control and treatment groups in both years (Figure 5).[4] This suggests that the extent of flooding was similar across the two years. However, the intensity, as measured by the number of alerts, was markedly different: in 2022, the average number of alerts per panchayat was around 50 for both control and treatment groups, whereas in 2023, it decreased to an average of 25 for both the groups (Figure 6). This indicates that although the floods were as extensive in both years, the intensity was significantly higher in 2022 compared to 2023.

Short-Run Impacts. *Accessibility.* Initial results suggest that our flood EWS effectively delivered warnings to households in both 2022 and 2023. 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 and accurate alerts; treatment communities were also more inclined to trust flood alerts.

During the 2022 flood season, households in treatment communities received 2.41 more alerts (a 298% increase) on average during the 2022 flood season (June-October), were 27% more likely to receive any alerts, 46.5% more likely to receive alerts before water reached their area, and 57% more likely to say they trust the alerts completely (Figures 7 - 10). In 2023, treatment communities received 4.35 more alerts on average (a 558% increase), were 74% more likely to receive any alert, 88% more likely to receive an alert before water reached their panchayat, and 89% more likely to say they trust alerts completely. Furthermore, 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 2). This indicates that the measures taken effectively bridged customary social divides, ensuring inclusive reach of the benefits.

Importantly, while treatment communities received more alerts, they also experienced a higher rate of false positive alerts (alerts without subsequent floods). The treatment group experienced more false positives, 8.09%, compared to the control group at 3.64% (Figure 11). 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 42.97%, significantly more than the treatment group's 32.84%. Overall, the treatment group had a lower incidence of forecast errors at 40.94% compared to the control group at 46.61%.

Ex ante adaptation and physical health. We also find encouraging effects on proactive adaptive behaviors and physical health in areas that experienced significant flooding, as proxied by the number of alerts sent via Google's forecasting and android-based alerting system (Figure 12). Specifically, we observed that households in the treatment group who received the most alerts (top tercile) were more likely to engage in precautionary actions against flooding and experienced

[4] As one might expect, the number of communities that were alerted by Google's flood forecasting and android-based alerting system is balanced across treatment and control groups.

fewer health issues due to flooding. Quantitatively, these households in the top tercile for alerts had a score that was 0.18 standard deviations higher on indices measuring proactive adaptation and physical health compared to control households receiving a similar number of alerts. Within the health index, the most heavily impacted treatment households showed a decrease in sickness and injury (Table 3), mainly due to fewer cases of waterborne diseases and slip-related accidents. Overall, treatment households observed 0.36 fewer illness symptoms (a 16.56% decrease) compared to control households (Table 4). As a result, households in treatment areas incurred roughly INR 6,500 less on illness treatment (a 32.87% decrease). In fact, based on the estimated reduction in medical expenditures alone, we estimate that for every \$1 spent on the program, the intervention would generate a minimum benefit of \$30 during a severe flooding season.

Next, we examine how flood EWS impact physical health differently across gender and age groups within households. Our findings don't indicate significant variations in sickness rates between men and women (Tables 5 and 6). However, women appear to benefit more in terms of injury prevention from the EWS than men. This difference may be attributed to the roles women usually play during floods, often being the primary caretakers in the home and, consequently, more exposed to risks of slip-related injuries. The protective effects of EWS against sickness are most pronounced in the oldest populations (those over 60 years of age) (Tables 7 - 9). In terms of injury prevention, the benefits are primarily observed in the 16-60 age group, supporting the hypothesis that the larger protective impacts on injury for women are due to their higher exposure to injury risks, as this age group includes many women in caretaker roles. The impacts on both sickness and injury for children under 16 are smaller than for the older members of households.

Economic well-being and ex post adaptation. We fail to find evidence for improved economic well-being or decrease in ex-post adaptation in severely flooded communities. This suggests that the lead time of 2-4 days is sufficient for households to take immediate actions like sandbagging homes or moving food to a safe location to protect their health against the impending flood. However, for economic well-being, particularly in the context of agricultural communities, such a short lead time may not be enough to take effective measures to protect agricultural land and crops, often caught between the post-planting and pre-harvest phases, making them especially vulnerable to flooding with limited mitigation options. Additionally, economic adaptation strategies like building protective structures or altering farming practices may require even greater trust in the EWS, which may take time to develop. Without this level of trust, farmers are less likely to undertake costly adaptive measures that could mitigate economic losses and lessen the necessity for extensive post-flood adaptation.

Furthermore, the absence of a decrease in ex-post adaptation could indicate that, notwithstanding the advance warning, the severity of floods overruns the capacity to safeguard economic assets like farmland. The resulting damage may render post-flood adaptive measures, such as repairing and improving infrastructure or investing in future flood prevention, unfeasible or ineffective in the immediate aftermath due to the extensive resources and planning required. Moreover, since health benefits are concentrated among males over 60 and women aged 16-65, who are likely home caretakers, it's entirely expected that we observe no reductions in work absences as post-flood adaptations, given their less direct involvement in external work. Overall, the lack of evidence for improved economic well-being and ex-post adaptation suggests that while EWS can be beneficial for immediate health, their utility in protecting economic assets and enabling effective post-disaster adaptation is limited without additional, more extensive measures and without overcoming technological and trust-related barriers.

Longer-Run Impacts. As underlined by the discussion above, understanding the longer-term impact of EWS, that is, estimates that incorporate behavioral responses to accurate alerts or inaccurate alerts, is crucial to evaluate the system's effectiveness. Multiple accurate alerts may foster trust and encourage more proactive safety measures, whereas false positive alerts could diminish trust.[5] In addition, drawing conclusions of the effectiveness of EWS based on one or two seasons could be misleading, especially if they are atypical in terms of flood frequency or severity. Therefore, our study will (i) analyze the aggregate effects of EWS over a set of highly variable flood seasons, (ii) investigate how the accuracy of alerts influences community trust and the adoption of proactive safety measures, considering that inaccurate alerts might undermine trust.

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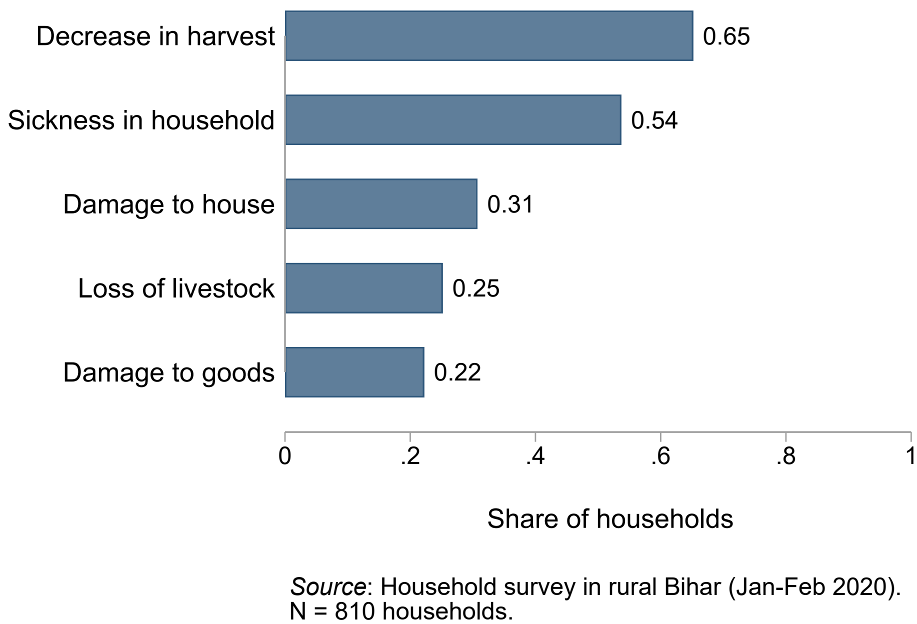
[5] For instance, Cole et al. (2023) use a lab-in-the-field experiment in India, to show that farmers update their beliefs about rainfall forecasts' (in)accuracy following false alarms, where forecasts erroneously predict events.

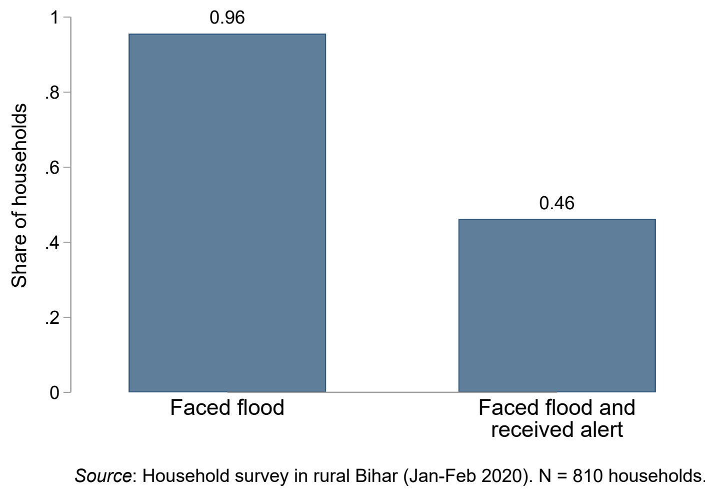
Figures and Tables

Figure 1: Floods are highly disruptive to lives and livelihoods in Bihar.



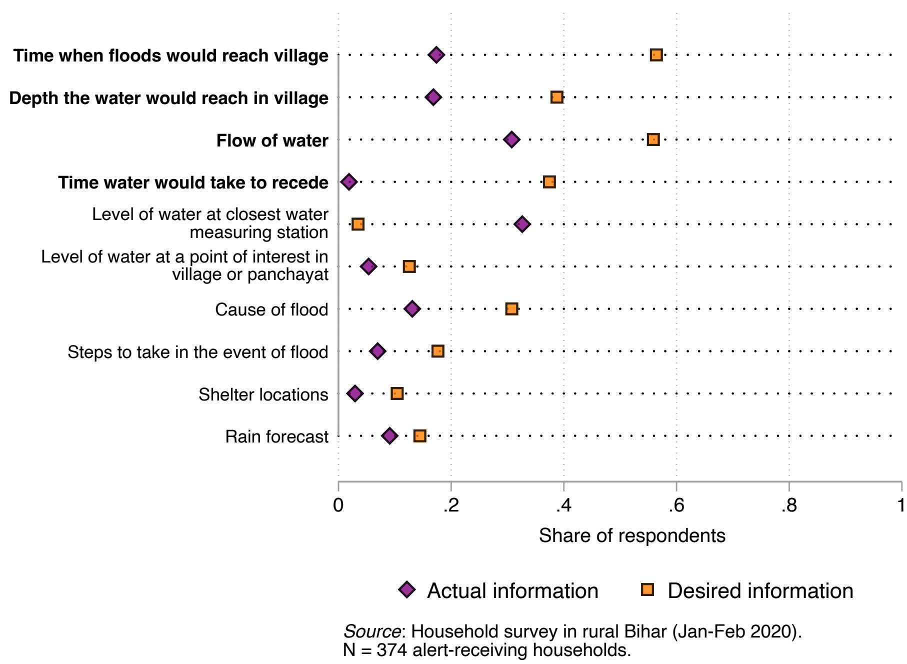
Notes. Figure reports the proportion of households who reported negative outcomes following the 2019 flood season.

Figure 2: Most at-risk households do not have access to flood warnings.



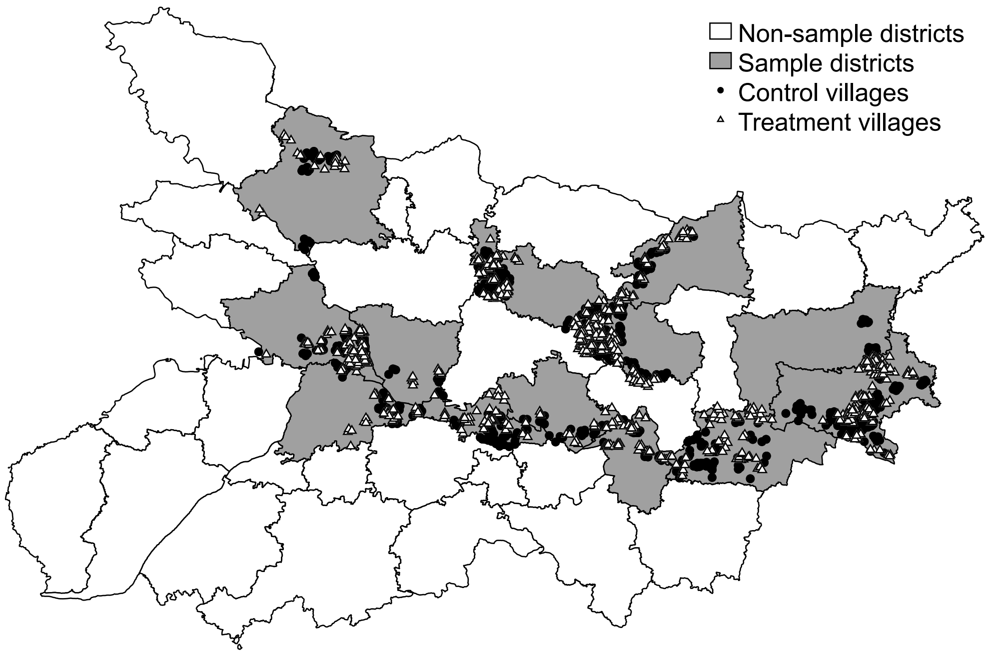
Notes. Figure reports the proportion of households who were a) affected by flooding in 2019 and b) were affected by flooding and received a flood warning.

Figure 3: Existing flood early warning systems don't provide information desired by at-risk households.



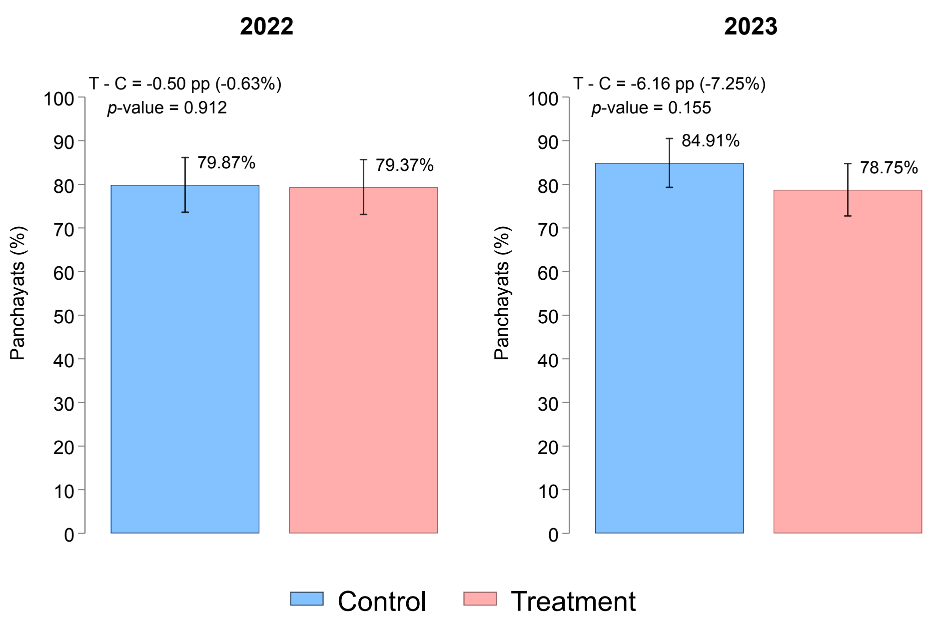
Notes. Figure reports - in purple - the share of households who *received* each type of information from flood alerts during the 2019 monsoon season, and - in orange - the share of households who *desired* each type of information.

Figure 4: Location of Sample Villages in Bihar



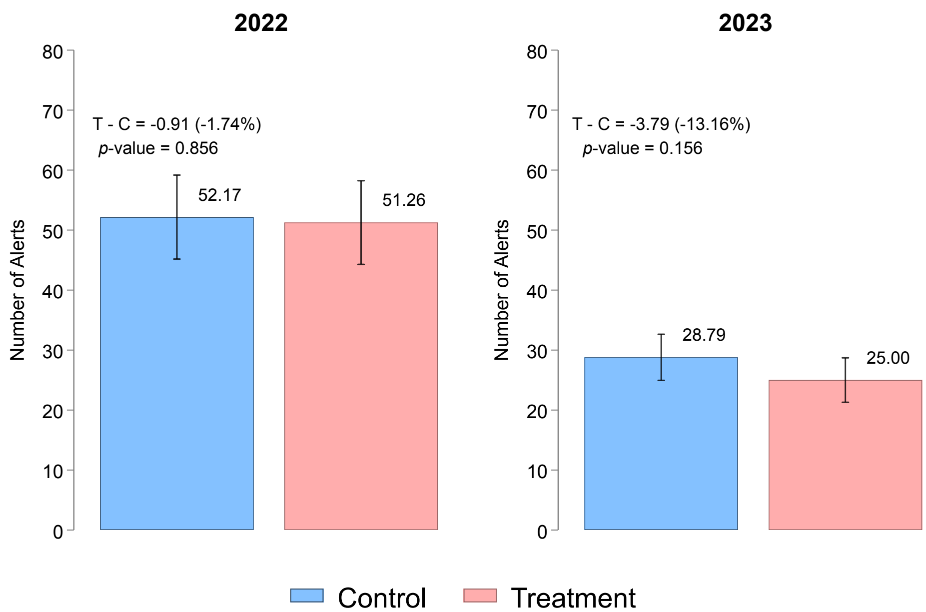
Notes. The map depicts Bihar, a northern state of India. Our sample consists of 159 control panchayats covering 291 villages and 160 treatment panchayats covering 300 villages in 12 districts.

Figure 5: Flooding was extensive and balanced across treatment and control.



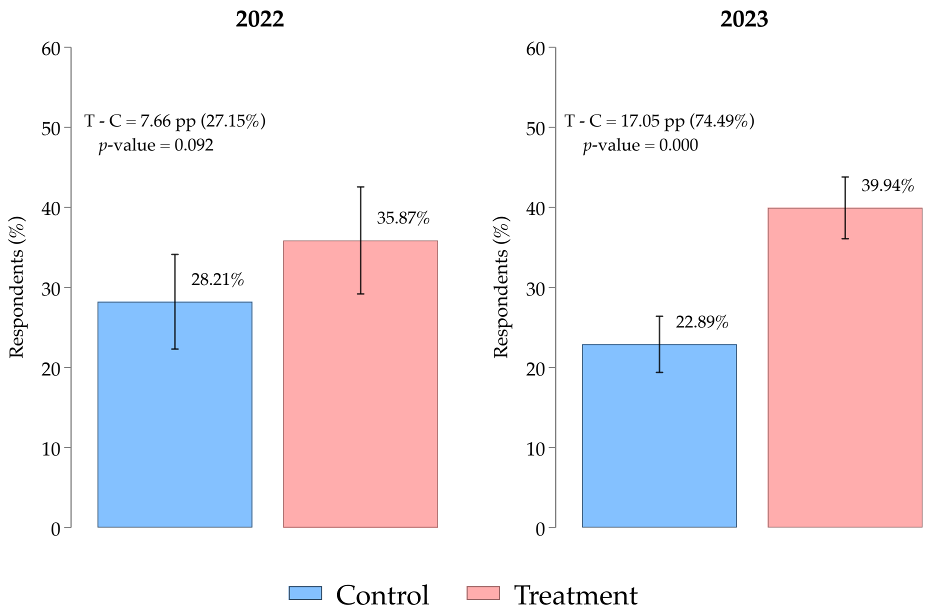
Notes. Figure reports the proportion of panchayats who were sent an alert by the Central Water Commission/Google between June and October. Treatment consists of 160 panchayats and control consists of 159 panchayats. Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals.

Figure 6: The intensity of flooding was higher in 2022, but balanced across treatment and control in both years.



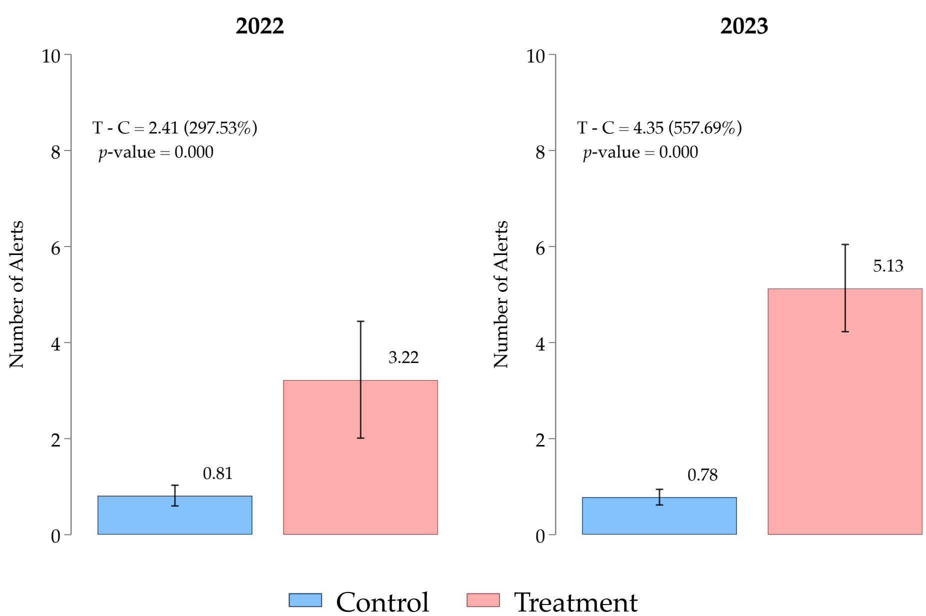
Notes. Figure reports the number of days in which panchayats were sent flood alerts by the Central Water Commission/Google between June and October. Treatment consists of 160 panchayats and control consists of 159 panchayats. Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals.

Figure 7: Treatment households are more likely to receive an alert.



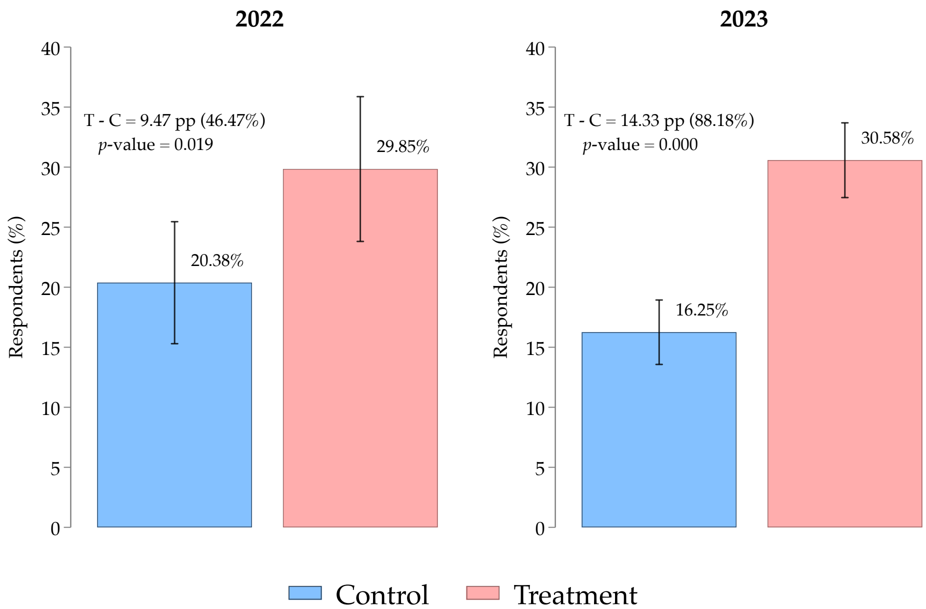
Notes. Figure reports the percentage of control and treatment households that reported receiving a flood alert from any source between June and October. Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals. Standard errors are clustered at the panchayat level.

Figure 8: Treatment households receive greater # of alerts.



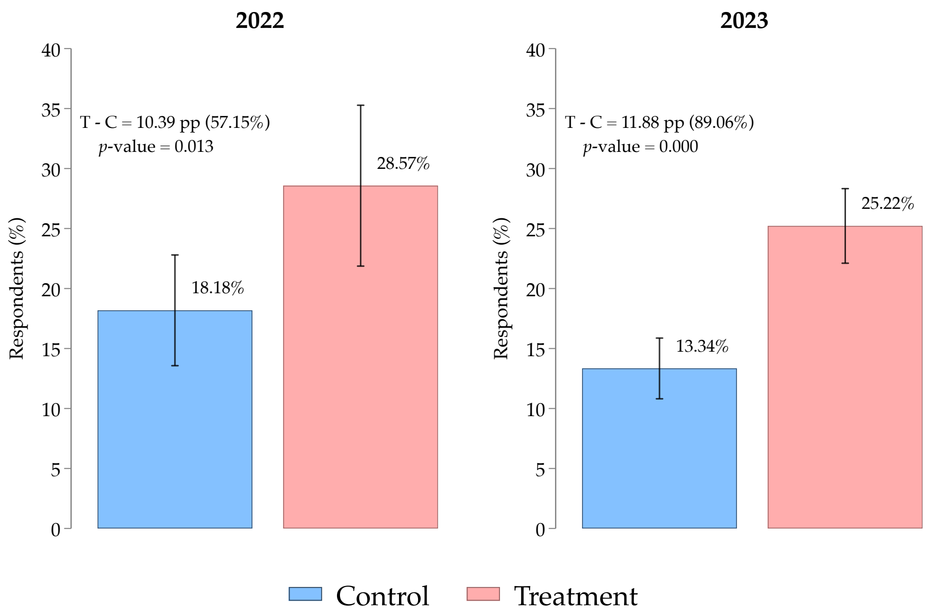
Notes. Figure reports the number of flood alerts received by control and treatment households, between June and October (top-coded at the 99th percentile). Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals. Standard errors are clustered at the panchayat level.

Figure 9: Treatment households are more likely to receive alerts before water reaches the community (panchayat).



Notes. Figure reports the percentage of control and treatment household households that reported - between June and October, for at least one source of alert - that alerts typically arrived before water reached their panchayat. Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals. Standard errors are clustered at the panchayat level.

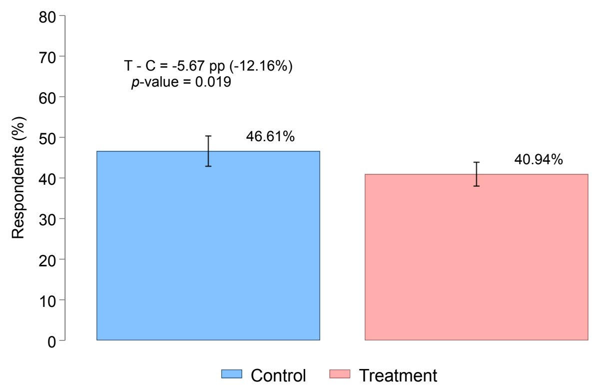
Figure 10: Treatment households are more likely to trust alerts completely.



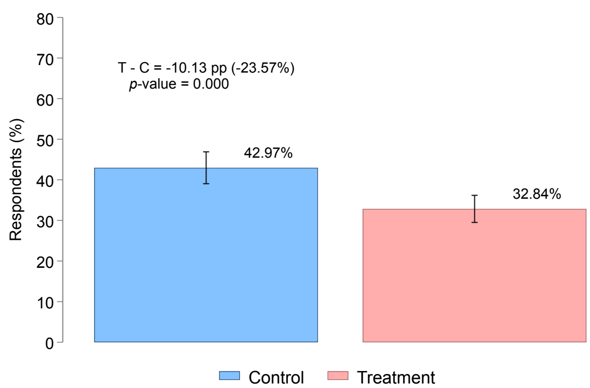
Notes. Figure reports the percentage of households that said - between June and October, for at least one source of alert - that they trusted alerts 'completely'. Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals. Standard errors are clustered at the panchayat level.

Figure 11: Treatment households experience less forecast error due to fewer instances of false negatives, but are more likely to receive false positives.

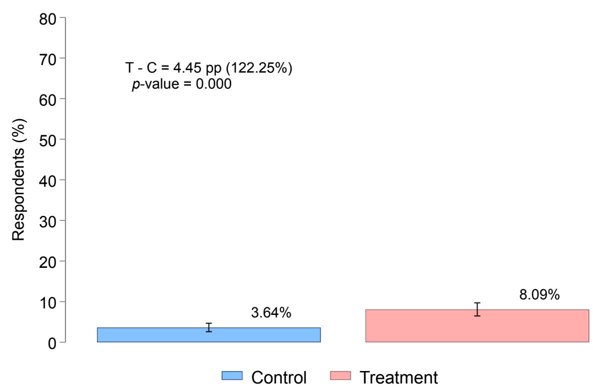
(a) Treatment HHs have a lower incidence of forecast errors.



(b) Treatment HHs are less likely to not receive alerts when flooded.

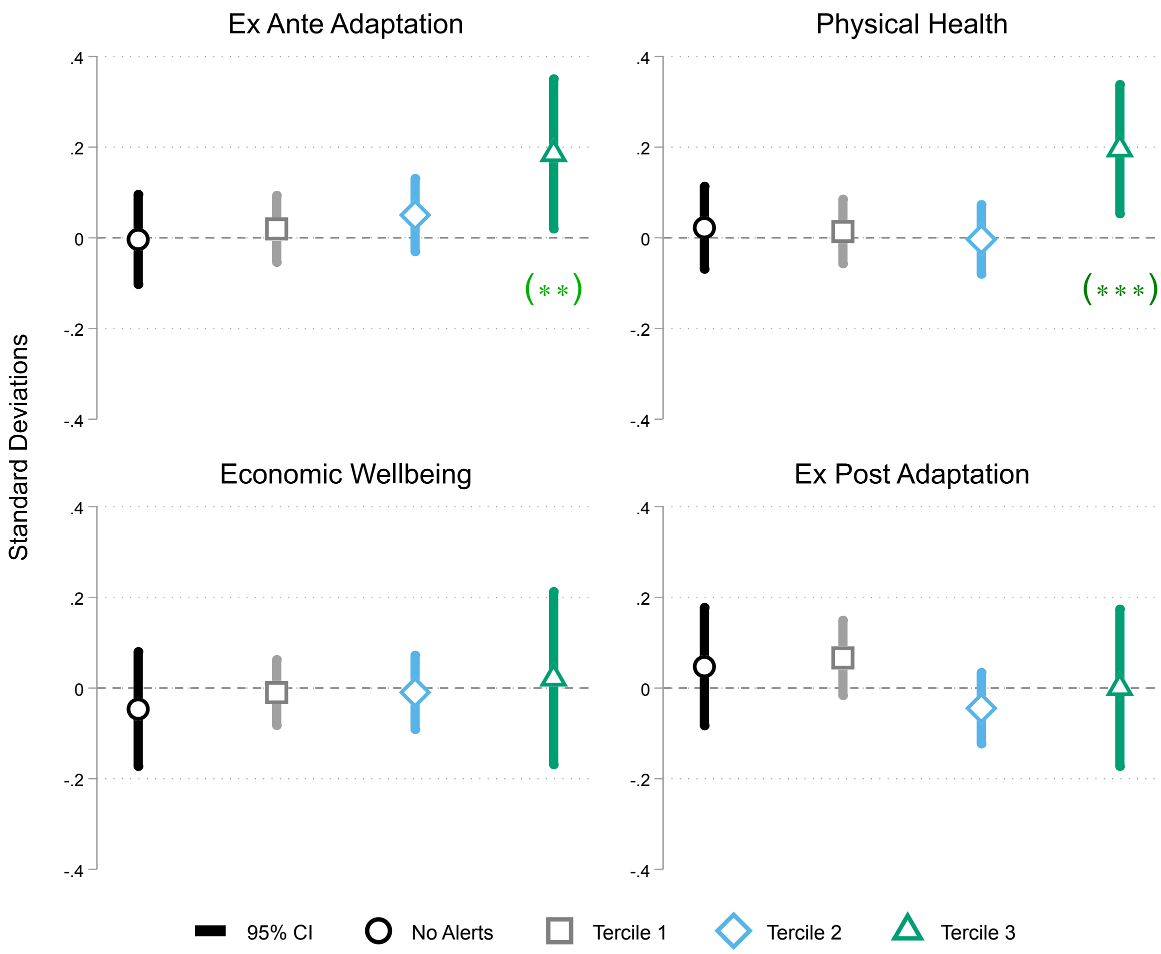


(c) Treatment HHs are more likely to be alerted, but not flooded.



Notes. Panel (a) reports the proportion of control and treatment households who experienced either false positive or false negative alerts. Panel (b) reports the proportion of control and treatment households who experienced false negatives between June and October - their panchayat was flooded and they did not receive any alert. Panel (c) reports the proportion of control and treatment households who experienced false positives - they received an alert and their panchayat was not flooded. Treatment-control differences are reported in the top left area of the plot region. In brackets, this is expressed as a percentage of the control mean. Whiskers are 95% confidence intervals. Standard errors are clustered at the panchayat-round level.

Figure 12: Treatment HHs take more proactive steps and are better protected, in terms of physical health, in severely flooded communities.



Notes. Figure reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Cutoffs for alerts terciles are defined by the panchayat-level distribution of alerts sent by the Central Water Commission/Google in 2022. The ex-ante adaptation estimates include a *midline* dummy, equal to 1 if this module was surveyed during the flood season. In the case this module was surveyed during the flood season, this household is binned according to the number of alerts received up to the day of the survey. Regression uses round and district fixed effects and standard errors are clustered at the panchayat-round level. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 1: Household characteristics are balanced across treatment and control communities.

Variables	(1) Control	(2) Treatment	(3) Difference	(4) N
HH size	5.479	5.431	-0.048	5,582
	[2.385]	[2.540]	(0.087)	
HH head's age (yrs)	44.713	44.903	0.190	5,582
	[15.000]	[15.446]	(0.524)	
Male HH head (=1)	0.999	0.998	-0.000	5,582
	[0.038]	[0.042]	(0.001)	
Proportion of females in the HH	0.478	0.475	-0.003	5,582
	[0.157]	[0.159]	(0.005)	
Hindu (=1)	0.890	0.914	0.025	5,582
	[0.314]	[0.280]	(0.020)	
Muslim (=1)	0.098	0.075	-0.023	5,582
	[0.297]	[0.264]	(0.020)	
Scheduled Castes (=1)	0.181	0.164	-0.017	5,567
	[0.385]	[0.370]	(0.018)	
HH head's education: Grad & above	0.166	0.152	-0.014	5,582
	[0.372]	[0.359]	(0.012)	
Number of members, 0-5 yrs	0.698	0.697	-0.000	5,582
	[1.042]	[1.030]	(0.035)	
Number of members, 6-15 yrs	1.172	1.133	-0.039	5,582
	[1.307]	[1.331]	(0.041)	
Number of members, 60+ yrs	0.496	0.523	0.027	5,582
	[0.709]	[0.725]	(0.023)	
Smartphone ownership (=1)	0.915	0.915	0.000	5,582
	[0.278]	[0.278]	(0.008)	
GIS distance to river (kms)	2.767	2.648	-0.119	5,556
	[2.198]	[2.035]	(0.235)	
Reported distance to river (kms)	7.036	5.475	-1.561	5,521
	[51.714]	[43.204]	(1.388)	
Panchayat flooded in Jun-Oct, 2022 (Satellite)	0.655	0.584	-0.070	5,582
	[0.476]	[0.493]	(0.056)	
Panchayat flooded in Aashadh-Kartik (Reported)	0.877	0.871	-0.006	5,582
	[0.328]	[0.335]	(0.020)	
Altitude (meters)	6.868	4.538	-2.330	5,582
	[214.140]	[113.645]	(6.924)	
Land owned (acres)	1.071	1.286	0.216	5,542
	[2.412]	[12.359]	(0.250)	
N	2,743	2,839	5,582	
Clusters	159	160	319	

*Notes.*Table reports balance for household-level characteristics. Columns (1) and (2) report control and treatment means, respectively. Column (3) reports treatment-control differences. Standard errors clustered at the level of panchayat in parentheses and standard deviations in brackets. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 2: Impacts on accessibility are similar across social strata.

Variables	(1) Control Mean	(2) Upper Strata	(3) Control Mean	(4) Lower Strata
Any Alert (=1)	0.220	0.168***	0.243	0.159***
		(0.036)		(0.019)
Number of Alerts	0.706	3.848***	0.817	4.157***
		(0.634)		(0.407)
Before Water Reached Panch. (=1)	0.153	0.180***	0.173	0.130***
		(0.034)		(0.017)
Trust Completely (=1)	0.118	0.128***	0.147	0.116***
		(0.027)		(0.016)

Notes. *Upper Strata* comprises non-EBC upper caste households. *Lower Strata* comprises OBC, SC, ST and EBC households. *Any Alert (=1)* is equal to 1 if the household reported receiving an alert between June and October. *Number of Alerts* is the number of alerts the household received, between June and October (top-coded at the 99th percentile). *Before Water Reached Panch. (=1)* is equal to 1 if the household reported that - between June and October, for at least one source - alerts typically were received before water reached their panchayat. *Trust Completely (=1)* is equal to 1 if the household reported that - between June and October, for at least one source - they trusted the source completely. Control means are reported in columns (1) and (3). Treatment effects are reported in columns (2) and (4). Standard errors clustered at the panchayat-round level in parentheses. Regression includes round and district fixed effects. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 3: Treatment HHs experienced less injury or illness in severely flooded communities

Variables	(1) No Alerts	(2) Tercile 1	(3) Tercile 2	(4) Tercile 3
Sickness	0.052	-0.002	0.047	0.188**†
	(0.048)	(0.036)	(0.037)	(0.080)
Injury	0.036	-0.009	-0.013	0.139*†
	(0.044)	(0.031)	(0.035)	(0.074)
Death	-0.045	0.038	-0.041	0.047
	(0.044)	(0.032)	(0.037)	(0.078)

Notes. Table reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Standard errors are clustered at the panchayat-round level. Regression includes round and district fixed effects. Cutoffs for alerts terciles are defined by the household distribution of alerts sent by the Central Water Commission in 2022. * 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 †.

Table 4: Treatment households are less likely to get sick, experience fewer types of disease, and spend less on treating illness, in severely flooded communities.

Variables	(1) No Alerts	(2) Tercile 1	(3) Tercile 2	(4) Control Mean	(5) Tercile 3
Any member sick (=1)	-0.004	0.007	-0.015	0.743	-0.037
	(0.021)	(0.017)	(0.016)		(0.039)
# members sick	-0.064	0.032	-0.077	2.070	-0.284$^{*}_{\dagger}$
	(0.090)	(0.069)	(0.073)		(0.157)
Avg # days sick	0.278	-0.090	-0.776	9.562	-0.605
	(0.622)	(0.438)	(0.482)		(1.273)
Number of Symptoms	-0.187*	0.021	-0.081	2.203	-0.365$^{**}_{\dagger}$
	(0.096)	(0.075)	(0.066)		(0.164)
Number of Causes	-0.083*	-0.034	-0.027	1.100	-0.183$^{**}_{\dagger}$
	(0.046)	(0.032)	(0.035)		(0.081)
Illness treatment (1K Rs)	-0.926	0.308	-0.293	19.685	-6.470$^{**}_{\dagger}$
	(1.858)	(1.151)	(1.250)		(2.739)

Notes. Columns (1), (2), (3) and (5) report treatment effects. Column (4) reports control means for *Tercile 3*. Standard errors are clustered at the panchayat-round level. Cutoffs for alerts terciles are defined by the household distribution of alerts sent by the Central Water Commission in 2022. Regression includes round and district fixed effects. Standard errors clustered at the level of panchayat in parentheses. * 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 †.

Table 5: Male members of treatment households are less likely to get sick in severely flooded communities.

Variables	(1) No Alerts	(2) Tercile 1	(3) Tercile 2	(4) Tercile 3
Sickness	0.058*	-0.006	0.045*	0.179***
	(0.034)	(0.024)	(0.027)	(0.053)
Injury	-0.000	0.022	-0.005	-0.000
	(0.033)	(0.022)	(0.025)	(0.049)

Notes. Table reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Sample is all male household members. Standard errors are clustered at the panchayat-round level. Regression includes round and district fixed effects. Alerts terciles are based on the household distribution of alerts recorded in 2022. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 6: Female members of treatment households are less likely to get injured in severely flooded communities.

	(1)	(2)	(3)	(4)
Variables	No Alerts	Tercile 1	Tercile 2	Tercile 3
Sickness	0.041	0.003	0.016	0.111
	(0.038)	(0.026)	(0.029)	(0.084)
Injury	0.026	-0.016	0.000	0.130***
	(0.028)	(0.020)	(0.021)	(0.035)

Notes. Table reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Sample is all female household members. Standard errors are clustered at the panchayat-round level. Regression includes round and district fixed effects. Alerts terciles are based on the household distribution of alerts recorded in 2022. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 7: Oldest members (over 60) of treatment households are less likely to get sick in severely flooded communities.

	(1)	(2)	(3)	(4)
Variables	No Alerts	Tercile 1	Tercile 2	Tercile 3
Sickness	-0.010	-0.035	0.051	0.273**
	(0.084)	(0.054)	(0.065)	(0.131)
Injury	0.019	-0.049	-0.088	-0.069
	(0.093)	(0.060)	(0.064)	(0.141)

Notes. Table reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Sample is all household members over the age of 60. Standard errors are clustered at the panchayat-round level. Regression includes round and district fixed effects. Alerts terciles are based on the household distribution of alerts recorded in 2022. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 8: Older members (16-60) of treatment households are less likely to get sick and injured in severely flooded communities.

Variables	(1) No Alerts	(2) Tercile 1	(3) Tercile 2	(4) Tercile 3
Sickness	0.037	0.014	0.033	0.188***
	(0.039)	(0.025)	(0.030)	(0.066)
Injury	0.010	0.003	0.029	0.113*
	(0.034)	(0.022)	(0.023)	(0.057)

Notes. Table reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Sample is all household members between the ages of 16 and 60. Standard errors are clustered at the panchayat-round level. Regression includes round and district fixed effects. Alerts terciles are based on the household distribution of alerts recorded in 2022. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 9: Health impacts on children (under 16) are qualitatively smaller compared to impacts on older members of treatment households.

Variables	(1) No Alerts	(2) Tercile 1	(3) Tercile 2	(4) Tercile 3
Sickness	0.069**	-0.012	0.028	0.086
	(0.033)	(0.028)	(0.029)	(0.077)
Injury	0.005	0.020	-0.026	0.033
	(0.031)	(0.018)	(0.021)	(0.038)

Notes. Table reports treatment effects on KLK indices constructed from families of related outcomes, standardized such that a 1-point increase reflects a 1 standard deviation improvement in outcomes. Sample is all household members under the age of 16. Standard errors are clustered at the panchayat-round level. Regression includes round and district fixed effects. Alerts terciles are based on the household distribution of alerts recorded in 2022. * Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.