Insurance and the demand for adaptation: theory and experimental evidence from West Bengal

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Abstract

Governments spend billions subsidizing climate insurance, despite concerns about discouraging adaptation. Our simple model shows that insurance and adaptation can be either substitutes or complements, depending on the overlap in the shocks they protect against. We test this prediction in a randomized experiment across 300 flood-prone villages in West Bengal, where we provide farmers with free flood insurance and measure demand for flood-tolerant seeds. Insurance does not crowd-out adaptation, instead leading to modest crowd-in. Consistent with theory, crowd-in is largest for those who expected the least overlap between insurance and adaptation. Subsidized insurance can therefore complement private climate adaptation.

Keywords: Climate; adaptation; insurance; agriculture
JEL Codes: D81; D25; O12; O13; Q12; Q54

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1 Introduction

The world urgently needs effective strategies to cope with climate change (Carleton et al., 2024). State-subsidized insurance is one of the most widespread policies in both low- and high-income countries. Insurance, which protects people in the event of shocks, can improve income, consumption and welfare outcomes (Karlan et al., 2014; Carter et al., 2017; Cole, Giné, and Vickery, 2017). However, economists have long raised concerns that public insurance may lead to moral hazard effects, as agents with inexpensive insurance forego other forms of adaptation (Buchanan, 1975; Coate, 1995).

In this paper, we ask: what is the effect of insurance on demand for adaptation? We use a simple theoretical model of decision-making under risk to show that, in contrast with standard theory (Ehrlich and Becker, 1972), insurance can either lower *or* raise willingness to pay for adaptation.[1] To see this, consider an agent facing climate shocks, who has two options to reduce their exposure: a free insurance product and an adaption technology they must pay for. There are three states of the world: a good state with no shock N, and two bad states with moderate events, M and extreme events E.[2] In the first case, the free insurance product pays out only in E, while the costly adaptation technology reduces damages in M but not in E. If the agent invests in the adaptation technology and E occurs, they are worse off than had they not invested. Insurance reduces this downside risk by providing compensation in E, increasing utility. As a result, insurance will raise willingness to pay for adaptation, generating "crowd-in." In the second case, suppose instead that the free insurance product continues to pay out in E only, but now the costly adaptation technology reduces damages in *both* M and E. In this case, insurance and adaptation are (partial) substitutes, meaning that insurance will lower willingness to pay for adaptation, generating "crowd-out." Whether insurance and adaptation are complements or substitutes, therefore, depends on the degree to which the shocks they protect against overlap.

We study this question in the high-stakes setting of developing-country agriculture. Farmers in low- and middle-income countries are highly vulnerable to climate shocks (Hultgren et al., 2022) and are increasingly receiving heavily-subsidized government insurance. The World Bank estimates that at least $20 billion is spent annually on insurance subsidies worldwide, which it deems a significant underestimate (Hazell, Sberro-Kessler, and Varangis, 2021). In India, the location of this study, the 40 million farmers enrolled in the central

[1] We define adaptation to be an investment that reduces losses in certain states of the world, but does not change the likelihood of a loss (i.e., "self-insurance" in Ehrlich and Becker (1972)'s terminology). Many investments that households can make to reduce climate damages fit this definition, including air conditioners, flood- or drought-tolerant seeds, umbrellas, etc.

[2] Appendix Table A.1 provides a toy numerical example which illustrates this intuition.

PMFBY crop insurance scheme as of 2023-24—up 27% from 2022-23—are only charged up to 2% of the actuarily fair premium (World Bank Group, 2024).[3] Under efficient pricing, farmers choosing to purchase insurance over adaptation need not be welfare-reducing. However, given the policy landscape, understanding the extent to which these substantial subsidies that bring prices well below the actuarially fair level are inefficiently crowding out other adaptation technologies is critical for policymaking (Carleton et al., 2024).

To test the predictions of our model, we run a two-year cluster-randomized trial in 300 villages in West Bengal in conjunction with the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), a well-respected international organization known for developing advanced crop varieties. We randomly assign villages to a control group or to receive a fully subsidized index insurance product, sampling six farmers per village. The insurance group is further divided into small- and large-payout treatments. After offering treated farmers the insurance product, we elicit every sampled farmers' willingness to pay for another adaptation technology – a minikit of high-quality flood-tolerant seeds (Dar et al., 2013; Emerick et al., 2016). We test for whether insurance crowds-in vs. crowds-out willingness to pay for climate adaptation by measuring the *difference* in willingness to pay for flood-tolerant seeds — for which both the crowd-in and crowd-out motives are present — as compared to high-yield-variety seeds — for which only the crowd-in motive is present — among treated vs. control farmers. This ensures that we account for any income effects or experimenter demand effects.

We run the experiment for two years in order to build trust in our new insurance product, following Cole, Stein, and Tobacman (2014) and Cai, de Janvry, and Sadoulet (2020). We document that farmers do not change their investments in response to insurance in year 1, consistent with limited trust in the product. Due to heavy flooding in the first year, 82% of treated farmers received an insurance payout at the end of this growing season. In the second year, we find that households respond to insurance by increasing risky investments, in line with prior work (Karlan et al., 2014; Cole, Giné, and Vickery, 2017; Burlig et al., 2024) and consistent with a substantial increase in trust. Our main test of whether insurance causes crowd-in or crowd-out of adaptation therefore comes from the willingness to pay elicitation we conduct at the beginning of the second year, once farmers' trust in the insurance product is established.

Our experiment generates two main empirical results. First, we strongly reject that insurance causes crowd-out of demand for flood-tolerant seeds. Instead, we find evidence that insurance causes a modest amount of crowd-in: in the second year of the experiment,

[3] Since the 2007 launch of China's agricultural insurance subsidy program, these subsidies have totaled over 41.4 billion USD, with year-over-year growth of 22% (Peoples' Republic of China (2024)).

we find that insurance increases willingness to pay for flood-tolerant seeds as compared to high-yield variety seeds by 2.7% of control mean willingness to pay for flood-tolerant seeds, or 80% of the willingness to pay gap in the control group ($p < 0.01$), enough to switch 10% of farmers towards having a higher willingness to pay for the flood-tolerant variety.[4] These results demonstrate that subsidized insurance need not crowd-out private adaptation, and provide the first proof-of-concept that crowd-in can instead occur.

Second, consistent with the prediction of our model, we find that the degree of crowd-in varies with farmers' perceptions of the effectiveness of the flood-tolerant seed. While the seed's quality is fixed across farmers in our experiment, we document that farmers' beliefs about the seed vary substantially. This heterogeneity strongly predicts willingness to pay. Farmers in the bottom tercile of the seed quality beliefs distribution, who anticipate that the flood-tolerant seeds offer only limited protection against flooding, have a crowd-in effect that is 47% larger than the average effect. In contrast, for farmers in the top tercile of the seed quality beliefs distribution, who anticipate that the flood-tolerant seeds are highly protective against flooding, we see no difference in willingness to pay with vs. without insurance. The close match between this finding and our theory makes alternative explanations for crowd-in, such as experimenter demand effects or salience, which would not adjust demand differentially along this margin, unlikely to be driving our results.

The main contribution of this study is to estimate the extent to which climate insurance crowds in or crowds out demand for private climate adaptation, motivated by a novel theoretical insight. Classic theory (Ehrlich and Becker, 1972) provides an unambiguous prediction: insurance crowds out adaptation (i.e., actions that reduce the size of a loss but not its probability, or "self-insurance").[5] This prediction relies on an assumption that is unlikely to hold in many real-world settings: namely, that the adaptation technology is effective in all bad states also covered by insurance.[6] When the adaptation technology reduces damages in only a subset of bad states, however, insurance that covers the residual risk makes adaptation *more* valuable by protecting the household precisely when adaptation fails. The

[4]In the first year, we see no effect of the insurance product on the willingness to pay for flood-tolerant seeds, high-yield variety seeds, nor the difference between the two. This, alongside the lack of investment response (Appendix Table A.14) is consistent with farmers not finding the insurance product credible in the first year.

[5]Ehrlich and Becker (1972) also consider the case of investments that reduce the probability of a loss, or "self-protection," and show that if the insurance premium falls when a household makes a self-protection investment (e.g., a good-driver discount for car insurance), this can lead to crowd-in. We instead focus on self-insurance, and document a distinct mechanism for crowd-in that exists even absent price adjustments.

[6]For example, sea walls, sand bags, and home elevation protect houses against moderate floods, but often leave them susceptible to extreme events. A fan may be an effective tool against moderately warm temperatures, but will be ineffective in high heat; an umbrella keeps its owner dry in a drizzle but not in a torrential downpour.

degree of overlap between the states in which insurance provides coverage and those in which adaptation is effective thus determines whether insurance crowds out or crowds in demand for adaptation.

We directly test the predictions of our model by conducting the first experimental evaluation of the impact of insurance on willingness to pay for adaptation. We find that insurance crowds in adaptation, particularly for farmers who believe our flood-tolerant seeds are likely to perform poorly, which contrasts with classic theory but comports with our model. In doing so, we connect what has broadly been two distinct strands of literature on insurance. On one hand, in high-income countries, both applied theory (Kousky, Luttmer, and Zeckhauser, 2006) and quasi-experimental work (Annan and Schlenker, 2015; Blickle and Santos, 2022) have focused on the possibility that government insurance will crowd-out private adaptation.[7] In contrast, work on insurance in low- and middle-income countries has not been concerned with either crowd-out or crowd-in of adaptation, instead focusing on how insurance can improve profit and consumption outcomes by promoting risky investments (Karlan et al., 2014; Mobarak and Rosenzweig, 2013; Cole and Xiong, 2017; Donovan, 2021) and trying to explain low demand for insurance itself (Cole et al., 2013; Mobarak and Rosenzweig, 2014; Casaburi and Willis, 2018; Carter et al., 2017). However, to our knowledge, no studies in a LMIC setting have examined whether, and under what circumstances, insurance changes demand for adaptive investments.[8]

Our results have important policy implications. Governments and international institutions spend billions of dollars each year subsidizing insurance. Our results show that the crowd-out concern discussed above need not hold: subsidized insurance does not necessarily reduce demand for private adaptation and may instead encourage it. When insurance protects households against states of the world in which adaptation is ineffective, it can increase the value of adaptation by reducing exposure to catastrophic losses. This insight is particularly relevant in LMICs, where subsidies are often needed to overcome market failures that limit insurance demand, where public spending on insurance programs is expanding rapidly, and where climate change is expected to have its most severe impacts.

The remainder of this paper proceeds as follows. Section 2 presents a simple theoretical model of farmer decision-making under risk. Section 3 describes our experimental design and

[7]There is a large literature on the inefficiency of subsidized insurance in the U.S., including Michel-Kerjan (2010); Glauber (2004); Boustan, Kahn, and Rhode (2012); Baylis and Boomhower (2023); Wagner (2022); Ostriker and Russo (2024).

[8]Both Bulte et al. (2020) and Boucher et al. (2022) provide farmers with two explicitly complementary technologies that cover different sources of risk: insurance and climate-tolerant seeds. Echoing results documented in the broader insurance literature, these two papers find that farmers with both insurance and seeds make riskier investments as compared to a control group with neither. We build on these papers by demonstrating that access to insurance directly affects demand for adaptation.

our measurement approach, including how we elicit willingness to pay. Section 4 presents our analysis and results. Section 5 concludes.

2 Model

To formalize the main argument that access to (subsidized weather index) insurance can influence demand for climate adaptation, consider a household living in a flood-prone area who has access to a productive activity (e.g., farming) with three types of available technology investments: traditional (T), adaptive (A), or risky (R). Adaptive and risky investments cost roughly the same amount, but are more expensive than the traditional method. Adaptive seeds are designed to protect output during moderate flooding events and are thus a form of climate adaptation. In contrast, the risky investment increases productivity only in the absence of floods. In our experimental context, the adaptive investment is the flood tolerant variety, the risky investment is the high-yield variety, and the traditional investment is a cheaper non-improved seed.

Our goal is to estimate how access to (subsidized) insurance changes farmers' willingness to pay for the adaptive and risky investments. If insurance increases demand for the adaptive choice *more* than for the risky choice, insurance "crowds in" climate adaptation; if instead insurance increases demand for the adaptive choice *less* than for the risky choice, insurance "crowds out" adaptation.

We consider three states of nature $s \in \{N, M, E\}$: no flood (N), moderate flood (M), and extreme flood (E), which occur with probabilities p_N, p_M, and p_E, respectively. Output $y_i(s)$ depends on both the investment choice i and the realized state s. Consistent with our empirical setting, traditional production produces $y_T(N) = Y_0 > 0$ in the no-flood state N and zero otherwise. Similarly, the risky investment increases output only in the no-flood state, yielding $y_R(N) = Y_R > Y_0$ and zero otherwise. The adaptive investment is known to produce $y_A(N) = Y_0$ in the no-flood state and $y_A(M) = Y_F > 0$ in the moderate flood state M. However, there is uncertainty about its ability to produce in the severe state E: it yields Y_F with probability π, known to the farmer, and yield zero with probability $1 - \pi$. Alternatively, π can be interpreted as the farmer's *beliefs* about the adaptive technology's quality, even if true quality is fixed. The insurance product, offered for free, pays a fixed amount $Y^I > 0$ in state E, and zero otherwise. The farmer can either be insured (I) or uninsured (U). The farmer has illiquid assets W.

Let $U_i^I(b)$ denote the expected utility from using technology $i \in \{T, R, A\}$ when paying b for the investment when insurance is offered. The farmer's expected utility from using the traditional process (where $b = 0$ without loss of generality) with access to insurance is:

$$U_T^I = p_N\, u(W + Y_0) + p_M u(W) + p_E\, u(W + Y^I).$$

Expected utility from investing in the risky technology (where $b > 0$) with insurance is:

$$U_R^I(b) = p_N\, u(W + Y_H - b) + p_M\, u(W - b) + p_E\, u(W + Y^I - b).$$

Finally, expected utility from investing in the adaptive technology (again where $b > 0$) with insurance is:

$$\begin{aligned} U_A^I(b) &= p_N\, u(W + Y_0 - b) + p_M\, u(W + Y_F - b) \\ &+ p_E\big[\pi\, u(W + Y_F + Y^I - b) + (1 - \pi)\, u(W + Y^I - b)\big]. \end{aligned}$$

Because premiums are zero, the corresponding uninsured utilities, $U_i^U(b)$, are obtained from the above expressions by setting $Y^I = 0$. We define the willingness to pay for each type of investment under insurance as the payment for the technology that makes the farmer indifferent between purchasing it and using the traditional method (at zero cost):

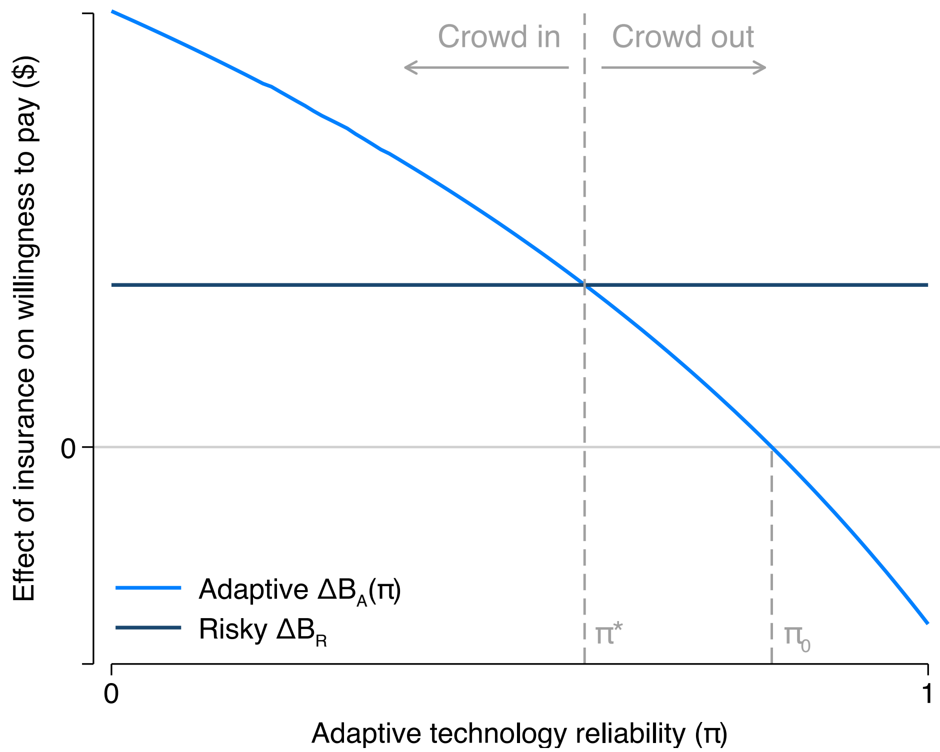
$$U_A^I(B_A^I(\pi)) = U_T^I, \qquad U_R^I(B_R^I) = U_T^I.$$

Because a farmer's willingness to pay for the adaptive technology depends on its reliability π in state E, B_F^I is a function of π. In contrast, since there is no uncertainty about the performance of the risky investment, B_H^I does not depend on π. Analogously, under no insurance, $Y^I = 0$ and

$$U_A^U(B_A^U(\pi)) = U_T^U, \qquad U_R^U(B_R^U) = U_T^U.$$

We summarize the effect of insurance on adoption incentives by the insurance-induced change in willingness to pay, $\Delta B_i \equiv B_i^I - B_i^U$ for $i \in \{A, R\}$. Our main object of interest is the effect that insurance has on the difference between willingness to pay for adaptive vs. risky investments, $\Delta B_A(\pi) - \Delta B_R$, as this determines whether insurance crowds in or crowds out adaptation. If willingness to pay for the adaptive investment *more* with insurance than does willingness to pay for the risky investment, the farmer is more likely to choose adaptation. Alternatively, if willingness to pay for the adaptive investment rises *less* with insurance than does willingness to pay for the risky investment, the farmer is less likely to choose adaptation.

Figure 1: Impact of insurance on willingness to pay for adaptation



Notes: This figure illustrates the main predictions of the model. The light blue line plots the effect of insurance on willingness to pay for the adaptive technology ($\Delta B_A(\pi)$) as a function of the (perceived) likelihood (π) that the adaptation will be effective in the extreme flood state E. The navy line plots the effect of insurance on willingness-to-pay for risky investment (ΔB_R), which does not depend on π because there is no uncertainty about the effectiveness of this technology. To the left of π^*, the insurance-induced increase in willingness to pay for the adaptive choice exceeds that for the risky choice, and thus insurance crowds in adaptation. To the right of π^*, the insurance-induced increase in willingness to pay for adaptive choice seed is less than for the risky choice, and thus insurance crowds out adaptation. To the right of π_0, farmers with insurance have lower demand for adaptation relative to farmers without insurance. To generate the figure, we simulate our model using the following parameter values: $Y_H = 5$, $Y_0 = 3$, $Y_F = 2$, $Y^I = 0.5$, $W = 3$, $p_N = 0.3$, $p_M = 0.4$, $p_E = 0.3$, and $\sigma = 0.75$.

To illustrate the model's implications, we parameterize the environment and compute $\Delta B_A(\pi)$, ΔB_R, and their difference numerically.[9] Figure 1 plots $\Delta B_A(\pi)$ as a function of the (perceived) reliability of the adaptive technology, π, together with ΔB_R (which does not depend on π).[10] Figure 1 shows that insurance increases willingness to pay for the adaptive technology most when π is low. When the adaptive investment is unlikely to deliver output in the extreme flood state E, insurance provides valuable protection in precisely those low-consumption realizations where farmers pay for the technology but receive no benefit. As π increases and the technology's performance overlaps more closely with insurance coverage, insurance becomes a closer substitute for adaptation and its incremental value declines. For sufficiently high reliability levels, $\pi > \pi_0$, the willingness to pay for the adaptive technology is lower with insurance relative to without insurance.

In contrast, the effect of insurance on the risky investment does not depend on π. Insurance always raises willingness to pay for the risky technology. Together with the fact that the effect of insurance on willingness to pay for the adaptive technology is monotonically decreasing in π, this means that there is a single point $\pi = \pi^*$ at which $\Delta B_A(\pi^*) = \Delta B_R$ (i.e., the effect of insurance on willingness to pay for the two investments is identical). For (farmers with beliefs) $\pi < \pi^*$, insurance causes willingness to pay for the adaptive technology to rise above willingness to pay for the risky technology, leading to crowd-in of adaptation. For (farmers with beliefs) $\pi > \pi^*$, insurance causes willingness to pay for the adaptive technology to fall below willingness to pay for the risky technology, leading to crowd-out of adaptation.

The model generates two key predictions that we take to the our experimental setting and test in the data:

Prediction 1. Insurance can lead to either crowd-out *or* crowd-in of adaptation, defined as the effect of insurance on willingness to pay for the adaptive investment vs. willingness to pay for the risky investment.

Prediction 2. Whether insurance leads to crowd-out or crowd-in depends on the degree of (perceived) overlap between the adaptive technology and insurance. If (farmers believe) the adaptive investment is relatively ineffective when insurance offers coverage, insurance will

[9]For this exercise, we assume that farmers have preferences represented by CRRA utility

$$u(c) = \frac{c^{1-\sigma} - 1}{1-\sigma}, \qquad 0 < \sigma < 1.$$

[10]Appendix Figure A.1 shows how the model predictions change if, instead of insurance paying out with certainty in state E, as presented here, the (perceived) chance of a payout is only 0.5. In this case, the effects of insurance on willingness to pay – and therefore on crowd-out or crowd-in – are attenuated.

cause greater crowd-in; if, in contrast, (farmers believe) the adaptive investment is relatively effective, insurance will cause lower crowd-in or may even lead to a crowd-out effect.

This second prediction allows for a sharp empirical test of the theory within out experimental setting where flood-tolerant seeds represent the adaptive technology and the high-yield variety the risky technology. While there are several other mechanisms (e.g., salience of flooding, experimenter demand effects, etc.) that could cause insurance to change willingness to pay for flood-tolerant seeds more than for high-yield variety seeds, these other mechanisms should not generate heterogeneity by farmer beliefs about the effectiveness of flood-tolerant seeds. We incorporate this test into our empirical exercise below.

3 Experimental design and data

3.1 Experimental design

Where we work We conduct our two-year study in the three districts of Murshidabad, Paschim Medinipur, and Hooghly in West Bengal, which are dominated by smallholder agriculture and experience frequent flooding (see Appendix Figure A.2 for a map). While both public and private crop insurance schemes exist, participation remains limited: internal ICRISAT survey data from 2022 shows that only about 34 percent of farmers in West Bengal insure their crops. Within these districts, we sample sub-districts (blocks) that are (i) relatively close to river gauges operated by the Government of West Bengal's Irrigation and Waterways Department, which we use to trigger our index insurance product, described below; (ii) most frequently flooded in the district, per the Government's Flood Hazard Atlas (Department of Space (2021)); (iii) suitable for Swarna-Sub1, a flood-tolerant seed (described further below), according to ICRISAT and the International Rice Research Institute; and (iv) with limited access to existing crop insurance, per a qualitative survey conducted by the research team. Within these blocks, we randomly sample 300 villages, using a geospatial algorithm to ensure that we do not include any neighboring villages in the sample, limiting the possibility of risk-sharing across villages in different treatment arms (see Appendix F for more detail).

We partner with ICRISAT for the delivery of our treatment arms in both years, described below. ICRISAT is an international organization headquartered in Hyderabad, Telangana, with a mandate to support farmers across India using data-driven solutions. Its extensive network of local partners allows it to procure and deliver agricultural interventions, such as seeds and insurance, effectively.

Randomization Appendix Figure A.4 presents a diagram of the experimental design, which follows a two-step randomization. The first layer of Appendix Figure A.4 shows the village-level randomization into the three groups: an insurance control group (125 villages who receive no insurance product); a high-payout insurance group (125 villages); and a low-payout insurance group (50 villages).[11] We stratify this village-level randomization by block. The second layer of Appendix Figure A.4 shows the household-level randomization into seed offers. We sample six farming households per village, excluding households that had not cultivated any rice in the three years prior to our baseline survey. We further randomize these six individuals per village to receive offers to purchase either a flood-tolerant seed minikit or a high-yield-variety seed minikit at either market price or for free. This randomization yields four groups: market-price flood-tolerant seed offer (1/6 of households); free flood-tolerant seed offer (1/3 of households); market-price high-yield-variety seed offer (1/6 of households); and free high-yield-variety seed offer (1/3 of households).[12] Because these seeds are already available outside of the experiment, we treat the market price groups as a "seed control" group, which we pool for the purposes of analysis.[13]

Insurance In the status quo, 49% of farmers report having been covered by insurance sometime in the past. However, insurance payouts in this region are infrequent: only 29% of farmers who reported having crop damage received a payout, and anecdotally, farmers reported substantial doubts about the likelihood of payouts. Thus, full insurance coverage is likely lacking in our sample.

We offer treated farmers an index insurance product tied to localized flooding. This ensures that the type of risk addressed by our flood-tolerant seeds is the same as that addressed by our insurance product, and avoids traditional issues of moral hazard and adverse selection. We ensure high insurance take-up by providing farmers with free insurance. Following Lane (2024), we assign each village in our sample to its closest upstream river gauge, maintained by the Government of West Bengal's Irrigation and Waterways Department. The insurance

[11] This layer of randomization remains constant across the two years of the study.

[12] In the second year of the study, we truthfully inform farmers that their BDM price has been re-randomized, in order to maintain incentive compatibility. In practice, unbeknownst to the farmers, we structured the re-randomization such that price draws changed for only a very small number of farmers.

[13] One concern with randomizing seed offers at the individual level is spillovers of seeds from seed-treatment farmers to seed-control farmers. We believe this is not a major issue for three reasons. First, we are only interacting with six households per village. The probability that, when sharing seeds from a 5 kg minikit, the two households in the high-yield-variety seed treatment group or the two households in the flood-tolerant seed treatment group chooses to share seeds with the two households in the seed control group is very low. In 2011 (the latest Census of India), West Bengal had approximately 540 households per village on average. Second, Emerick et al. (2016) provided Swarna-Sub1 seeds to households in Odisha, finding no evidence of within-village spillovers. Finally, any sharing of seeds between treatment and control farmers will attenuate our estimated impacts of these seeds towards zero.

product pays out if and only if the relevant river gauge reaches a trigger height at least one day between June 25th and October 31st. We set the gauge-specific trigger heights such that they had been reached 30% of the years from 2014 to 2023. We provide each farmer an info-sheet describing the insurance product, and confirm their participation in the insurance product by signing a slip (Appendix C). If a village's gauge is triggered, we notify farmers via SMS. In the first year of the experiment, 82% of farmers in the insurance group received payouts; in the second year, 41% of farmers received payouts (Appendix Figure A.3 presents the set of gauges and when they triggered). Finally, to measure whether the effect of insurance on demand for adaptation varies with the generosity of the insurance product, we further randomize insurance villages into a low-payout product and a high-payout product. Both products have the same trigger. If triggered, the high-payout product pays out INR 10,000 (approximately USD 120), while the low-payout product pays out INR 5,000 (approximately USD 60). These payouts are substantial compared to average farm profits in the control group (approximately $65) and input expenditure (approximately $370).

Specialty seeds We also offer farmers a 5 kg flood-tolerant variety (Swarna-Sub1) seed mini-kit and a 5 kg high-yield variety (Pratiksha) seed mini-kit using a BDM mechanism, described immediately below. Both seeds were selected to be high-quality varieties suitable for the study areas of West Bengal and were available in local markets at similar prices.[14] Although both seeds were likely known to farmers, neither was fully adopted at the time of our study. Prior to our intervention, 16% of farmers reported having purchased any flood-tolerant seed, and only 6% reported having ever purchased Swarna-Sub1 seeds, indicating low private adoption of specialty seeds for risk mitigation. In contrast, while 94% of farmers reported having purchased some high-yield variety seed in the past, only 15% reported having ever purchased Pratiksha seeds.[15]

BDM mechanism We elicit farmers' willingness to pay for Swarna-Sub1 and Pratiksha mini-kits through a Becker-Degroot-Marshack (BDM) mechanism. We model the BDM procedure closely after Berkouwer and Dean (2022) and Burlig et al. (2024). To measure farmers' willingness to pay for each seed, the enumerator explains that they will offer the farmer the opportunity to buy seeds through a two-step procedure. In the first step, they elicit the farmer's stated willingness to pay for the seed using a grid search. They repeat the

[14] We present further details about the particular rice varieties we use in our study in Appendix Figures C.2b and C.2a, which we also shared with farmers.

[15] These adoption patterns motivate our modeling assumption. While both seeds were available in local markets, flood-tolerant seeds were less familiar to farmers, creating greater uncertainty about their effectiveness in extreme flood conditions. We therefore model uncertainty in flood-tolerant seed performance, captured by π, while assuming high-yield variety performance is known with certainty.

grid search for both 5 kg seed mini-kits. After these willingness to pay amounts are confirmed for each seed, the enumerator displays a screen on their tablet that shows a randomized draw containing (A) which seed the farmer may purchase during the interview and (B) the price at which the farmer may buy that seed. If the price on the tablet exceeds the farmer's willingness to pay for that seed, they may not purchase the product, and no cash changes hands. If the price on the tablet is equal to or below the farmer's willingness to pay, the enumerator provides the farmer with the seed mini-kit in exchange for the price in cash.[16]

We set the distribution of BDM prices to create a wedge in seed take-up between the "seed control" groups, whose BDM price is set to the market price, and the "seed treatment" groups, whose BDM price is set to zero, to induce seed take-up. The underlying distribution is unknown to both farmers and enumerators, following Burchardi et al. (2021), so farmers have no incentive to bid strategically. Prices are randomly assigned to each participant prior to the baseline visit. The enumerator is not aware of the seed or price draw prior to conducting the survey. Appendix Table A.5 shows that take-up among farmers assigned to receive free seeds is nearly universal, and that most of these farmers planted their mini-kits in both years.

Timeline The experiment spanned two agricultural seasons from June 2024 to February 2026. The year 1 baseline survey was conducted in early June 2024, prior to the start of planting. During the baseline, eligible households first received their insurance offer (if applicable). We then elicited willingness to pay for flood-tolerant and high-yield variety seeds. Farmers who purchased seeds through the willingness to pay elicitation game received their seed kits after completing the survey. Throughout the growing season, we monitored river gauge levels by scraping daily administrative river gauge data from the West Bengal Irrigation and Waterways Department.

In November 2024, we conducted a field visit to notify eligible households of insurance payouts and to collect bank account information. Insurance payouts were disbursed in March 2025 (with some delays due to political sensitivities in the region), and the year 1 endline survey was conducted in April 2025. We launched the year 2 baseline in May 2025, and the sequence of activities broadly mirrors that of year 1. Insurance was offered at baseline, followed by the elicitation of willingness to pay for seeds and subsequent seed delivery. River gauge levels were then monitored throughout the season, with the endline survey conducted between December 2025 and January 2026, and insurance payouts made in March and April

[16]Because it is vital that this procedure is thoroughly understood by households before they begin, the enumerator plays a "practice" round with a common household product (either a bar of soap or a small bottle of shampoo). Therefore, any misunderstandings about the process are resolved before the BDM procedure for the seeds begins.

of 2026.[17]

3.2 Key variables

Willingness to pay Our main outcome of interest is willingness to pay for flood-tolerant seeds. As described above, we elicit this measure using the BDM mechanism, which allows us to trace out the full demand curve in our sample. We also elicit willingness to pay for high-yield variety seeds in order to net out channels (e.g. experimenter demand, trust) affecting WTP that arise solely from being offered insurance.

Appendix Figure A.6 plots the density of willingness to pay among pure control farmers who receive neither free seed nor an insurance offer, for flood tolerant seeds (left panel) and the difference between flood-tolerant and high-yield variety seeds (right panel), for both year 1 (solid light blue) and year 2 (dashed navy). Mean willingness to pay for pure control farmers who received neither an insurance offer nor a free seed offer was \$1.77 for flood-tolerant seeds and \$1.83 for high-yield variety seeds in year 1, and \$3.20 for flood-tolerant seeds and \$3.11 for high-yield variety seeds in year 2. While mean willingness to pay was below the market price of \$4.81, in year 2 the average farmer is willing to pay two thirds of the market price, while roughly a quarter of the sample has WTP above \$4.[18]

Appendix Table A.6 shows that our willingness to pay measures correlate with baseline observables. While none of the demographic characteristics predict willingness to pay, we find that prior exposure to flooding raises willingness to pay for flood-tolerant seeds. Previous experience with flood-tolerant seeds is associated with lower willingness to pay for these seeds, possibly because households that used them in non-flood years did not realize sufficient benefits to justify repeat adoption. In contrast, exposure to high-yield variety seeds increases willingness to pay for both seed types. Negative beliefs about either seed type reduce willingness to pay for both types, as does risk aversion. The negative correlation between risk aversion and willingness to pay for flood-tolerant seeds is consistent with farmers' understanding that these seeds do not provide full protection against floods. As expected, wealthier households and those with higher consumption exhibit a higher willingness to pay for both seed types.

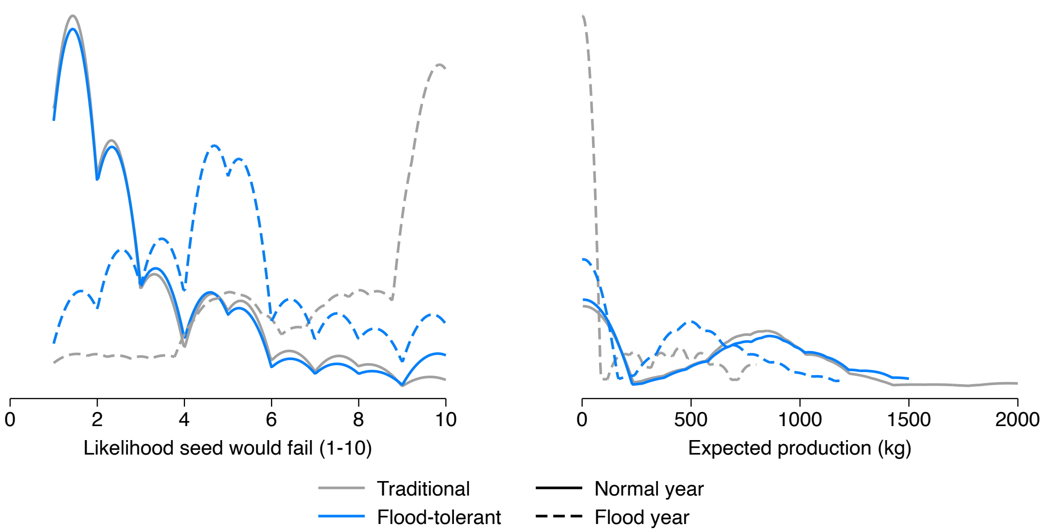
[17] While the original plan was to make insurance payouts prior to the endline survey in year 2 as well, political sensitivity around surveying activities prior to the 2026 elections delayed payments.

[18] Willingness to pay for flood-tolerant seeds is higher overall in year 2 than in year 1. Appendix Table A.10 reveals that receiving *either* the flood-tolerant seed *or* the high-yield variety seed in year 1 increases willingness to pay for flood-tolerant seeds in year 2, regardless of insurance status. These effects hold for households in both the insurance treatment and control groups.

Perceptions of seed effectiveness The theoretical framework in Section 2 predicts that the effectiveness of flood-tolerant seeds, π, is a key driver of whether insurance will crowd-in or crowd-out demand for adaptation. While the seeds we provide to each farmer are the same, varying *beliefs* about seed effectiveness among farmers will generate the same effects as varying π. We elicit farmers' perceptions of seed effectiveness under both normal and flood conditions in two ways: how likely is a given seed type to fail on a 1–10 scale, and what is the expected production of that seed type? Figure 2 plots the distribution of these perceptions for traditional (grey) and flood-tolerant (blue) seeds under a normal year (solid line) and a flood year (dotted line). The left panel shows that farmers believe that flood-tolerant seeds and traditional seeds have a similarly low chance of failure under normal conditions. However, in a flood year, farmers believe that flood-tolerant seeds are much less likely to fail than traditional seeds. Similarly, the right panel shows that under normal conditions, farmers expect both seed types to deliver similar output. However, they also expect that flood-tolerant seeds will produce more output in flood conditions than traditional seeds, largely because traditional seeds have a high probability of zero output in the flood state. These data suggest that farmers are broadly correct about the properties of flood-tolerant seeds – that they perform normally in non-flood year and offer greater production in a flood year – but there is a relatively wide distribution of farmer beliefs about the degree of their effectiveness in protecting against floods.[19]

[19] Farmers' beliefs about the high-yield variety are also broadly accurate: they expect it to outperform traditional seeds in a normal year, while anticipating similarly poor performance for both varieties in a flood year (Appendix Figure A.5.)

Figure 2: Perceived effectiveness of flood-tolerant seeds



Notes: This plot shows the distribution of farmers' beliefs about the effectiveness of traditional-variety seeds (gray) and flood-tolerant seeds (blue) under normal conditions (solid lines) and flood conditions (dashed lines). On the left, we plot farmers' belief that each seed type will fail under each condition, on a 1–10 scale. On the right, we plot expected production from both seeds under each condition. We winsorize expected production at the 5th and 95th percentiles.

For our primary heterogeneity analysis, we construct a single index of perceived effectiveness from the two variables above. This measure of respondents' perceptions of flood-tolerant seeds is constructed as outlined in our pre-analysis plan. We first create four variables. The first two are measures of how likely flood-tolerant seeds are to fail under flood conditions (on a 1-10 scale) compared to both high-yield variety seeds and to traditional seeds.[20] The second two measures compare output (in kg) for food-tolerant seeds versus output from both high-yield variety seeds and traditional seeds, all under flood conditions. From these four variables, we create a standardized index, with higher values indicating that the respondent perceives flood-tolerant seeds as providing greater protection against flooding than available alternatives.

Agricultural and welfare outcomes Although it is not the main focus of the paper, we also collect a set of outcomes to measure how farmers respond to receiving insurance and seeds. These outcomes include agricultural inputs (including land cultivated, seeds planted, fertilizer use, labor, irrigation, and expenditures), agricultural outputs (including total production, crop revenue, and farm profits), off-farm economic activity (including labor force

[20]For each of these measures, we net out how likely each seed is to fail under normal conditions to control for baseline counterfeit rates unrelated to flooding.

participation and income and business ownership, investment, and profit), and economic and psychosocial well-being measures (including assets, savings, loans, per-capita consumption, and depression via a PHQ (Bhat et al., 2022)).

3.3 Experimental integrity

Balance and attrition Appendix Table A.2 tests for balance between our control group and our insurance group using a series of household characteristics collected at baseline (prior to insurance offers): household demographics, number of plots, area cultivated, man-days of labor used, fertilizer quantities, and total input expenditure.[21] We fail to reject that the control group and insurance group are the same on all dimensions, except for potash usage and total input spending, where the insurance group is lower by 10.9% of the control mean ($p < 0.1$) in both cases. In our analysis, we allow all of these baseline characteristics to be selected by the PDS-LASSO procedure described in Section 4. Correcting for imbalance does not meaningfully affect our willingness to pay results. Appendix Table A.4 shows that overall attrition is very low: less than 4% of farmers in the control group fail to complete any of our survey rounds, and attrition rates do not differ between control and insurance treatment groups.

Pre-analysis plan This research was pre-registered at the AEA RCT registry under Identification No. AEARCTR-0013781. Deviations are, in general, minor; the full list is in Appendix D. Unless otherwise noted, analyses in the main text and Appendix are pre-specified. Additional pre-specified results that do not appear in the main text or elsewhere in the Appendix can be found in Appendix E. Note that while we still report these results in the Appendix, we de-emphasize two sets of analyses relative to the PAP. First, we cannot reject that the treatment effects of insurance with a low payout and insurance with a high payout are identical, so we present pooled results in the main text and relegate a limited set of split results to the Appendix. Second, because the focus is on crowd-in vs. crowd-out effects of insurance, we present *ex post* outcomes only in the Appendix. Finally, we were unable to collect reliable measures of flooding, so we do not examine heterogeneity in flood-affectedness.

[21] Appendix Table A.3 presents balance between seed control farmers, farmers who received a free flood-tolerant seed offer, and farmers who received a free high-yield variety seed offer. The groups are balanced.

4 Analysis and results

4.1 Trust in insurance

Before evaluating the impact of insurance on demand for adaptation, we establish the credibility of our insurance product by measuring whether it impacts farmers' use of risky investments. To do so, we estimate the following specification separately for both years of our experiment:

$$\begin{aligned} Y_{iv} = \alpha &+ \beta_1 \, \text{Insurance}_v \\ &+ \beta_2 \, \text{Free FT}_{iv} + \beta_3 \, \text{Free HYV}_{iv} \\ &+ \beta_4 \text{Insurance}_v \times \text{Free FT}_{iv} + \beta_4 \text{Insurance}_v \times \text{Free HYV}_{iv} \\ &+ \gamma X_{iv} + \psi_s + \varepsilon_{iv} \end{aligned} \tag{1}$$

where Y_{iv} are a series of agricultural outcomes for farmer i in village v, and Insurance_v is an indicator for whether village v is assigned to the insurance treatment group. To isolate the impact of insurance on agricultural outcomes for farmers who did *not* receive free seeds, we also control for indicators for free flood-tolerant and high-yield-variety seed assignment, as well as their interaction with insurance. X_{iv} are a set of baseline controls selected via LASSO, ψ_s are a set of strata fixed effects, and ε_{iv} is an error term, clustered at the village level. Our main parameter of interest is β_1, the effect of insurance on agricultural outcomes for farmers in the seed control group.

Appendix Table A.14 shows that in year 1, in contrast to prior work (Karlan et al., 2014; Cole, Giné, and Vickery, 2017; Burlig et al., 2024), insurance had no impact on the number of plots cultivated, area planted, number of crops, total input expenditure, or a standardized inverse-covariance weighted index made up of these four measures (point estimate: 0.065 SD, $p > 0.1$). These results suggest that farmers did not believe the insurance treatment was credible in the first year, and we should expect insurance to have no impact on demand for adaptation.[22]

In contrast, in year 2, after the vast majority of insured farmers (82%) received a substantial payout following flooding in year 1, these farmers meaningfully invest in riskier farm inputs relative to the control group. Insurance increases the number of plots cultivated (0.144 plots, or 8.6% of the control mean, $p < 0.01$) and area cultivated (0.029 hectares, or 7.5% of the control mean, $p < 0.1$). We find no economically meaningful or statistically

[22] In terms of the model in Section 2, the results in the first year correspond to uncertainty about whether insurance will pay in state E. As Appendix Figure A.1 shows, the effect of insurance on crowd-in or crowd-out attenuate as this uncertainty rises.

significant effects on the number of distinct crops cultivated, or on total input expenditures. However, the overall investment index increases (0.118 SD, $p < 0.01$), an effect comparable in magnitude to that documented by prior work. Consistent with evidence from the insurance literature (Cole, Stein, and Tobacman, 2014; Cai, de Janvry, and Sadoulet, 2020), farmers in the second year treat insurance as a meaningful source of protection against flood risk. We therefore assess how insurance crowds in or crowds out adaptation using willingness to pay elicited in the second year of the study.[23]

4.2 Effects of insurance on willingness to pay for adaptation

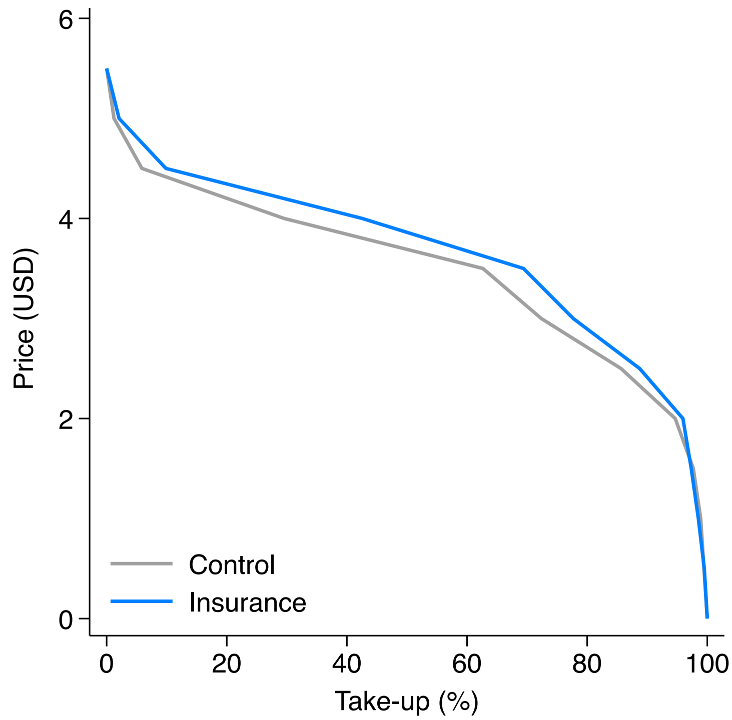
Having established that farmers treat insurance as credible in year 2, we test the first prediction of our model: whether insurance impacts demand for private adaptation. Specifically, to detect crowd-out or crowd-in effects, we measure insurance's impact on willingness to pay for flood-tolerant seeds using the BDM exercise described above.

Figure 3 plots the demand curve for flood-tolerant seeds among farmers in the control group (gray) and the insurance group (blue).[24] We find that willingness to pay is *higher* in the insurance group than in the control. This provides suggestive evidence that insurance may have caused crowd-in of adaptation.

[23]Appendix Table A.14 also shows that farmers responded to offers of free flood-tolerant seeds and free high-yield variety seeds with increased investment in both year 1 and year 2 of the study. By revealed preference, farmers found the seeds worth using in both years. The table also demonstrates that there are no meaningful interaction effects.

[24]Appendix Figure A.7 provides an analogous plot for year 1. Consistent with farmers not trusting the insurance during the first year of the study, we find no difference in willingness to pay between insurance and control.

Figure 3: Willingness to pay for flood-tolerant seeds



Notes: This figure plots demand curves for flood-tolerant seeds, elicited using the BDM mechanism described in Section 3 during the baseline survey conducted in the second year of the experiment. We plot the control group in light gray and the insurance treatment group (pooled across the low and high payouts) in blue.

We formalize this via regression. We first measure the effects of insurance on demand for each seed individually:

$$\text{Flood-tolerant}_{iv} = \alpha + \beta \text{ Insurance}_v + \gamma X_{iv} + \psi_s + \varepsilon_{iv}$$
$$\text{High-yield variety}_{iv} = \alpha + \beta \text{ Insurance}_v + \gamma X_{iv} + \psi_s + \varepsilon_{iv}$$

where Flood-tolerant$_{iv}$ (High-yield variety$_{iv}$) is the willingness to pay for the flood-tolerant seed (the high-yield variety seed) for farmer i in village v in strata s, and Insurance$_v$ is an indicator for our (randomly-assigned) flood insurance product. X_{iv} is a set of controls, chosen from available baseline variables using double-selection LASSO, as well as enumerator fixed effects. ψ_s is a strata fixed effect. ε_{iv} is an error term which we cluster at the village level.

Following the model in Section 2, our test for crowd-in vs. crowd-out compares willingness to pay for flood-tolerant seeds against willingness to pay for high-yield variety seeds. This avoids concerns about experimenter demand effects, income effects, or other issues that may bias willingness to pay for *any* seeds upwards in the insurance group. Moreover, because high-yield variety seeds are commonly available on the market, this test mimics the variety choice farmers make when purchasing seeds from a dealer. Specifically, we estimate:

$$\text{Difference}_{iv} = \alpha + \beta \text{ Insurance}_v + \gamma X_{iv} + \psi_s + \varepsilon_{iv} \tag{2}$$

where Difference_{iv} is the difference in willingness to pay for flood-tolerant seeds vs. high-yield variety seeds, and all other terms are as in the specifications immediately above. Our key parameter of interest, β, measures whether there is a crowd-in or a crowd-out effect. If $\beta > 0$, insurance raises demand for flood-tolerant seeds relatively more than high-yield variety seeds: the "crowd-in" effect dominates. If $\beta < 0$, insurance lowers demand for the flood-tolerant variety seed relatively more than for the high-yield variety seeds: the "crowd-out" effect dominates.

Table 1: Effects of insurance on willingness to pay

	(1) Flood-tolerant	(2) High-yield variety	(3) Difference
Insurance	0.133***	0.040	0.094***
	(0.045)	(0.042)	(0.026)
Control mean	3.441	3.323	0.118
Observations	1746	1746	1746

Notes: This table presents estimates of the treatment effect of insurance on willingness to pay for flood tolerant seeds (1), high-yielding variety seeds (2), and their difference (3) elicited in the second year of the study, all measured in USD. Willingness to pay is elicited using the Becker, DeGroot, and Marschak (BDM) game explained in Section B. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1 presents the results. In keeping with Figure 3, Column (1) shows that insurance raised willingness to pay for flood tolerant seeds by \$0.133 ($p < 0.01$), a 4% increase over the control group mean. In Column (2), we find no impact of insurance on willingness to pay for high-yield variety seeds. The point estimate of \$0.04 is positive and approximately 1% of the control mean, but is not statistically distinguishable from zero. Finally, Column (3) presents our main test of crowd-out or crowd-in. We find that insurance moderately crowds in demand for adaptation, increasing willingness to pay for flood-tolerant seeds by \$0.094 more than for high-yield variety seeds ($p < 0.01$), approximately 2.7% of the control group's mean willingness to pay for flood-tolerant seeds, or 80% of the difference in willingness to pay between the two seeds among control farmers.[25]

[25] Appendix Table A.11 demonstrates that the effect of insurance on crowd-in of adaptation is similar in

While the absolute magnitude of our crowd-in effect appears modest, our estimates suggest that insurance could have a substantial impact farmers' purchasing behavior. Figure 4 plots the CDF of the difference between farmers' willingness to pay for flood tolerant vs. high-yield variety seeds, separately for the insurance treatment group and for the control group. Insurance shifts the CDF to the right, leading roughly 10% more farmers to prefer flood-tolerant seeds to high-yield variety seeds relative to the control group. That is, conditional on choosing to purchase an improved seed of some kind, the insurance treatment meaningfully shifts farmers towards buying the flood-tolerant seed.

We rule out three alternative explanations for the effect of insurance on crowd-in of adaptation in year 2. First, income or liquidity effects from receiving an insurance payout and experimenter demand effects should affect demand for both seed types; using the difference accounts for these. Second, insurance may have increased the salience of flood risk, leading insured farmers to place greater value on flood protection even if the underlying decision problem remained unchanged. However, we see no impact of receiving flood-tolerant seeds in year 1 of the study, itself a strong reminder about flood risk, on willingness to pay in year 2; we also find no interaction effect between insurance and flood-tolerant seeds (Appendix Table A.8). Lastly, insurance may have altered farmers' beliefs about the effectiveness of the flood-tolerant variety – by making farmers believe that FT seeds are better at protecting against floods for example – thereby increasing willingness to pay. We find no effects of insurance on beliefs about seed quality (Appendix Table A.9); including these beliefs as controls in Equation (2) does not change the results (Appendix Table A.8).

In keeping with our evidence above that farmers did not view the insurance product as credible during year 1, the insurance product had no impact on willingness to pay for the flood-tolerant seed alone, the high-yield variety seed alone, or the difference between the two in the first year (Appendix Table A.7).

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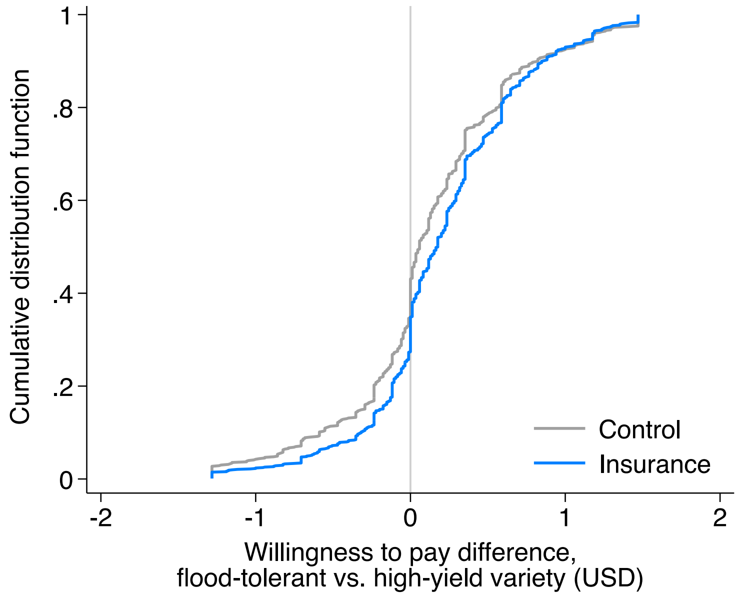
magnitude between our low-payout (INR 5,000 in the event of a flood) and high-payout (INR 10,000 in the event of a flood) sub-treatment arms; we cannot reject that the effects are the same.

Figure 4: Willingness to pay difference, flood-tolerant vs. high-yield variety (CDF)



Notes: This figure plots the CDF of the difference in willingness to pay for the between the flood-tolerant seed and the high-yield variety seed, as elicited using the BDM mechanism described in Section 3 during the baseline survey conducted in the second year of the experiment. Negative values indicate a higher willingness to pay for the high-yield variety seed, while positive numbers indicate a higher willingness to pay for the flood-tolerant seed. We plot the control group in light gray and the insurance treatment group (pooled across the low and high payouts) in blue.

Our estimates have two main implications. First, we reject the classic prediction (Ehrlich and Becker, 1972; Buchanan, 1975) that free insurance causes farmers to meaningfully *reduce* their investments in private climate adaptation. As subsidized agricultural insurance becomes more widespread, our results imply that farmers need not view insurance as a substitute for private investment. Second, we see evidence that the opposite is true: farmers *increase* their investment in flood-tolerant seeds when provided with insurance. To the extent that this finding generalizes across adaptation technologies, it suggests that subsidies for insurance may in fact be helpful in driving adoption of private adaptation.

4.3 Crowd-in and farmers' perception of seed effectiveness

Having established evidence of insurance modestly increasing willingness to pay for flood-tolerant seeds both in absolute terms and relative to the high-yield variety (i.e. crowd-in), we test our model's second prediction: that the magnitude of crowd-in (or crowd-out) depends on farmers' perceived effectiveness of flood-tolerant seeds.[26] Specifically, providing

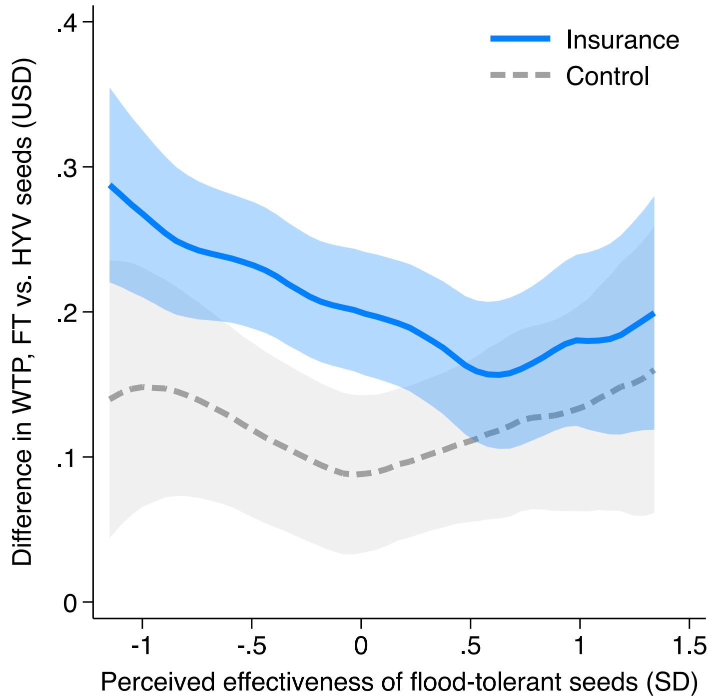
[26](Perceived) seed effectiveness is a key driver of the model in our pre-analysis plan and the updated model we present in Section 2. In Appendix Table A.13, we also measure how the effect of insurance on willingness

farmers who believe that flood-tolerant seeds perform poorly under many flood conditions with insurance should increase their demand for these seeds (relative to high-yield varieties), as insurance reduces the downside risk of investing in expensive seeds that may fail during more severe floods. By contrast, farmers who expect flood-tolerant seeds to perform well across most flood conditions should show little or no response to insurance. In fact, insurance may even reduce their willingness to pay for flood-tolerant seeds because they view insurance and seeds as closer substitutes.

Figure 5 plots the difference in willingness to pay for flood-tolerant vs. high-yield variety seeds against farmers' perceived effectiveness of flood-tolerant seeds. We proxy the latter by an inverse-covariance weighted index, made up of a series of variables at baseline intended to measure seed quality: how much more output farmers expect to receive from flood-tolerant seeds (vs. both high-yield variety and traditional variety seeds) in the event of a flood, and how much less likely farmers believed the flood-tolerant seed is to fail in the event of a flood (as compared both to high-yield variety and traditional variety seeds). We plot this association separately for the insurance treatment group (solid blue) and the control group (dashed gray).

to pay for flood-tolerant vs. high-yield-variety seeds varies with risk aversion, past flood exposure, whether the river gauge danger level was breached in the previous year, ownership of a non-agricultural business, and liquidity. These features mainly capture general sensitivity to the insurance product. For example, risk-averse individuals will likely respond more to insurance coverage, only those exposed to floods will find it relevant, and less liquidity constrained households may be less affected. These factors primarily determine the magnitude of the insurance effect, that is, how large any potential crowd-out might be, but do not predict the *direction* of the effect (i.e., whether there is crowd-in or crowd-out). Empirically, none of these characteristics predicts significant heterogeneity in crowd-in.

Figure 5: Heterogeneous crowd-in by beliefs about flood tolerant seed effectiveness



Notes: This figure plots the lowess relationship between the difference in willingness to pay for flood-tolerant seeds vs. high-yield variety seeds (in year 2) against the perceived effectiveness of flood-tolerant seeds, as proxied by a standardized index over a series of measures of both the absolute and relative effectiveness of flood-tolerant seeds. A higher value in the index implies that a farmer views the flood-tolerant seeds as more effective. We plot separate curves for the insurance treatment (solid blue) and the control group (dashed gray).

The results corroborate our theory. For farmers who believe that the flood-tolerant seed is relatively ineffective (low π, towards the left of the plot), we find strong evidence of crowd-in: compared to the control group, farmers in the insurance group have meaningfully higher willingness to pay for the flood-tolerant seeds relative to the high-yield variety seeds. As farmers' perceptions of the effectiveness of the flood-tolerant seed improve (higher π, to the right of the plot), however, the gap between the insurance group and the control group shrinks.[27] Because even farmers with the most optimistic beliefs about flood-tolerant seed effectiveness do not display crowd-out, Figure 5 suggests that in our empirical setting, beliefs about seed effectiveness are close to or below π^*, and do not approach π_0 in Figure 1.

[27] We present these results in regression form in Appendix Table A.12 by interacting the perceived flood-tolerant seed effectiveness index with the insurance treatment. On average, insurance increases the gap in willingness to pay between flood-tolerant and high-yield variety seeds by \$0.093 ($p < 0.01$), but this effect would be almost entirely removed for farmers with seed effectiveness beliefs one standard deviation above average (point estimate on the interaction: -0.077, $p < 0.05$).

In addition to supporting the mechanism outlined in our theory, these results make alternative explanations for crowd-in, such as experimenter demand effects or increased salience of floods in the insurance group, unlikely. Such mechanisms would increase willingness to pay for flood-tolerant seeds uniformly among insured farmers, rather than generate the heterogeneity we observe along the seed-effectiveness margin.

5 Conclusion

In this paper, we use a randomized controlled trial in flood-prone West Bengal, India, to show that subsidized flood insurance does not crowd out demand for private flood adaptation. Instead, we find modest evidence of "crowd-in": insurance *increases* farmers' demand for flood-tolerant seeds. Consistent with a simple theoretical model, this effect is concentrated among farmers who initially believe that flood-tolerant seeds provide limited protection in extreme flood events.

These results have important implications for policy amidst a rapid worldwide expansion of agricultural insurance products. In contrast with a simple heuristic, our findings demonstrate that subsidized insurance need not crowd-out private investments in adaptation technologies. Moreover, because both flood-tolerant seeds (Emerick et al., 2016) and insurance (Karlan et al., 2014) improve outcomes for farmers, our results suggest that the crowd-in effect of agricultural insurance will lead insurance subsidies to increase welfare even more than previously thought.

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Insurance and the demand for adaptation: theory and experimental evidence from West Bengal

Online appendix

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Contents

A Appendix tables and figures

A.1 Theory

A.1.1 Toy example

Table A.1: Toy example: Payoffs and the welfare value of adaptation given insurance

	G	B_1	B_2	
Panel A. Overlap (Crowd-out)				
Insurance pays in B_2; adaptation effective in B_1 and B_2				
No adaptation, no insurance	100	60	60	
Adaptation only	90	80	80	
Insurance only	100	60	100	
Adaptation + insurance	90	80	90	
	ΔG	ΔB_1	ΔB_2	ΔCE
MB of adaptation (w/o insurance)	−10	+20	+20	+11.57
MB of adaptation (w/ insurance)	−10	+20	−10	+1.62
Δ MB due to insurance				**−9.95**
	G	B_1	B_2	
Panel B. No Overlap (Crowd-in)				
Insurance pays in B_2; adaptation effective only in B_1				
No adaptation, no insurance	100	60	60	
Adaptation only	90	80	50	
Insurance only	100	60	100	
Adaptation + insurance	90	80	90	
	ΔG	ΔB_1	ΔB_2	ΔCE
MB of adaptation (w/o insurance)	−10	+20	−10	+0.04
MB of adaptation (w/ insurance)	−10	+20	−10	+1.62
Δ MB due to insurance				**+1.58**

Notes: This table illustrates the intuition of our theoretical model. There are three states of the world: a good state (G), where income is 100 in the baseline scenario, and two bad states (B_1, B_2), where income is 60 in the baseline scenario. Adaptation has an up-front cost of −10, which affects all states equally. Insurance is free and pays 40 in state B_2 only. Adaptation increases payoffs by 30 in states where it is effective. In the columns labeled G, B_1, and B_2, we report payoffs under each state. In the columns labeled ΔG, ΔB_1, and ΔB_2, we report differences in payoffs moving from either baseline to adaptation only or insurance only to insurance + adaptation. We also report welfare in certainty-equivalent (CE) units under CRRA preferences with coefficient of relative risk aversion $\sigma = .75$, using $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$ and assuming equal probabilities across states. The certainty equivalent CE solves $u(CE) = EU$; for $\sigma = .75$, $u(c) = -1/c$. The reported ΔCE equals $CE(A{+}I) - CE(I)$ within each panel. The row "Δ MB due to insurance" equals $[CE(A{+}I) - CE(I)] - [CE(A) - CE(\varnothing)]$; negative indicates crowd-out and positive indicates crowd-in.

A.1.2 Extension: Uncertainty over whether insurance will pay out

Here we expand the theory presented in Section 2 to include farmer uncertainty about the probability of the insurance product paying out in the extreme flood state E. We denote this probability $\alpha \in [0,1]$. For simplicity, we assume that this probability is independent of π (the probability that flood-tolerant seeds produce in the severe state E).

As before, let $U_i^I(b)$ denote the expected utility from using technology $i \in \{T, R, A\}$ when paying b for the technology when insurance is offered. The farmer's expected utility from using the traditional method (where $b = 0$ without loss of generality) with access to insurance is:

$$U_T^I = p_N\, u(W + Y_0) + p_M u(W) + p_E\,[\alpha\, u(W + Y^I) + (1-\alpha)\, u(W)].$$

Expected utility from using the risky variety (where $b > 0$) with insurance is:

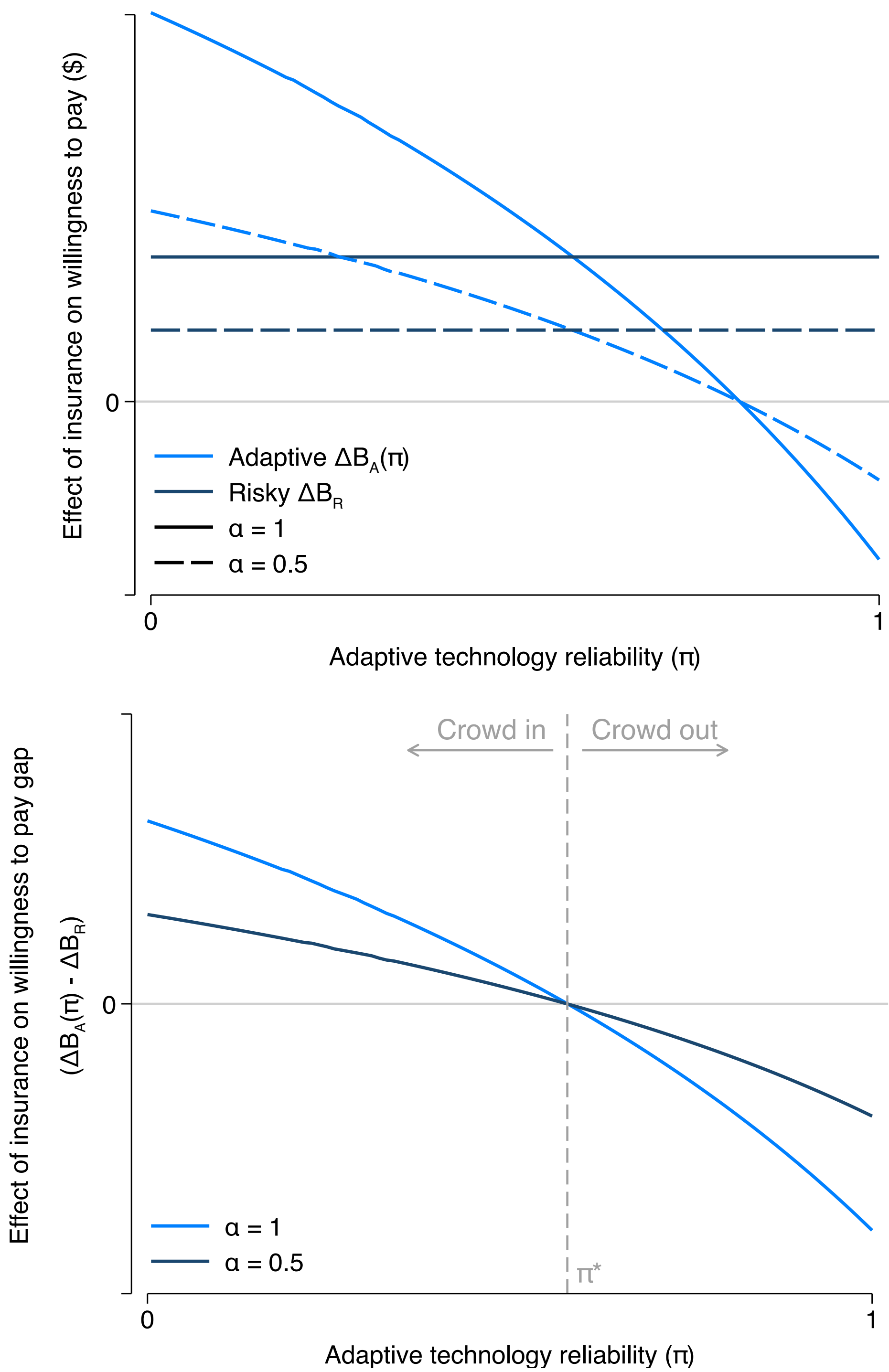
$$U_R^I(b) = p_N\, u(W + Y_R - b) + p_M\, u(W - b) + p_E\,[\alpha\, u(W + Y^I - b) + (1-\alpha)\, u(W - b)].$$

Finally, expected utility from using the adaptive technology (again where $b > 0$) with insurance is:

$$\begin{aligned} U_A^I(b) &= p_N\, u(W + Y_0 - b) + p_M\, u(W + Y_F - b) \\ &+ p_E\big(\alpha[\pi\, u(W + Y_F + Y^I - b) + (1-\pi)\, u(W + Y^I - b)] \\ &+ (1-\alpha)[\pi\, u(W + Y_F - b) + (1-\pi)\, u(W - b)]\big). \end{aligned}$$

Figure A.1 demonstrates how the degree of crowd-in or crowd-out ($\Delta B_A(\pi) - \Delta B_R$) created by insurance dampens as farmers are more skeptical about receiving a payout from the product. Intuitively, as α approaches zero, farmers increasingly behave as if they are uninsured, making the possibility of crowd-in or crowd-out impossible.

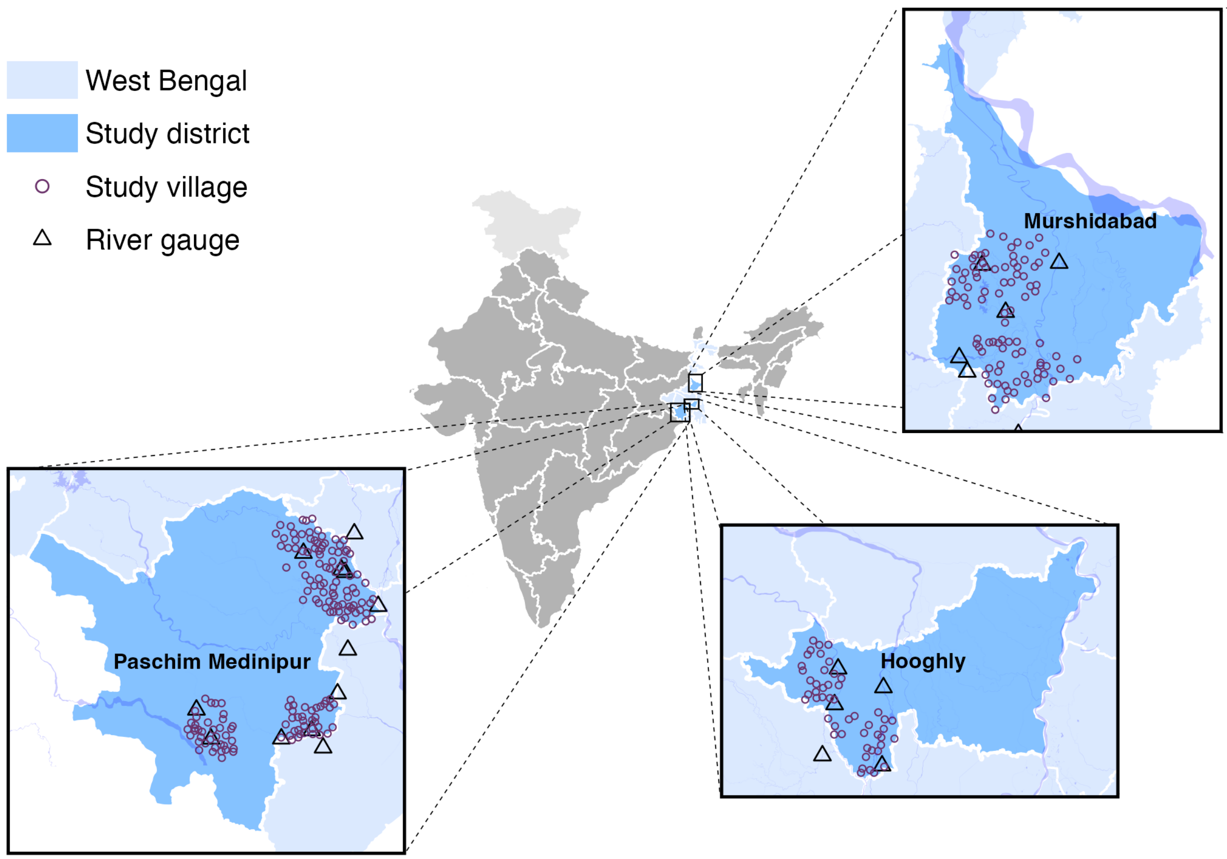
Figure A.1: Impact of insurance on willingness to pay for adaptation, low insurance reliability



Notes: This figure illustrates how the predictions of the model change if the probability that insurance pays out in state E, denoted by α, falls from 1 (as in the version of the model in the main text) to 0.5. In the top panel, the light blue line plots the effect of insurance on willingness to pay for adaptation ($\Delta B_A(\pi)$) as a function of the (perceived) likelihood (π) that the adaptation will be effective in the severe flood state E, and the navy line plots the effect of insurance on willingness-to-pay for the risky investment (ΔB_R). Solid lines indicate $\alpha = 1$, and long dashes indicate $\alpha = 0.5$. In the bottom panel, we plot the effect of insurance on the gap between willingness to pay for the adaptive investment and for the risky investment, $\Delta B_A(\pi) - \Delta B_R$, with $\alpha = 1$ in light blue and $\alpha = 0.5$ in navy. As insurance reliability declines, the magnitude of the crowd-in or crowd-out effect is attenuated. All other parameters are identical to Figure 1.

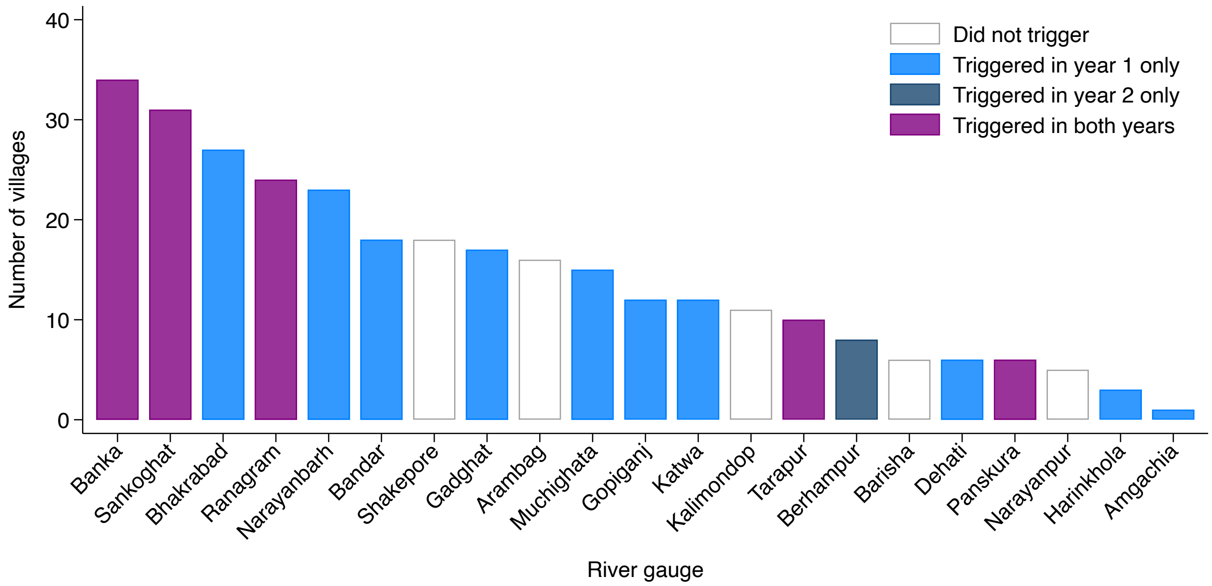
A.2 Experimental design

Figure A.2: Map of study villages



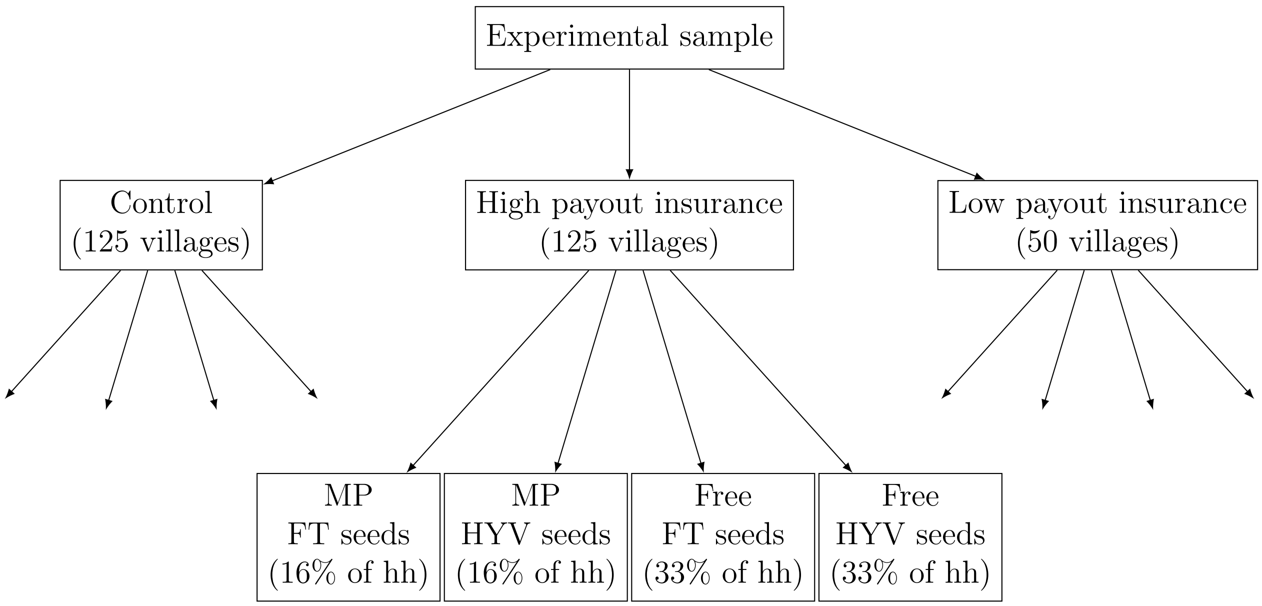
Notes: This figure plots the location of our study villages in India. The light blue shaded districts plot the state of West Bengal. Our experiment took place in the three districts of Paschim Medinipur, Hooghly, and Murshidabad, colored in dark blue and shown in the extruded view. The locations of the 302 study villages are denoted by purple circles, and the associated river gauge stations are denoted by black triangles.

Figure A.3: Study flood gauges and trigger years



Notes: This figure shows the set of gauges used to track flooding. The y-axis reports the number of villages associated with each gauge. Gauges are color-coded as follows: White indicates gauges that were not triggered in either year; blue indicates gauges triggered in year 1 only; gray indicates gauges triggered in year 2 only; and purple indicates gauges that were triggered in both years.

Figure A.4: Experimental design



Notes: This figure shows the design for our cluster-randomized experiment. We randomly divide the 300 villages that make up the experimental sample into an insurance control group, a low-payout insurance group, and a high-payout insurance group. We then randomize the six sampled households per village into a group that is offered flood-tolerant (FT) seeds at market price (MP), a group that is offered high-yield-variety seeds (HYV) at market price (MP), a group that is offered FT seeds for free, and a group that is offered HYV seeds for free. The two MP groups together make up the "seed control" group.

A.3 Experimental integrity

Table A.2: Balance – Insurance treatment

			Difference
	(1) Control	(2) Insurance	(3) (2)-(1)
Household size	5.24	5.16	-0.10
	(2.55)	(2.50)	(0.13)
Head female	1.05	1.04	-0.01
	(0.22)	(0.18)	(0.01)
Head age	49.57	49.39	-0.07
	(12.41)	(12.50)	(0.63)
Head married	0.95	0.94	-0.02
	(0.21)	(0.23)	(0.01)
Head education	7.38	7.11	-0.29
	(3.96)	(4.10)	(0.26)
No. of plots	1.72	1.83	0.09
	(1.05)	(1.15)	(0.06)
No. of cult. plots	1.70	1.82	0.09
	(1.05)	(1.16)	(0.06)
Total area (ha.)	0.43	0.42	-0.01
	(0.42)	(0.44)	(0.02)
Cult. area (ha.)	0.42	0.41	-0.01
	(0.42)	(0.43)	(0.02)
Rented-in area (ha.)	0.04	0.05	0.01
	(0.14)	(0.14)	(0.01)
Labor man-days	69.70	63.10	-5.64
	(67.25)	(63.39)	(3.89)
Urea amount (kg)	57.74	53.55	-4.57
	(57.55)	(60.38)	(3.46)
DAP amount (kg)	62.90	57.60	-5.84
	(63.59)	(59.98)	(3.78)
Potash amount (kg)	31.52	28.42	-3.36
	(34.92)	(33.08)	(2.06)
Joint F-test (p-value)			0.369

Notes: This table presents tests for balance across the two insurance treatment arms. Columns (1) – (2) show means and (standard deviations). The remaining columns present pair-wise differences and (standard errors), where each row reports the coefficient from a separate regression of the baseline characteristic on treatment indicators, controlling for village strata fixed effects. Standard errors are clustered at the village level. The joint F-test p-value is from a reverse regression of the treatment indicator on all baseline characteristics simultaneously. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Balance – Seed treatments

	(1) Control	(2) Free FT	(3) Free HYV	Difference (4) (2)-(1)	(5) (3)-(1)	(6) (2)-(3)
Household size	5.17	5.30	5.12	0.12	-0.04	0.16
	(2.20)	(2.67)	(2.67)	(0.13)	(0.14)	(0.15)
Head female	1.04	1.04	1.04	-0.00	0.00	-0.01
	(0.21)	(0.19)	(0.20)	(0.01)	(0.01)	(0.01)
Head age	49.65	49.59	49.15	-0.10	-0.51	0.41
	(12.82)	(12.27)	(12.29)	(0.69)	(0.68)	(0.69)
Head married	0.95	0.96	0.94	0.01	-0.01	0.02
	(0.22)	(0.20)	(0.24)	(0.01)	(0.01)	(0.01)
Head education	7.29	7.25	7.12	-0.04	-0.18	0.14
	(3.97)	(4.13)	(4.02)	(0.21)	(0.21)	(0.21)
No. of plots	1.72	1.82	1.81	0.09	0.09	0.00
	(1.00)	(1.15)	(1.18)	(0.06)	(0.06)	(0.06)
No. of cult. plots	1.71	1.79	1.79	0.07	0.08	-0.01
	(1.04)	(1.14)	(1.17)	(0.06)	(0.06)	(0.06)
Total area (ha.)	0.43	0.42	0.42	-0.01	-0.01	0.00
	(0.44)	(0.43)	(0.42)	(0.02)	(0.02)	(0.02)
Cult. area (ha.)	0.42	0.42	0.41	-0.00	-0.01	0.01
	(0.43)	(0.43)	(0.41)	(0.02)	(0.02)	(0.02)
Rented-in area (ha.)	0.05	0.05	0.05	0.00	0.01	-0.00
	(0.14)	(0.13)	(0.14)	(0.01)	(0.01)	(0.01)
Labor man-days	66.08	66.74	64.71	0.52	-1.63	2.15
	(67.28)	(66.60)	(61.29)	(3.13)	(3.06)	(3.02)
Urea amount (kg)	56.73	57.07	52.07	0.17	-5.03*	5.21*
	(61.08)	(64.09)	(51.78)	(2.98)	(2.82)	(2.89)
DAP amount (kg)	60.57	59.19	59.66	-1.47	-0.87	-0.60
	(62.96)	(61.85)	(59.89)	(3.20)	(3.25)	(3.15)
Potash amount (kg)	30.77	30.36	28.00	-0.49	-2.68	2.19
	(35.12)	(35.03)	(31.33)	(1.87)	(1.76)	(1.79)
Joint F-test (p-value)				0.474	0.282	0.236

Notes: This table presents tests for balance across the two insurance treatment arms. Columns (1) – (3) show means and (standard deviations). The remaining columns present pair-wise differences and (standard errors), where each row reports the coefficient from a separate regression of the baseline characteristic on treatment indicators, controlling for village strata fixed effects. Standard errors are clustered at the village level. The joint F-test p-value is from a reverse regression of the treatment indicator on all baseline characteristics simultaneously. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

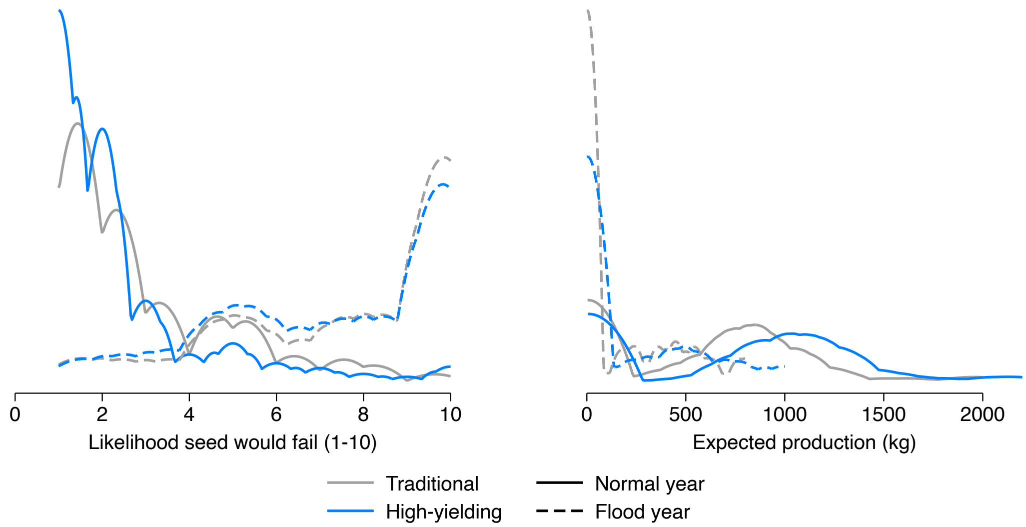
Table A.4: Attrition

	(1) Baseline	(2) Y1 Endline	(3) Y2 Baseline	(4) Y2 Midline	(5) Y2 Endline
Insurance	-0.001	-0.004	-0.012	-0.007	-0.003
	(0.005)	(0.006)	(0.011)	(0.013)	(0.014)
Control mean	0.972	0.991	0.973	0.964	0.956
Observations	1804	1804	1804	1804	1804

Notes: This table reports the effect of insurance treatment assignment on survey completion (attrition). The outcome variable in each column is an indicator equal to 1 if the household completed the respective survey round. All regressions include village strata fixed effects and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4 Seed perception and utilization

Figure A.5: Perceived effectiveness of high-yielding seeds



Notes: This plot shows the distribution of farmers' beliefs about the effectiveness of traditional-variety seeds (gray) and high-yielding seeds (blue) under normal conditions (solid lines) and flood conditions (dashed lines). On the left, we plot farmers' belief that each seed type will fail under each condition, on a 1–10 scale. On the right, we plot expected production from both seeds under each condition. We winsorize expected production at the 5th and 95th percentiles.

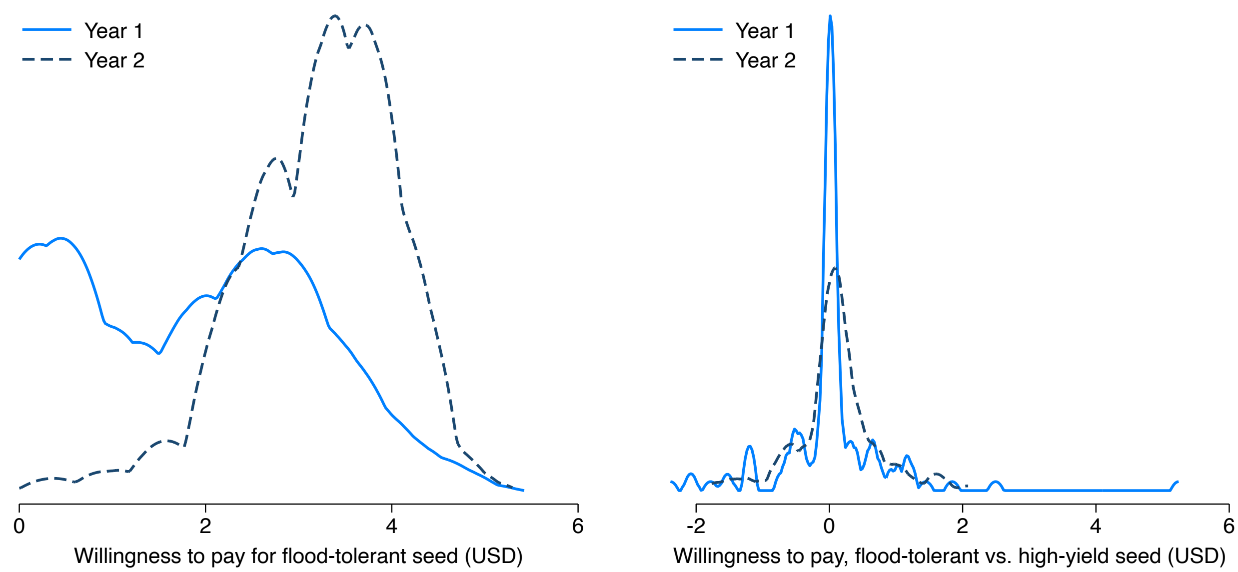
Table A.5: Effect of free seed offers on take-up and planting

	Year 1		Year 2	
	(1) Takeup	(2) Planted	(3) Takeup	(4) Planted
Free FT	0.984***	0.842***	0.980***	0.926***
	(0.004)	(0.014)	(0.005)	(0.010)
Free HYV	0.988***	0.812***	0.984***	0.925***
	(0.004)	(0.015)	(0.005)	(0.010)
Test FT == HYV	0.296	0.043	0.360	0.964
Control mean	0.005	0.064	0.014	0.012
Observations	1804	1784	1746	1735

Notes: This table presents the effects of offering free flood-tolerant and free high-yield variety seeds on take-up of those seeds immediately after the BDM exercise (Columns 1 and 3) and planting of those seeds during the growing season (Columns 2 and 4) in both years of the experiment. All regressions use year 1 treatment assignments, include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5 Measuring willingness to pay

Figure A.6: Willingness to pay for specialty seeds



Notes: This figure plots the density of willingness to pay for flood tolerant seeds (left panel) and the difference between flood-tolerant and high-yield variety seeds (right panel), for both year 1 (solid light blue) and year 2 (dashed navy). We restrict the sample to pure control farmers who received neither a free seed offer nor an insurance offer.

Table A.6: Correlates of willingness to pay

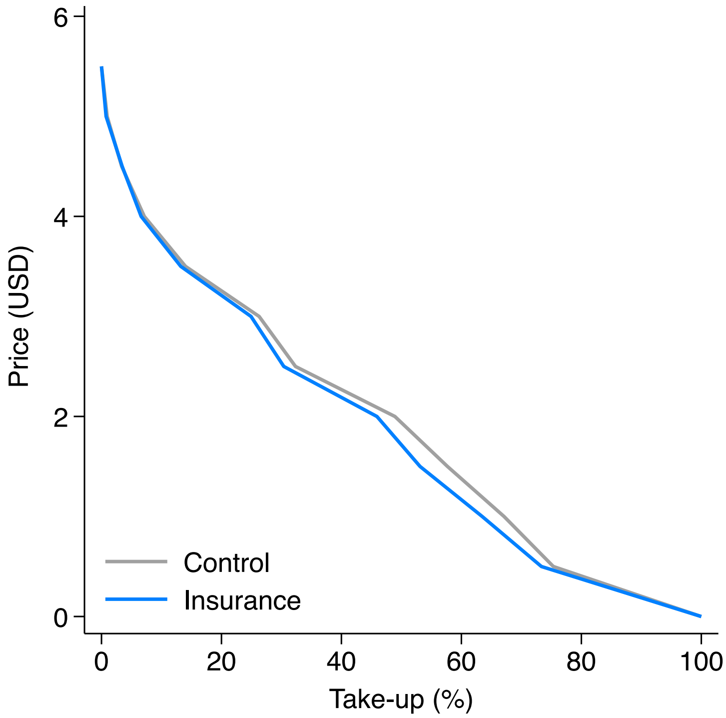
	Willingness to pay		
	(1) Flood-tolerant	(2) High-yield variety	(3) Correlate mean
Household size	0.002 (0.008)	-0.003 (0.008)	5.195 [2.520]
Head female	-0.095 (0.093)	0.002 (0.097)	1.041 [0.201]
Head age	-0.000 (0.002)	-0.001 (0.002)	49.463 [12.459]
Head married	-0.001 (0.065)	-0.044 (0.074)	0.948 [0.222]
Head education	0.008 (0.005)	0.008 (0.005)	7.220 [4.041]
Past flooding no. of years	0.041** (0.018)	0.029 (0.018)	2.166 [1.358]
Flood expected no. of years	0.016 (0.018)	0.014 (0.019)	2.447 [1.261]
Any FT experience	-0.107* (0.064)	-0.067 (0.068)	0.164 [0.370]
Any HYV experience	0.152* (0.079)	0.171* (0.089)	0.942 [0.233]
FT failure expectation	-0.036*** (0.008)	-0.052*** (0.008)	5.055 [2.466]
HYV failure expectation	-0.023*** (0.007)	-0.027*** (0.007)	7.409 [2.730]
Savings (000s USD)	0.408*** (0.124)	0.388*** (0.115)	0.124 [0.202]
Consumption (000s USD)	0.453*** (0.127)	0.371*** (0.140)	0.118 [0.133]
Assets (000s USD)	0.152*** (0.039)	0.150*** (0.038)	0.445 [0.539]
Risk aversion	-0.019** (0.008)	-0.023*** (0.008)	3.416 [3.313]

Notes: This table presents how willingness to pay for flood-tolerant seeds and high-yield variety seeds correlates with year 1 baseline (i.e., pre-experiment) characteristics. Willingness to pay for each seed is pooled across both years of the experiment. All monetary amounts are in USD. Savings, consumption, and assets are scaled by 1/1000. Each cell in Columns (1) and (2) presents a single regression. Risk aversion measures the farmer's choice in an incentivized risk game, where higher values indicate that the farmer is more risk averse. All regressions include enumerator and village strata fixed effects. Standard errors (in parentheses) are clustered at the village level. Column (3) shows the mean and [standard deviation] of each covariate in the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.6 Effects of insurance on willingness to pay

A.6.1 Year 1 effects

Figure A.7: Willingness to pay for flood-tolerant seeds (year 1)



Notes: This figure plots demand curves for flood-tolerant seeds, elicited using the BDM mechanism described in Section 3 during the baseline survey conducted in the first year of the experiment. The control group is plotted in a light gray line and the insurance treatment group (pooled across the low and high payouts) is plotted in blue.

Table A.7: Effects of insurance on willingness to pay (year 1)

	(1) Flood-tolerant	(2) High-yield variety	(3) Difference
Insurance	-0.042 (0.098)	-0.068 (0.096)	0.025 (0.035)
Control mean	1.874	1.898	-0.023
Observations	1785	1786	1785

Notes: This table presents estimates of the treatment effect of insurance on willingness to pay for flood tolerant seeds (1), high-yielding variety seeds (2), and their difference (3), elicited during the baseline of year 1 of the experiment, in USD. We elicit willingness to pay using the BDM game explained in Section B. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Effect of Insurance, Seed Treatment, and Beliefs on WTP Difference

	(1) WTP Difference	(2) WTP Difference
Insurance	0.131***	0.137***
	(0.044)	(0.045)
Free FT	0.088**	0.087**
	(0.044)	(0.044)
Ins × Free FT	-0.057	-0.063
	(0.059)	(0.059)
Free HYV	-0.004	-0.004
	(0.054)	(0.055)
Ins × Free HYV	-0.055	-0.066
	(0.068)	(0.069)
Control for seed beliefs	No	Yes
Control mean	0.118	0.118
Observations	1746	1731

Notes: This table presents estimates of the treatment effect of insurance and free seeds on the WTP difference between the FT and HYV variety elicited in the second year of the study. Column (2) adds controls for farmer beliefs about expected seed production both with and without flooding. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Effect of Insurance and Seed Treatment on Seed Beliefs

	FT Prodn belief (0 = none, 1 = some, 2 = full)			Min days to fail	
	(1) 1-7d flood	(2) 8-14d flood	(3) 14+d flood	(4) FT	(5) Trad
Insurance	-0.059*	-0.032	-0.002	-0.002	0.003
	(0.035)	(0.035)	(0.015)	(0.015)	(0.003)
Free FT	0.013	0.023	0.008	0.008	-0.000
	(0.032)	(0.038)	(0.016)	(0.016)	(0.000)
Ins × Free FT	0.059	-0.015	0.008	0.004	-0.003
	(0.044)	(0.048)	(0.021)	(0.020)	(0.003)
Free HYV	0.044	0.016	-0.006	-0.006	0.004
	(0.034)	(0.033)	(0.015)	(0.015)	(0.004)
Ins × Free HYV	-0.017	-0.011	0.003	0.003	-0.007
	(0.044)	(0.045)	(0.019)	(0.019)	(0.005)
Control mean	1.258	0.639	0.037	3.037	3.000
Observations	1777	1774	1776	1776	1783

Notes: This table presents estimates of the effect of insurance and free seeds on farmers' beliefs about the effectiveness of flood-tolerant (FT) seed. Columns (1)-(3) report effects on farmers beliefs about FT seed output under a 1-7 day flood, a 8-14 day flood, and a 14 plus day flood respectively. Farmers were asked under those flood conditions whether the FT seed would produce no output (=0), some output (=1), or normal output (=2). Columns (4) and (5) report effects on the minimum number of days the seeds could survive flooding before output would be affected. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Effects of insurance on willingness to pay by seed treatment

	Insurance treatment			Insurance control		
	(1) Flood-tolerant	(2) High-yield variety	(3) Difference	(4) Flood-tolerant	(5) High-yield variety	(6) Difference
Free FT	0.276***	0.217***	0.059	0.388***	0.320***	0.068
	(0.052)	(0.049)	(0.040)	(0.075)	(0.075)	(0.048)
Free HYV	0.198***	0.220***	-0.022	0.335***	0.319***	0.016
	(0.061)	(0.058)	(0.043)	(0.070)	(0.074)	(0.059)
Control mean	3.452	3.243	0.209	3.203	3.114	0.089
Observations	1015	1015	1015	731	731	731

Notes: This table presents estimates of the treatment effect of providing free flood-tolerant seeds or free high-yield-variety seeds in year 1 on willingness to pay for flood tolerant seeds (1), high-yielding variety seeds (2), and their difference (3), elicited during the baseline of year 2 of the experiment, in USD. We elicit willingness to pay using the BDM game explained in Section B. We estimate treatment effects separately for farmers in the insurance treatment group (on the left) and farmers in the insurance control group (on the right). All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Effects of insurance on willingness to pay by generosity

	(1) Flood-tolerant	(2) High-yield variety	(3) Difference
Low Insurance	0.143**	0.073	0.071**
	(0.061)	(0.062)	(0.031)
High Insurance	0.129***	0.025	0.104***
	(0.050)	(0.047)	(0.029)
Test Low == High	0.824	0.470	0.284
Control mean			
Observations	1746	1746	1746

Notes: This table presents estimates of the treatment effect of our low (INR 5,000) and high (INR 10,000) payout insurance contracts on willingness to pay for flood tolerant seeds (1), high-yielding variety seeds (2), and their difference (3), elicited during the baseline of year 2 of the experiment, in USD. We elicit willingness to pay using the BDM game explained in Section B. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.6.2 Heterogeneity

Table A.12: Heterogeneity in crowd-in by beliefs about flood-tolerant seed effectiveness

	(1) Flood-tolerant	(2) High-yield variety	(3) Difference
Insurance	0.135***	0.042	0.093***
	(0.045)	(0.042)	(0.026)
Good FT	0.033	0.009	0.025
	(0.033)	(0.034)	(0.027)
Insurance × Good FT	-0.024	0.053	-0.077**
	(0.043)	(0.042)	(0.035)
Control mean	3.441	3.323	0.118
Observations	1746	1746	1746

Notes: This table presents heterogeneous treatment effects of insurance on the difference between willingness to pay for flood-tolerant and high-yield variety seeds, elicited during the baseline of year 2 of the experiment and measured in USD. We elicit willingness to pay using the BDM game explained in section B. We construct a standardized index of perceived flood-tolerant seed effectiveness ("Good FT"). All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Heterogeneity in crowd-in by other characteristics

	(1) Risk aversion	(2) Any FT experience	(3) Any HYV experience	(4) No. of past flood years	(5) Exceed DL no. of years	(6) Savings	(7) Liquidity	(8) Off-farm activity
Panel A : Flood-tolerant variety								
Insurance	0.137**	0.136***	0.231*	0.024	0.106	0.148***	0.126***	0.158***
	(0.063)	(0.046)	(0.130)	(0.081)	(0.067)	(0.052)	(0.046)	(0.051)
Hetero	-0.003	-0.020	0.046	-0.002	0.035	0.000	-0.000	-0.009
	(0.012)	(0.082)	(0.106)	(0.021)	(0.037)	(0.000)	(0.000)	(0.055)
Insurance × hetero	-0.002	-0.015	-0.104	0.049*	0.011	-0.000	0.001	-0.094
	(0.014)	(0.105)	(0.135)	(0.030)	(0.031)	(0.000)	(0.001)	(0.081)
Observations	1394	1746	1746	1745	1746	1658	1746	1746
Panel B : High-yielding variety								
Insurance	0.004	0.051	0.085	-0.064	-0.039	0.026	0.027	0.053
	(0.060)	(0.045)	(0.129)	(0.081)	(0.065)	(0.050)	(0.044)	(0.049)
Hetero	-0.013	0.060	0.051	-0.008	0.006	0.000	-0.001*	-0.034
	(0.011)	(0.078)	(0.096)	(0.021)	(0.037)	(0.000)	(0.000)	(0.064)
Insurance × hetero	0.009	-0.068	-0.049	0.048*	0.037	0.000	0.001	-0.051
	(0.013)	(0.108)	(0.133)	(0.029)	(0.029)	(0.000)	(0.001)	(0.086)
Observations	1394	1746	1746	1745	1746	1658	1746	1746
Panel C : Difference								
Insurance	0.132***	0.085***	0.146	0.088**	0.145***	0.122***	0.098***	0.105***
	(0.043)	(0.028)	(0.112)	(0.044)	(0.040)	(0.033)	(0.028)	(0.029)
Hetero	0.010	-0.080	-0.005	0.005	0.029	0.000*	0.000	0.025
	(0.008)	(0.053)	(0.099)	(0.014)	(0.018)	(0.000)	(0.000)	(0.046)
Insurance × hetero	-0.011	0.053	-0.055	0.001	-0.026*	-0.000	-0.000	-0.043
	(0.009)	(0.064)	(0.114)	(0.017)	(0.015)	(0.000)	(0.001)	(0.061)
Ctrl mean hetero								
Observations	1394	1746	1746	1745	1746	1658	1746	1746

Notes: This table presents heterogeneous treatment effects of insurance on the difference between willingness to pay for flood-tolerant and high-yield variety seeds, elicited during the baseline of year 2 of the experiment and measured in USD. We elicit willingness to pay using the BDM game explained in section B. We test for heterogeneity along five key dimensions: risk aversion (measured using an incentivized risk game, where higher values indicate that the farmer is more risk averse), how many years out of the previous five the farmer reported flooding, whether the river gauge danger level was breached in the previous year, ownership of a non-agricultural business, and access to liquidity. The outcome in all columns is (the difference in) willingness to pay, and the column headers indicate the form of heterogeneity we evaluate. Insurance is an indicator for being in the insurance treatment group, Hetero is the mean effect of the characteristic, and Insurance × hetero is their interaction. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. Control means for the willingness to pay for flood tolerant, high-yielding variety, and difference are 3.441, 3.323, and 0.118 USD respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.7 Effect of treatments on farm inputs

Table A.14: Effect of insurance and free seed type on ex-ante inputs

	(1) No. of plots	(2) Total area (ha.)	(3) No. of crops	(4) Input cost	(5) Invest index
			Panel A: Year 1		
Insurance	0.023	0.001	0.037	1.659	0.065
	(0.042)	(0.014)	(0.037)	(16.729)	(0.041)
Free FT	0.094**	0.016	0.633***	18.846	0.330***
	(0.043)	(0.016)	(0.045)	(17.327)	(0.045)
Insurance × Free FT	-0.017	-0.025	0.005	-35.005	-0.068
	(0.057)	(0.020)	(0.057)	(21.721)	(0.059)
Free HYV	0.045	-0.004	0.171***	5.635	0.116***
	(0.045)	(0.013)	(0.042)	(14.631)	(0.039)
Insurance × Free HYV	0.044	0.017	0.033	2.311	0.024
	(0.060)	(0.018)	(0.055)	(19.277)	(0.053)
q-val Insurance	1.000	1.000	1.000	1.000	-
q-val Free FT	0.044	0.186	0.001	0.186	-
q-val Ins × Free FT	0.870	0.739	0.870	0.739	-
q-val Free HYV	0.910	1.000	0.001	1.000	-
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	-
Control mean	1.549	0.383	1.171	408.358	0.000
Observations	1784	1784	1784	1784	1784
			Panel B: Year 2		
Insurance	0.144***	0.029*	0.045	6.824	0.118***
	(0.055)	(0.016)	(0.047)	(13.930)	(0.045)
Free FT	0.193***	0.007	0.778***	8.900	0.500***
	(0.059)	(0.016)	(0.044)	(13.615)	(0.042)
Insurance × Free FT	-0.074	-0.010	-0.048	-1.705	-0.066
	(0.077)	(0.022)	(0.058)	(17.870)	(0.059)
Free HYV	0.125*	0.007	0.101**	3.845	0.119***
	(0.069)	(0.014)	(0.051)	(12.405)	(0.046)
Insurance × Free HYV	-0.094	-0.012	-0.038	-1.104	-0.072
	(0.086)	(0.021)	(0.065)	(17.112)	(0.060)
q-val Insurance	0.037	0.118	0.295	0.454	-
q-val Free FT	0.002	0.509	0.001	0.509	-
q-val Ins × Free FT	1.000	1.000	1.000	1.000	-
q-val Free HYV	0.169	0.609	0.169	0.609	-
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	-
Control mean	1.660	0.390	1.238	340.651	0.027
Observations	1735	1735	1735	1735	1735

Notes: This table presents estimates of the treatment effect of insurance and free seeds on farmers' agricultural investments. No. of plots is the total number of plots cultivated. Total area (ha.) is the total area cultivated in hectares. No. of crops is the number of crops cultivated by the farmer where traditional, HYV and FT paddy are considered as distinct crops. Input cost is the amount (in USD) spent on all inputs, including fertilizer, labor, seeds, irrigation, machinery, and other expenses. Invest index is an inverse-covariance–weighted (ICW) index constructed using the number of crops cultivated, number of plots cultivated, area cultivated, and input cost. All regressions include enumerator and village strata fixed effects, baseline values if available, and other baseline controls chosen by double-selection LASSO. All variables other than No. of plots cultivated, No. of crops, and Invest index are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes except the invest index. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.8 Self-reported flooding

Table A.15: Effect of insurance on self-reported flooding

	(1) Flooding (baseline)	(2) Flooding (Y1 endline)	(3) Flooding (Y2 midline)
Insurance Treatment Arm	0.018	0.093^{***}	0.071^{***}
	(0.016)	(0.017)	(0.017)
Control mean	0.425	0.534	0.446
Observations	1804	1777	1735

Notes: This table presents the effect of our insurance treatment on self-reported flooding at three stages during the experiment. Flooding (baseline) was collected prior to implementing the treatment. Flooding (Y1 endline) was collected during the endline survey at the end of the first year. Flooding (Y2 midline) was collected during the midline survey in the middle of the second year. All regressions include enumerator and village strata fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors (in parentheses) are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Becker et al. (1964) appendix

B.1 Methodological overview

The Becker, DeGroot, and Marschak (BDM) is an incentive compatible process through which a rational participant should reveal their true maximum WTP. We implement the BDM procedure using the following steps, modeled closely after Burlig et al. (2024) and Berkouwer and Dean (2022):

1. Prior to the baseline visit, we randomly assign each household (A) randomly receive an offer for either high-yield variety seeds or flood-tolerant seeds; and (B) a price for the given seed, drawn from a BDM price distribution (described below).

2. Each enumerator is then given a "sealed envelope" (implemented digitally within SurveyCTO) that contains the household's seed draw and price draw for the participants they are visiting that day. The enumerators are not aware of the assigned prices.

3. When the BDM procedure begins, the enumerator explains to the household that the survey tablet has a randomized hidden seed type draw and price, and shows the household both seed mini-kits.

4. Beginning with a starting price of INR 500 for both of the seed types, the enumerator asks if the participant would commit to purchasing the respective product at that price. If the participant agrees, the enumerator subsequently increases the price by INR 500 and asks again if the participant would be willing to purchase the product at this new price. If the participant again agrees to purchase the product, the price is again raised by INR 500. If the participant declines this new price, the enumerator reduces the prices by INR 250.

   Instead, if the participant declines to buy the product at the initial price, the enumerator lowers the price by half (to 250) and asks again if the participant would be willing to purchase at this new, lower price.This process in repeated 11 times with the relevant intervals shrinking each iteration (or until the relevant interval drops below 1 rupee), so that by the end of the process we approach the participant's true WTP.

   For concreteness, we illustrate the beginning iterations of this process:

   (a) If the tablet said the price was INR 500, would you choose to purchase the high-yield (flood-tolerant) seed?

      i. If yes: If the tablet said the price was INR 1,000, would you choose to purchase the high-yield (flood-tolerant) seed?

         A. If yes: If the tablet said the price was INR 1,500, would you choose to purchase the high-yield (flood-tolerant) seed?

            - Etc.

         B. If no: If the envelope said the price was INR 1,250 would you choose to purchase the high-yield (flood-tolerant) seed?

            - Etc.

ii. If no: If the tablet said the price was INR 250, would you choose to purchase the high-yield (flood-tolerant) seed?

A. If yes: If the tablet said the price was INR 375, would you choose to purchase the high-yield (flood-tolerant) seed?

- Etc.

B. If no: If the tablet said the price was INR 125, would you choose to purchase the high-yield (flood-tolerant) seed?

- Etc.

At the end of this process (which is repeated for both seed types), the enumerator confirms that the participant fully understands their decision and the consequences of once the seed-price pair is revealed. They then ask that the participant retrieves the agreed upon amount in cash and place the bank notes next to the tablet containing the price. Finally, they will allow the participant a final chance to change their mind before the seed-price pair is revealed.

5. Once the participant has confirmed their price for both seeds and has placed the cash, the enumerator reveal the seed-type and price draw.

6. If the participant's maximum WTP for the offered seed type is lower than the BDM price on the tablet, the participant will not be able to purchase the high-yield (flood-tolerant) seed and will instead take back their cash.

7. If the participant's maximum WTP is at least as high as the BDM price on the tablet, the participant purchases the high-yield (flood-tolerant) seed, paying the price that was written on the tablet out of their cash.

8. The participant will not have the opportunity to buy the other seed type.

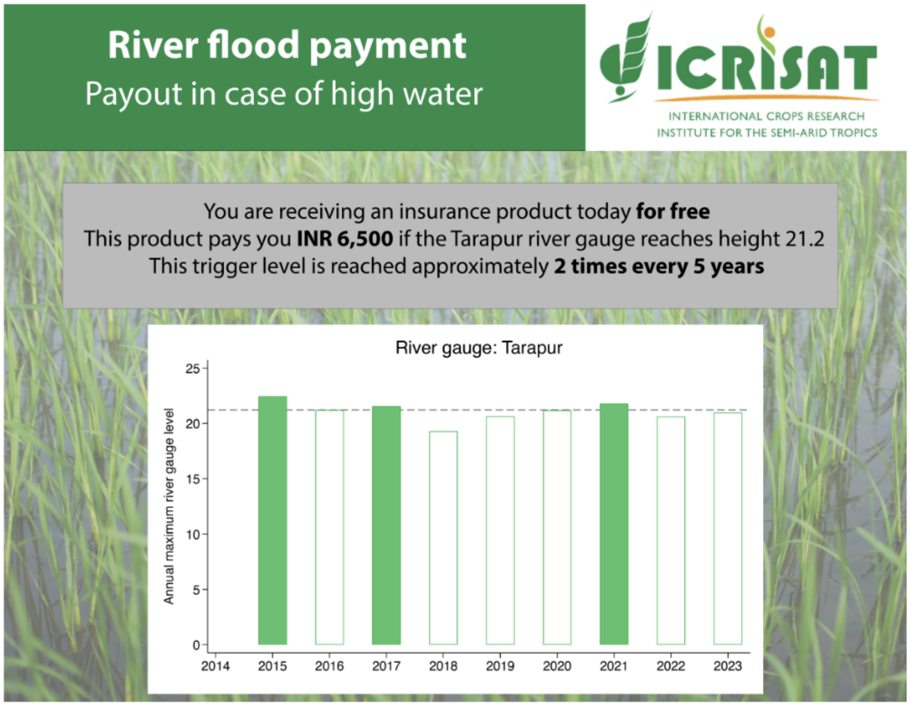
B.2 Distribution of BDM prices

We begin by setting the share of farmers to receive offers for each seed: 50% will be randomized to receive a high-yield variety seed offer, and 50% will be randomized to receive a flood-tolerant variety seed offer.

We next set the BDM price distribution for each seed, with the goals of maximizing experimental power while maintaining incentive compatibility. We use the following distribution: 1/3 of participants are allocated a BDM price of INR 0, and 2/3 are allocated a BDM price equal to the market price for the seed type. Neither the participants nor the enumerators will be informed about the underlying price distribution.

C Information sheets

Figure C.1: Insurance information sheet



Notes: We provided farmers with this information sheet about the insurance product. The information sheet was translated into Bengali before being presented to farmers.

Figure C.2: Seed information sheets

(a) HYV (Pratiksha) information sheet

(b) FT (Swarna) information sheet

Notes: Panel (a) shows the information sheet for our high-yield variety seed, Pratiksha. Pratiksha is a medium slender rice grain that measures 40-42 inches, and matures in 140-145 days. It outperforms traditional rice varieties in the area (by almost 1,000kg/ha under normal conditions), producing yields comparable to Swarna, another common high-yield variety in West Bengal. Panel (b) shows the information sheet for our flood-tolerant seed, Swarna-Sub1. Swarna-Sub1 is a medium long rice grain that measures 46-48 inches, and matures in 135-140 days. This seed performs similarly to the standard Swarna variety under non-flood conditions, but substantially better under flood conditions (Singh, Mackill, and Ismail (2009); Singh, Mackill, and Ismail (2011); Dar et al. (2013); Emerick et al. (2016)). More specifically, it produces yields of 2,200-2,400 kg/hectare in both flood and non-flood years.

D Deviations from our pre-analysis plan

We broadly followed our pre-analysis plan, and deviations are minimal. Here, we enumerate the full set of deviations:

- **Analysis.** We pre-specified a number of specifications to test for differential effects by insurance contract generosity (either with dummies for low- vs. high-payout insurance groups, or with a linear "insurance payout" term). Because we see no evidence of differences in willingness to pay for flood-tolerant seeds (Appendix Table A.11) or differences in agricultural investments (Appendix Table E.2) when estimating separate treatment effects for the two insurance groups, we omit the remaining specifications for parsimony.

- **Analysis.** We pre-specified a number of specifications pooling all insurance farmers together. Because these effects may vary between seed control farmers and free seed farmers, we instead present only the (also pre-specified) fully interacted regressions for all outcomes outside of the main willingness to pay results.

- **Analysis.** We pre-specified a number of specifications pooling all *free* seed farmers together. Because farmers should react differently to flood-tolerant seeds vs. high-yield variety seeds, these specifications are difficult to interpret. We instead only present regressions where we split seed offers by type.

- **Analysis.** While we were clear in the pre-analysis plan that willingness to pay is our main outcome of interest, we also pre-specified a series of regressions with outcomes about agriculture, other economic activity, and well-being. We present these specifications in Appendix E, but do not highlight them in the main text.

E Additional pre-specified results

E.1 Ex-ante outcomes

Table E.1: Effect of free seed types (pooled across insurance) on ex-ante inputs

	(1) No. of plots	(2) Total area (ha.)	(3) No. of crops	(4) Input cost	(5) Invest index
			Panel A: Year 1		
Free FT	0.084***	0.001	0.635***	-1.490	0.290***
	(0.028)	(0.010)	(0.027)	(10.590)	(0.029)
Free HYV	0.070**	0.006	0.190***	7.017	0.129***
	(0.030)	(0.009)	(0.028)	(9.668)	(0.027)
q-val Free FT	0.005	0.799	0.001	0.799	-
q-val Free HYV	0.028	0.379	0.001	0.379	-
Control mean	1.640	0.373	1.187	399.615	0.018
Observations	1784	1784	1784	1784	1784
			Panel B: Year 2		
Free FT	0.149***	0.000	0.750***	7.860	0.461***
	(0.038)	(0.011)	(0.029)	(8.919)	(0.030)
Free HYV	0.069*	-0.000	0.079**	3.143	0.077**
	(0.041)	(0.011)	(0.032)	(8.575)	(0.030)
q-val Free FT	0.001	0.949	0.001	0.338	-
q-val Free HYV	0.158	0.979	0.059	0.909	-
Control mean	1.829	0.398	1.262	337.693	0.086
Observations	1735	1735	1735	1735	1735

Notes: This table presents estimates of the treatment effect of free seeds on farmers' agricultural investments. No. of plots is the total number of plots cultivated. Total area (ha.) is the total area cultivated in hectares. No. of crops is the number of crops cultivated by the farmer where traditional, HYV and FT paddy are considered as distinct crops. Input cost is the amount (in USD) spent on all inputs, including fertilizer, labor, seeds, irrigation, machinery, and other expenses. Invest index is an inverse-covariance–weighted (ICW) index constructed using the number of crops cultivated, number of plots cultivated, area cultivated, and input cost. All regressions include enumerator and village strata fixed effects, baseline values if available, and other baseline controls chosen by double-selection LASSO. All variables other than No. of plots cultivated, No. of crops, and Invest index are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes except the invest index. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.2: Effect of insurance (by generosity) on ex-ante inputs

	(1) No. of plots	(2) Total area (ha.)	(3) No. of crops	(4) Input cost	(5) Invest index
			Panel A: Year 1		
Low Insurance	0.007	-0.000	0.038	-20.392	0.048
	(0.042)	(0.012)	(0.037)	(14.116)	(0.040)
High Insurance	0.043	-0.002	0.053*	-4.026	0.050
	(0.033)	(0.010)	(0.030)	(12.333)	(0.032)
q-val Low insurance	1.000	1.000	1.000	1.000	-
q-val High insurance	0.469	0.707	0.469	0.707	-
Test Low == High	0.389	0.875	0.697	0.228	0.961
Control mean	1.651	0.379	1.438	410.494	0.130
Observations	1784	1784	1784	1784	1784
			Panel B: Year 2		
Low Insurance	0.066	0.028**	0.004	8.195	0.080**
	(0.049)	(0.014)	(0.037)	(12.128)	(0.041)
High Insurance	0.097**	0.018	0.017	4.707	0.065*
	(0.044)	(0.012)	(0.035)	(10.679)	(0.036)
q-val Low insurance	0.376	0.180	0.830	0.573	-
q-val High insurance	0.129	0.220	0.492	0.492	-
Test Low == High	0.495	0.459	0.736	0.769	0.711
Control mean	1.831	0.392	1.543	340.976	0.235
Observations	1735	1735	1735	1735	1735

Notes: This table presents estimates of the treatment effect of our low (INR 5,000) and high (INR 10,000) payout insurance contracts on farmers' agricultural investments. No. of plots is the total number of plots cultivated. Total area (ha.) is the total area cultivated in hectares. No. of crops is the number of crops cultivated by the farmer where traditional, HYV and FT paddy are considered as distinct crops. Input cost is the amount (in USD) spent on all inputs, including fertilizer, labor, seeds, irrigation, machinery, and other expenses. Invest index is an inverse-covariance–weighted (ICW) index constructed using the number of crops cultivated, number of plots cultivated, area cultivated, and input cost. All regressions include enumerator and village strata fixed effects, baseline values if available, and other baseline controls chosen by double-selection LASSO. All variables other than No. of plots cultivated, No. of crops, and Invest index are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes except the invest index. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.2 Ex-post outcomes

Table E.3: Effect of insurance and free seed type on agricultural output and profit

	(1) Prodn (kg)	(2) Prodn value	(3) Sales revenue	(4) Yield (kg/ha)	(5) Profit (calctd)	(6) Profit (self-rep)
			Panel A: Year 1			
Insurance	-328.587***	-59.776**	-0.705***	-432.897	-58.043***	-32.754
	(123.690)	(26.360)	(0.256)	(486.032)	(20.007)	(22.250)
Free FT	154.424	15.171	0.212	341.082	-0.212	11.795
	(122.055)	(23.496)	(0.244)	(269.378)	(14.958)	(19.656)
Insurance × Free FT	-104.416	-14.604	-0.165	-435.328	16.141	-18.233
	(145.084)	(29.396)	(0.289)	(453.967)	(19.914)	(25.347)
Free HYV	21.225	27.195	0.161	516.493	24.182	-5.095
	(120.648)	(22.755)	(0.285)	(317.722)	(17.507)	(19.297)
Insurance × Free HYV	184.427	-4.837	0.429	-252.305	-11.450	11.522
	(142.728)	(28.136)	(0.329)	(488.912)	(21.512)	(24.057)
q-val Insurance	0.017	0.018	0.017	0.143	0.017	0.060
q-val Free FT	1.000	1.000	1.000	1.000	1.000	1.000
q-val Ins × Free FT	1.000	1.000	1.000	1.000	1.000	1.000
q-val Free HYV	0.868	0.868	0.868	0.868	0.868	0.868
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	1.000	1.000
Control mean	1725.224	381.980	2.809	4518.958	-26.868	48.614
Observations	1784	1784	1784	1784	1784	1773
			Panel B: Year 2			
Insurance	-49.120	-29.027	0.284	-297.130	-31.312	-6.101
	(139.826)	(26.753)	(0.271)	(285.979)	(19.859)	(17.185)
Free FT	24.032	-2.191	-0.091	56.594	-11.358	8.838
	(113.122)	(22.536)	(0.225)	(208.979)	(17.443)	(14.643)
Insurance × Free FT	-68.996	0.182	-0.312	-172.765	0.793	-3.983
	(157.801)	(28.974)	(0.297)	(298.757)	(22.524)	(19.672)
Free HYV	56.065	15.816	0.093	92.100	13.465	-4.199
	(121.117)	(20.378)	(0.253)	(206.093)	(16.328)	(15.940)
Insurance × Free HYV	4.678	5.450	-0.276	-133.763	4.090	-1.707
	(164.631)	(27.360)	(0.335)	(291.901)	(21.472)	(20.218)
q-val Insurance	0.814	0.814	0.814	0.814	0.814	0.814
q-val Free FT	1.000	1.000	1.000	1.000	1.000	1.000
q-val Ins × Free FT	1.000	1.000	1.000	1.000	1.000	1.000
q-val Free HYV	1.000	1.000	1.000	1.000	1.000	1.000
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	1.000	1.000
Control mean	2130.819	439.872	1.638	5609.660	100.036	78.147
Observations	1724	1724	1724	1709	1724	1703

Notes: This table presents estimates of the treatment effect of insurance and free seeds on agricultural output and profit. Prodn (kg) is the total production across all crops in kg. Prodn value is the value of production in USD, calculated using district-median crop prices. Sales revenue is the value of crop sold in USD, using district median crop prices. Yield is the total production in kg per hectare of cultivated land. Profit (calctd) is the total production value minus total input costs. Profit (self-rep) is the profit self-reported by the farmer. All regressions include enumerator and village strata fixed effects, baseline values if available, and other baseline controls chosen by double-selection LASSO. All values are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes in this table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.4: Effect of insurance and free seed type on off-farm economic activity

	(1) Off-farm labor (y/n)	(2) Off-farm labor income	(3) Non-ag bus. (y/n)	(4) Non-ag bus. profit	(5) Non-ag bus. investment
			Panel A: Year 1		
Insurance	0.074**	21.874*	-0.011	0.370	-1.003
	(0.037)	(12.958)	(0.032)	(12.501)	(67.920)
Free FT	-0.002	9.688	-0.023	5.901	-37.369
	(0.039)	(12.833)	(0.033)	(15.256)	(66.351)
Insurance × Free FT	-0.056	-25.989	0.058	10.123	-31.093
	(0.051)	(18.526)	(0.047)	(20.431)	(91.105)
Free HYV	-0.010	13.909	-0.015	-3.980	-34.218
	(0.044)	(14.073)	(0.034)	(11.110)	(53.646)
Insurance × Free HYV	-0.020	-16.509	0.022	14.908	-10.813
	(0.055)	(19.367)	(0.043)	(17.188)	(80.356)
q-val Insurance	0.297	0.297	1.000	1.000	1.000
q-val Free FT	1.000	1.000	1.000	1.000	1.000
q-val Ins × Free FT	0.822	0.822	0.822	0.822	0.822
q-val Free HYV	1.000	1.000	1.000	1.000	1.000
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	1.000
Control mean	0.500	84.998	0.211	45.332	257.628
Observations	1784	1784	1784	1784	1784
			Panel B: Year 2		
Insurance	0.005	8.909	0.025	3.652	9.237
	(0.040)	(15.033)	(0.033)	(5.849)	(44.167)
Free FT	0.063	22.905	0.016	6.352	69.311
	(0.039)	(15.192)	(0.035)	(6.395)	(46.336)
Insurance × Free FT	-0.015	-20.327	-0.008	-3.115	-103.447*
	(0.054)	(21.013)	(0.046)	(8.391)	(61.967)
Free HYV	-0.051	-12.307	0.009	0.593	-37.909
	(0.041)	(16.207)	(0.030)	(5.061)	(30.074)
Insurance × Free HYV	0.084	7.865	-0.007	0.830	-21.993
	(0.053)	(19.657)	(0.040)	(7.384)	(44.006)
q-val Insurance	1.000	1.000	1.000	1.000	1.000
q-val Free FT	0.290	0.290	0.356	0.290	0.290
q-val Ins × Free FT	1.000	1.000	1.000	1.000	0.909
q-val Free HYV	1.000	1.000	1.000	1.000	1.000
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	1.000
Control mean	0.517	100.135	0.177	21.723	160.609
Observations	1724	1724	1724	1724	1724

Notes: This table presents estimates of the treatment effect of insurance and free seeds on off-farm economic activity. Off-farm labor (y/n) is an indicator for having worked on someone else's farm or business. Non-ag bus. (y/n) is an indicator for owning a non-agricultural business. All regressions include enumerator and village strata fixed effects, baseline values if available, and other baseline controls chosen by double-selection LASSO. Off-farm labor income, non-ag business profits and investments are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes in this table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.5: Effect of insurance and free seed type on economic and mental well-being

	(1) Assets	(2) Savings	(3) Loans	(4) Lstock	(5) Food cons.	(6) Total cons.	(7) No. of migrants	(8) PHQ
Panel A: Year 1								
Insurance	1.419	7.775	-47.879	19.575	-0.146	1.983	0.013	0.553
	(36.788)	(15.113)	(50.351)	(38.863)	(0.638)	(1.928)	(0.050)	(0.677)
Free FT	39.788	-4.585	-30.692	1.688	-0.799	2.058	-0.055	-0.675
	(40.652)	(15.049)	(52.498)	(34.151)	(0.595)	(2.250)	(0.050)	(0.609)
Insurance × Free FT	-72.531	10.355	12.288	-33.579	-0.458	-1.143	-0.003	1.501*
	(50.343)	(20.338)	(70.351)	(42.307)	(0.813)	(3.146)	(0.064)	(0.847)
Free HYV	-35.166	-5.581	-16.944	53.394	-0.637	-0.038	0.003	-0.538
	(40.824)	(14.584)	(48.769)	(39.656)	(0.555)	(1.602)	(0.057)	(0.706)
Insurance × Free HYV	28.867	9.293	54.781	-42.518	0.541	-0.133	-0.008	0.703
	(50.508)	(19.862)	(66.712)	(51.695)	(0.766)	(2.430)	(0.074)	(0.916)
q-val Insurance	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Free FT	1.000	1.000	1.000	1.000	0.561	0.561	-	-
q-val Ins × Free FT	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Free HYV	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Ins × Free HYV	1.000	1.000	1.000	1.000	1.000	1.000	-	-
Control mean	394.831	151.513	419.236	314.717	23.823	44.007	0.341	12.695
Observations	1784	1674	1780	1784	1784	1784	1784	1784
Panel B: Year 2								
Insurance	65.584*	-4.752	-8.237	49.724	0.676	1.043	0.008	0.964
	(33.745)	(14.236)	(60.178)	(49.103)	(0.623)	(1.560)	(0.050)	(0.674)
Free FT	60.333*	-18.202	-34.649	14.886	0.543	2.260	-0.045	0.003
	(35.294)	(15.134)	(61.501)	(47.958)	(0.648)	(1.826)	(0.053)	(0.676)
Insurance × Free FT	-92.408**	11.973	6.469	-27.737	-0.873	-1.236	-0.010	-0.011
	(45.573)	(19.137)	(76.359)	(59.491)	(0.816)	(2.399)	(0.066)	(0.863)
Free HYV	24.862	-8.862	-1.312	24.749	0.199	0.056	0.021	0.222
	(34.371)	(16.106)	(58.898)	(52.686)	(0.603)	(1.517)	(0.063)	(0.676)
Insurance × Free HYV	-82.600*	-4.251	36.864	-32.005	-0.126	-0.477	-0.055	-0.682
	(43.686)	(19.927)	(77.423)	(63.523)	(0.846)	(2.194)	(0.074)	(0.868)
q-val Insurance	0.264	1.000	1.000	0.877	1.000	1.000	-	-
q-val Free FT	0.539	0.539	0.847	0.847	0.673	0.673	-	-
q-val Ins × Free FT	0.207	1.000	1.000	1.000	1.000	1.000	-	-
q-val Free HYV	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Ins × Free HYV	0.308	1.000	1.000	1.000	1.000	1.000	-	-
Control mean	349.817	129.948	436.904	319.316	20.572	37.095	0.371	11.052
Observations	1724	1542	1685	1724	1724	1724	1724	1724

Notes: This table presents estimates of the treatment effect of insurance and free seeds on economic and mental well-being. Lstock is the total value in USD of all owned livestock. Food consumption is the monthly expense on nine pre-defined categories from the FCS index. Total consumption is the sum of food, non-food, and any other consumption expenditure reported by the farmer. All consumption values are per-capita and are calculated per household member. No. of migrants is the number of household members who temporarily migrated outside the village. We measure mental well-being using the PHQ-8 screening tool, a standard and locally validated depression metric (Bhat et al., 2022). All regressions include enumerator and village strata fixed effects, baseline values if available, and other baseline controls chosen by double-selection LASSO. All values except PHQ are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the village level and sharpened q-values are adjusted across outcomes in (1)-(3) and (4)-(6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.3 Flooding Heterogeneity

Table E.6: Effect of gauge-based flooding (exceeded DL) on agricultural output and profit

	(1) Prodn (kg)	(2) Prodn value	(3) Sales revenue	(4) Yield (kg/ha)	(5) Profit (calctd)	(6) Profit (self-rep)
Panel A: Year 1						
Insurance	-308.062*	-51.986*	-0.578*	-710.053*	-25.168	-25.754
	(160.979)	(29.355)	(0.330)	(388.410)	(19.476)	(24.645)
Insurance × Flooding	-49.512	-33.003	-0.162	-97.685	-54.489**	-24.117
	(180.949)	(35.789)	(0.377)	(483.743)	(24.982)	(29.258)
Free FT	194.723	2.207	0.235	428.517	-2.481	9.876
	(168.750)	(28.679)	(0.303)	(336.789)	(18.168)	(21.506)
Free HYV	315.507**	48.254*	0.653**	1449.909***	41.695**	6.651
	(131.827)	(24.713)	(0.313)	(533.378)	(20.046)	(19.536)
Free FT × Flooding	-133.449	6.192	-0.168	-472.277	15.161	-10.302
	(179.144)	(31.398)	(0.328)	(460.987)	(21.048)	(24.304)
Free HYV × Flooding	-243.874*	-31.778	-0.330	-1447.858**	-32.994	-5.866
	(145.444)	(29.571)	(0.340)	(595.863)	(23.344)	(22.817)
q-val Insurance	0.137	0.137	0.137	0.137	0.137	0.137
q-val Ins × Flood	1.000	1.000	1.000	1.000	0.214	1.000
q-val Free FT	1.000	1.000	1.000	1.000	1.000	1.000
q-val Free HYV	0.044	0.054	0.050	0.042	0.050	0.140
q-val Free FT × Flood	1.000	1.000	1.000	1.000	1.000	1.000
q-val Free HYV × Flood	0.307	0.392	0.392	0.101	0.357	0.663
Control mean	2227.459	455.904	3.884	6084.215	-11.271	110.479
Observations	1754	1754	1754	1754	1754	1743
Panel B: Year 2						
Insurance	366.276***	38.315	0.630**	406.909	13.335	9.801
	(136.122)	(26.461)	(0.254)	(309.379)	(20.223)	(14.236)
Insurance × Flooding	-710.247***	-107.025***	-0.871***	-1262.409***	-68.820***	-28.579
	(157.917)	(30.947)	(0.296)	(365.994)	(25.007)	(18.426)
Free FT	-100.367	-20.228	-0.369*	225.543	-16.635	15.178
	(127.129)	(21.646)	(0.217)	(263.405)	(15.887)	(14.837)
Free HYV	59.743	21.468	-0.211	341.684	18.460	-0.386
	(133.192)	(22.614)	(0.252)	(253.990)	(18.247)	(15.404)
Free FT × Flooding	138.114	29.651	0.143	-506.369	8.654	-15.429
	(151.268)	(28.596)	(0.262)	(323.256)	(21.084)	(19.817)
Free HYV × Flooding	13.266	-2.489	0.212	-530.804	-5.026	-7.160
	(167.767)	(29.966)	(0.297)	(327.260)	(22.289)	(19.752)
q-val Insurance	0.041	0.233	0.041	0.233	0.395	0.395
q-val Ins × Flood	0.001	0.001	0.003	0.001	0.004	0.021
q-val Free FT	0.755	0.755	0.755	0.755	0.755	0.755
q-val Free HYV	1.000	1.000	1.000	1.000	1.000	1.000
q-val Free FT × Flood	1.000	1.000	1.000	1.000	1.000	1.000
q-val Free HYV × Flood	1.000	1.000	1.000	1.000	1.000	1.000
Control mean	2067.830	421.447	1.787	5561.523	104.171	93.171
Observations	1693	1693	1693	1680	1693	1674

Notes: This table presents estimates of the treatment effect of insurance, free seeds, and flooding on agricultural output and profit. Flooding is defined based on whether your nearest river gauge was triggered. Prodn (kg) is the total production across all crops in kg. Prodn value is the value of production in USD, calculated using district-median crop prices. Sales revenue is the value of crop sold in USD, using district median crop prices. Yield is the total production in kg per hectare of cultivated land. Profit (calctd) is the total production value minus total input costs. Profit (self-rep) is the profit self-reported by the farmer. All regressions include enumerator and village strata fixed effects, baseline values if available, flood hazard index, and other baseline controls chosen by double-selection LASSO. All values are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes in this table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.7: Effect of gauge-based flooding (exceeded DL) on off-farm economic activity

	(1) Off-farm labor (y/n)	(2) Off-farm labor income	(3) Non-ag bus. (y/n)	(4) Non-ag bus. profit	(5) Non-ag bus. investment
			Panel A: Year 1		
Insurance	0.045	-0.548	0.001	1.778	-90.078
	(0.044)	(15.117)	(0.038)	(18.791)	(99.018)
Insurance × Flooding	0.002	11.666	0.023	10.094	110.045
	(0.049)	(17.723)	(0.042)	(19.994)	(99.150)
Free FT	-0.065*	0.944	-0.016	27.054	32.037
	(0.039)	(15.073)	(0.047)	(25.385)	(118.430)
Free HYV	0.011	19.347	0.021	25.791	-14.338
	(0.046)	(14.296)	(0.045)	(22.390)	(91.774)
Free FT × Flooding	0.034	-10.405	0.035	-18.929	-106.332
	(0.046)	(16.848)	(0.050)	(25.214)	(115.366)
Free HYV × Flooding	-0.048	-23.320	-0.031	-26.663	-22.957
	(0.053)	(16.806)	(0.050)	(22.705)	(94.926)
q-val Insurance	1.000	1.000	1.000	1.000	1.000
q-val Ins × Flood	1.000	1.000	1.000	1.000	1.000
q-val Free FT	0.959	1.000	1.000	1.000	1.000
q-val Free HYV	1.000	1.000	1.000	1.000	1.000
q-val Free FT × Flood	1.000	1.000	1.000	1.000	1.000
q-val Free HYV × Flood	1.000	1.000	1.000	1.000	1.000
Control mean	0.361	55.159	0.393	96.316	517.840
Observations	1754	1754	1754	1754	1754
			Panel B: Year 2		
Insurance	0.013	12.536	0.031	4.584	27.947
	(0.037)	(13.887)	(0.034)	(6.643)	(43.587)
Insurance × Flooding	0.015	-13.382	-0.021	-3.781	-100.311**
	(0.046)	(16.794)	(0.041)	(7.992)	(50.578)
Free FT	0.045	4.629	0.020	6.440	-38.757
	(0.040)	(17.199)	(0.034)	(6.614)	(50.886)
Free HYV	0.001	-2.916	-0.016	-3.344	-97.510**
	(0.041)	(16.102)	(0.032)	(6.144)	(41.138)
Free FT × Flooding	0.017	8.394	-0.020	-3.415	79.120
	(0.048)	(20.982)	(0.041)	(7.448)	(59.090)
Free HYV × Flooding	-0.002	-9.320	0.033	6.737	78.797
	(0.048)	(16.648)	(0.040)	(7.640)	(48.559)
q-val Insurance	1.000	1.000	1.000	1.000	1.000
q-val Ins × Flood	1.000	1.000	1.000	1.000	0.312
q-val Free FT	1.000	1.000	1.000	1.000	1.000
q-val Free HYV	1.000	1.000	1.000	1.000	0.099
q-val Free FT × Flood	1.000	1.000	1.000	1.000	1.000
q-val Free HYV × Flood	1.000	1.000	1.000	1.000	1.000
Control mean	0.462	94.602	0.226	28.141	184.123
Observations	1693	1693	1693	1693	1693

Notes: This table presents estimates of the treatment effect of insurance, free seeds, and flooding on off-farm economic activity. Off-farm labor (y/n) is an indicator for having worked on someone else's farm or business. Non-ag bus. (y/n) is an indicator for owning a non-agricultural business. All regressions include enumerator and village strata fixed effects, baseline values if available, flood hazard index, and other baseline controls chosen by double-selection LASSO. Off-farm labor income, non-ag business profits and investments are winsorized at the 1st and 99th percentiles. Standard errors (in parenthesis) are clustered at the village level and sharpened q-values are adjusted across all outcomes in this table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.8: Effect of gauge-based flooding (exceeded DL) on economic and mental well-being

	(1) Assets	(2) Savings	(3) Loans	(4) Lstock	(5) Food cons.	(6) Total cons.	(7) No. of migrants	(8) PHQ
Panel A: Year 1								
Insurance	-39.189	24.616	-0.485	-22.173	-0.386	0.687	0.000	0.866
	(43.405)	(16.247)	(54.331)	(65.673)	(0.812)	(2.852)	(0.057)	(0.722)
Insurance × Flooding	34.682	-12.476	-33.961	17.800	0.183	0.868	0.007	0.589
	(46.163)	(18.638)	(59.069)	(64.510)	(0.891)	(3.117)	(0.065)	(0.830)
Free FT	42.625	-0.046	-20.650	-78.144	-0.252	5.533*	-0.158***	-0.831
	(53.060)	(20.263)	(65.477)	(49.160)	(0.763)	(3.291)	(0.056)	(0.762)
Free HYV	-38.734	-2.416	27.293	89.120	-0.267	1.326	-0.083	-0.056
	(47.575)	(20.793)	(65.490)	(63.130)	(0.721)	(2.580)	(0.068)	(0.667)
Free FT × Flooding	-59.710	2.969	-0.510	83.938	-1.102	-5.517	0.133**	1.462*
	(58.659)	(21.748)	(73.734)	(52.456)	(0.841)	(3.601)	(0.062)	(0.859)
Free HYV × Flooding	26.329	4.496	-13.994	-81.932	-0.080	-1.849	0.108	-0.047
	(53.013)	(22.428)	(71.938)	(65.277)	(0.816)	(2.829)	(0.075)	(0.825)
q-val Insurance	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Ins × Flood	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Free FT	1.000	1.000	1.000	0.814	0.589	0.229	-	-
q-val Free HYV	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Free FT × Flood	0.864	1.000	1.000	0.783	0.235	0.235	-	-
q-val Free HYV × Flood	1.000	1.000	1.000	1.000	1.000	1.000	-	-
Control mean	427.101	158.959	412.922	489.585	25.754	49.490	0.344	11.787
Observations	1754	1649	1750	1754	1754	1754	1754	1754
Panel B: Year 2								
Insurance	30.829	1.015	9.862	104.278**	0.314	-0.101	0.055	1.013*
	(29.387)	(12.876)	(54.557)	(52.464)	(0.599)	(1.477)	(0.043)	(0.612)
Insurance × Flooding	-28.777	-7.071	-13.834	-126.483**	0.059	1.096	-0.125**	-0.214
	(37.736)	(15.058)	(61.458)	(57.534)	(0.733)	(1.881)	(0.052)	(0.801)
Free FT	-21.092	-20.684	-46.117	-13.448	-0.074	0.306	-0.134***	-0.131
	(30.797)	(13.056)	(48.787)	(57.701)	(0.612)	(1.522)	(0.049)	(0.621)
Free HYV	-15.996	-27.756*	37.168	-0.107	0.590	0.586	-0.027	-0.135
	(34.582)	(16.645)	(58.487)	(52.745)	(0.613)	(1.508)	(0.054)	(0.596)
Free FT × Flooding	48.125	16.500	20.861	18.507	0.129	1.956	0.137**	0.188
	(40.518)	(16.812)	(59.523)	(63.200)	(0.765)	(2.199)	(0.055)	(0.773)
Free HYV × Flooding	-15.456	25.707	-31.099	6.836	-0.678	-1.236	0.013	-0.195
	(38.535)	(19.520)	(67.790)	(57.159)	(0.760)	(1.991)	(0.062)	(0.750)
q-val Insurance	0.791	1.000	1.000	0.232	1.000	1.000	-	-
q-val Ins × Flood	1.000	1.000	1.000	0.127	1.000	1.000	-	-
q-val Free FT	0.975	0.830	0.975	1.000	1.000	1.000	-	-
q-val Free HYV	1.000	0.620	1.000	1.000	1.000	1.000	-	-
q-val Free FT × Flood	1.000	1.000	1.000	1.000	1.000	1.000	-	-
q-val Free HYV × Flood	1.000	1.000	1.000	1.000	1.000	1.000	-	-
Control mean	381.450	134.726	558.394	315.872	20.059	37.048	0.349	9.151
Observations	1693	1516	1654	1693	1693	1693	1693	1693

Notes: This table presents estimates of the treatment effect of insurance, free seeds, and flooding on economic and mental well-being. Flooding is defined based on whether your nearest river gauge was triggered. Lstock is the total value in USD of all owned livestock. Food consumption is the monthly expense on nine pre-defined categories from the FCS index. Total consumption is the sum of food, non-food, and any other consumption expenditure reported by the farmer. All consumption values are per-capita and are calculated per household member. No. of migrants is the number of household members that temporarily migrated outside the village. We measure mental well-being using the PHQ-8 screening tool, a standard and locally validated depression metric (Bhat et al., 2022). All regressions include enumerator and village strata fixed effects, baseline values if available, flood hazard index, and other baseline controls chosen by double-selection LASSO. All values except PHQ are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the village level and sharpened q-values are adjusted across outcomes in (1)-(3) and (4)-(6).

F Village selection

Choosing districts First, we match villages from ML Infomap, which provides specialized GIS datasets, to flood hazard categories using the 2021 West Bengal Flood Hazard Atlas produced by the government (2021 West Bengal Flood Atlas). This satellite-based dataset classifies villages according to how frequently they were inundated between 2000 and 2020: 'Very Low' (1–2 times), 'Low' (3–5 times), 'Moderate' (6–9 times), and 'High' (10–13 times). We then tabulate the number of villages in each category by district. This exercise shows that Murshidabad, Paschim Medinipur, and Hooghly contain the largest number of villages classified as 'Moderate' or 'High' flood risk. We therefore select these three districts.

We apply four criteria when selecting blocks within these districts:

1. First, we prioritize blocks that are especially prone to flooding. The Flood Hazard Atlas allows us to calculate the share of villages contained in each block that fall under "Moderate" or "High" categories. We remove any blocks in this list which have no "Moderate" or "High" villages.

2. Second, we want to prioritize blocks where villages are located close to flood gauge stations. For each village, we can calculate the distance (from it's centroid) to the nearest river gauge using data on locations of such gauges from the West Bengal I&W Department's website. We then summarize blocks by the average distance between villages and their nearest river gauge. We exclude blocks whose average distance from the gauge exceeds 10km.

3. Third, we restrict attention to areas identified by IRRI as suitable for the flood-tolerant seed variety we introduce (SS1); and remove any blocks which have no SS1 eligible villages.

4. Fourth, we target areas with low penetration of the Kisan Credit Card (KCC) program, which provides free insurance to farmers. Because up-to-date KCC coverage data are unavailable from secondary sources, we collect this information ourselves by contacting local officials (e.g., Pradhans) to obtain approximate figures. We disqualify any blocks that have a KCC penetration of greater than 40%.

Within each of the three districts, we select the 10 blocks with the highest number of villages classified as "Moderate" or "High," after applying the exclusions described above. From these blocks, we randomly sample 350 villages (300 for the main sample and 50 as backups). To minimize potential spillovers through risk-sharing networks, we impose a constraint that no two sampled villages are adjacent. We implement an algorithm that repeatedly draws samples of 350 villages, identifies clusters of neighboring villages, removes one village from each cluster, and then resamples (excluding the dropped villages) until it converges to a set of 350 villages with no neighboring pairs.