Long-range forecasts as climate adaptation: Experimental evidence from developing-country agriculture

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Abstract

Climate change increases weather variability, making it harder for farmers to tailor planting decisions to the coming growing season. In theory, accurate, long-range forecasts overcome this challenge. We experimentally evaluate monsoon onset forecasts in India, randomizing 250 villages into control, forecast, and a benchmark index insurance group. Forecast farmers update their beliefs and behavior: receiving "bad news" relative to farmers' priors reduces cultivated land; receiving "good news" increases cultivation, inputs, and cash cropping. We see suggestive evidence of corresponding changes in agricultural output and welfare. Unlike insurance, forecasts reduce climate risk by enabling farmers to tailor investments to the monsoon.

Keywords: Climate; forecasts; agriculture; risk
JEL Codes: D81; D25; O12; O13; Q12; Q54

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1 Introduction

Climate change is disrupting weather patterns around the world (IPCC (2021)), with extreme temperatures occurring more frequently and rainfall patterns becoming less predictable (Bathiany et al. (2018); Wang et al. (2021)). Agriculture is particularly sensitive to climatic conditions (Hultgren et al. (2022)), putting the 65% of the world's working poor who depend on agriculture for their livelihoods in jeopardy (The World Bank (2022)). Absent insurance, weather risk causes farmers to make fewer profitable investments (Rosenzweig and Binswanger (1993)). Moreover, when the growing season weather is difficult to predict, farmers cannot easily optimize their investments for the upcoming season. As a result, poor farmers are limited in their ability to adapt to climate change. New tools for adaptation are therefore essential but existing approaches, such as insurance, new seed varieties, or new infrastructure, have proven prohibitively costly (Donovan (2021); Emerick et al. (2016); Lybbert and Sumner (2012)).

In this paper, we use a cluster-randomized experiment to estimate the causal effects of a novel and, in principle, cost-effective approach to helping farmers cope with a changing climate: accurate long-range (or "seasonal") forecasts. In theory, and in contrast to short-range (e.g., day-ahead) forecasts, these forecasts enable farmers to tailor their investment decisions to the upcoming growing season, making significant changes to their seasonal agricultural practices such as deciding how much land to cultivate, adjusting the crop mix, and ordering inputs in advance. Our empirical results focus on a forecast that provides information about when the Indian Summer Monsoon will arrive. Using historical data, we show that monsoon onset timing is an important determinant of agricultural outcomes in India, with earlier monsoons leading to higher yields both on average and for cash crops in particular. However, the timing of monsoon rainfall is highly variable, making these features difficult for farmers to predict and optimize around (Kumar et al. (2013)).

We overcome this challenge with a novel forecast of the onset of the monsoon, produced by the Potsdam Institute for Climate Impact Research (PIK) and described in Stolbova et al. (2016).[1] While accurate forecasts could enable substantial behavior change (FAO (2019)), their use is not widespread in practice, in part because existing forecasts of this type have limited accuracy (Rosenzweig and Udry (2019); Mase and Prokopy (2014)).[2] In contrast, the PIK forecast is extremely accurate, locally-resolved, and can be provided to farmers well in advance of the monsoon's arrival. Released approximately 40 days before onset, the forecast enables farmers to make early decisions about key inputs such as crops, labor supply, and fertilizer purchases (Gine et al. (2015)). The PIK forecast has particular accuracy over Telangana, the site of our experiment: in this region, the forecasted onset date has been accurate to within one week in each of the past 10 years.

[1]The PIK forecast relies on recent improvements in weather modeling (e.g., Rajeevan et al. (2007)), and statistically identifies "tipping points" that are relevant for monsoon rainfall onset in a particular location.

[2]Long-range monsoon onset forecasts, which provide information about when the monsoon will arrive over a month in advance, are notably distinct from short-range forecasts, which typically provide information about day-ahead or week-ahead weather conditions (as studied in Fosu et al. (2018) and Fabregas et al. (2019)). In contrast to these short-run forecasts, which enable marginal behavioral changes, long-range forecasts allow farmers to make decisions at the growing-season level, such as what crops to plant and how much land to cultivate.

We randomize 250 villages in Telangana into a control group, a group that receives a forecast offer, and a group that receives an index insurance offer to serve as a benchmark. The forecast reduces risk by providing farmers with information about the upcoming growing season, allowing them to tailor their inputs accordingly. In contrast, insurance – the canonical risk-coping instrument– enables farmers to shift consumption across states but provides no information, making it a useful comparison. We sample 5-10 farmers per village for inclusion in the experiment. To avoid bias from spillovers, all main sample farmers in a given village receive the same treatment. To ensure that farmers view the forecast as credible, we partner with the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), a respected international organization based in Hyderabad.

We ask three main research questions. First, how does the forecast change farmers' beliefs about monsoon onset? We anticipate that receipt of the forecast should shift farmers' beliefs closer to the forecasted monsoon date.

Second, how does the forecast impact farmers' *ex ante* (i.e., pre-harvest) agricultural behavior? To generate predictions, we develop a theoretical model which shows that the effects of a forecast should depend on a farmer's prior. In particular, if the forecasted onset aligns with a farmer's prior (such that the farmer receives "neutral news" from the forecast), they should not substantially adjust their input decisions. If the forecasted onset is earlier (later) than the farmer's prior—henceforth "good news" ("bad news")—the profit-maximizing farmer should respond by increasing (reducing) their investments in risky agricultural production. We next use historical data on crop yields and rainfall to show that an earlier monsoon onset (i) leads to higher yields of two key crops, staple rice and cash crop cotton, and (ii) differentially improves cotton yields. We therefore expect good-news farmers to increase overall agricultural investment and to shift into cash cropping, and bad-news farmers to invest less in agriculture.

Third, how do forecasts impact *ex post* welfare metrics such as agricultural output, farm profits, non-agricultural business, consumption, and net savings? We predict that *ex-post* agricultural outputs should generally align with *ex-ante* investments, such that higher investments should lead to increased production, yields, and profits, and that welfare should (weakly) rise overall. However, as Rosenzweig and Udry (2020) point out, agriculture is an inherently stochastic process, meaning that in any given year, there may be an imperfect correspondence between inputs and outputs.

Our empirical results broadly follow these predictions. Figure 4 presents our results on beliefs, and Figure 5 summarizes our main findings on *ex ante* and *ex post* outcomes. First, farmers update their beliefs in response to our forecast.[3] After receiving the information, farmers in forecast villages have beliefs about the monsoon onset date that are 26% closer to the forecasted onset date than farmers in control villages. In addition, farmers demand the forecast. Using a Becker et al. (1964) mechanism (henceforth "BDM") to elicit willingness-to-pay (WTP), we find that average WTP for the forecast is comparable to the average WTP for our index insurance product.[4]

[3]There is substantial within-village heterogeneity in priors, with 46% of the total variation in mean prior remaining after removing village fixed effects.

[4]We interpret our WTP results with some caution, as farmers could share information within the village, though we find no evidence of information sharing in practice (see Appendix Table A.8).

Second, farmers alter their *ex ante* investments—land use, crop choice, and input expenditures—in response to the forecast. Farmers who received bad news meaningfully reduced land under cultivation (−22% of the control mean), with a point estimate suggesting an approximately 10% decline in expenditure. Farmers who received neutral news did not alter their investments. Farmers who received good news increased land under cultivation (21%) and total expenditure considerably (31%), and were 33% percent more likely to plant cash crops. Summarizing these outcomes in an index, we find that farmers who receive bad news reduce investment by 0.08 relative to farmers *with similar priors* in the control group; we see no impact on neutral-news farmers' investments; and good-news farmers increase *ex ante* investment by a standardized effect of 0.31 (while the former is imprecisely estimated, the difference between bad- and good-news responses is highly significant).

Third, we see evidence that these changes in *ex ante* investments led to changes in *ex post* agricultural outcomes. Bad-news farmers' agricultural output (and the value of this output) declined by 25% (22%), in line these farmers' reduction in land under cultivation. Neutral-news farmers experience no change in agricultural output, consistent with their (lack of) input response. While imprecisely estimated, we find a 22% increase in agricultural output for good news farmers, also in line with their *ex-ante* treatment effects. We fail to reject zero yield effects for all groups. Turning to agricultural profits, we find that bad-news farmers have meaningfully lower farm profits (-$400). We see no statistically significant impacts on neutral- and good-news farmers, but the good-news point estimate in particular is quite close to zero (-$64).

What explains the lack of agricultural profits for good-news farmers? Point estimates imply that good-news farmers experienced meaningful crop losses ($200), consistent with having planted more valuable crops. Calculating profits including the value of these losses yields a good-news treatment effect of $155 (9%). Though not statistically different from zero, this aligns with *ex ante* impacts for good-news farmers. Finally, we restrict the sample to households who did not report agricultural losses from heavy flooding which hit Telangana in early July (Business Line, 2022; The New Indian Express, 2022), finding a pattern of agricultural profits (−$341 for bad-news farmers, −$96 for neutral-news farmers, and +$498 for good-news farmers) that is consistent with agronomically and economically appropriate *ex ante* input responses to the forecast.

We also measure treatment effects on *ex post* outcomes beyond agriculture. We observe that bad-news (good-news) farmers increase (decrease) non-agricultural business activity, investment, and profits, consistent with farmers treating business as a substitute for agriculture, though these estimates are imprecise. We find null effects on mental health for good- and neutral-news farmers, with suggestive evidence of a worsening for bad-news farmers, consistent with their experiencing stress from receiving bad news about the growing season. Point estimates on food consumption are positive for all groups, but relatively small, and imprecise for all but neutral-news farmers. Lastly, we find large positive — albeit insignificant — effects on net savings, largely driven by reductions in outstanding debt, consistent with forecasts helping farmers optimize their full portfolio of decisions.

As a final exercise, we compare the impacts of the forecast against index insurance. First, we reproduce the standard results that index insurance causes farmers to increase investment (0.13 SD increase in our investment index). Second and per our model, we demonstrate that these effects are concentrated among "optimistic" farmers with early priors – those for whom the forecast would have been bad news (0.18 SD increase with insurance vs. 0.08 SD decrease under the forecast). Third, unlike good-news forecast farmers, insurance farmers are not more likely to grow cash crops – and we can reject equality between these two groups. Fourth, we only find positive effects on agricultural profits for insurance farmers who were unaffected by floods, despite impacts on *ex ante* investments. This corroborates our agricultural profit finding for good-news farmers, further highlighting the importance of stochasticity in determining agricultural outcomes (Rosenzweig and Udry (2020)). Fifth, insurance farmers increase non-agricultural business activity (significantly different from good-news farmers). Finally, we find no effects on consumption and negative impacts on net savings among the insurance group. These results show that while both forecasts and insurance influence farmer investments and ex-post outcomes, they do so in fundamentally different ways. Forecasts help reduce climate risk by enabling farmers to tailor their inputs to the coming growing season, whereas insurance does not.

Taken together, our results demonstrate that long-range monsoon forecasts can help farmers cope with increasing agricultural risk in a changing climate. As a result, this study makes three primary contributions. We begin by providing the first experimental evidence on the impact of a new climate adaptation technology – an accurate long-range monsoon forecast – on farmer behavior.[5] We identify a key determinant of farmer responses to the forecast: farmers' prior beliefs. We measure farmer priors over the upcoming monsoon's onset, and document substantial heterogeneity – even *within* village – at baseline. We therefore build heterogeneous priors into a simple theoretical model of farmer decision-making under risk to generate predictions about how farmers will respond to forecasts, and test these predictions using our randomized trial. Our treatment causes farmers to update their beliefs in the direction of the PIK forecast, resulting in meaningful changes in both *ex ante* investment and *ex post* outcomes. Our results shed light on the mechanism through which forecasts work: enabling farmers to tailor their behavior to the coming growing season. These findings demonstrate the value of considering prior beliefs in estimating the impacts of information, and illustrate the benefits of a high-quality forecast of the Indian Summer Monsoon. Our results build on important work by Rosenzweig and Udry (2019), who use a farmer fixed-effect design to study the Indian Meterological Department's (IMD) monsoon forecast, and argue that while the IMD's forecast has remarkably low accuracy, an accurate long-range forecast of the Indian summer monsoon has the potential to be worth tens of billions of rupees.[6] Our results highlight the promise

[5]See Meza et al. (2008) for a review of prior research in this area. As Rosenzweig and Udry (2019) write, prior to their own paper and "[despite the potential] importance of both weather outcomes and the existence of direct forecast effects on the overall economy in India, there is [sic] as of yet no rigorous assessments of the impact of long-term weather forecasts and improvements in weather forecast skill on the rural poor." There is a growing body of work on the impacts of short-run forecasts on agriculture (e.g., Fosu et al. (2018); Fabregas et al. (2019); Yegbemey et al. (2023)). Outside of the agricultural sector, a nascent literature in environmental economics uses quasi-experiments to estimate the value of (improving) short-range forecasts of hurricanes (Molina and Rudik (2023)), temperatures (Shrader (2023), Song (2023)), and pollution (Ahmad et al. (2023)), which highlights the value of forecasting under climate change.

[6]In India, the monsoon's onset is extremely important for the Indian economy (Rosenzweig and Binswanger (1993))

of such a forecast, which will only become more valuable as the climate continues to change.

Second, experimentally demonstrating that the forecast is effective at changing farmer behavior contributes to a broad literature on agricultural risk whose importance is increasing as low-income countries bear the brunt of global climate change (Hultgren et al. (2022)). Our results show that by providing information about the coming growing season, forecasts allow farmers to decide whether to plant at all, what to plant, and how to adjust inputs across crops. This demonstrates that the mechanism behind the effects of forecasts on farmer behavior differs from previous approaches in this literature. In the same experiment, we contrast the forecast with insurance, the most prominent risk-coping technology (Karlan et al. (2014); Cole and Xiong (2017)). We show that this canonical approach allows farmers to smooth risk across states of the world, but does not enable tailored investment.[7] We extend the insurance literature by showing that prior beliefs matter for determining farmer responses to insurance, and that the farmers with the most positive responses to insurance have the most negative responses to the forecast.[8] Additionally, we find there is a demand for forecasts, suggesting their potential to be disseminated cheaply at scale.

Finally, by empirically demonstrating the effectiveness of a specific climate adaptation technology – the forecast – we advance the growing climate change economics literature. The majority of this work has focused on the economics of mitigation (see Nordhaus (1993) and Pindyck (2013) for reviews), or on the costs of climate change (e.g., Deschênes and Greenstone (2007); Hsiang et al. (2017); Carleton and Hsiang (2016)). We build on a much smaller body of newer work which highlights the importance of adaptation (e.g., Hultgren et al. (2022); Carleton et al. (2022)) but is unable to examine the role of specific adaptation strategies.[9] In contrast, we experimentally evaluate a generally applicable adaptation strategy in the context of a population that is highly vulnerable to climate, and find that the forecast has substantial impacts on farmers' decision-making.

The remainder of this paper proceeds as follows. Section 2 provides relevant details about the research setting. Section 3 presents a simple theoretical model of farmer decision-making under risk. Section 4 describes our experimental design. Section 6 presents our analysis, including our regression specifications and results. Section 7 compares forecasts to insurance. Section 8 concludes.

and that farmers' own predictions about monsoon onset shape their planting decisions (Gine et al. (2015)). Though a monsoon forecast would be extremely beneficial – and even more so under a changing climate – India's climatology is complex, which has made modeling and accurate forecasting difficult (Webster (2006); Wang et al. (2015)). Up until now, farmers have had very limited access to high-quality monsoon forecasts as a result.

[7] A nascent literature explores other up-front approaches to coping with risk, such as the adoption of high performing seed varieties and irrigation technologies (Emerick et al. (2016); Jones et al. (2022)). While these approaches are promising, they lock farmers into a particular technology, and technology adoption in low-income contexts has proven challenging (e.g., Duflo et al. (2008)).

[8] Prior work has focused on the low demand for insurance (Mobarak and Rosenzweig (2014); Jensen and Barrett (2017); Carter et al. (2017)), highlighting the large subsidies needed to increase take-up. Newer research aims to increase demand (e.g., through repeated relationships which allow for delayed premium payments (Casaburi and Willis (2018)), but the role of expectations about the coming growing season remains unexplored.

[9] A notable exception is Lane (2024), which demonstrates that an emergency credit product is an effective strategy for coping with flood risk. We build on this with an approach that does not require significant pre-existing financial infrastructure and can be disseminated at low cost.

2 Research context

2.1 Historical impacts of monsoon onset timing on agricultural yields

We begin by documenting the importance of monsoon onset timing for Indian agriculture. Prior work has shown that an earlier monsoon – and therefore a longer growing season – is better for farmers, as delays are negatively associated with agricultural output (Mobarak and Rosenzweig (2014), Amale et al. (2023)). We build on this work, using historical data on agriculture across India to document both that monsoon onset delays negatively impact crop production, and also that these damaging impacts are substantially worse for cotton – a key cash crop in our setting – than for rice – a key staple crop.

Specifically, we use district-level yield data across the country from the Indian Ministry of Agriculture and Farmers' Welfare and daily gridded precipitation data from the European Centre for Medium Range Weather Forecasting Reanalysis data (ERA-5) spanning 2001 to 2018 to estimate the historical effect of monsoon onset delay on crop yields.[10] We estimate a simple panel fixed effects regression, with a preferred specification of:

$$\log(\text{Yield})_{dy} = \beta \text{Onset}_{dy} + \alpha_d + \delta_t + \varepsilon_{dt} \quad (1)$$

where the outcome variable is log yield of cotton or rice in district d in year y, Onset_{dy} is standardized onset, α_d are district fixed effects, δ_t are year fixed effects, and ε_{dt} is an error term, clustered either on district or state. Table 1 presents the results, including robustness to alternate fixed effects.

Later monsoon onset is associated with lower yields for both rice (Panel A, 3.9 percent decline per SD of onset delay in our preferred specification) and cotton (Panel B, 9.2 percent decline per SD of onset delay). Importantly, the yield decline is 2 to 3 times larger for cotton than rice. These results are robust across four different specifications (though the estimates become somewhat smaller and imprecise once we include state-by-year fixed effects, the gap between rice and cotton remains). These results have two main implications, which we take to the data from our experiment below. First, we expect that farmers who face an earlier monsoon should increase their investments in agriculture. Second, these results suggest that farmers facing an earlier monsoon ought to increase their investments in cash crops in particular. Importantly, we note that while this analysis uses 20 years of historical data to show how farmers ought respond to an earlier monsoon *on average*, whether this strategy would lead to higher yields and profits in any given year will depend on unpredictable weather conditions (Rosenzweig and Udry (2020), Suri and Udry (2022)).

[10] Appendix F provides more detail about the data and estimation. We define monsoon onset following Moron and Robertson (2014), and restrict the sample to districts in the monsoonal region of India (excluding the northern, southern, and eastern tips of the country.

Table 1: Effect of monsoon onset timing on rice and cotton yield

	(1) Log(Yield)	(2) Log(Yield)	(3) Log(Yield)
		Panel A: Rice	
Onset (std. dev.)	-0.024	-0.016	-0.039
	(0.011)**	(0.008)**	(0.012)***
		Panel B: Cotton	
Onset (std. dev.)	-0.047	-0.038	-0.092
	(0.024)***	(0.025)**	(0.046)***
N (rice)	2321	2321	2321
N (cotton)	1098	1098	1098
State FEs	Yes		
District FEs		Yes	Yes
Year FEs	Yes	Yes	
State $\times$ Year trend			Yes

Notes: This table presents the effect of monsoon onset delay on yields of rice (panel A) and cotton (panel B), estimated using Equation (1). The outcome in each column is crop yield in logs, and the independent variable is monsoon onset in standard deviations, both observed at the district-by-year level. Higher onset values indicate later monsoon arrival. We define monsoon onset per Moron and Robertson (2014), and restrict the sample to monsoonal regions of India, defined using a k-means clustering algorithm (see Appendix F for more details). Standard errors are clustered by state. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2.2 Forecasting the monsoon

We study a novel approach to reducing agricultural risk: long-range monsoon *onset* forecasts. These forecasts have the potential to substantially improve farmer welfare, because they enable farmers to materially alter their planting and other input decisions in advance of the monsoon's arrival.

We rely on a new long-range forecast of the monsoon's onset produced by PIK, and described in Stolbova et al. (2016).[11] This forecast uses climate data from the months leading up to the beginning of the monsoon to predict the timing of the monsoon's onset over specific regions of India, including Telangana.[12] The PIK model produces a probability distribution of potential onset dates, which can be summarized as a likely onset date range, making it easy for farmers to understand. The forecast is issued at least a month in advance of the monsoon onset, enabling farmers to substantively adjust their production decisions. In particular, a month-long period provides farmers with sufficient time to alter their crop selection, adjust the seeds they buy, redistribute their land among the chosen crops, and modify the inputs used along with the quantities purchased (Gine et al. (2015)). Backcasting over the past 10 years, the PIK forecast was correct each year. When evaluated from

[11] See Appendix E for more details on monsoon forecasting.

[12] At the time of this writing, PIK provides three monsoon onset forecasts for India: Telangana, central India, and Delhi. We use the Telangana forecast as it covers one of the country's key agricultural regions.

1965–2015, the forecast was correct for 73% of the years in the sample. This forecast is not yet widely available to farmers, leaving us with a unique opportunity to evaluate its impacts.

We prefer the PIK forecast to (i) existing monsoon onset forecasts; (ii) forecasts of monsoon rainfall quantity; and (iii) short-range weather forecasts. First, the PIK forecast represents a significant improvement over existing monsoon onset information. The IMD produces a monsoon onset forecast over Kerala rather than for specific locations around the country, and Moron and Robertson (2014) demonstrate that there is virtually no correlation between the monsoon's onset over Kerala and local onset anywhere else in India.[13] Moreover, the IMD forecast only arrives two weeks in advance of the monsoon's onset, which also limits its usefulness relative to the PIK forecast. Second, the PIK forecast provides a highly accurate forecast of onset *timing*, and there exist no corresponding accurate monsoon rainfall *quantity* forecasts. The most widely-available existing quantity forecast in India, produced by the IMD, is uncorrelated with actual rainfall in much of the country (Rosenzweig and Udry (2019)). Finally, the PIK monsoon forecast is distinct from the more common short-run "weather forecasts" that aim to predict exact weather conditions at a specific point in the upcoming week or two and cannot be used to make large-scale changes to *ex ante* inputs.[14]

2.3 Agriculture in Telangana

We conduct our experiment in Telangana. The state is home to 35 million people, and agricultural productivity per worker is low. While 55% of the labor force is employed in agriculture, the sector provides only 15% of the Gross State Value Added (Government of Telangana (2020)). The majority of farms are small, with the average landholding being 1 hectare. Rice is the main staple crop in the state, but Telangana also grows a number of important cash crops. In our research sample, 65% of farmers reported cultivating rice, 44% growing cotton, and 14% growing maize during the previous monsoon season. Appendix Figure A.1 demonstrates that there are substantial year-over-year fluctuations in both the amount of land under cultivation and in the share of land planted to rice, cotton, and other crops over time, making the state an ideal place to evaluate the effect of forecasts on crop land and crop choice.

Telangana, like much of central India, is dependent on the monsoon for agriculture with about 80% of the total annual rainfall occurring in the monsoon months from June to September. While the monsoon arrives in early–mid June on average, uncertainty over monsoon onset is high: between 1979 and 2019, the standard deviation of the onset date was approximately 20 days. Consequently, weather risk is a substantial concern for agriculture in the state, as it rests in one of the most variable areas of the monsoonal region of India. Both formal and informal methods to smooth risk

[13] Unlike PIK, the IMD forecasts the monsoon's onset over Kerala. The IMD does not produce any other regional onset forecasts. However, the monsoon does not progress northwards from Kerala in a predictable manner – meaning that onset over Kerala carries little signal about onset timing over the rest of the country.

[14] Seasonal climate forecasts are a relatively new innovation (see Kirtman et al. (2014) for a review), and are typically physics-based models of the climate system linked to slower-moving conditions. In contrast, short-range weather forecasts use deterministic, numerical simulations of weather variables based on current conditions. Weather forecasting techniques, therefore, are not well-suited to forecasting beyond a short time window.

exist in Telangana. The Government of Telangana, through its *Rythu Bandhu* scheme, provides farmers with a number of pre-season incentives. Primary among these is the unconditional cash transfer of INR 5,000 for each acre planted for each season (Government of Telangana (2020)). This scheme also provides access to credit for farmers to spend on inputs including seeds and fertilizers. One notable national crop insurance program, Pradhan Mantri Fasal Bima Yojana (PMFBY), has ceased to operate in the state.[15] Private insurance exists, but is severely underutilised. At baseline, only 0.75% of farmers in our sample had heard of rainfall insurance (Appendix Figure A.3).

Information about the weather is also limited. While 65% of farmers in our sample report having received information about the upcoming Kharif season at baseline (conducted prior to planting in early May; see Figure 2), the reliability of these sources is unclear. Appendix Figure A.2 shows the breakdown of farmers' information by source. Very few farmers rely on information from the government (7.4%) or extension services (7.3%). Instead, a large share of farmers report receiving information from other farmers in their village (63.3%) or outside of their village (41.5%).

3 Model

In this section we present a simple two-period model of farmers' decision-making under uncertainty, which we use to illustrate the effects of the monsoon forecasts and insurance product.[16] In period one, farmers decide how much to save (s), how much to consume (c_1), and how much to invest ($x \geq 0$) by forming expectations across monsoon onset states ϵ_i and a concave, risky agricultural production technology $f(x, \epsilon_i)$. In the period two, farmers consume (c_2^i) from production and savings.

Production The output from this production technology is modified by the state of the world ϵ_i for $i \in \{1, ..., S\}$, where ϵ_i are ordered so that for any $i > j$ we have higher production and a greater marginal product: $f(x, \epsilon_i) > f(x, \epsilon_j)$ and $f'(x, \epsilon_i) > f'(x, \epsilon_j)$ for all $x > 0$.[17] There is no product at zero investment regardless of the state: $f(0, \epsilon_i) = 0$ for all i. These states can be thought of as approximations for when the monsoon will arrive, with an earlier arrival being associated with greater returns to investment.[18]

[15]The program initially required all agricultural loan-holders to purchase insurance, but when the government subsequently made this condition voluntary, demand collapsed.

[16]We provide extended model details in Appendix B.

[17]For simplicity, we assume that monsoon onset is the only determinant of production and that output is monotonically decreasing in onset timing. Of course, in reality, agricultural output will depend on a variety of factors (e.g., temperature, the pest environment, etc), which can be thought of as an error term on the production function, and does not affect the results of the model. One such factor is monsoon rainfall *quantity*, which surely matters for production but has been shown to be largely orthogonal to onset timing (Moron and Robertson (2014)). While it is possible that extremely early rain could be detrimental to agricultural output, in general, delayed monsoons are associated with lower output (Amale et al. (2023)).

[18]The investment level x can also be interpreted as a continuum of crop choices, with varying productivities which depend on the state and are correlated with planting costs. In that sense, for any given state, there is an optimal crop choice x that would maximize production subject to budget constraints.

Farmer decisions The farmer's prior belief over the probability distribution of ϵ for the coming agricultural season is given by $G(\cdot)$. They use these beliefs to weight possible future outcomes. The farmer therefore solves the following problem:

$$\begin{aligned} \max_{s,x} \quad & u(c_1) + \beta \textstyle\sum_{i=1}^{S} u(c_2^i|\epsilon_i)g(\epsilon_i) \\ \text{s.t.} \quad & c_1 = y - s - p \cdot x \ \&\ c_2^i = f(x, \epsilon_i) + s \end{aligned} \tag{2}$$

where $u(\cdot)$ is a concave utility function, c_1 is first period consumption, c_2^i is second period consumption in state i, $g(\epsilon_i)$ is the probability density of the farmer's prior over ϵ, y is starting wealth, s is risk-free savings (or interest free borrowing), p is the price of the input x, and β is the discount factor.

Appendix B.2 shows that, for sufficiently risk-seeking farmers, the optimal investment is an increasing function of their beliefs on the realization of ϵ. In other words, the higher a farmer's prior that it will be a good year, the more they will choose to invest.

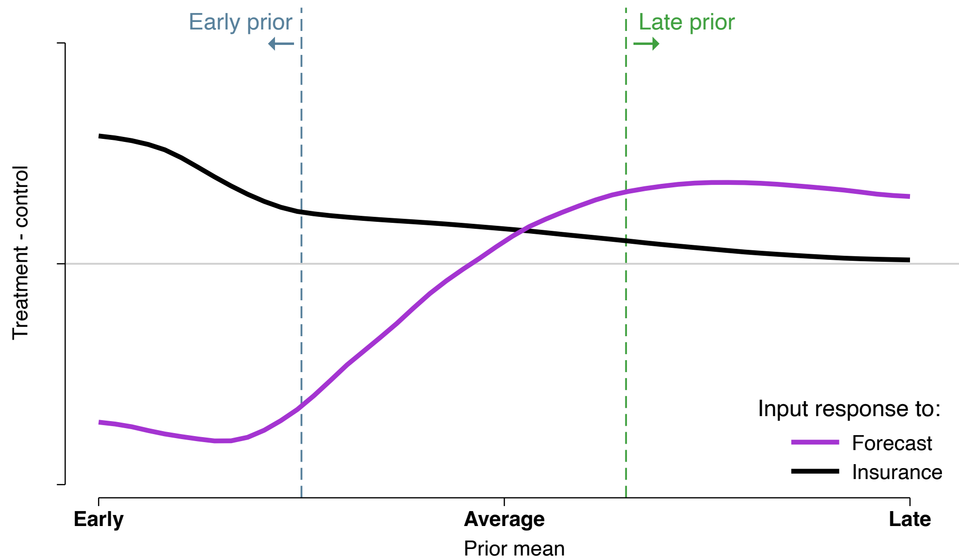
Forecasts We now introduce a forecast, μ_f, which provides farmers with information on the likelihood of future states of the world. We assume that the forecast is unbiased (such that $\mu_f = \mathbf{E}[\epsilon]$), but has some noise ($\text{Var}(\mu_f) = \sigma_f^2$, with lower σ_f^2 indicating higher forecast accuracy). The farmer uses this prediction and combines it with their prior $G(\cdot)$ via Bayes' rule to calculate a posterior probability distribution for ϵ, say $G'(\cdot)$. The farmer's average posterior will fall between their prior and the forecast prediction, and will have a smaller standard deviation (less uncertainty) than their prior. How the farmer changes their behavior after receiving the forecast depends on both their priors and the realization of the forecast. Note that any given year will only have *one* such realization, but it is nevertheless valuable to consider treatment effects of different possible forecast realizations.

Figure 1 illustrates the key results of the model, plotting the treatment effect of a forecast (purple) on agricultural investment.This figure depicts responses to a forecast of an average monsoon.[19] In this case, farmers with early (and therefore overly-optimistic) priors receive bad news from the forecast, and as a result, reduce their investments. Farmers with average (and therefore correct) priors receive neutral news from the forecast, and do not change their investment behavior strongly. Farmers with late (and therefore overly-pessimistic) priors receive good news from the forecast, and increase their investment. This figure therefore illustrates how forecasts help farmers to tailor their behavior to the coming growing season.

We also plot responses to an insurance product (black), which delivers a payout in sufficiently bad states. Regardless of farmers' priors on the upcoming growing season conditions, insurance – which conveys no information about the state – causes all farmers to weakly increase their investment in agriculture. This reduces risk by shrinking the variance in consumption across states. In contrast, the forecast (purple) enables farmers to tailor their investments to the upcoming

[19] Appendix Figure B.1 plots farmer responses to forecasts of early or late monsoons, under which the shape of the treatment effects is broadly preserved but the level shifts.

Figure 1: Investment choice with a forecast or insurance (model)



Notes: This figure plots the simulated relationship between the treatment effect on optimal investment and the farmer's prior that the good state of the world will be realized with a forecast or with insurance resulting from our model. The y-axis represents the difference between farmers who receive a treatment and those who do not. The grey horizontal line is centered at zero. The x-axis reflects whether farmers believe the monsoon will arrive early, at the average time, or late. The figure shows differential investment responses between the forecast, as shown here for an average monsoon (purple), and the insurance product (black) for farmers with different priors. See Appendix B.3 for simulation details.

growing season realization. This highlights the different mechanisms behind forecasts and insurance.

4 Experimental design and data

4.1 Experimental design

Informed by our theoretical framework, we designed a randomized controlled trial to estimate the benefits of forecasts. We randomized 250 villages (sampling 5-10 farmers each) in Telangana into either a forecast group (100 villages), an insurance group (50 villages), or a control group (100 villages).

We sampled villages in two districts in Telangana, Medak and Mahabubnagar, and restricted the sample by excluding villages with high penetration of irrigation, based on data from ICRISAT and the 2011 Indian Census, as these villages were already insulated from the variability of the monsoon. We also drew our sample with a distance buffer between villages, to prevent across-village information sharing. To increase statistical power and ensure balance, we stratified our randomization by district and an indicator for having an above-median number of farmers per acre – a measure of agricultural intensity. We then sampled households within each village for inclusion in our experiment. Each sampled household in a given village received the same treatment. In order to directly measure spillover effects on beliefs within villages, we also conducted a short survey on monsoon beliefs with 2-3 *untreated* households in the forecast villages.

We partnered with ICRISAT to implement this experiment. ICRISAT is an international organization headquartered in Hyderabad, Telangana, close to our study locations. They have over 50 years of experience in Telangana, and are known across the region for breeding and disseminating high-performance crops. They have become one of the most trusted partners for farmers and local extension services working in the area, with an extensive network of partners, which makes them uniquely positioned to deliver these technologies to those in need. Working with ICRISAT and their partners lent credibility to the forecasts for farmers who were encountering this information for the first time.

Forecasts Farmers were told about the forecast using the following text:

> *"In late May/early June each year, we can offer you a forecast which tells you which karte* [an approximately two-week local time step] *the monsoon will arrive in. In 37 of the past 50 years, this forecast has been within one week of the actual start of the rains. It has been better in the past recently: all of the past 10 years' forecasts have been correct."*

We also provided farmers with an information sheet to showcase the forecast's historical accuracy (Appendix Figure H.1). We offered farmers this forecast through a BDM mechanism to elicit farmer willingness-to-pay, which we describe in more detail below. If a farmer purchased the forecast, the enumerator would provide the farmer with the following information (which predicts an average monsoon):

> *"This year's forecast says that the monsoon is likely to start over Telangana between June 11th and June 19th, in Mrigashira karte. This is likely to be followed by a dry*

spell from June 20th to June 29th, in the first half of Aarudra karte. The continuous monsoon rainfall is expected after June 29th, in the second half of Aarudra karte."

After visiting the farmers in person to deliver this information, ICRISAT sent a follow-up SMS with the same text.

Insurance Our insurance product provided farmers with financial protection against a late monsoon. We modeled this product directly on Mobarak and Rosenzweig (2014): farmers would receive a sliding-scale payout at harvest time if the monsoon onset was delayed, and not otherwise. We define a village-specific "on time" monsoon onset date based on the average monsoon onset date in that location, using reanalysis data from the ECMWF ERA-5 (Muñoz-Sabater et al. (2021)), and following the approach of Moron and Robertson (2014), as shown in Figure E.1. We installed rain gauges close to each village (approximately one rain gauge per 10 villages), and hired local staff to record their measurements throughout the growing season. For insurance payout purposes, we define onset conservatively (such that payouts are generous): when our rain gauges accumulated 30mm of rainfall over five days and this was not followed by a dry spell of 10 or more days with less than 1mm of rain per day (Mobarak and Rosenzweig (2014)).[20]

Farmers were informed that they would receive a low payout if the monsoon were 15-19 days late compared to the local "on time" onset date; a medium payout if the monsoon were 20-29 days late; and a large payout if the monsoon were 30 days late or later. The maximum payout was set to approximately $190 USD, and was designed to cover approximately 20 percent of the average farmer's agricultural revenues (Ministry of Statistics and Programme Implementation, Government of India (2013)).[21] Farmers in the insurance treatment arm received an information sheet covering these details (Figure H.2). As with the forecast product, we offered farmers this insurance product through a BDM mechanism to elicit willingness-to-pay, which we describe in more detail below. In September, households were notified about whether they would receive a payout, and the actual payments were disbursed in October.

Product offers and takeup In order to ensure high takeup of forecasts and insurance, while as an added benefit, allowing us to measure WTP, we offered these products to farmers through a BDM mechanism, with a price distribution set such that nearly all farmers with positive WTP would ultimately purchase the product (though this distribution was unknown to farmers).[22] We present take-up of the forecast and insurance product in Appendix Figure A.4 and Appendix Table A.4. We find that take-up is over 85 percent for both treatment groups.[23] The remaining farmers reported no interest in the product or declined to participate in the BDM.

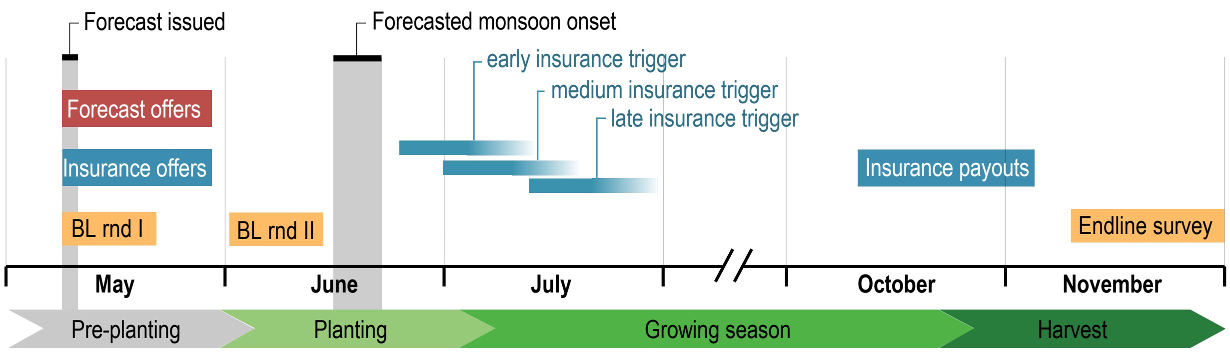
[20] See Appendix Figure A.5 for our rain gauge data. In order to assess the accuracy of the forecast, we use a less strict measure, focused on whether measurable rainfall occurred within the forecasted onset range.

[21] For this calculation, as for all others in the paper, we use an exchange rate of $1 = INR 82.

[22] For more details on our BDM, which was modeled on Berkouwer and Dean (2022), see Appendix G.

[23] Appendix Figure A.4 and Appendix Table A.4 document the later the farmer thinks the monsoon is likely to be, the more likely farmers are to purchase each product when offered.

Figure 2: Experimental timeline



Notes: This figure presents the timeline of the first year of our experiment in relation to the agricultural cycle. The first year of the experiment took place during the 2022 Kharif season. We implemented the baseline survey, and provided treatment offers, and gave farmers the forecast in early May. We visited farmers in early June to collect posterior beliefs. Insurance payouts were triggered by monsoon onset timing, and insurance payouts occurred in October/November. We conclude with a November endline.

Timeline Figure 2 presents the timeline for the experiment. We conducted a baseline survey in May 2022, timed such that we could deliver the PIK forecast at the end of the survey, but still several weeks before the IMD's forecast arrived. Households in the forecast and insurance villages were offered their respective products. For purchasing households in the forecast arm, the information was provided at the end of this visit. This was followed by another visit to households in June 2022, approximately two weeks after the baseline, where we collected data on farmer posterior beliefs about the monsoon. Finally, we conducted our endline survey in November 2022.

The realized monsoon As predicted, over Telangana, the monsoon rain arrived in Mrigashira karte (June 7 - June 20), followed by a dry spell, and then continuous rain beginning in Aarudra karte (June 21 - July 5). As a result, just as was predicted by the forecast, the realized monsoon was very close to average. The forecast was also extremely accurate in our study sample. All 25 of our rain gauges received rainfall by Mrigashira karte. As the forecast also predicted, we find that the amount of rain declined for approximately two weeks following onset, and began to increase again after June 29th. Appendix Figure A.5 shows rainfall across the weather gauges we installed in our sample.

4.2 Data

Outcome data We collected detailed data on three main categories: beliefs, *ex ante* investment, and *ex post* outcomes.

Our first outcome of interest is farmer beliefs about the arrival of the coming monsoon. To measure this, we elicited the farmers' subjective probability distribution of when the monsoon would arrive this year. We did so by providing the farmers with 10 beans to distribute across kartes within a year, following Cole and Xiong (2017). We first asked them to place the beans according to the historical distribution for the past 10 years, where we told farmers to think of each bean as representing one year's monsoon. Once the historical distribution was laid out on the table in front of the farmer, we asked them to consider whether they believed the monsoon would arrive on time, early or late in the coming year. We then asked how they would like to move the beans around in light of their response. We gathered this information during baseline round I and baseline round II to establish whether (and by how much) the forecast changed farmers' priors.

Figure 3 takes the mean of the prior distribution for each farmer, and plots a histogram of these means. The forecast is represented as a purple dashed vertical line. The forecast in 2022 was for an average monsoon, close to the mean of the prior distribution. We divide this distribution into terciles: tercile 1 (indicated by the blue vertical line) are farmers who expected an early monsoon, and would receive bad news from the forecast. Tercile 2 (between the dashed vertical lines) are farmers who (correctly) expected an average monsoon, and would receive neutral news from the forecast. Finally, Tercile 3 (indicated by the green vertical line) are farmers who expected a late monsoon, and would receive good news from the forecast. Appendix Table A.7 and Appendix Table A.15 suggest that these measures are informative: beliefs correlate with whether the farmer is in their home village and the farmer's land holdings, and control farmers' investments during our study year correlate strongly with their beliefs.[24]

The second main category of outcomes are *ex ante* agricultural investment decisions made by the farmers. We consider a number of choices that may be affected by our treatments, including the amount of land cultivated, which crops they cultivate, and the amount of inputs applied to each plot. For crop choice, we are particularly interested in whether farmers choose to plant cash crops and how these crop choices differ from what the farmer cultivated in the past.

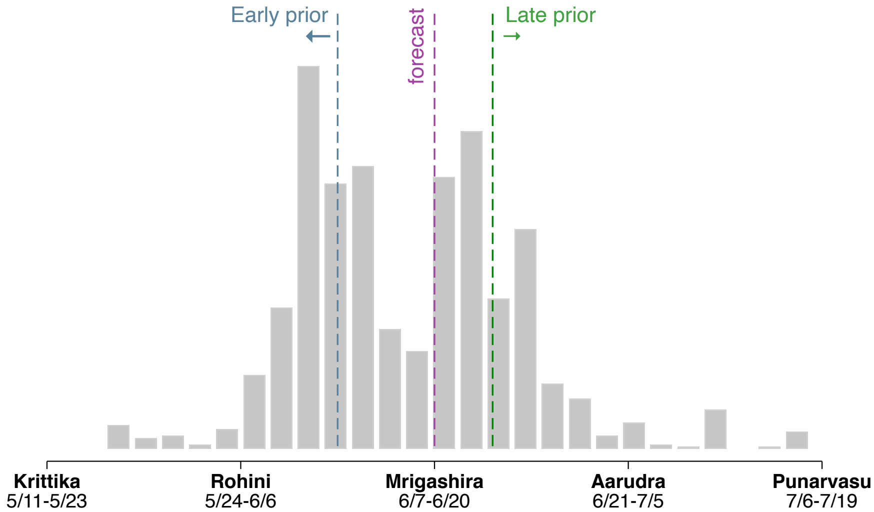
The third main group of outcomes includes downstream *ex post* outcomes for the household. Of primary interest are agricultural output (including profits), the household's financial position, non-agricultural business, and overall household welfare. We measure agricultural output by the weight of crops harvested, the value of crops sold, the value of crops they produced, average yield, and profits (defined as the value of crops produced minus total expenditure). Our main indicator of the household's financial position is savings net of debt. For non-agricultural business, we consider ownership, investment amount, and business profits. For overall well-being, we focus on two measures: household consumption per-capita across eight consumption categories over the past month and the PHQ-9 screening tool, a standard and locally-validated depression metric to measure mental health (Bhat et al. (2022)). We further consider effects of our treatments on other outcomes, including assets and migration.[25]

Attrition, descriptive statistics, and balance Before proceeding with main results, we test for differential attrition and balance between villages in the control group, forecast treatment group,

[24]The linear regression of our standardized investment index on the mean of prior beliefs in the control group yields a coefficient of -0.14 and p-value of -0.014.

[25]We measure assets via a count of individual asset items, the self-reported value of these assets, and a count of livestock holdings. Finally, we measure migration by capturing how many individuals from the household migrated elsewhere over the cropping season and the value of remittances they sent home.

Figure 3: Farmers' priors and the monsoon forecast



Notes: This figure presents the distribution of farmers' mean priors over the 2022 monsoon onset, measured in kartes (a local approximately two-week long unit of time). To elicit these priors, we use the beans task described in Section 4; we then take the mean of each farmer's prior distribution to form this histogram. The forecasted monsoon onset date is represented by the dashed purple vertical line. The 2022 forecast was for an average monsoon, and the forecast lies close to the mean of the prior distribution. We shade the terciles of beliefs. Tercile 1 (indicated by the blue dashed line) are farmers who expected an early monsoon, and receive bad news in the forecast group. Tercile 2 (white) are farmers who (correctly) expected an average monsoon, and receive neutral news in the forecast group. Finally, Tercile 3 (indicated by the green dashed line) are farmers who expected a late monsoon, and receive good news in the forecast group.

and insurance treatment group. Appendix Table A.1 shows that overall attrition (defined as being present in baseline round I but absent from *either* baseline round II or endline) is extremely low: only 4% of households in the control group attrited from the study. Households in the insurance treatment arm are more likely to answer all surveys (if anything, this is likely to bias our insurance treatment effects downwards as we anticipate that those who do not respond are likely to have experienced worse outcomes).[26] Appendix Table A.2 explores the correlation between attrition and baseline characteristics. The mean of a farmer's beliefs about monsoon onset this year does not predict differential attrition, though we find that farmers with more diffuse priors (higher SD) are more likely to exit the sample. Taken together, these results imply that the offer of insurance likely retained some farmers with uncertain beliefs over this year's monsoon.

Appendix Table A.3 presents some descriptive statistics and our balance checks. As expected, we find that villages are similar between groups on a variety of characteristics. Villages contain approximately 400 households on average, and span 360 hectares of cultivated land. The share of irrigated land is low by design (approximately 30%). We also find balance across characteristics of our sample households. On average, households consist of five members. The head of the household is typically in their mid-40s and has received 6 years of education. Households have two plots of land on average and cultivate 2.5 hectares of land. The sample is broadly well-balanced, although we

[26] Of the 495 control group households, 497 forecast group households, and 248 insurance group households, we were unable to conduct all three surveys with 21, 16, and 1 household(s), respectively.

see statistically significant differences between the control and forecast treatment villages in terms of the standard deviation of the monsoon onset timing distribution and the standard deviation of expectations over this year's monsoon. However, these differences are quite minor, accounting for only 3% and 4% of the control mean, respectively. As such, we do not consider them to be a significant cause for concern.

Pre-registration This research was pre-registered at the AEA and the analysis plan was accepted via the pre-results review at the *Journal of Development Economics.* Our pre-registered analysis includes splitting our forecast treatment effects by prior beliefs. We include footnotes in the main text to discuss any changes in regression specification from our analysis plan. A full list of deviations from the PAP is described in Appendix C.

5 Forecast effects on beliefs

Impact on beliefs The "first stage" effect of a forecast should be to update a farmer's beliefs about monsoon onset. We test for this by comparing prior beliefs elicited at baseline with posterior beliefs measured during baseline round II in the treatment groups compared with the control group and the insurance group (which ought to act as a placebo group, having not received the forecast):

$$Y_{iv} = \beta_0 + \beta_1 \text{Forecast offer}_v + \beta_2 \text{Insurance offer}_v + \gamma \mathbf{X}_{iv} + \eta_{iv} \tag{3}$$

where Y_{iv} are various measures of beliefs for household i in village v; Forecast offer$_v$ is an indicator for being in a forecast offer village, Insurance offer$_v$ is an indicator for being in an insurance offer village, $\mathbf{X}_{iv}$ are strata fixed effects, enumerator fixed effects, and a set of controls chosen by double-selection LASSO, and η_{iv} is an error term, clustered at the village level.[27]

Table 2 presents the results. We find that the absolute difference between the forecast and the prior is 26% lower in the forecast group than the control group (Column 1). As this year's forecast was for an average monsoon – and therefore close to the mean of the overall prior distribution – we also find that the distance between the posterior and prior distribution is smaller in the forecast treatment arm, measured both in absolute value (27% lower than control, Column 2) and in the Komolgorov-Smirnov test (11% lower than control, Column 3). Reassuringly, we find no evidence that the insurance treatment affected farmers' beliefs. As a result, we conclude that the forecast was successful in shifting farmers beliefs' about the monsoon's arrival. Figure 4 corroborates these results, showing that while prior beliefs (dashed gray) were approximately centered on the forecast (as shown in Figure 3), posterior beliefs in the control group (solid gray) shifted substantially later. In the forecast group (solid purple), the distribution of posterior beliefs is meaningfully earlier and therefore closer to the forecast.

[27]Because take-up of the forecast and insurance products was not 100% (as documented in Appendix Figure A.4 and Appendix Table A.4, we present IV versions of all of the results in Section 6 in Appendix D, where we instrument for forecast (insurance) take-up with an indicator for being in a forecast (insurance) village. As expected, our estimated magnitudes increase somewhat, and significance is broadly unchanged.

Table 2: Effect of the forecast and insurance on beliefs

	(1) | posterior − forecast |	(2) | posterior − prior |	(3) K-S Stat
Forecast	-0.180**	-0.239**	-0.050*
	(0.083)	(0.095)	(0.027)
Insurance	-0.024	-0.095	-0.020
	(0.096)	(0.111)	(0.032)
Control Mean	0.70	0.89	0.44
Observations	921	921	921

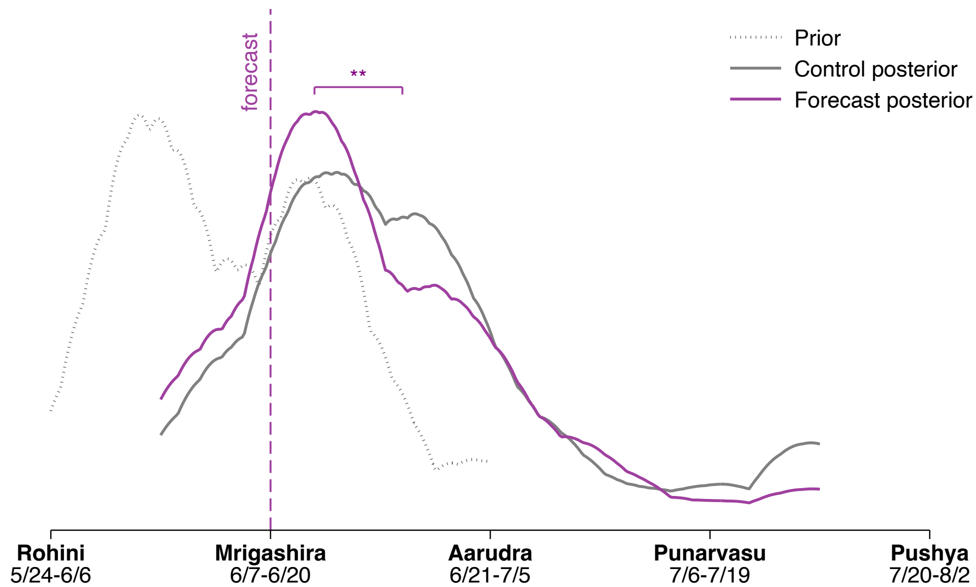
Notes: This table presents estimates of the treatment effects of forecasts and insurance on farmers' beliefs about the onset timing of the Indian Summer Monsoon, estimated using Equation (3). To compute priors and posteriors, we use the beans task described in Section 4. |posterior - forecast| is the absolute difference between a respondent's posterior and the forecast date for the monsoon onset. |posterior - prior| is the absolute difference between a respondent's prior and posterior belief for when the monsoon will arrive. K-S Stat is the Kolmogorov–Smirnov test statistic for the difference between a respondent's prior distribution and their posterior distribution. We exclude households where we were unable to speak to the same respondent when eliciting priors and posteriors. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, ** $p < 0.10$. We present an IV analogue in Appendix Table D.20.

Willingness-to-pay We find that farmers' willingness to pay (WTP) for forecasts is similar to their WTP for insurance, which provides $190 in case the monsoon is delayed by 30 days or more, suggesting that farmers find forecasts valuable. Lending credence to our WTP measure, we find suggestive evidence that the strength of farmers' priors is negatively correlated with WTP (Appendix Table D.6).[28] Nevertheless, we interpret these results with some caution. As forecast information is a public good which can be readily disseminated within the village, farmers may offer a lower price in the BDM game compared to their true valuation.

Information spillovers Finally, we check whether our forecast treatment caused any spillover effects on beliefs. To do so, we compare monsoon beliefs from a sample of untreated farmers living in treated villages (where some farmers received our forecast) to a similar spillover sample in control villages (where no one did). Appendix Table A.8 shows no evidence of information spillovers. While this exercise is informative, it does not rule out the possibility of future information spillovers once farmers have more experience with the forecast, or spillovers in other dimensions (spillover farmers mimicking treated farmers' crop decisions, price changes, etc.).

[28] In our pre-analysis plan, we erroneously included controls in these regressions. Because these regressions study a single experimental group at a time – rather than comparing treatment to control – this removes useful variation rather than adding precision. Therefore we present the unconditional correlations here.

Figure 4: Distribution of prior and posterior beliefs



Notes: This figure plots prior and posterior beliefs over this year's monsoon onset, measured in kartes (a local approximately two-week long unit of time), and elicited via the beans tasked described in Section 4. We then plot the mean of each farmer's prior and posterior distributions. The light gray dashed line plots the distribution of priors. The solid gray line plots the distribution of posteriors in the control group, and the solid purple line plots the distribution of posteriors in the forecast group. The vertical purple dashed line indicates the forecast. The overbrace represents the significance level on the test of the null hypothesis on the forecast coefficient in Equation (3), estimated using the posterior mean as the outcome variable (coefficient of -0.177 and p-value 0.061 without controlling for prior beliefs, coefficient -0.176 and p-value 0.063 when controlling for priors). We exclude households where we were unable to speak to the same respondent when eliciting priors and posteriors. We winsorize priors and posteriors at the 3rd and 97th percentile for display purposes, but this does not have a quantitative impact on the regression results nor statistical significance. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6 Forecast effects on agricultural inputs, production, and welfare

Because our theory implies that the effect of the forecast will differ depending on a farmer's prior, our main specification is:

$$\begin{aligned} Y_{iv} = \beta_0 + \sum_{b=1,2,3} \beta_1^b \text{Forecast offer}_v \times [\text{Prior bin} = \text{b}]_i \\ + \beta_2 \text{Insurance offer}_v + \rho_b [\text{Prior bin} = \text{b}]_i + \gamma \mathbf{X}_{iv} + \eta_{iv} \end{aligned} \tag{4}$$

where $[\text{Prior bin} = \text{b}]_i$ are indicators which divide farmers into terciles on the basis of their priors.[29] Those in the first tercile have priors that the monsoon will arrive relatively early (and therefore if they are in the forecast group they will receive bad news); those in the second tercile have priors

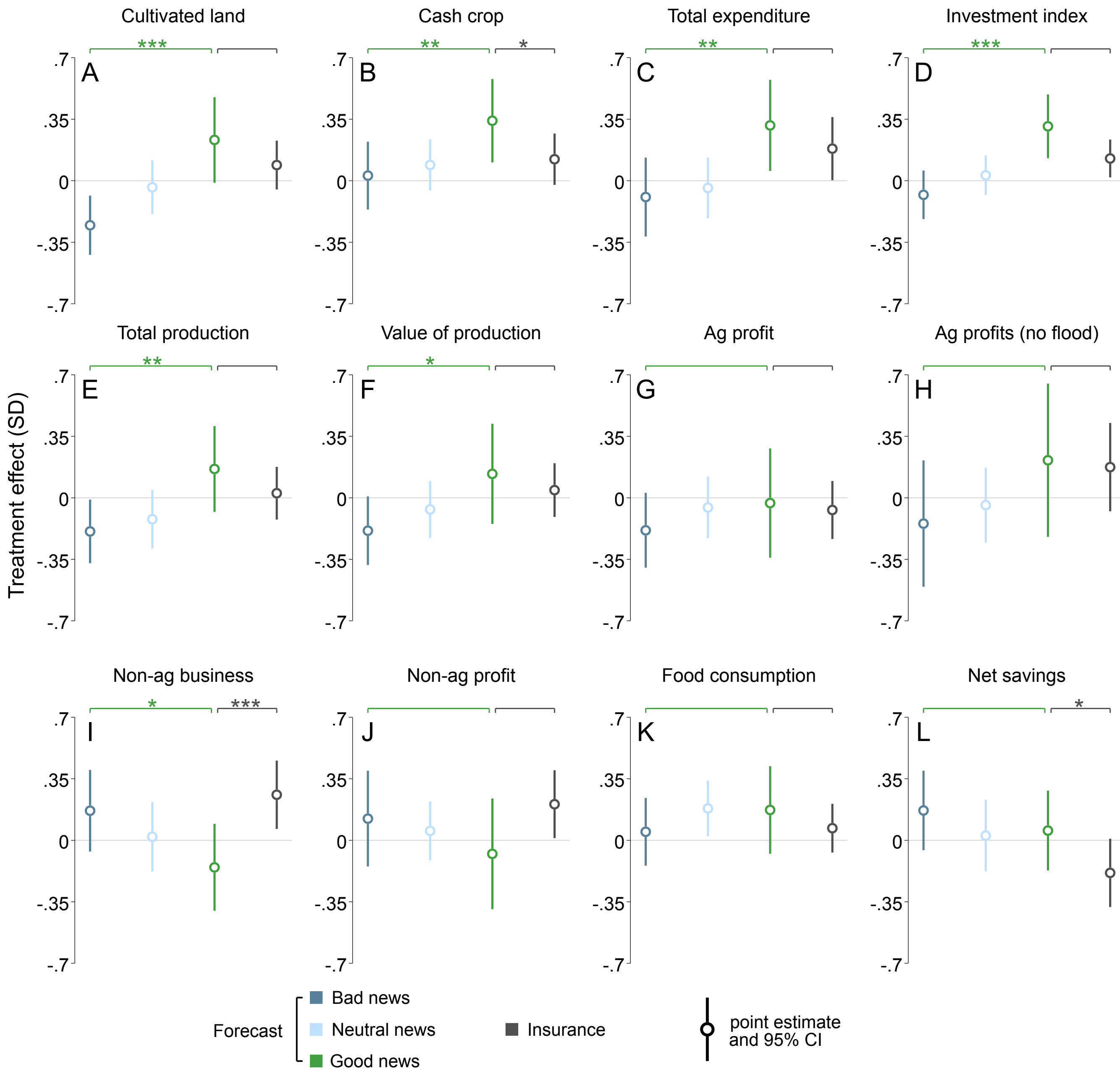
[29] In our pre-analysis plan, we specified that we would split the sample into bad-news and good-news farmers. Given that the monsoon was average, with a large mass of farmers with priors around the forecast, we divide the sample into terciles to better reflect this heterogeneity. We present continuous treatment effects on our summary investment index in Figure 6. In Appendix D, we also present results from a specification where we pool all forecast farmers. As expected, the results tend to aggregate to zero across a variety of outcome variables, as they average negative and positive treatment effects.

that the monsoon will be average (and therefore receive neutral news from the forecast); and those in the third tercile have priors that the monsoon will arrive relatively late (and therefore receive good news from the forecast). All other variables are as defined in Equation (3) above.[30] In this section, we discuss the treatment effects of the forecast. In Section 7, we compare these impacts to those of insurance.

The realized forecast was for an average monsoon, close to the mean of farmer beliefs (Figure 3). According to our theoretical model and our historical yield analysis, we therefore expect (bad-news) farmers in the first tercile to *reduce* investment in agriculture, (good-news) farmers in the third tercile to *increase* agricultural activity, including investing in cash crops, and (neutral-news) farmers in the second tercile not to change their behavior. On average, we would expect these *ex ante* input changes to lead to corresponding changes in *ex post* agricultural output. However, prior work has demonstrated that agriculture is an inherently stochastic process, as *ex post* outcomes dependent both on *ex ante* inputs and growing season conditions (Rosenzweig and Udry (2020), McCullough et al. (2020), and Suri and Udry (2022)). Therefore, input changes in any given year may not result in changes in agricultural production. We conclude our main analysis with estimates of treatment effects on non-agricultural business and welfare. While the effect of the forecast on off-farm enterprise is theoretically ambiguous, we expect our overall welfare outcomes to weakly improve for all forecast treatment arms as farmers tailor their decisions to the coming growing season. Our results, which we summarize in Figure 5 (standardizing all effects for comparability across outcomes), are broadly in line with these predictions.

[30]Because we are testing multiple outcomes, in addition to reporting standard p-values, we present sharpened False Discovery Rate (FDR) q-values, which control for the expected proportion of rejections that are Type I errors, following Anderson (2008). We apply these q-values within outcome categories that we measure using multiple questions. This includes all *ex ante* agricultural investment choices, *ex post* agricultural productivity measures, *ex post* welfare measures, *ex post* asset measures, and *ex post* income-generating opportunity measures.

Figure 5: Summary of main results



Notes: This figure summarizes our main results. All effects are in standard deviations. The top row plots *ex ante* outcomes; the middle row plots *ex post* agricultural outcomes; and the bottom row plots other *ex post* outcomes. We divide the distribution of farmer priors into terciles. Tercile 1 farmers were the most optimistic about the monsoon onset, and received bad news from the forecast. Tercile 2 farmers' beliefs were essentially in line with the forecast, and therefore received neutral news. Tercile 3 farmers were the most pessimistic about the monsoon onset, and received good news from the forecast. Coefficients and 95% confidence intervals are plotted for the forecast and insurance treatments, estimated using Equation (4), where we interact the forecast treatment with the prior belief terciles. Green and gray overbraces indicate the significance level of tests for equality between bad-news and good-news coefficients and between good-news and insurance coefficients, respectively. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.1 Effects on agricultural inputs

Land and crop choice We first investigate the impact of our treatments on land use and crop choice (Table 3), and find evidence in support of our theory. Farmers who received bad news *reduce* land under cultivation by 22% of the control mean, and were 31% less likely to add a crop type from last year to this year.[31] While they were also less likely to change crops, this effect is not statistically significant. Farmers who received neutral news do not change their land under cultivation (point estimate of -3.3%), or their crop choices.

In contrast, farmers who received good news *increase* land under cultivation by 21%. They were also 17 percentage points more likely to grow a cash crop, 13 percentage points more likely to have changed a crop compared to last year, and 14 percentage points more likely to have added a new crop type compared to last year, all compared to control group farmers with similar priors. We do not find evidence that these farmers replaced a previous-year crop with something else, suggesting that the changes we see were driven by new crops being added to the mix, rather than substitution.

We find statistically significant differences between farmers who received good news and bad news on land cultivation (p-value 0.001), cash cropping (p-value 0.032), changing crops from last year (p-value 0.023), and adding a crop between last year and this year (p-value 0.004). These results are consistent with the forecast enabling tailored investments: farmers in this treatment group adjusted their crop mix to match their expectations about the upcoming growing season.

[31] Throughout the results section, for the sake of interpretation, we present results in percent of the control mean. To do so, we scale our treatment effects (which compare forecast group farmers in each prior tercile with control group farmers in each prior tercile) against the *overall* control mean, ensuring that the three tercile treatment effects remain comparable when converting into percent terms.

Table 3: Effect of the forecast and insurance on land use and cropping

	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast × Ind Bin 1	-0.475***	0.015	-0.053	-0.113*	0.012
	(0.161)	(0.049)	(0.053)	(0.059)	(0.045)
Forecast × Ind Bin 2	-0.070	0.045	0.043	0.011	0.014
	(0.147)	(0.037)	(0.051)	(0.047)	(0.038)
Forecast × Ind Bin 3	0.435*	0.171***	0.130**	0.135*	0.027
	(0.233)	(0.061)	(0.064)	(0.072)	(0.054)
Insurance	0.167	0.061	0.043	0.042	-0.004
	(0.133)	(0.037)	(0.046)	(0.048)	(0.037)
q-val Tercile 1	0.035	1.000	1.000	0.316	1.000
q-val Tercile 2	1.000	1.000	1.000	1.000	1.000
q-val Tercile 3	0.079	0.051	0.078	0.079	0.230
q-val Insurance	0.336	0.303	0.483	0.483	0.962
Test Tercile 1=3	0.001	0.032	0.023	0.004	0.830
Test Insur. = Ter. 3	0.279	0.093	0.207	0.210	0.604
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on farmers' land use and cropping decisions, estimated using Equation (4). Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed crop is an indicator for planting a different crop mix in the 2022 Kharif season than the 2021 Kharif season. Added Crop is an indicator for planting at least one additional crop in the 2022 Kharif season compared to 2021. Sub Crop is an indicator for planting at least one fewer crop in the 2022 Kharif season compared to 2021. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in Tables 3 and 4 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Appendix Table D.21 presents an IV analogue.

Inputs We also investigate the impact of our treatments on agricultural input expenditures (Table 4).[32] While imprecise, points estimates for farmers who received bad news show reduced input expenditures consistent with the reduction in land cultivation. Total expenditures fell by 9%. This reduction is driven by roughly proportional decreases in spending on fertilizer (8%), seed (10%), irrigation and labor (7% and 6%).[33] We find no effect on farmers who received neutral news. However, good-news farmers increase their investments substantially, with total expenditures increasing by 31% of the control mean, driven by significant changes in labor expenditure and fertilizer (35% and 26% of the control mean, respectively), and positive but noisy impacts for seed and irrigation. We reject equality between good-news and bad-news farmers at the 5% level for total spending (p-value 0.019).[34]

We also create an index from outcomes in Table 3 (land cultivation and cash crop) and Table 4

[32] Appendix Table D.10 contains treatment effects on per-acre input use. Broadly, we do not find changes in per-acre input use for neutral or good news farmers, but find an increase in total per-acre inputs for bad news farmers. This is consistent bad-news farmers decreasing land area cultivated by 22% but total inputs by 10%.

[33] Appendix Table D.9 splits labor into "early" and "late" relative to the growing season.

[34] We also reject equality between good-news and bad-news farmers at at least the 10% level for fertilizer expenditure (p-value 0.058), and labor expenditure (p-value 0.026).

(total input expenditure). The point estimate for bad-news farmers shows reduced investment by 0.08 standard deviations, but is insignificant. We find no impacts on farmers who received neutral news, with a standardized treatment effect on the investment index of 0.03 SD. However, good-news farmers experience a 0.31 SD effect on the investment index. We reject equality between good-news and bad-news farmers at the 1% level. All but one of our ex-ante treatment effects (adding a crop for bad-news farmers) remain statistically significant at conventional levels after correcting for multiple hypothesis testing.

These treatment effects suggest that the impact of forecasts differs significantly across farmers with different prior beliefs. Farmers who receive good news are more likely to increase their agricultural investment and experimentation (including land cultivation, crops, inputs), while farmers who receive bad news are more likely to reduce it. This is consistent with our theoretical model. Even in cases where we cannot reject zero for the good- or bad-news group on their own, we can often reject equality between them.

Table 4: Effect of the forecast and insurance on inputs

	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast ×	-30.93	-0.68	-1.98	-42.36	-130.18	-0.08
Ind Bin 1	(42.19)	(2.61)	(7.78)	(85.27)	(160.55)	(0.07)
Forecast ×	-28.94	-2.01	-1.21	-44.45	-57.46	0.03
Ind Bin 2	(39.38)	(1.60)	(4.92)	(67.61)	(123.98)	(0.06)
Forecast ×	96.40*	2.20	9.90	263.23**	441.92**	0.31***
Ind Bin 3	(55.61)	(3.35)	(7.99)	(105.20)	(185.41)	(0.09)
Insurance	95.98**	-0.93	-0.14	109.85*	256.27**	0.13**
	(42.81)	(1.34)	(5.67)	(63.63)	(128.57)	(0.05)
q-val Tercile 1	1.000	1.000	1.000	1.000	1.000	
q-val Tercile 2	1.000	1.000	1.000	1.000	1.000	
q-val Tercile 3	0.091	0.206	0.121	0.055	0.055	
q-val Insurance	0.303	0.575	0.962	0.303	0.303	
Test Tercile 1=3	0.058	0.493	0.305	0.026	0.019	0.000
Test Insur. = Ter. 3	0.994	0.368	0.274	0.204	0.373	0.065
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs, estimated using Equation (4). Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor throughout the cropping season. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. It has been excluded from the MHT correction as it is a composite of three outcomes already included. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 were the most pessimistic, and received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in Tables 3 and 4 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We present an IV analogue in Appendix Table D.22.

6.2 Effects on agricultural production

Agricultural output We examine three measures of agricultural production: total crop output in kilograms, the value of crop production, and crop yield per hectare (Table 5). The forecast treatment effects follow the broad pattern we documented in the *ex ante* results. We find negative effects for farmers receiving bad news, including a 25% decline in production and a 22% decline in crop value — consistent with *ex ante* reductions in land area (22%) and total expenditure (10%).[35] We find close to zero effects for farmers receiving neutral news, in line with their having not changed agricultural inputs. Though both are imprecisely estimated, for good-news farmers, we find a 22% increase in agricultural output and a 16% increase in the value of production — aligned with *ex ante* increases in cultivated land (21%), input expenditure (31%), and the probability of cash cropping (34%). We reject equality between bad- and good-news farmers on both production ($p = 0.017$) and value of production ($p = 0.056$). Finally, we see no meaningful changes in yield for any group. Thus, increases in output are likely due to expansions in production rather than intensification.

Table 5: Effect of the forecast and insurance on agricultural output

	(1) Prod (Kg)	(2) Value Prod ($)	(3) Yield
Forecast × Ind Bin 1	-16.90**	-534.76*	-6.59
	(8.17)	(284.81)	(4.35)
Forecast × Ind Bin 2	-10.75	-188.75	-0.73
	(7.50)	(235.57)	(3.61)
Forecast × Ind Bin 3	14.52	390.05	-0.49
	(11.00)	(415.47)	(4.12)
Insurance	2.33	125.42	-1.66
	(6.77)	(222.97)	(2.59)
q-val Tercile 1	0.218	0.218	0.218
q-val Tercile 2	0.839	1.000	1.000
q-val Tercile 3	1.000	1.000	1.000
q-val Insurance	1.000	1.000	1.000
Test Tercile 1=3	0.017	0.056	0.261
Test Insur. = Ter. 3	0.284	0.519	0.776
Control Mean	66.91	2419.93	35.37
Observations	1201	1201	1170

Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural output, estimated using Equation (4). Prod (Kg) is total agricultural production in kilograms. Value Prod ($) is the value of all crops produced in USD, whether they were sold or not, using median district prices for each crop. Yield is kilograms of production per hectare. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We present an IV analogue in Appendix Table D.23.

[35] We use district median prices to value production, to avoid selection in which farmers had actually sold their crop by the time of the survey from biasing our results. District median prices for key crops (e.g., cotton and paddy) are in line with the AgMarkNet mandi prices for Telangana in 2022.

Agricultural profits Table 6 presents impacts of the forecast on agricultural profits. We find that bad-news farmers have meaningfully lower farm profits (−\$401) than the control group. We do not find statistically significant impacts on profits for either neutral- or good-news farmers. Though both point estimates are negative, the effect for good-news farmers is quite close to zero (−\$64).

Theory would predict that agricultural profit should improve on average as a result of an accurate forecast. What, therefore, explains these negative profit effects? For bad-news farmers, negative effects on agricultural profits are consistent with overall reductions in agricultural activity. Similarly, neutral-news farmers did not change land use, inputs, or production, so a null result on profit is expected. However, good-news farmers increased land, inputs, production, and the value of production, but do not see an increase agricultural profits.

The remainder of Table 6 explores this puzzle (and was not pre-specified). Column (2) presents the value of crop losses (i.e., production that was lost to shocks, valued at district-median prices). We find that neutral-news farmers and good-news farmers experienced meaningful crop losses of approximately \$200, or 33% of the control mean (p-value 0.077), and 31% (p-value 0.165), and insurance farmers a 30% loss (p-value 0.032), respectively. We confirm that the higher crop losses for forecast farmers are not due to differing exposure to shocks (Table A.14). Instead, the losses likely result from these groups planting and losing higher-value crops. Indeed, local reports from the study area confirmed that unusual floods struck the area in July, likely leading to these losses (The New Indian Express, 2022). Column (3) shows a counterfactual profit calculation where the value of these losses are added. Though all estimates are noisy, we find a pattern that is more in line with farmers' *ex ante* adjustments: bad-news farmers see a profit reduction of 18%, neutral-news farmers see approximately no change, and good-news farmers see an increase of 9%. In Column (4), we show agricultural profits excluding farmers who reported losses from flooding or cyclones.[36] Again, all estimates are noisy – as the sample is considerably smaller – but we find evidence consistent with agricultural profits responding as expected. The point estimates imply that agricultural profits for bad-news farmers fell by 35%, neutral-news farmers fell by 10%, and good-news farmers increased by 50%.

We interpret these results as consistent with the external validity point made in Rosenzweig and Udry (2020): agriculture is an inherently stochastic process, and while the forecast appears to have led farmers to make choices that would have been profit-improving on average, it did not with the occurrence of an important, but orthogonal, flood shock. Appendix Figure A.6, which shows that farmers' self-reported trust in the forecast increased substantially over the course of the growing season, further demonstrates that farmers understand the distinction between monsoon onset and other growing season realizations.[37]

[36] Because there were no documented cyclones in Telangana in 2022, we interpret "cyclone" as heavy rain or flooding.

[37] If anything, the average *ex post* trust is *higher* for farmers who experienced the flood shock (7.1 on a 1-10 scale) than for those who did not (6.8).

Table 6: Effect of the forecast and insurance on agricultural profit

	(1) Ag Profit ($)	(2) Loss ($)	(3) Profit w/ Loss ($)	(4) Ag Profit Non-Flood ($)
Forecast × Ind Bin 1	-401.08*	54.39	-296.60	-341.47
	(235.92)	(135.32)	(322.80)	(427.31)
Forecast × Ind Bin 2	-118.98	217.10*	99.46	-96.46
	(194.07)	(122.61)	(221.38)	(253.28)
Forecast × Ind Bin 3	-64.98	207.89	154.50	498.33
	(344.39)	(149.61)	(373.22)	(518.06)
Insurance	-150.43	195.48**	-1.21	407.19
	(182.82)	(91.02)	(207.73)	(298.57)
q-val Tercile 1	0.218	0.298	0.243	
q-val Tercile 2	1.000	0.839	1.000	
q-val Tercile 3	1.000	1.000	1.000	
q-val Insurance	1.000	0.238	1.000	
Test Tercile 1=3	0.400	0.411	0.338	0.222
Test Insur. = Ter. 3	0.805	0.935	0.670	0.871
Control Mean	970.62	661.07	1654.24	1052.59
Observations	1201	1201	1201	554

Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural profit and loss, estimated using Equation (4). Ag Profit ($) is the value of production (evaluated at district-median prices) less total expenditure in USD. Loss ($) is the value of reported crop losses (evaluated at district-median prices) in USD. Profit w/ loss ($) is the value of production plus the value of crop losses, less total expenditure in USD. Ag Profit Non-Flood ($) is agricultural profits for the sample of households that did not report crop losses due to flooding or cyclones. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We present an IV analogue in Appendix Table D.24.

6.3 Effects on non-agricultural outcomes and welfare

Table 7 presents the effects of the forecast on non-agricultural outcomes and welfare. In Columns (1)–(3), we find suggestive evidence that farmers who received bad news engaged in *more* non-agricultural activity, while farmers who received good news engaged in less. While not statistically significant, the point estimates imply that bad-news farmers were 42% more likely than control to own a non-agricultural business, increased non-agricultural investment by 17%, and increased business profits by 48%. In contrast, we see suggestive evidence that good-news farmers were less likely to own a non-agricultural business, reduced non-agricultural investment by more than 76% (significant at the 10% level), and saw a 26% decline in business profits. These results, which are in the opposite direction to our agricultural input findings, are consistent with farmers treating business as a substitute for agriculture.

Turning to welfare, we measure impacts on three key indicators. First, we find no impacts on PHQ for neutral- or good-news farmers. For bad-news farmers, we see an increase of 0.14 SD, consistent with stress from receiving bad news or subsequent disappointment in not being able to grow as much as they had hoped for this year. Our treatment effects on food consumption show weakly positive effects for all treatment groups: a 2% increase (p-value 0.623) for bad-news farmers, a 9% (p-value 0.025) increase for neutral-news farmers, and a 8% increase for good-news farmers (p-value 0.174). We cannot reject equality between any groups of farmers.[38] Finally, Column (6) suggestively shows that farmers who received bad news increased net savings by $372 ($p$-value 0.141), driven by a reduction in debt (see Appendix Table A.9). We find no evidence for a change in net savings for neutral news or good-news farmers.[39] Taken together, our *ex post* results suggest that the forecast made farmers weakly better off.

Table 7: Effect of the forecast and insurance on business activity and welfare

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit	(4) PhQ	(5) Food Cons	(6) Net savings
Forecast × Ind Bin 1	0.06	0.32	79.97	0.14*	0.32	372.18
	(0.04)	(0.88)	(76.02)	(0.08)	(0.65)	(252.96)
Forecast × Ind Bin 2	0.01	0.08	17.15	0.04	1.19**	59.12
	(0.03)	(0.71)	(48.16)	(0.07)	(0.53)	(228.47)
Forecast × Ind Bin 3	-0.05	-1.49*	-43.70	0.02	1.14	121.49
	(0.04)	(0.83)	(90.32)	(0.13)	(0.84)	(253.87)
Insurance	0.09***	1.24	104.95*	-0.00	0.45	-406.54*
	(0.03)	(0.77)	(55.11)	(0.05)	(0.47)	(217.24)
q-val Tercile 1	0.452	0.554	0.452	0.452	0.554	0.452
q-val Tercile 2	1.000	1.000	1.000	1.000	0.177	1.000
q-val Tercile 3	0.782	0.782	0.803	0.824	0.782	0.803
q-val Insurance	0.058	0.141	0.115	0.464	0.195	0.115
Test Tercile 1=3	0.060	0.130	0.268	0.420	0.413	0.515
Test Insur. = Ter. 3	0.007	0.002	0.151	0.887	0.449	0.064
Control Mean	0.14	1.93	165.51	-0.02	13.22	-1031.41
Observations	1197	1199	1197	1201	1201	1129

Notes: This table presents estimates of the treatment effects of forecasts and insurance on savings, business activity, and welfare, estimated using Equation (4). Non-Ag Bus. is a dummy for owning a non-agricultural business. Non-Ag Invest is investment outside of agriculture in USD. Bus Profit is business profit in USD. PhQ is the standardized score of the PHQ-9 screening tool; higher values are worse. Food Cons is food consumption per household member in USD over the past 30 days. Net savings is savings less outstanding debt in USD. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We present an IV analogue in Appendix Table D.25.

[38] Appendix Tab A.13 reports effects on dis-aggregated consumption categories as well as non-food consumption.

[39] In Appendix A, we present results for additional *ex post* outcomes: household finances (Appendix Table A.9), other income sources (Appendix Table A.10) assets (Appendix Table A.11), and migration (Appendix Table A.12).If anything, the forecast appears to have reduced borrowing on net, with the strongest effects for bad-news farmers, who reduced their outstanding debt by nearly 40%. Forecasts had no significant impacts on assets, though we see suggestive evidence that bad-news farmers increased their asset value, while good-news farmers reduced asset value – perhaps selling assets to fund their agricultural production. Finally, we see that the forecast reduced the number of migrants that left the household. These reductions are concentrated among bad news and good-news farmers, with the strongest effects on bad news households. To the extent that migration is a hedging strategy against agricultural risk, households ought to reduce their migration in response to lower risk exposure. In contrast, the reduction in migration rates among farmers with the earliest priors does not fit this explanation.

7 Forecasts vs. insurance

As a final exercise, we compare forecasts to insurance, the canonical risk-coping tool. In principle, forecasts and insurance should work in fundamentally different ways. Accurate forecasts provide farmers with information, allowing them to tailor their investments to a given state of the world, thereby reducing risk. In contrast, insurance allows farmers to shift consumption between states of the world but provides no information, increasing welfare without reducing risk. We therefore predict that insurance farmers should increase investments in general, but should not match these changes to the coming growing season. Figure 5 summarizes the effects of insurance, and compares these impacts to those of the good-news forecast group, on twelve key outcomes. Our results, which we discuss in more detail below, broadly align with these predictions.

Land, crop choice, and inputs Tables 3 and 4 documents that insurance led farmers to engage in more agricultural activity. Though imprecisely-estimated, these farmers increased their land under cultivation by approximately 9 percent. This effect is similar in magnitude to the impacts of index insurance in other settings (Karlan et al. (2014)), and we cannot reject equality between insurance and good-news-forecast farmers (p-value 0.279). We also find that insurance caused farmers to increase total expenditures by 18%, driven by a 15% increase in labor expenditures and a 25% increase in fertilizer spending, and again cannot reject equality between good-news farmers in the forecast group and insurance on any expenditure category.

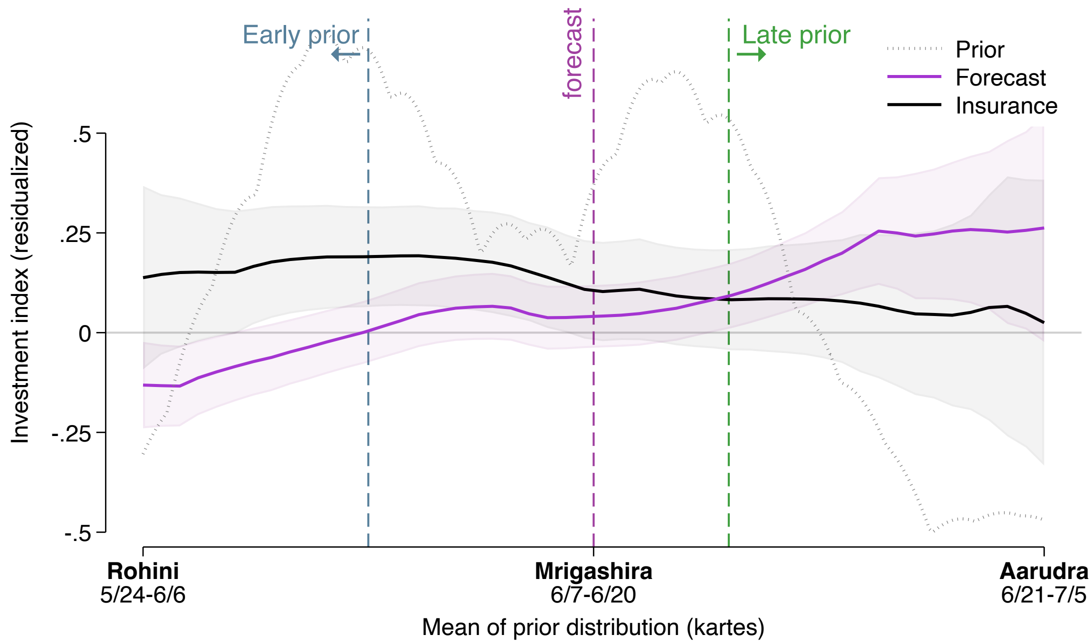
However, we do find meaningful differences in *ex ante* outcomes between the forecast and insurance. Specifically, we find that good-news farmers meaningfully changed crop choice but insurance farmers do not. Though the insurance point estimates on cash crop (6.1 percentage points), changing the crop mix from last year to this year (4.3 percentage points), and adding a crop (4.2 percentage points) are positive, they are meaningfully smaller (just one-third the size) than the good-news effects. We reject equality between the good-news and insurance coefficients on growing cash crops (p-value 0.093). Our overall investment index increases by 0.13 SD for the insurance group, but this is also meaningfully smaller than the good-news group (p-value on equality 0.065). Taken together, these results demonstrate that while insurance increases agricultural investments, it lacks the forecast's ability to target investments to the coming growing season.

Heterogeneity by prior beliefs Our forecasts results emphasize heterogeneity by prior beliefs. While not typically modeled in the insurance literature, these same priors may also change how farmers respond to insurance. To illustrate this, we add an insurance product to the model presented in Section 3.[40] The model predicts (Figure 1, black line) that while insurance should weakly increase *ex ante* investments for all farmers, these impacts will be largest among "optimistic" farmers with early priors – those who would have received bad news from the forecast – and smallest among "pessimistic" farmers with late priors – those who would have received bad news from

[40]To do so, we model farmers as gaining a fixed amount of income if the realized state falls below some predetermined threshold. See Appendix B for more details.

the forecast. Intuitively, insurance enables optimistic (but risk-averse) to substantially increase agricultural activity in anticipation of a favorable season by protecting against downside risk, but it does not increase the appeal of farming for a pessimistic farmer who believes that agricultural investments are likely to go to waste in an unfavorable season.

Figure 6: Investment choice with a forecast or insurance (empirics)



Notes: This figure plots the relationship between the treatment effect on investments and farmers' prior beliefs for the forecast and for insurance: the empirical analogue to Figure 1. We first residualize investments (measured as a standardized index over inputs and land use) using strata fixed effects, enumerator fixed effects, and crop choice from 2021. We then perform two local linear regressions of these residuals on the difference between the mean of the farmer's prior distribution and the forecast date: one for the forecast group vs. control (in purple) and one for insurance vs. control (in black). We winsorize priors at the 3rd and 97th percentile. The purple vertical line denotes the realized forecast (an average monsoon). The dotted gray line plots the prior distribution. The vertical blue and green dashed lines denote the terciles of this distribution.

Figure 6 presents an empirical test of these predictions, using the *ex ante* investment index as our key outcome of interest. As shown above, early-prior (bad news) respond to the forecast by investing less, while late-prior (good news) farmers respond to the forecast by investing more, both compared to control farmers with similar priors. In contrast, early-prior (optimistic) insurance farmers invest more than the control, while late-prior (pessimistic) farmers do not change their investments. Appendix Table D.19 reports effects of the insurance treatment by prior tercile on our core *ex ante* outcomes. For early-prior insurance farmers, we find large effects on land under cultivation (23% of the control mean), input expenditures (29%), and the investment index index (0.17 SD), while for late-prior insurance farmers, we find null results on all outcomes, summarized in an investment index effect of 0.02 SD, though we cannot reject equality. We do not find economically meaningful or statistically significant impacts on crop change for early- or late-prior farmers, consistent with insurance providing no information. Taken together, these results demonstrate that insurance is more effective at encouraging investment among optimistic farmers than pessimistic farmers. These findings contrast sharply with the forecast, which helps to correct farmer beliefs, reducing investment among overly-optimistic farmers and encouraging investment among overly-pessimistic farmers.

Agricultural output As with good-news forecast farmers, Table 5 reveals a mismatch between *ex ante* agricultural inputs and *ex post* farm output for the insurance group. Insurance led to virtually no change in production (3%), the value of production (5%), or yields (−5%). Table 6 shows that insurance reduced agricultural profits by −$150, though this is not different from zero, and reveals that insurance farmers faced meaningful crop losses ($195). In contrast to the forecast farmers, we do see that the insurance group was 12 percentage points more likely to report negative shocks, driven by cyclones (Appendix Table A.14). Among farmers reporting neither flood nor cyclone shocks, insurance increased farm profits by $407 (39%), though this is imprecisely estimated. These results thus demonstrate that the discrepancy between *ex ante* input and *ex post* output effects is not unique to forecasts, but rather likely driven by exogenous weather shocks beyond what these two risk-coping instruments were designed to address.

Non-agricultural outcomes and welfare In addition to impacts on the farm, Table 7 shows that insurance meaningfully increased non-agricultural business ownership (64% relative to the control), investment in non-agricultural business (64%, not different from zero), and business profits (63%). These effects are similar to those in the *bad-news* group (and the former two are statistically distinguishable from the good-news group), suggesting that insurance farmers increased investment across the board, rather than treating farming and business as substitutes. Turning to welfare measures, we find no impacts on mental health, a small positive (3%) effect on food consumption, and a large reduction in net savings for the insurance group. These results are consistent with prior work demonstrating that while insurance can be expected to improve welfare on average (Mobarak and Rosenzweig (2014), Cole and Xiong (2017)), in any given year, farmers may see negative impacts (Karlan et al. (2014)) – particularly if, as we discuss above, insurance induces investments from overly-optimistic farmers.

Discussion We document that both forecasts and index insurance meaningfully alter farmers' planting behavior, but that these instruments operate along different margins. As a result, forecasts and insurance may be complements rather than substitutes. Access to insurance protects farmers from the possibility of an incorrect forecast, enabling farmers to shift even more resources onto the farm under a forecast of a good state. It is therefore possible that access to a forecast could improve demand for insurance, and that both products together could substantially increase farmer welfare.[41] Measuring this interaction is therefore an important topic for future research.

[41] Because of the potential for adverse selection into insurance on the basis of the realized forecast, the relevant question is whether knowing that a farmer *will receive* a forecast changes their demand for insurance.

8 Conclusion

In this paper, we use a cluster-randomized trial to study a novel approach for climate adaptation among farmers in low-income countries: long-range monsoon forecasts of the onset timing of the Indian Summer Monsoon well in advance of its arrival. Our simple theoretical model predicts that such a forecast will enable farmers to tailor their planting decisions to the coming growing season, and that these responses should depend on farmers' prior beliefs. Our estimated treatment effects confirm these predictions.

The forecast caused bad-news farmers to reduce *ex ante* agricultural inputs, had no impact on neutral-news farmers, and caused good-news farmers to increase these inputs. In keeping with these input changes, we broadly see negative, close-to-zero, and positive point estimates on *ex post* agricultural outcomes for the three groups of forecast farmers. Turning to farm profits, while we find negative impacts for bad-news farmers, we estimate close-to-zero effects for good-news farmers. We document that this is likely due to severe flooding, a growing-season shock that was orthogonal to the forecast; both agricultural profits net of crop losses and profits among flood-unaffected farmers are positive in the good-news group. Our results on non-agricultural business are the mirror-image of the impacts on agriculture, with positive point estimates for bad-news farmers, and negative point estimates for good-news farmers. Finally, we see suggestive evidence that the forecast weakly increased welfare, with increases in both food consumption and net savings for all forecast farmers.

Our findings demonstrate that forecasts are a useful tool for coping with a variable climate, as they reduce agricultural risk, which will become increasingly important as the climate changes further. Our evidence also reveals important areas for future work. Additional research is needed to develop accurate, long-range forecasts of growing season conditions throughout the tropics. Our findings demonstrate that these forecasts have the potential to improve farmer decision-making in the face of variable weather. In addition, while we find strong evidence that forecasts enable farmers to tailor their *ex ante* investments to the upcoming growing season, information about onset timing does not shield farmers from the full set of shocks that make agriculture inherently risky. Future research should therefore seek to evaluate the extent to which complimentary policies such as crop insurance can increase the welfare impacts of forecasts.

While we study long-range forecasts in the context of one Indian state, their usefulness as a tool for climate adaptation likely extends much further. More than a third of the global population lives in the Asian monsoon region, and two thirds live in areas with monsoonal systems writ large. There already exist similar forecasts elsewhere in India, and advances in climate science are enabling their wider development. Broadly representing the global meterological, humanitarian, and food sectors, the COP28 Presidency identified improved forecasts as one of seven priority areas with "the potential to not only help address the impact of climate change on food security and agriculture, but also transform the lives and livelihoods of millions of farmers" (COP28 Presidency (2023)).

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Long-range forecasts as climate adaptation: Experimental evidence from developing-country agriculture

Online appendix

Fiona Burlig, Amir Jina, Erin M. Kelley, Gregory Lane, and Harshil Sahai

Contents

A Appendix tables and figures

Table A.1: Differential attrition by treatment group

	(1)
Forecast	-0.010
	(0.016)
Insurance	-0.038***
	(0.014)
Control mean	0.04
Observations	1240

Notes: This table presents attrition (defined as being present in the first baseline round but not present in *either* baseline round II or endline) by treatment status. The regression includes strata fixed effects. Errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.2: Correlates of attrition (control only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2022 onset prior	0.023							
	(0.024)							
2022 onset SD		0.154^{**}						
		(0.071)						
# of households			-0.000					
			(0.000)					
# of farmers				-0.000				
				(0.000)				
% area rain-fed					0.000			
					(0.000)			
% area irrigated						-0.000		
						(0.001)		
Cultivated area (ha)							-0.000	
							(0.000)	
District = Medak								-0.056^{**}
								(0.024)
Ctrl. mean indep. var.	4.91	1.00	411.89	449.61	55.61	30.69	364.30	0.41
Observations	495	495	495	495	495	495	495	495

Notes: This table presents correlates of attrition (defined as being present in the first baseline round but not present in *either* baseline round II or endline). We restrict the sample to control group households only. 2022 onset prior (SD) is the mean (SD) of a household's prior belief distribution (elicited using the beans task described in Section 4 and measured in kartes), and are measured at the individual level. All other covariates are measured at the village level. Errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.3: Balance across treatment arms

	(1)	(2)	(3)	Difference		
	Control	**Forecast**	**Insurance**	(2)-(1)	(3)-(1)	(2)-(3)
	Panel A: Village characteristics					
# of households	413.82	470.45	378.68	56.63	−35.14	91.77
	[367.61]	[647.08]	[249.78]	(74.51)	(51.08)	(73.76)
# of farmers	453.16	480.57	549.70	27.41	96.54	−69.13
	[526.19]	[461.82]	[615.04]	(70.21)	(101.59)	(98.26)
Cultivated area (ha)	365.67	362.94	420.78	−2.73	55.10	−57.84
	[375.22]	[356.27]	[451.81]	(51.88)	(74.04)	(73.00)
% area rain-fed	55.63	56.47	59.65	0.84	4.02	−3.19
	[23.15]	[23.67]	[21.39]	(3.32)	(3.81)	(3.84)
% area irrigated	30.77	29.73	32.17	−1.05	1.39	−2.44
	[19.84]	[20.16]	[19.37]	(2.84)	(3.38)	(3.40)
Observations	100	100	50			
	Panel B: Household-level characteristics					
HH size	5.39	5.30	5.25	−0.08	−0.14	0.06
	[2.52]	[2.35]	[2.07]	(0.18)	(0.20)	(0.20)
HH head age	47.99	47.48	46.43	−0.51	−1.57	1.06
	[12.31]	[11.67]	[11.78]	(0.93)	(1.24)	(1.20)
HH head educ	6.05	6.03	6.45	−0.03	0.39	−0.42
	[5.12]	[5.05]	[5.04]	(0.38)	(0.50)	(0.51)
# of plots	2.01	1.98	2.07	−0.03	0.06	−0.10
	[1.20]	[1.09]	[1.12]	(0.10)	(0.12)	(0.11)
Total land (ha)	2.71	2.32	2.54	−0.38	−0.16	−0.22
	[4.75]	[2.38]	[2.24]	(0.28)	(0.31)	(0.26)
Observations	472	481	247			
	Panel C: Beliefs about the monsoon					
2022 onset mean	4.89	4.84	4.86	−0.05	−0.03	−0.03
	[0.63]	[0.50]	[0.51]	(0.07)	(0.09)	(0.08)
2022 onset SD	0.98	0.89	0.90	−0.09**	−0.08*	−0.01
	[0.32]	[0.27]	[0.29]	(0.04)	(0.04)	(0.04)
Historical onset mean	4.84	4.82	4.96	−0.01	0.12	−0.14*
	[0.56]	[0.49]	[0.46]	(0.07)	(0.08)	(0.07)
Historical onset SD	0.82	0.77	0.79	−0.05**	−0.03	−0.01
	[0.19]	[0.19]	[0.19]	(0.02)	(0.03)	(0.03)
Observations	472	481	247			

Notes: This table presents balance across the three treatment arms. Panel A presents balance at the village level. Panels B and C present balance at the household level. All outcomes in Panel C are measured in kartes using the beans task described in Section 4. errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.4: Effect of forecast and insurance offers on takeup

	(1) Forecast takeup	(2) Insurance takeup	(3) Forecast Bin 1	(4) Forecast Bin 2	(5) Forecast Bin 3	(6) Insurance takeup
Forecast	0.878***	0.004				
	(0.021)	(0.007)				
Insurance	0.024	0.865***	0.018	0.002	0.002	0.866***
	(0.016)	(0.031)	(0.012)	(0.005)	(0.002)	(0.031)
Forecast × Ind Bin 1			0.820***	-0.004	0.003	0.022
			(0.043)	(0.007)	(0.003)	(0.017)
Forecast × Ind Bin 2			-0.000	0.891***	0.004	0.003
			(0.010)	(0.026)	(0.003)	(0.013)
Forecast × Ind Bin 3			0.011	0.002	0.926***	-0.025*
			(0.014)	(0.006)	(0.024)	(0.013)
Control Mean	0.00	0.00	0.00	0.00	0.00	0.00
Observations	1201	1201	1201	1201	1201	1201

Notes: This table presents the treatment effect of offering the forecast and insurance treatments on takeup of those treatments. We estimate Columns (1) and (2) using Equation (3) with forecast take-up and insurance takeup as the outcome variable, respectively. Columns (3) through (6) present results estimated using Equation (4), with the interaction between forecast takeup and prior bins 1–3 (Columns 3–5), and insurance takeup (Column 6) as the outcome variable. All columns include strata fixed effects and control variables selected by double-selection LASSO. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5: Relationship between forecast and insurance takeup and prior beliefs

	(1) Forecast takeup	(2) Forecast takeup	(3) Insurance takeup	(4) Insurance takeup
Mean of Prior Distribution	0.121**		0.099*	
	(0.059)		(0.055)	
Individual Prior Terciles=2		0.090		0.057
		(0.060)		(0.068)
Individual Prior Terciles=3		0.124*		0.128*
		(0.063)		(0.069)
Test Tercile 2=3		0.366		0.158
Mean	0.86	0.80	0.86	0.80
Observations	481	481	247	247

Notes: This table presents the relationship between prior beliefs and takeup of the forecast or insurance offer. Mean of Prior Distribution is the mean of the farmer's beans task. Individual Prior Terciles = 2 and = 3 are indicators for the second tercile (average prior) and the third tercile (late prior) of farmer beliefs, respectively. In Columns (2) and (4), the first tercile (early prior) is the omitted category. Columns (1) and (2) consider takeup of the forecast, and restrict the sample to households who were in forecast villages only. Columns (3) and (4) consider takeup of insurance, and restrict the sample to households who were in insurance villages only. In Columns (1) and (3), the mean is the mean of the overall group; in Columns (2) and (4), the mean is for Prior Tercile 1. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.6: Effect of the forecast on beliefs by prior strength

	(1) $\mid$ posterior $-$ forecast $\mid$	(2) $\mid$ posterior $-$ prior $\mid$	(3) K-S Stat
Forecast	-0.163**	-0.215**	-0.046*
	(0.083)	(0.094)	(0.027)
Stdv of Prior × Forecast	-0.211	-0.312	-0.056
	(0.185)	(0.213)	(0.070)
Stdv of Prior Distribution	0.239**	0.372**	0.054
	(0.107)	(0.155)	(0.049)
Control Mean	0.70	0.89	0.44
Observations	921	921	921

Notes: This table presents estimates of the treatment effect of forecasts on farmers' beliefs about the onset timing of the Indian Summer Monsoon, estimated using Equation (3). To compute priors and posteriors, we use the beans task described in Section 4. |posterior - forecast| is the absolute difference between a respondent's posterior and the forecast date for the monsoon onset. |posterior - prior| is the absolute difference between a respondent's prior and posterior belief for when the monsoon will arrive. K-S Stat is the Kolmogorov–Smirnov test statistic for the difference between a respondent's prior distribution and their posterior distribution. Stdv of Prior is the standard deviation of the respondent's prior belief distribution, where higher values reflect more uncertainty. We exclude households where we were unable to speak to the same respondent when eliciting priors and posteriors. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.7: Correlation between beliefs and farmer characteristics

	Mean of prior belief distribution (kartes)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HH size	0.008							
	(0.008)							
HH head age		0.001						
		(0.002)						
HH head education			0.003					
			(0.004)					
HH head home village (1/0)				0.225**				
				(0.091)				
# of plots					-0.018			
					(0.019)			
Total land (ha)						-0.011**		
						(0.005)		
Cash crops 2021 (1/0)							-0.035	
							(0.054)	
Risk aversion								-0.002
								(0.007)
Ctrl. mean indep. var.	5.39	47.99	6.05	0.92	2.01	2.71	0.52	4.64
Observations	1202	1202	1202	267	1202	1202	1202	1202

Notes: Notes: This table presents the correlation between farmers' prior beliefs (measured in kartes, using the beans task described in Section 4) and baseline characteristics. HH size is the number of household members (including the head), HH head age is the age of the household head in years, HH head education is the household head's years of schooling. HH head home village is an indicator for whether the household head was born in their current village. # of plots is the number of plots farmed by the household. Total land (ha) is acres of land farmed by the household. Cash crops 2021 (1/0) is an indicator for having farmed cash crops in Kharif 2021. Risk aversion measures the farmer's choice in an incentivized risk game where higher values indicate that the farmer is more risk averse. Ctrl. mean indep. var. is the mean of the independent variable in the control group. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8: Effect of forecast on untreated farmer beliefs (spillover sample)

	(1) Arrival Date	(2) Arrive Ontime
Forecast Village	0.066	-0.007
	(2.139)	(0.007)
Control Mean	1.27	0.00
Observations	303	304

Notes: Notes: This table presents the effect of information spillovers on beliefs. Forecast Village is an indicator for being an untreated village (ie, not in the main sample) in a forecast offer village. Arrival Date is the date that the farmer expected the monsoon to arrive in kartes. Arrive On time is an indicator for whether the farmer believed the monsoon would arrive on time, using their own criteria. The sample includes only farmers in the control group and *untreated* farmers in the forecast. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.9: Effect of the forecast and insurance on household finances

	Panel A: Forecast vs. Insurance				
	(1) Savings	(2) Took Loan	(3) Debt Out	(4) Missed Payment	(5) Farm Loan
Forecast	-14.20	-0.06	-193.13	-0.11*	-0.09**
	(23.92)	(0.04)	(138.02)	(0.06)	(0.04)
Insurance	-47.90**	0.18***	374.72*	-0.01	0.18***
	(21.53)	(0.04)	(207.07)	(0.06)	(0.04)
q-val Forecast	0.254	0.175	0.194	0.175	0.085
q-val Insurance	0.027	0.001	0.046	0.211	0.001
	Panel B: Forecast Terciles				
Forecast × Ind Bin 1	-48.58	-0.07	-449.03*	-0.15*	-0.09*
	(33.80)	(0.05)	(238.37)	(0.09)	(0.05)
Forecast × Ind Bin 2	-0.84	-0.06	-47.90	-0.17*	-0.11**
	(31.62)	(0.05)	(206.16)	(0.09)	(0.05)
Forecast × Ind Bin 3	19.67	-0.02	-30.84	0.02	-0.04
	(41.86)	(0.07)	(256.32)	(0.14)	(0.07)
q-val Tercile 1	0.171	0.171	0.171	0.171	0.171
q-val Tercile 2	0.644	0.266	0.644	0.176	0.176
q-val Tercile 3	1.000	1.000	1.000	1.000	1.000
Test Tercile 1=3	0.163	0.583	0.258	0.254	0.567
Test Insur. = Ter. 3	0.127	0.008	0.163	0.879	0.006
Control Mean	149.23	0.50	1173.75	0.43	0.47
Observations	1129	1201	1201	269	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on household finances, estimated using Equations (3, panel A) and (4, panel B). Savings is total savings in USD, Took Loan is an indicator for whether the household took a loan in the last 12 months, Debt Out is the amount of outstanding debt in USD, Missed Payment is an indicator for having missed a loan payment in the last 12 months, and Farm Loan is an indicator for having taken a farm loan in the last 12 months. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.10: Effect of the forecast and insurance on other income-generating activities

	Panel A: Forecast vs. Insurance	
	(1) Labor Inc.	(2) Livestock Inc.
Forecast	-44.45	-81.30
	(33.59)	(70.69)
Insurance	-29.11	-41.70
	(40.93)	(113.22)
q-val Forecast	0.338	0.338
q-val Insurance	1.000	1.000

	Panel B: Forecast Terciles	
Forecast × Ind Bin 1	-114.22**	-0.18
	(54.72)	(100.40)
Forecast × Ind Bin 2	7.33	-143.86
	(44.15)	(101.26)
Forecast × Ind Bin 3	-20.22	-177.44
	(67.89)	(129.70)
q-val Tercile 1	0.081	0.998
q-val Tercile 2	0.768	0.462
q-val Tercile 3	0.621	0.533
Test Tercile 1=3	0.264	0.290
Insur. = Ter. 3	0.895	0.405
Control Mean	324.53	496.70
Observations	1199	125

Notes: This table presents estimates of the treatment effects of forecasts and insurance on other income-generating activities, estimated using Equations (3, panel A) and (4, panel B). Labor Inc. is labor income and Livestock Inc. is income from selling livestock in the last 12 months, both in USD. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.11: Effect of the forecast and insurance on assets

	Panel A: Forecast vs. Insurance		
	(1) Asset Count	(2) Asset Value	(3) Livestock Count
Forecast	-0.05	113.68	0.05
	(0.15)	(134.09)	(0.04)
Insurance	0.19	-123.01	0.01
	(0.20)	(160.52)	(0.04)
q-val Forecast	1.000	1.000	1.000
q-val Insurance	1.000	1.000	1.000

	Panel B: Forecast Terciles		
Forecast × Ind Bin 1	0.25	349.12	0.06
	(0.23)	(264.89)	(0.05)
Forecast × Ind Bin 2	-0.17	29.35	0.04
	(0.21)	(153.43)	(0.05)
Forecast × Ind Bin 3	-0.35	-135.55	0.04
	(0.24)	(145.83)	(0.07)
q-val Tercile 1	0.375	0.375	0.375
q-val Tercile 2	1.000	1.000	1.000
q-val Tercile 3	0.828	0.828	0.828
Test Tercile 1=3	0.060	0.094	0.894
Test Insur. = Ter. 3	0.043	0.906	0.679
Control Mean	6.82	1503.10	0.45
Observations	1201	1201	572

Notes: This table presents estimates of the treatment effects of forecasts and insurance on assets, estimated using Equations (3, panel A) and (4, panel B). Non-Asset Count is the number of assets reported by the household. Asset value is the value of these assets in USD. Livestock count is the number of livestock reported by the household. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.12: Effect of the forecast and insurance on migration

	Panel A: Forecast vs. Insurance				
	(1) Any Migrant	(2) Num Temp Mig.	(3) N. Female	(4) N. Male	(5) Remittances
Forecast	-0.03	-0.09**	-0.03**	-0.05*	-2.77
	(0.02)	(0.04)	(0.01)	(0.03)	(2.37)
Insurance	-0.00	-0.08**	-0.04**	-0.04	-5.72**
	(0.03)	(0.04)	(0.02)	(0.03)	(2.53)
q-val Forecast	0.131	0.072	0.072	0.095	0.168
q-val Insurance	0.218	0.085	0.085	0.091	0.085

	Panel B: Forecast Terciles				
Forecast × Ind Bin 1	-0.05	-0.15**	-0.06**	-0.08*	-1.37
	(0.04)	(0.06)	(0.02)	(0.04)	(4.72)
Forecast × Ind Bin 2	-0.03	-0.04	-0.02	-0.02	-2.10
	(0.03)	(0.05)	(0.02)	(0.04)	(2.26)
Forecast × Ind Bin 3	0.00	-0.07	-0.02	-0.04	-6.79**
	(0.04)	(0.06)	(0.03)	(0.05)	(3.41)
q-val Tercile 1	0.094	0.046	0.046	0.054	0.258
q-val Tercile 2	0.956	0.956	0.956	0.956	0.956
q-val Tercile 3	0.934	0.630	0.630	0.630	0.304
Test Tercile 1=3	0.329	0.401	0.245	0.534	0.323
Insur. = Ter. 3	0.863	0.851	0.546	0.963	0.691
Control Mean	0.15	0.22	0.06	0.15	7.46
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on migration, estimated using Equations (3, panel A) and (4, panel B). Any migrant is an indicator for any migrant having left the household in the past 12 months. Num Temp Mig. is the number of temporary migrants who left the household in the last 1 months. NḞemale and N. Male are the number of temporary female and male migrants, respectively. Remittances is the amount of money remitted by all migrants in the past 30 days in USD. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.13: Effect of the forecast and insurance on per-capita consumption categories

	Panel A: Forecast vs. Insurance								
	(1) Cereals	(2) Milk	(3) Tab / Alc	(4) Meat	(5) Mobile	(6) Clothing	(7) Medicine	(8) Celebration	(9) Total
Forecast	0.64**	0.19*	-0.68**	-0.07	0.08	0.14	-0.27	-0.23	-1.02
	(0.29)	(0.11)	(0.27)	(0.17)	(0.06)	(0.35)	(0.64)	(0.36)	(1.72)
Insurance	0.11	0.11	-0.36	0.20	0.11	0.40	-0.55	0.60	0.27
	(0.32)	(0.13)	(0.38)	(0.20)	(0.07)	(0.42)	(0.72)	(0.48)	(1.92)
q-val Forecast	0.134	0.213	0.105	0.626	0.307	0.626	0.626	0.626	0.626
q-val Insurance	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

	Panel B: Forecast Terciles								
Forecast × Ind Bin 1	0.16	0.05	-1.00***	0.11	0.03	1.36**	-0.28	-0.17	-1.76
	(0.41)	(0.17)	(0.38)	(0.27)	(0.09)	(0.58)	(1.03)	(0.70)	(2.93)
Forecast × Ind Bin 2	0.99***	0.15	-0.61*	-0.15	0.09	-0.76	0.01	-0.46	-0.76
	(0.38)	(0.14)	(0.36)	(0.22)	(0.08)	(0.48)	(0.84)	(0.44)	(2.24)
Forecast × Ind Bin 3	0.84	0.48**	-0.30	-0.25	0.11	-0.28	-0.85	0.10	-0.81
	(0.55)	(0.22)	(0.54)	(0.34)	(0.10)	(0.60)	(1.13)	(0.55)	(2.82)
q-val Tercile 1	1.000	1.000	0.085	1.000	1.000	0.085	1.000	1.000	1.000
q-val Tercile 2	0.088	0.515	0.433	0.740	0.515	0.433	0.793	0.515	0.793
q-val Tercile 3	0.984	0.352	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Test Tercile 1=3	0.298	0.105	0.273	0.384	0.513	0.041	0.693	0.761	0.807
Test Insur. = Ter. 3	0.208	0.112	0.909	0.206	0.923	0.277	0.784	0.464	0.716
Control Mean	7.28	1.96	3.23	3.80	1.55	2.64	6.34	1.71	32.46
Observations	1200	1201	1201	1201	1201	1200	1200	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on disaggregated per-capita consumption expenditure categories, estimated using Equations (3, panel A) and (4, panel B). All outcomes are measured in dollars spent during the past 30 days. Cereals is spending on rice, millet, suji, ragi, or any other grain. Milk is spending on dairy products. Tab / Alc is spending on tabacco or alchohol. Meat is spending on chicken, beef, goat, fish, or eggs. Mobile is spending on phone credit. Clothing is spending on any clothing for household members. Medicine is spending on medical expenses. Celebrations is spending on celebrations or festivals. All outcomes are winsorized at the 5th and 9th percent level. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.14: Shock realizations across treatments

	(1) Flood	(2) Drought	(3) Animal	(4) Cyclone	(5) Any
Panel A: Forecast vs. Insurance					
Forecast	-0.04	0.01	0.03	0.02	0.03
	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)
Insurance	0.02	0.04*	-0.03	0.17***	0.12***
	(0.04)	(0.02)	(0.03)	(0.04)	(0.04)
q-val Forecast	1.000	1.000	1.000	1.000	1.000
q-val Insurance	0.274	0.093	0.197	0.001	0.008
Panel B: Forecast Terciles					
Forecast × Ind Bin 1	-0.07	0.01	0.01	0.04	0.01
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)
Forecast × Ind Bin 2	-0.05	0.00	0.05	0.04	0.05
	(0.04)	(0.02)	(0.03)	(0.05)	(0.06)
Forecast × Ind Bin 3	0.03	0.03	0.01	-0.05	0.04
	(0.06)	(0.03)	(0.05)	(0.07)	(0.06)
q-val Tercile 1	1.000	1.000	1.000	1.000	1.000
q-val Tercile 2	1.000	1.000	1.000	1.000	1.000
q-val Tercile 3	1.000	1.000	1.000	1.000	1.000
Test Tercile 1=3	0.184	0.505	0.929	0.208	0.674
Test Insur. = Ter. 3	0.915	0.845	0.383	0.001	0.222
Control Mean	0.24	0.07	0.12	0.31	0.67
Observations	1201	1201	1201	1201	1201

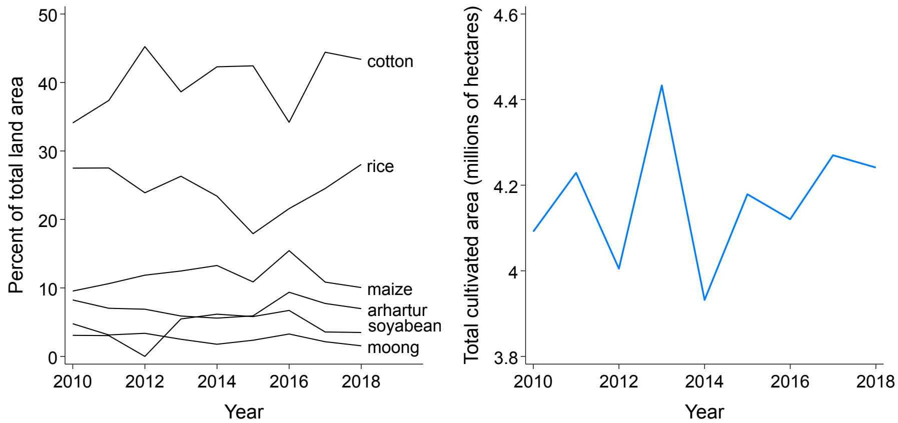
Notes: This table presents estimates of the difference in shock realizations across treatment groups estimated using Equations (3, panel A) and (4, panel B). All outcomes are indicators for self-reported crop damage resulting from that shock. Flood is an indicator for flood damage, Drought for damage from too little rain, Animal for damage from animals eating or trampling crops, Cyclone for damage from wind or excessive rain, and Any is an indicator for suffering loss from any of four shocks. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.15: Association between control-group priors and agricultural investment

	(1) Invest Index
Mean of Prior Distribution	-0.137**
	(0.056)
Control Mean	0.06
Observations	473

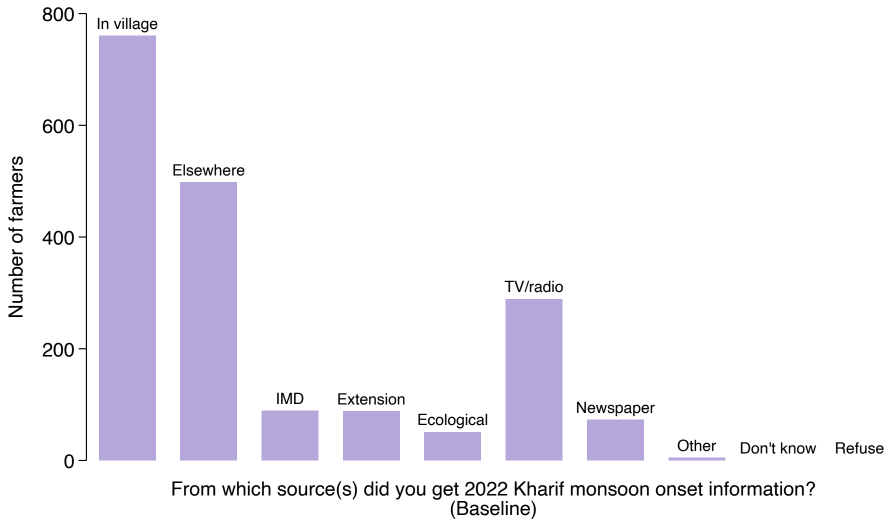
Notes: This table reports the relationship between investment (measured as an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure) and mean of prior beliefs (elicited using the bean task described in Section 4) in the control group only.

Figure A.1: Variability of cultivation in Telangana



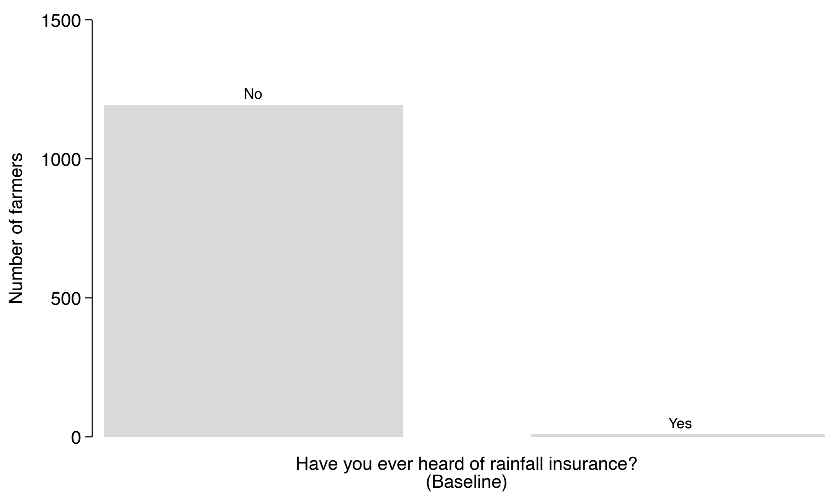
Notes: This figure presents statistics on the use of agricultural land in Telangana over time. The left panel shows the percent of agricultural land area cropped to six major crops: cotton (the main cash crop), rice (the main staple crop), maize, arhartur, soyabean, and moong. The right panel shows total land under cultivation.

Figure A.2: Sources of information about the 2022 monsoon at baseline



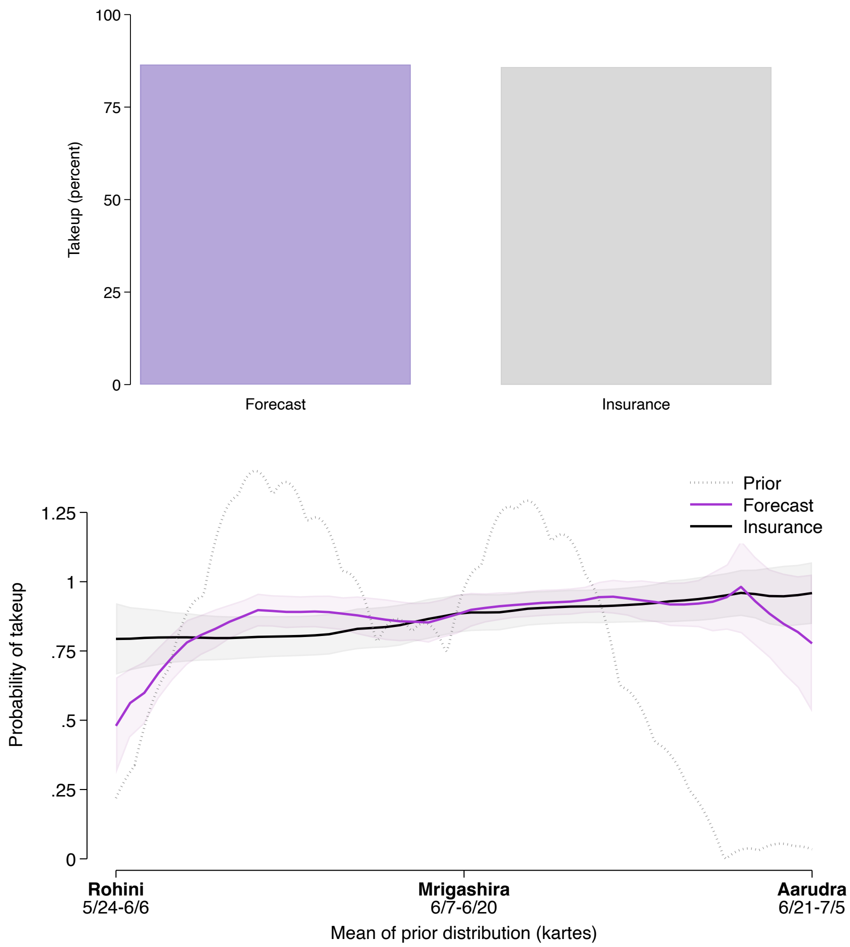
Notes: This figure presents farmers' reported sources of information on monsoon onset timing for the 2022 Kharif season. Data were collected at baseline. Farmers were able to report the use of multiple sources. In village is farmers in the respondent's village; Elsewhere is farmers in other villages; IMD is the government forecast; Extension is other extension services; Ecological is ecological signals (such as animal behavior); TV/radio, Newspaper, Other, Don't know, and Refuse are self-explanatory.

Figure A.3: Baseline knowledge of rainfall insurance



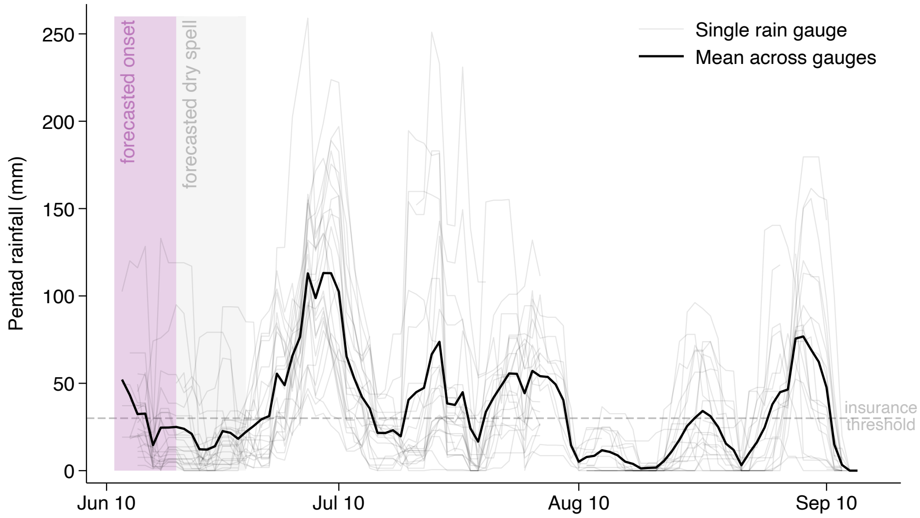
Notes: This figure presents farmers' reported exposure to rainfall insurance at baseline.

Figure A.4: Takeup of forecasts and insurance



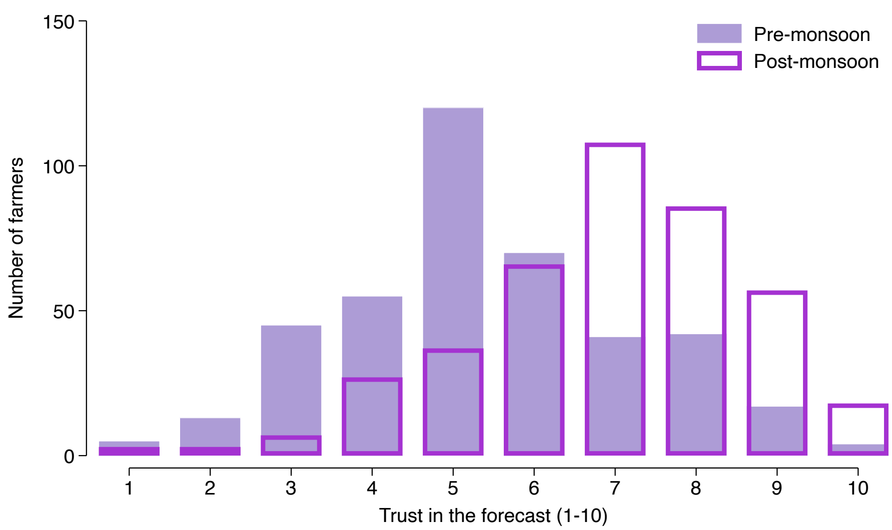
Notes: This figure presents takeup for the forecast (purple) and insurance (gray) products. The top panel shows takeup as a share of households in each treatment arm, while the bottom plots takeup against the mean of the prior distribution, measured in kartes. The dashed line presents the prior distribution. Priors are winsorized at the 3rd and 97th percentile..

Figure A.5: Rainfall realizations and forecast accuracy in our sample



Notes: This figure shows rainfall over our sample. Following standard practice in climate science, each of the 25 light gray lines plots rainfall amounts for one of our sample's gauges calculated in moving cumulative 5-day sums (or pentads). The solid black line plots the mean over all 25 gauges. The purple shaded area shows the monsoon onset window predicted by the forecast, during which time *all* 25 gauges reported non-zero rainfall. The gray shaded area shows the subsequent dry spell predicted by the forecast. Finally, the dashed horizontal line shows the rainfall threshold used to determine insurance payouts. We use a very generous insurance payout rule. Insurance payments were triggered if rainfall had not reached 30mm of precipitation over a 5-day period before the trigger date (and if there was a dry spell within 30 days of the first rains lasting 10 days with less than 5mm of cumulative rainfall). This ensured that as many people as possible would be paid. Using this threshold, 13 out of 25 gauges triggered insurance payouts, even though all of these rain gauges saw rainfall during the forecasted onset period.

Figure A.6: Farmer trust in the forecast



Notes: This figure presents farmers' stated trust in the forecast. The solid histogram presents trust in the forecast when farmers received the information, while the hollow histogram presents trust after the monsoon had arrived.

B Model details

B.1 Setup

In period one, farmers decide how much to save (s), how much to consume (c_1), and how much to invest ($x \geq 0$) by forming expectations across monsoon states ϵ_i and a concave, risky agricultural production technology $f(x, \epsilon_i)$. In the period two, farmers consume (c_2^i) from production and savings.

Production The output from this production technology is modified by the state of the world ϵ_i for $i \in \{1, ..., S\}$, where ϵ_i are ordered so that for any $i > j$ we have higher production and a greater marginal product: $f(x, \epsilon_i) > f(x, \epsilon_j)$ and $f'(x, \epsilon_i) > f'(x, \epsilon_j)$ for all $x > 0$. There is no product at zero investment regardless of the state: $f(0, \epsilon_i) = 0$ for all i. These states can be thought of as approximations for when the monsoon will arrive, with an earlier arrival being associated with greater returns to investment.[42]

Farmer decisions The farmer's prior belief over the probability distribution of ϵ for the coming agricultural season is given by $G(\cdot)$. They use these beliefs to weight possible future outcomes. The farmer therefore solves the following problem:

$$\begin{aligned} \max_{s,x} \quad & u(c_1) + \beta \textstyle\sum_{i=1}^{S} u(c_2^i|\epsilon_i) g(\epsilon_i) \\ \text{s.t.} \quad & c_1 = y - s - p \cdot x \\ & c_2^i = f(x, \epsilon_i) + s \end{aligned} \tag{B.1}$$

where $u(\cdot)$ is a concave utility function, c_1 is first period consumption, c_2^i is second period consumption in state i, $g(\epsilon_i)$ is the probability density of the farmer's prior over ϵ, y is starting wealth, s is risk-free savings (or interest free borrowing), and p is the price of the input x, and β is the discount factor.

We next turn to optimal farmer behavior, and then study how forecasts and insurance would affect these decisions.

B.2 Optimal farmer investment and saving decisions

We present first-order conditions to illustrate how beliefs affect farmers' decisions.

[42] The investment level x can also be interpreted as a continuum of crop choices, with varying levels of productivity. These productivities depend on the state and are correlated with how expensive each crop is to plant. In that sense, for any given state, there is an optimal crop choice x that would maximize production subject to budget constraints.

Savings The first-order condition for savings s implies the following Euler equation:[43]

$$\beta = \frac{u'(c_1)}{\mathbf{E}[u'(c_2)]} \tag{B.2}$$

where $\mathbf{E}[u'(c_2)]$ is the expected consumption in the second period:

$$\mathbf{E}[u'(c_2)] = \sum_i u'(c_2^i, \epsilon_i) g(\epsilon_i) \tag{B.3}$$

Thus, conditional on investment level x, farmers choose savings such that the ratio of marginal utilities between the first and second period equals the patience parameter (discount factor) β.

Investment The first-order condition for investment x implies that investment prices should equal a weighted marginal product:

$$p = \mathbf{E}[wf'(x)] \tag{B.4}$$

where $\mathbf{E}[wf'(x)]$ is the (weighted) expected marginal product of investment level x:

$$\mathbf{E}[wf'(x)] = \sum_i w(c_1, c_2^i, \epsilon_i) f'(x, \epsilon_i) g(\epsilon_i) \tag{B.5}$$

with weights:

$$w(c_1, c_2^i, \epsilon_i) = \beta \frac{u'(c_2^i, \epsilon_i)}{u'(c_1)} = \frac{u'(c_2^i, \epsilon_i)}{\mathbf{E}[u'(c_2)]} = w(c_2^i, \epsilon_i), \tag{B.6}$$

where the second equality comes from plugging in the FOC for savings in (B.2).

The farmer thus sets investment levels to at expected marginal products over all states, weighting states by their relative marginal utility of consumption. While the investment decision deals with smoothing consumption across states in the second period, the savings decision smooths consumption across periods.

Forecasts Consider first a forecast that shifts beliefs from late G_l to early G_e'. In other words, G_e' puts higher probability ϵ_i for higher i. Suppose the farmer was previously solving the problem with G_l, setting optimal investment levels at x^l:

$$\mathbf{E}_{G_l}[wf'(x^l)] = p \tag{B.7}$$

[43]The results are qualitatively unchanged with additional constraints that limit borrowing and savings:

$$\underline{s} \leq s \leq \bar{s}$$

Conditional on weights w, the previous investment level x^l has larger marginal product under the new beliefs G'_e:

$$\mathbf{E}_{G'_e}[wf'(x^l)] > \mathbf{E}_{G_l}[wf'(x^l)] = p \tag{B.8}$$

This is because the new beliefs are weighted toward higher states, which have higher marginal product at any x (f' rises with ϵ). To meet the optimal marginal product of p, the farmer must thus lower the marginal product by raising x (f' is concave). Thus, the optimal investment level increases:

$$x^e > x^l \tag{B.9}$$

By symmetry, a forecast that shifts beliefs from early G_e to late G'_l would *decrease* investment levels.

The argument above is conditional on weights w, that capture the relative marginal utility of consumption across states. To the degree farmers are risk averse, they will reduce investment levels x so as to smooth consumption across states. Suppose now that farmers shift beliefs from G_l to G'_e. For any given investment level of x, the farmer's beliefs shift the expected w toward higher states, which have lower marginal utility. While the marginal product is higher in higher states, the weights are higher in lower states. This mechanism would thus *lower* the weighted marginal product $\mathbf{E}_{G'_e}[wf'(x^l)]$ in contrast to the mechanism above. Thus, changes in investment from forecasts are dampened by the degree of risk aversion (concavity of u).

Insurance To incorporate insurance, we now include an additional payout b that occurs in the second period, depending on the state:

$$c_2^i = f(x, \epsilon_i) + s + b \cdot 1\{\epsilon_i \in S_I\},$$

where E is the set of (low) states for which the insurance payout applies. Note that because this additional term is not a function of either investment or savings, the first-order conditions are unchanged.

Under insurance, the following changes occur *ceterus parbius*: for low states, c_2^i increases from the payouts, causing $u'(c_2^i)$ to fall by concavity the weights; for high states, c_2^i is unchanged; on net, $\mathbf{E}[u'(c_2^i)]$ falls. Thus, the weights $w(c_2^i, \epsilon_i)$ in (B.6) will fall for low states (because $u'(c_2^i)$ falls) and rise for high states (because $\mathbf{E}[u'(c_2^i)]$ falls). Intuitively, for the investment decision, farmers now place relatively higher weight on higher states, as insurance allows them to smooth relatively more. Because higher states are more productive, this raises the optimal level of investment.

Note that these effects are heterogeneous. If farmers have *early* priors, they place higher probability weight on *low* states, dampening the above channel. Thus, insurance would cause these farmers to increase investment relatively *less*. In contrast, if farmers have later priors, they will increase investment relatively more in response to insurance.

B.3 Parametrization for simulations

To quantitatively simulate farmer behavior under various counterfactuals, we impose functional form assumptions.

Utility Farmers' preferences have constant relative risk aversion (CRRA):

$$u(c) = \frac{c^{1-r} - 1}{1 - r} \tag{B.10}$$

Production The technology is Cobb-Douglas in investment:

$$f(x, \epsilon) = \bar{z} \cdot z(\epsilon) \cdot x^{\alpha} \tag{B.11}$$

where $z(\epsilon) \in (0, 1)$ is a (logistic) productivity shock that increases with the state ϵ:

$$z(\epsilon) = \frac{1}{4k} \exp\left(-\frac{\epsilon}{k}\right) \left[1 + \exp\left(-\frac{\epsilon}{k}\right)\right]^{-2} \tag{B.12}$$

The scale parameter k governs how states map into productivity, with lower values driving larger productivity differences across states.

Beliefs and updating The set of possible states S is discrete with 40 possible values $\epsilon_1, \ldots, \epsilon_{40}$. This is distributed according a (rescaled) normal distribution with mean μ and standard deviation parameter σ that is unknown to the farmer:

$$\bar{g}(\epsilon) = \frac{\phi(\epsilon, \mu, \sigma)}{\sum_i \phi(\epsilon_i, \mu, \sigma)} \tag{B.13}$$

where $\phi(., \mu, \sigma)$ is the PDF of a normal distribution. Farmers have (potentially incorrect) prior beliefs with mean μ_p and SD σ_p:

$$g(\epsilon) = \frac{\phi(\epsilon, \mu_p, \sigma_p)}{\sum_i \phi(\epsilon_i, \mu_p, \sigma_p)} \tag{B.14}$$

The forecast distribution is centered around the actual mean μ with SD σ_f that reflects forecast accuracy:

$$h(\epsilon) = \frac{\phi(\epsilon, \mu, \sigma_f)}{\sum_i \phi(\epsilon_i, \mu, \sigma_f)} \tag{B.15}$$

Upon receiving forecast h, the farmer updates from prior g to posterior g' in a Bayesian fashion:

$$g'(\epsilon) = \frac{\phi(\epsilon, \mu', \sigma')}{\sum_i \phi(\epsilon_i, \mu', \sigma')} \tag{B.16}$$

where the posterior mean μ' is a variance-weighted average of the prior and forecast means:

$$\mu' = \frac{\sigma_f^2 \mu_p + \sigma_p^2 \mu}{\sigma_p^2 + \sigma_f^2} \tag{B.17}$$

and the posterior SD σ' scales down the prior in proportion to the (relative) forecast SD:

$$\sigma' = \frac{\sigma_p \sigma_f}{\sqrt{\sigma_p^2 + \sigma_f^2}} \tag{B.18}$$

The parameters are set according to Table B.1 below. Note that we choose parameters such that even the most optimistic farmers believe they face some agriculture risk. This is necessary for the strictly decreasing relationship between insurance treatment effects and priors.

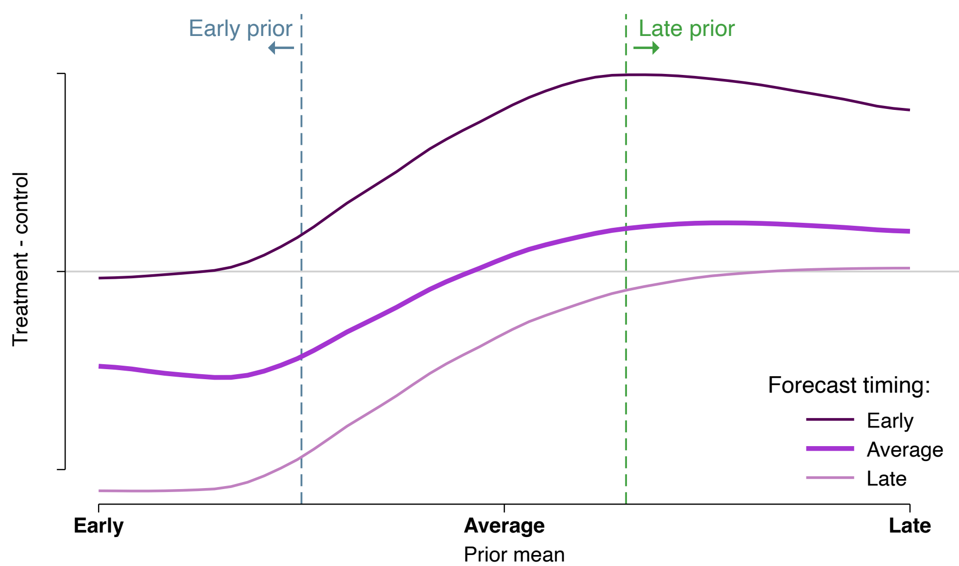
Table B.1: Parameters for model simulation

Parameter	Description	Value
Panel A: Utility Parameters		
r	Relative risk aversion	0.5
β	Discount factor	0.95
y	Starting wealth	5
p	Input price	1
Panel B: Production Parameters		
α	Production function curvature	0.6
$\bar{z}$	Max productivity	3
k	Scale parameter of productivity	2
Panel C: State Parameters		
S	Possible states	$-10, -9.5, -9, \ldots, 9.5, 10$
μ	Mean of actual & forecast distribution	0
σ_f	SD of forecast (accuracy)	2
σ_p	SD of farmer beliefs	5
Panel D: Insurance Parameters		
S_I	States for insurance payout	$-10, -9.5, \ldots, -3.5$
b	Insurance payout	3

B.4 Model predictions for alternative forecast realizations

Appendix Figure B.1 plots treatment effects of a forecast in our model under a forecast of an average monsoon (as depicted in Figure 1 in the main text), a forecast of an early monsoon, or a forecast of a late monsoon. The central curve replicates the effects of a forecast of an average monsoon. The top curve shows farmers' responses to a forecast of an early monsoon. Now, the early-prior farmers are correct, and do not update their behavior in response to the forecast, while the average- and late-prior farmers both receive information that they were likely too pessimistic, and invest more. The bottom curve shows responses to a forecast of a late monsoon. Here, early- and average- prior farmers receive a signal that the growing season will be later than they expected, so they reduce investments. The late-prior farmers receive corroborating information from the forecast, and do not adjust their behavior.

Figure B.1: Investment choice with a forecast, alternative realizations (model)



Notes: This figure plots the simulated relationship between the treatment effect on optimal investment and the farmer's prior that the good state of the world will be realized with a forecast resulting from our model. The y-axis represents the difference between farmers who receive a treatment and those who do not. The grey horizontal line is centered at zero. The x-axis reflects whether farmers believe the monsoon will arrive early, at the average time, or late. This plot indicates the investment response of farmers with different priors under different counterfactual realizations of the forecast. Responses to an early forecast realization are depicted by the dark line; responses to an average forecast realization (as was the case in our empirical setting) are depicted by the solid central line; and responses to a late forecast realization are depicted in the light bottom line.

C Deviations from our pre-analysis plan

This experiment was pre-registered with the AEA as Trial No. AEARCTR-0008846 and accepted by the *Journal of Development Economics* via pre-results review. We have endeavored to follow the PAP as closely as possible, but have nevertheless had some deviations, which we list here. Changes to regression specifications are noted with footnotes in the main text.

- **Data.** Due to time constraints, we left out several variables from our baseline survey: information on time preferences and intra-household bargaining, both of which we had planned to use in heterogeneity analysis.

- **Data.** Due to time constraints, we left out several variables from our endline survey: information on how much of each planted crop had spoiled, was already consumed, and was stored. We had intended to use these as supplementary outcome measures. We instead focus only on production in this analysis.

- **Outcome variables.** We pre-specified measuring agricultural inputs on a per-acre basis. In the main text, we instead use total expenditure, which we believe better reflects decisions to expand agricultural investment. This is because households ought to make a joint decision to expand land and inputs, maintaining a similar input-to-land ratio. We present results on a per-acre basis in Appendix Table D.10.

- **Outcome variables.** In addition to our pre-specified variables on input expenditure, we add an investment index to Table 4. This is complementary to the q-value approach to dealing with multiple hypotheses, serving as a single summary measure of *ex ante* behavior change. An advantage of the index over the FWER correction is that this index accounts for changes in the *direction* of different measures of investment, while the FWER approach only considers p-values irrespective of sign.

- **Outcome variables.** We pre-specified a comparison between 2022 Kharif crop choice and *planned* 2022 Kharif crop choice (measured at baseline). In the main text, we instead compare 2022 Kharif crop choice to 2021 Kharif crop choice, because this is a revealed preference measure rather than a stated preference measure. We include the stated preference result in Appendix Table D.9 for completeness.

- **Analysis.** For the correlations between WTP and prior beliefs (described in Section **??** and presented in Appendix Tables D.6, D.7, and D.8, we erroneously pre-specified a regression equation that included strata fixed effects and controls chosen by double-selection LASSO.

However, these regressions include only a single experimental group at a time (and do not include the control group), meaning that these control variables remove useful variation rather than adding precision. We therefore omit these controls from the tables.

- **Analysis.** For the correlations between WTP and prior beliefs, we had pre-specified a regression that included standard deviation and squared standard deviation of farmers' prior distributions on the right-hand side to test for possible non-linearity in the relationship between WTP and prior strength. Appendix Table D.6 additionally uses the absolute distance between the share of the prior distribution above an on-time cutoff and an early cutoff and 0.5, because we believe this is easier to interpret. For insurance, our theory predicts that WTP strictly falls with an increase in the farmer's belief that the coming year will be good. We therefore use the simple share before the farmer's on-time cutoff and share before the farmer's early cutoff as regressors in Appendix Table D.8, rather than the difference between the shares and 0.5.

- **Analysis.** For the belief change regressions, we pre-specified heterogeneity with respect to multiple measures of prior strength. Here, we present results with respect to prior SD only, as our outcome measures are all relative to the prior or the forecast (and therefore we do not have specific predictions of movement on the basis of binned prior strength).

- **Analysis.** We pre-specified that we would estimate separate treatment effects for forecast farmers receiving bad news vs. bad news. Because the forecast in 2022 was for an average monsoon, there is a large mass of farmers with priors that are very close to the forecast. We therefore estimate treatment effects by *tercile* of prior, which splits the sample into an optimistic group (who receives bad news), an accurate group (who receives neutral news), and a pessimistic group (who receives good news). Given that the forecast itself gave a date range for the monsoon arrival, and that theoretically we would not expect changes in behavior for netural news farmers, we believe our current approach is a better representation of the impact of the forecast on farmer decisions. This avoids the attenuation bias that would be created by including the neutral news group in the good news and bad news groups.

- **Analysis.** We pre-specified that we would estimate heterogeneous treatment effects by the change in belief (absolute difference between prior and posterior). However, this is endogenous and therefore difficult to interpret, so we omit it here.

- **Analysis.** We pre-specified that we would estimate treatment effects on crop prices. Because our survey was conducted in early December, many farmers had not yet sold their crops, leading our individual price data to be extremely noisy and poorly aligned with administrative data on prices. We therefore use district median prices for all outcomes involving crop value, and omit crop price results.

D Additional pre-specified results

Table D.1: Effect of the forecast (pooled) and insurance on land use and cropping

	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast	-0.119	0.057*	0.020	-0.012	0.005
	(0.111)	(0.032)	(0.037)	(0.039)	(0.028)
Insurance	0.178	0.062	0.045	0.044	-0.005
	(0.136)	(0.038)	(0.046)	(0.048)	(0.037)
q-val Forecast	1.000	1.000	1.000	1.000	1.000
q-val Insurance	0.347	0.279	0.437	0.437	0.963

Notes: This table presents estimates of the treatment effects of forecasts and insurance on farmers' land use and cropping decisions, estimated using Equation (4). Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Sharpened q-values are adjusted across all outcomes in Tables D.1 and D.2 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.2: Effect of the forecast (pooled) and insurance on inputs

	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast	-1.99	-0.77	1.10	24.38	26.48	0.04
	(29.19)	(1.54)	(3.96)	(50.20)	(95.44)	(0.05)
Insurance	97.60**	-0.94	0.02	113.49*	263.16**	0.13**
	(43.35)	(1.34)	(5.70)	(64.16)	(130.28)	(0.06)
q-val Forecast	1.000	1.000	1.000	1.000	1.000	
q-val Insurance	0.279	0.566	0.996	0.279	0.279	
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs, estimated using Equation (4). Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor throughout the cropping season. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. It has been excluded from the MHT correction as it is a composite of three outcomes already included. Sharpened q-values are adjusted across all outcomes in Tables D.1 and D.2 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.3: Effect of the forecast (pooled) and insurance on agricultural output

	(1) Prod (Kg)	(2) Value Prod ($)	(3) Yield
Forecast	-8.55	-186.72	-2.92
	(5.32)	(193.85)	(2.73)
Insurance	2.55	134.85	-1.59
	(6.80)	(224.80)	(2.59)
q-val Forecast	0.480	0.480	0.480
q-val Insurance	1.000	1.000	1.000
Control Mean	66.91	2419.93	35.37
Observations	1201	1201	1170

Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural output, estimated using Equation (4). Prod (Kg) is total agricultural production in kilograms. Crop sold ($) is the total value of crops that were sold in USD. Value Prod ($) is the value of all crops produced in USD, whether they were sold or not, using median village prices for each crop. Yield is kilograms of production per hectare. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.4: Effect of the forecast (pooled) and insurance on agricultural profits

	(1) Ag Profit ($)	(2) Loss ($)	(3) Profit w/ Loss ($)	(4) Ag Profit Non-Flood ($)
Forecast	-213.20	161.83*	-31.73	-114.66
	(160.64)	(90.09)	(193.39)	(237.23)
Insurance	-146.68	198.41**	4.42	402.92
	(183.47)	(91.41)	(209.65)	(297.66)
q-val Forecast	0.480	0.480	0.675	
q-val Insurance	1.000	0.221	1.000	
Control Mean	970.62	661.07	1654.24	970.62
Observations	1201	1201	1201	554

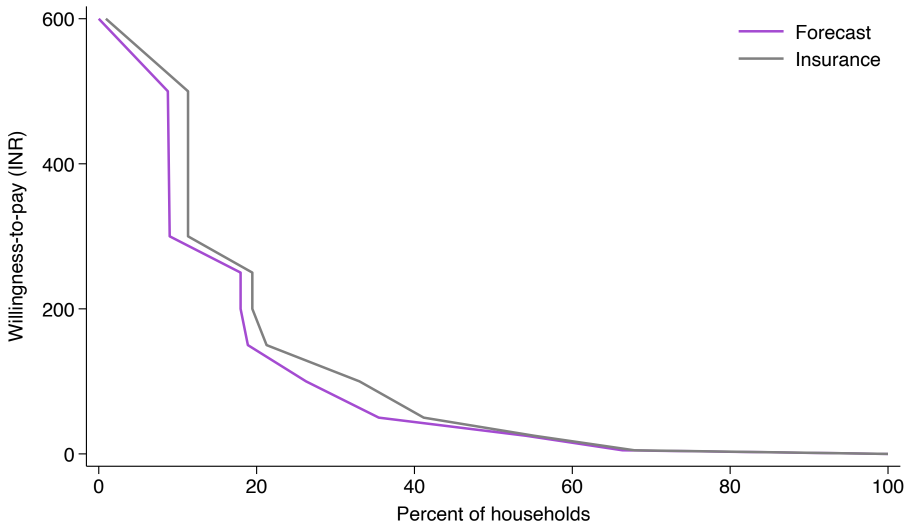
Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural output, estimated using Equation (4). Ag Profit ($) is the value of production (evaluated at district-median prices) less total expenditure in USD. Loss ($) is the value of reported crop losses (evaluated at district-median prices) in USD. Profit w/ loss ($) is the value ofproduction plus the value of crop losses, less total expenditure in USD. Ag Profit Non-Flood ($) is agricultural profits forvthe sample of households that did not report crop losses due to flooding or cyclones Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.5: Effect of the forecast (pooled) and insurance on savings, business activity, and welfare

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit	(4) PhQ	(5) Food Cons	(6) Net savings
Forecast	0.01	-0.16	26.93	0.07	0.87**	184.33
	(0.02)	(0.52)	(41.46)	(0.05)	(0.42)	(145.68)
Insurance	0.09***	1.21	103.06*	-0.01	0.46	-405.18*
	(0.03)	(0.77)	(55.59)	(0.05)	(0.47)	(219.80)
q-val Forecast	0.701	0.701	0.701	0.523	0.314	0.523
q-val Insurance	0.065	0.151	0.123	0.421	0.210	0.123
Control Mean	0.14	1.93	165.51	-0.02	13.22	-1031.41
Observations	1197	1199	1197	1201	1201	1129

Notes: This table presents estimates of the treatment effects of forecasts and insurance on welfare, estimated using Equation (4). Non-Ag Bus. is a dummy for owning a non-agricultural business. Non-Ag Invest is investment outside of agriculture in USD. Bus Profit is business profit in USD. PhQ is the standardized score of the PHQ-9 screening tool; higher values are worse. Food Cons is consumption per household member in USD. Net savings is savings less outstanding debt in USD. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure D.1: Willingness-to-pay for forecasts and insurance



Notes: This figure presents willingness-to-pay curves for the forecast (purple) and insurance product (gray), elicited using the BDM mechanism described in Section 4 and Appendix G. Mean WTP for the forecast (insurance) is \$1.08 (\$1.29). The area under the demand curve for forecasts (insurance) is \$1.42 (\$1.56).

Table D.6: Correlation between willingness-to-pay for the forecast and priors/risk aversion

	Willingness-to-pay for onset forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Std. Prior	12.172	-17.142				
	(26.242)	(115.338)				
Std. Prior2		13.634				
		(48.269)				
| Share Before On Time Cutoff − 0.5 |			-92.939*			
			(50.585)			
| Share Before Early Cutoff − 0.5|				-31.460		
				(63.441)		
|Prior − Vg. Historical|					17.368	
					(24.289)	
Risk Aversion						-2.722
						(1.948)
Mean in Forecast Group	88.84	88.84	88.84	88.84	88.84	88.84
Observations	434	434	434	434	434	434

Notes: This table presents the correlation between forecast treatment group farmers' willingness to pay for the forecast and measures of prior strength and risk aversion. Std. Prior is the standard deviation of the farmer's prior as measured at baseline. Std. Prior2 is this SD squared. The absolute value of the share before on time (and early) cutoff minus 0.5, measures the distance between the likelihood a farmer thinks the monsoon is to arrive (at least) on time and 0.5 such that farmers that are more certain the monsoon either will or will not arrive on time will have higher values, while those who are more uncertain will have low values. The variables' range is between 0 and 0.5. The absolute value of the difference between the farmer's prior and the village's historical average measures the distance between the farmer's belief about this year and the average beliefs of past monsoon arrival within the village. Risk Aversion measures the farmer's choice in an incentivized risk game where higher values indicate that the farmer is more risk averse. The sample includes only farmers in the forecast group. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.7: Correlation between willingness-to-pay for the forecast and prior strength terciles

	Willingness-to-pay for onset forecast
	(1)
Std Prior 2nd Tercile	9.944
	(16.462)
Std Prior 3rd Tercile	4.115
	(20.868)
Mean in Forecast Group	88.84
Observations	434

Notes: This table presents WTP for the forcast by tercile of the standard deviation of farmers' priors. Std. Prior 2nd / 3rd Tercile is an indicator for the respondent's prior standard deviation being in the 2nd or 3rd tercile as measured at baseline. The omitted group is the 1st tercile. The sample includes only farmers in the forecast group. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.8: Correlation between willingness-to-pay for insurance and priors/risk aversion

	Willingness-to-pay for insurance			
	(1)	(2)	(3)	(4)
Stdv of Prior Distribution	76.008 (69.880)			
Prob mass of beans before individual ontime cutoff		1.055 (37.747)		
Prob mass of beans before individual early cutoff			-75.258 (75.603)	
Risk Preference - higher is more risk averse				-3.867 (4.671)
Mean in Insurance Group	106.02	106.02	106.02	106.02
Observations	221	221	221	221

Notes: This table presents the correlation between insurance treatment group farmers' willingness to pay for insurance and measures of prior strength and risk aversion. Std. Prior is the standard deviation of the farmer's prior as measured at baseline. Share before On Time/Early cutoff is the respondent's reported probability that the monsoon will arrive on time or early. Risk Aversion measures the farmer's choice in an incentivized risk game where higher values indicate that the farmer is more risk averse. The sample includes only farmers in the insurance group. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, * $p < 0.05$, ** $p < 0.10$.

Table D.9: Effect of the forecast and insurance on additional inputs

	Panel A: Forecast vs. Insurance		
	(1) Changed plans	(2) Early labor	(3) Late labor
Forecast	-0.020	-40.199*	59.135*
	(0.038)	(22.841)	(33.020)
Insurance	0.024	33.839	78.034*
	(0.046)	(28.878)	(41.640)
	Panel B: Forecast Terciles		
Forecast × Ind Bin 1	-0.067	-72.159**	7.779
	(0.056)	(35.587)	(58.702)
Forecast × Ind Bin 2	0.001	-61.669**	26.606
	(0.052)	(30.567)	(42.893)
Forecast × Ind Bin 3	0.056	51.839	207.148***
	(0.073)	(44.406)	(69.816)
Test Tercile 1=3	0.158	0.027	0.032
Test Insur. = Ter. 3	0.677	0.708	0.090
Control Mean	0.61	355.10	397.97
Observations	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs, estimated using Equations (3, panel A) and (4, panel B). Changed plans is an indicator for whether the farmer said they had changed their plans relative to what they said would do in an "on time" monsoon year. Early labor is total labor expenditure on pre-planting and planting activities in USD. Late labor is total labor expenditure between planting and harvest and during harvest in USD. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.10: Effect of the forecast and insurance on inputs per acre

	Panel A: Forecast vs. Insurance				
	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total
Forecast	16.26*	-1.21	0.11	37.50*	89.76***
	(9.66)	(1.24)	(2.52)	(21.34)	(34.01)
Insurance	36.21**	-1.74	-5.94**	23.14	83.10**
	(14.32)	(1.23)	(2.54)	(23.12)	(39.87)
q-val Forecast	0.141	0.199	0.630	0.141	0.044
q-val Insurance	0.052	0.087	0.052	0.146	0.052

	Panel B: Forecast Terciles				
Forecast × Ind Bin 1	19.24	-0.50	-1.70	64.12*	120.87**
	(15.62)	(1.63)	(4.46)	(37.51)	(60.37)
Forecast × Ind Bin 2	9.24	-2.60*	0.83	25.98	63.54
	(13.05)	(1.38)	(3.51)	(27.07)	(42.84)
Forecast × Ind Bin 3	22.22	0.37	0.80	13.63	90.65
	(18.10)	(3.23)	(4.17)	(33.55)	(58.77)
q-val Tercile 1	0.281	0.572	0.572	0.281	0.281
q-val Tercile 2	0.561	0.426	0.952	0.529	0.426
q-val Tercile 3	1.000	1.000	1.000	1.000	1.000
Test Tercile 1=3	0.901	0.804	0.665	0.302	0.717
Test Insur. = Ter. 3	0.489	0.533	0.142	0.771	0.914
Control Mean	182.96	5.17	16.80	400.21	712.92
Observations	1170	1170	1170	1170	1170

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs per acre, estimated using Equations (3, panel A) and (4, panel B). Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor throughout the cropping season, all per acre. Total is the total amount spent on all inputs per acre, including all previous outcomes and any other costs reported by farmers. All outcomes are in USD per acre. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in Tables 3 and 4, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.11: Effect of the forecast on land and crop choice by prior strength

	Panel A: Forecast × Prior Strength				
	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast	-0.127	0.059*	0.021	-0.011	0.008
	(0.110)	(0.032)	(0.037)	(0.039)	(0.027)
Forecast × Prior Str.	0.076	0.013	0.035	-0.038	-0.109
	(0.338)	(0.073)	(0.094)	(0.098)	(0.078)
	Panel B: Forecast Terciles × Prior Strength				
Forecast × Ind Bin 1	-0.461***	0.012	-0.053	-0.115*	0.011
	(0.160)	(0.050)	(0.053)	(0.059)	(0.045)
Forecast × Ind Bin 2	-0.110	0.050	0.046	0.026	0.023
	(0.142)	(0.038)	(0.051)	(0.048)	(0.038)
Forecast × Ind Bin 3	0.429*	0.167***	0.125*	0.140**	0.013
	(0.241)	(0.060)	(0.065)	(0.071)	(0.053)
Forecast × Bin 1 × Prior Str.	-0.007	-0.062	0.026	-0.125	-0.035
	(0.446)	(0.107)	(0.140)	(0.155)	(0.114)
Forecast × Bin 2 × Prior Str.	0.516	-0.057	0.015	-0.200	-0.056
	(0.512)	(0.126)	(0.162)	(0.138)	(0.137)
Forecast × Bin 3 × Prior Str.	0.369	-0.046	-0.097	0.161	-0.300**
	(0.649)	(0.120)	(0.159)	(0.159)	(0.130)
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	1200	1200	1200	1200	1200

Notes: This table presents estimates of the treatment effects of forecasts on farmers' land use and cropping decisions by prior strength. Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed Crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Added Crop is an indicator for planting an additional crop in 2022 as compared to 2021. Sub Crop is an indicator for removing a crop in 2022 as compared to 2021. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. Prior Str. is the difference of the respondent's on-time probability from 0.5. It has been de-meaned. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.12: Effect of the forecast on inputs by prior strength

	Panel A: Forecast × Prior Strength					
	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast	-2.98	-0.68	1.12	23.00	23.53	0.04
	(29.04)	(1.54)	(3.99)	(50.07)	(94.96)	(0.05)
Forecast × Prior Str.	15.06	-6.98	-8.89	-71.80	-89.53	-0.02
	(72.62)	(4.45)	(11.75)	(148.38)	(257.03)	(0.12)

	Panel B: Forecast Terciles × Prior Strength					
Forecast × Ind Bin 1	-36.87	-0.40	-0.21	-33.41	-109.11	-0.08
	(42.66)	(2.65)	(7.57)	(86.83)	(162.16)	(0.07)
Forecast × Ind Bin 2	-33.04	-1.84	-0.69	-61.34	-87.62	0.03
	(39.13)	(1.55)	(4.91)	(65.74)	(121.35)	(0.06)
Forecast × Ind Bin 3	88.54	1.92	8.95	264.26**	440.63**	0.30***
	(54.73)	(3.15)	(7.19)	(108.06)	(185.76)	(0.09)
Forecast × Bin 1 × Prior Str.	39.93	-4.94	24.83	-229.70	-276.43	-0.16
	(104.35)	(7.96)	(19.05)	(203.53)	(374.79)	(0.17)
Forecast × Bin 2 × Prior Str.	91.57	-4.68	-6.49	317.96	519.96	0.06
	(128.82)	(5.62)	(17.67)	(235.87)	(428.40)	(0.20)
Forecast × Bin 3 × Prior Str.	11.86	-6.16	-27.21	122.04	161.91	0.02
	(126.11)	(7.07)	(21.08)	(298.82)	(481.58)	(0.23)
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	1200	1200	1200	1200	1200	1200

Notes: This table presents estimates of the treatment effects of forecasts on farmers' input use by prior strength. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. Prior Str. is the difference of the respondent's on-time probability from 0.5. It has been de-meaned. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.13: Effect of the forecast on land and crop choice by gap between forecast and prior

	Panel A: Forecast × Prior. - Fore.				
	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast	-0.137	0.059*	0.015	-0.010	0.002
	(0.117)	(0.032)	(0.037)	(0.039)	(0.028)
Forecast × Diff. Prior and Forecast.	0.081	0.010	-0.000	-0.012	0.003
	(0.125)	(0.029)	(0.038)	(0.039)	(0.027)

	Panel B: Forecast Terciles × Prior. - Fore.				
Forecast × Ind Bin 1	-0.341	0.074	-0.019	-0.024	-0.040
	(0.215)	(0.061)	(0.077)	(0.083)	(0.056)
Forecast × Ind Bin 2	0.208	0.019	0.187*	0.196*	-0.025
	(0.354)	(0.093)	(0.112)	(0.114)	(0.085)
Forecast × Ind Bin 3	0.317	0.152**	0.110*	0.116	0.036
	(0.227)	(0.065)	(0.064)	(0.075)	(0.056)
Forecast × Bin 1 × Prior. - Fore.	-0.321	-0.101*	-0.061	-0.161*	0.088
	(0.225)	(0.061)	(0.088)	(0.089)	(0.064)
Forecast × Bin 2 × Prior. - Fore.	0.371	-0.031	0.183	0.235*	-0.051
	(0.371)	(0.108)	(0.132)	(0.133)	(0.095)
Forecast × Bin 3 × Prior. - Fore.	0.301	-0.009	0.029	0.035	-0.022
	(0.292)	(0.043)	(0.074)	(0.069)	(0.053)
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts on farmers' land use and cropping decisions by the gap between the forecast and the prior. Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed Crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Added Crop is an indicator for planting an additional crop in 2022 as compared to 2021. Sub Crop is an indicator for removing a crop in 2022 as compared to 2021. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. Prior. - Fore. is the standardized absolute difference between the prior and the forecast. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.14: Effect of the forecast on inputs by gap between forecast and prior

	Panel A: Forecast × Prior. - Fore.					
	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast	-4.81	-0.74	0.55	26.01	20.95	0.04
	(30.29)	(1.60)	(4.05)	(54.15)	(101.90)	(0.05)
Forecast × Diff. Prior and Forecast.	17.37	0.13	4.51	41.53	63.63	0.04
	(27.33)	(1.08)	(3.74)	(60.93)	(99.75)	(0.05)
	Panel B: Forecast Terciles × Prior. - Fore.					
Forecast × Ind Bin 1	29.77	3.98	-11.07	112.44	135.61	0.02
	(52.34)	(4.13)	(9.76)	(110.18)	(208.39)	(0.09)
Forecast × Ind Bin 2	30.34	2.62	3.62	10.51	63.37	0.10
	(89.16)	(2.98)	(10.03)	(163.33)	(309.12)	(0.15)
Forecast × Ind Bin 3	79.43	1.94	7.74	222.46**	375.66*	0.26***
	(59.33)	(3.42)	(8.64)	(104.88)	(192.17)	(0.10)
Forecast × Bin 1 × Prior. - Fore.	-119.13	-7.63**	13.82	-288.84**	-526.83**	-0.20**
	(72.49)	(3.55)	(10.72)	(123.45)	(222.91)	(0.08)
Forecast × Bin 2 × Prior. - Fore.	77.93	5.77*	6.50	74.61	164.96	0.10
	(101.48)	(3.45)	(11.68)	(185.36)	(350.68)	(0.16)
Forecast × Bin 3 × Prior. - Fore.	19.64	-1.19	3.50	123.51	155.68	0.05
	(35.55)	(2.27)	(4.24)	(125.19)	(162.47)	(0.09)
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts on farmers' inputs by the gap between the forecast and the prior. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. Prior. - Fore. is the standardized absolute difference between the prior and the forecast. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.15: Effect of the forecast on land and crop choice by WTP

	Panel A: Forecast × WTP				
	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast	-0.262* (0.141)	-0.011 (0.040)	-0.041 (0.044)	-0.050 (0.040)	0.007 (0.034)
Forecast × WTP	-0.099 (0.122)	-0.019 (0.039)	-0.030 (0.050)	-0.071 (0.045)	0.004 (0.036)
WTP	0.059 (0.102)	0.012 (0.035)	0.027 (0.045)	0.041 (0.038)	0.032 (0.034)

	Panel B: Forecast Terciles × WTP				
Forecast × Ind Bin 1	-0.776*** (0.253)	-0.005 (0.066)	-0.120 (0.075)	-0.128* (0.072)	0.060 (0.053)
Forecast × Ind Bin 2	-0.095 (0.194)	-0.075 (0.054)	-0.051 (0.065)	-0.061 (0.057)	0.020 (0.052)
Forecast × Ind Bin 3	0.371 (0.304)	0.119 (0.084)	0.027 (0.082)	0.071 (0.077)	-0.042 (0.074)
Forecast × Bin 1 × WTP	0.019 (0.212)	-0.002 (0.068)	-0.052 (0.089)	-0.159* (0.090)	0.032 (0.070)
Forecast × Bin 2 × WTP	-0.202 (0.150)	-0.035 (0.049)	-0.013 (0.052)	-0.045 (0.054)	-0.013 (0.042)
Forecast × Bin 3 × WTP	0.105 (0.253)	0.048 (0.089)	0.098 (0.077)	-0.001 (0.074)	0.128* (0.070)
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	655	655	655	655	655

Notes: This table presents estimates of the treatment effects of forecasts on farmers' land use and cropping decisions by WTP. Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed Crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Added Crop is an indicator for planting an additional crop in 2022 as compared to 2021. Sub Crop is an indicator for removing a crop in 2022 as compared to 2021. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. WTP is the willingness-to-pay for the forecast and insurance product. The sample excludes the control group because WTP is undefined for them. The omitted category is insurance. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.16: Effect of the forecast on inputs by WTP

	Panel A: Forecast × WTP					
	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast	-83.97**	0.54	1.69	-41.81	-173.16	-0.06
	(40.37)	(1.48)	(6.15)	(67.91)	(125.31)	(0.06)
Forecast × WTP	-37.17	0.57	1.33	21.13	20.26	-0.04
	(44.85)	(1.13)	(4.01)	(54.52)	(106.94)	(0.05)
WTP	71.06	-0.21	-1.58	26.56	84.26	0.02
	(50.90)	(0.88)	(3.15)	(54.73)	(111.88)	(0.05)

	Panel B: Forecast Terciles × WTP					
Forecast × Ind Bin 1	-192.75***	-1.04	-5.79	-137.33	-512.87**	-0.20**
	(63.92)	(2.26)	(14.05)	(110.53)	(227.87)	(0.10)
Forecast × Ind Bin 2	-104.08**	-0.55	0.53	-151.49	-236.75	-0.11
	(52.38)	(1.26)	(7.63)	(100.33)	(177.16)	(0.09)
Forecast × Ind Bin 3	69.64	3.65	14.46	233.37	312.29	0.25*
	(73.14)	(3.19)	(12.08)	(166.24)	(275.14)	(0.14)
Forecast × Bin 1 × WTP	-192.03**	-0.55	13.89	-72.35	-176.68	0.02
	(80.10)	(1.69)	(8.78)	(108.93)	(222.45)	(0.10)
Forecast × Bin 2 × WTP	23.05	0.73	0.37	60.87	97.24	-0.07
	(42.54)	(1.06)	(5.42)	(69.13)	(119.79)	(0.07)
Forecast × Bin 3 × WTP	48.91	2.87	-4.33	143.45	247.85	0.08
	(67.11)	(2.56)	(9.37)	(168.71)	(259.90)	(0.12)
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	655	655	655	655	655	655

Notes: This table presents estimates of the treatment effects of forecasts on farmers' land use and cropping decisions by WTP. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. WTP is the willingness-to-pay for the forecast and insurance product. The sample excludes the control group because WTP is undefined for them. The omitted category is insurance. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.17: Effect of the forecast on land use and crop choice by risk aversion

	Panel A: Forecast × Risk Aversion				
	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast	-0.298**	0.037	0.032	-0.030	0.028
	(0.138)	(0.037)	(0.045)	(0.044)	(0.034)
Forecast × Risk Av.	0.456**	0.049	-0.040	0.042	-0.065
	(0.195)	(0.059)	(0.062)	(0.068)	(0.052)
	Panel B: Forecast Terciles × Risk Aversion				
Forecast × Ind Bin 1	-0.550***	-0.019	-0.054	-0.122*	0.039
	(0.196)	(0.055)	(0.067)	(0.069)	(0.052)
Forecast × Ind Bin 2	-0.112	0.037	0.030	-0.002	0.015
	(0.181)	(0.048)	(0.064)	(0.058)	(0.048)
Forecast × Ind Bin 3	0.079	0.128*	0.133*	0.064	0.019
	(0.275)	(0.077)	(0.074)	(0.076)	(0.068)
Forecast × Bin 1 × Risk Av.	0.225	0.084	0.012	0.041	-0.063
	(0.253)	(0.084)	(0.094)	(0.096)	(0.071)
Forecast × Bin 2 × Risk Av.	0.139	0.019	0.032	0.040	0.000
	(0.256)	(0.070)	(0.086)	(0.082)	(0.073)
Forecast × Bin 3 × Risk Av.	0.848**	0.105	-0.018	0.158	0.013
	(0.422)	(0.114)	(0.109)	(0.127)	(0.091)
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts on farmers' inputs by the risk aversion. Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed Crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Added Crop is an indicator for planting an additional crop in 2022 as compared to 2021. Sub Crop is an indicator for removing a crop in 2022 as compared to 2021. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. Risk. Av. is the result of an incentivized risk game. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.18: Effect of the forecast on inputs by risk aversion

	Panel A: Forecast × Risk Aversion					
	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast	-40.04	0.04	-0.18	-19.22	-77.19	-0.02
	(36.36)	(1.77)	(4.35)	(61.59)	(119.12)	(0.06)
Forecast × Risk Av.	96.15*	-2.03	3.08	107.77	258.64	0.16*
	(52.33)	(2.16)	(9.04)	(88.57)	(172.56)	(0.08)

	Panel B: Forecast Terciles × Risk Aversion					
Forecast × Ind Bin 1	-9.19	-0.59	8.10	-28.95	-50.22	-0.13
	(49.82)	(2.90)	(9.38)	(114.18)	(217.35)	(0.08)
Forecast × Ind Bin 2	-74.39	-1.99	-6.83	-133.95*	-265.44*	0.00
	(45.97)	(1.77)	(5.40)	(81.07)	(145.41)	(0.07)
Forecast × Ind Bin 3	-4.80	4.93	-3.84	136.45	141.04	0.18
	(61.58)	(4.85)	(4.93)	(118.52)	(200.18)	(0.12)
Forecast × Bin 1 × Risk Av.	-46.18	-0.25	-24.57	-30.52	-189.94	0.13
	(67.49)	(3.09)	(17.62)	(129.97)	(256.07)	(0.11)
Forecast × Bin 2 × Risk Av.	129.31*	0.14	16.17	247.32**	577.31***	0.08
	(67.24)	(2.58)	(10.01)	(114.44)	(214.05)	(0.10)
Forecast × Bin 3 × Risk Av.	242.16**	-6.59	33.02**	306.70	725.92**	0.31*
	(97.67)	(5.19)	(16.38)	(202.58)	(340.70)	(0.17)
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts on farmers' inputs by the risk aversion. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. Risk. Av. is the result of an incentivized risk game. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.19: Effect of insurance on inputs by prior terciles

	(1) Land Ha.	(2) Cash Crop	(3) Total Inputs	(4) Invest Index
Insurance × Ind Bin 1	0.486**	0.023	415.311*	0.172*
	(0.226)	(0.065)	(217.148)	(0.095)
Insurance × Ind Bin 2	0.110	0.092*	274.439	0.157**
	(0.172)	(0.051)	(172.141)	(0.076)
Insurance × Ind Bin 3	-0.073	0.048	59.705	0.017
	(0.303)	(0.077)	(243.760)	(0.127)
q-val Insure Ter. 1	0.092	0.321	0.092	
q-val Insure Ter. 2	0.210	0.201	0.201	
q-val Insure Ter. 3	1.000	1.000	1.000	
Test Tercile 1=3	0.140	0.802	0.254	0.323
Control Mean	2.12	0.51	1443.49	0.00
Observations	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of insurance on farmers' inputs by prior belief. Land Ha. is cultivated land in hectares. Cash crop is an indicator for growing at least one cash crop. Total inputs is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers, in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. It has been excluded from the MHT correction as it is a composite of three outcomes already included. Bins 1–3 indicate the prior tercile for a respondent. Prior tercile 1 were the most optimistic. Prior bin 2 had average (correct) beliefs. Prior bin 3 were the most pessimistic. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Additionally, each regression also controls for the forecast treatment by prior belief as in Equation (4). Sharpened q- values are adjusted across all outcomes shown (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.20: Effect of forecast and insurance takeup on beliefs

	(1) $\mid$ posterior $-$ forecast $\mid$	(2) $\mid$ posterior $-$ prior $\mid$	(3) K-S Stat
Forecast takeup	-0.204**	-0.272**	-0.057*
	(0.095)	(0.108)	(0.030)
Insurance takeup	-0.023	-0.101	-0.021
	(0.108)	(0.125)	(0.036)
Control Mean	0.70	0.89	0.44
Observations	921	921	921

Notes: This table presents estimates of the treatment effects of forecast and insurance take-up on farmers' beliefs about the onset timing of the Indian Summer Monsoon, estimated using an IV version of Equation (3) where we instrument for forecast and insurance takeup with an indicator for being in a forecast or insurance village. To compute priors and posteriors, we use the beans task described in Section 4. |posterior - forecast| is the absolute difference between a respondent's posterior and the forecast date for the monsoon onset. |posterior - prior| is the absolute difference between a respondent's prior and posterior belief for when the monsoon will arrive. K-S Stat is the Kolmogorov–Smirnov test statistic for the difference between a respondent's prior distribution and their posterior distribution. We exclude households where we were unable to speak to the same respondent when eliciting priors and posteriors. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, ** $p < 0.10$.

Table D.21: Effect of forecast and insurance takeup on land use and cropping

	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast takeup	-0.588***	0.016	-0.066	-0.140**	0.015
× Ind Bin 1	(0.205)	(0.059)	(0.064)	(0.071)	(0.054)
Forecast takeup	-0.089	0.048	0.044	0.014	0.012
× Ind Bin 2	(0.164)	(0.042)	(0.057)	(0.053)	(0.042)
Forecast takeup	0.454*	0.176***	0.130*	0.160**	0.010
× Ind Bin 3	(0.265)	(0.067)	(0.071)	(0.078)	(0.060)
Insurance takeup	0.206	0.071*	0.051	0.050	-0.005
	(0.155)	(0.043)	(0.053)	(0.055)	(0.042)
q-val Tercile 1	0.043	1.000	1.000	0.286	1.000
q-val Tercile 2	1.000	1.000	1.000	1.000	1.000
q-val Tercile 3	0.095	0.058	0.091	0.075	0.354
Test Tercile 1=3	0.002	0.055	0.037	0.003	0.949
Test Insur. = Ter. 3	0.380	0.144	0.311	0.177	0.823
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on farmers' land use and cropping decisions, estimated using an IV version of Equation (4) where we instrument for forecast and insurance takeup with indicators for being in a forecast or insurance village. Land Ha. is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in Tables 3 and 4 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.22: Effect of forecast and insurance takeup on inputs

	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total	(6) Invest Index
Forecast takeup	-40.13	-0.82	-2.46	-55.57	-166.27	-0.10
× Ind Bin 1	(51.97)	(3.18)	(9.50)	(104.29)	(197.03)	(0.09)
Forecast takeup	-32.44	-2.28	-1.51	-51.50	-66.09	0.03
× Ind Bin 2	(44.04)	(1.80)	(5.54)	(75.96)	(139.22)	(0.06)
Forecast takeup	112.07*	2.29	10.26	289.85**	495.81**	0.32***
× Ind Bin 3	(62.04)	(3.92)	(8.96)	(116.78)	(206.44)	(0.11)
Insurance takeup	112.03**	-1.06	-0.12	128.06*	299.90**	0.15**
	(49.71)	(1.52)	(6.55)	(73.96)	(150.00)	(0.06)
q-val Tercile 1	1.000	1.000	1.000	1.000	1.000	
q-val Tercile 2	1.000	1.000	1.000	1.000	1.000	
q-val Tercile 3	0.091	0.230	0.141	0.058	0.058	
Test Tercile 1=3	0.053	0.535	0.351	0.031	0.020	0.001
Test Insur. = Ter. 3	1.000	0.410	0.315	0.231	0.403	0.138
Control Mean	372.80	7.22	26.81	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on inputs, estimated using an IV version of Equation (4) where we instrument for forecast and insurance takeup with indicators for being in a forecast or insurance village. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, Irri the amount spent on irrigation, and Labor the amount spent on labor throughout the cropping season. Total is the total amount spent on all inputs, including all previous outcomes and any other costs reported by farmers. All outcomes in Columns 1–5 are in USD. Invest Index is an inverse covariance weighted index of land cultivated, cash crop cultivation, and total input expenditure. It has been excluded from the MHT correction as it is a composite of three outcomes already included. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. Sharpened q-values are adjusted across all outcomes in Tables 3 and 4 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.23: Effect of forecast and insurance takeup on agricultural output

	(1) Prod (Kg)	(2) Value Prod ($)	(3) Yield
Forecast takeup	-20.83**	-657.27*	-7.94
× Ind Bin 1	(9.98)	(346.04)	(5.28)
Forecast takeup	-11.94	-199.74	-0.55
× Ind Bin 2	(8.53)	(264.44)	(4.05)
Forecast takeup	16.96	493.54	0.79
× Ind Bin 3	(12.08)	(450.55)	(4.48)
Insurance takeup	3.03	156.65	-1.75
	(7.79)	(255.27)	(2.88)
q-val Tercile 1	0.209	0.209	0.209
q-val Tercile 2	0.942	1.000	1.000
q-val Tercile 3	1.000	1.000	1.000
Test Tercile 1=3	0.012	0.037	0.163
Test Insur. = Ter. 3	0.262	0.449	0.567
Control Mean	66.91	2419.93	35.37
Observations	1201	1201	1170

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on agricultural output, estimated using an instrumental variables version of Equation (4) where we use an indicator for being in a forecast or insurance offer village as an instrument for forecast or insurance takeup. Prod (Kg) is total agricultural production in kilograms. Crop sold ($) is the total value of crops that were sold in USD. Value Prod ($) is the value of all crops produced in USD, whether they were sold or not, using district median prices for each crop. Yield is kilograms of production per hectare. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.24: Effect of forecast and insurance takeup on agricultural profits

	(1) Ag Profit ($)	(2) Loss ($)	(3) Profit w/ Loss ($)	(4) Ag Profit Non-Flood ($)
Forecast takeup	-484.34*	59.45	-360.30	-447.17
× Ind Bin 1	(283.73)	(164.47)	(390.26)	(541.64)
Forecast takeup	-124.07	236.75*	112.99	-117.11
× Ind Bin 2	(218.77)	(137.60)	(249.83)	(277.83)
Forecast takeup	-33.63	208.87	180.70	593.43
× Ind Bin 3	(377.11)	(166.68)	(411.86)	(590.37)
Insurance takeup	-164.23	223.52**	6.07	561.19
	(207.59)	(104.54)	(238.66)	(419.67)
q-val Tercile 1	0.209	0.315	0.249	
q-val Tercile 2	1.000	0.942	1.000	
q-val Tercile 3	1.000	1.000	1.000	
q-val Insurance				
Test Tercile 1=3	0.322	0.496	0.322	0.208
Test Insur. = Ter. 3	0.731	0.933	0.666	0.962
Control Mean	970.62	661.07	1654.24	970.62
Observations	1201	1201	1201	554

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on agricultural profits, estimated using an instrumental variables version of Equation (4) where we use an indicator for being in a forecast or insurance offer village as an instrument for forecast or insurance takeup. Ag Profit ($) is the value of production (evaluated at district-median prices) less total expenditure in USD. Loss ($) is the value of reported crop losses (evaluated at district-median prices) in USD. Profit w/ loss ($) is the value of production plus the value of crop losses, less total expenditure in USD. Ag Profit Non-Flood ($) is agricultural profits for the sample of households that did not report crop losses due to flooding or cyclones. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.25: Effect of the forecast and insurance takeup on savings, business activity, and welfare

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit	(4) PhQ	(5) Food Cons	(6) Net savings
Forecast takeup	0.07	0.37	94.75	0.17*	0.38	421.96
× Ind Bin 1	(0.05)	(1.07)	(92.38)	(0.09)	(0.78)	(285.42)
Forecast takeup	0.01	0.11	21.71	0.05	1.34**	78.00
× Ind Bin 2	(0.04)	(0.80)	(53.91)	(0.08)	(0.59)	(247.94)
Forecast takeup	-0.05	-1.51*	-33.86	0.00	1.27	159.19
× Ind Bin 3	(0.05)	(0.88)	(98.27)	(0.14)	(0.93)	(285.52)
Insurance takeup	0.10***	1.42	119.14*	-0.01	0.51	-465.43*
	(0.04)	(0.89)	(63.55)	(0.06)	(0.53)	(245.98)
q-val Tercile 1	0.508	0.578	0.508	0.508	0.578	0.508
q-val Tercile 2	1.000	1.000	1.000	1.000	0.169	1.000
q-val Tercile 3	1.000	1.000	1.000	1.000	1.000	1.000
Test Tercile 1=3	0.082	0.180	0.316	0.350	0.438	0.545
Test Insur. = Ter. 3	0.009	0.003	0.181	0.936	0.450	0.053
Control Mean	0.14	1.93	165.51	-0.02	13.22	-1031.41
Observations	1197	1199	1197	1201	1201	1129

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on welfare, estimated using an instrumental variables version of Equation (4) where we use an indicator for being in a forecast or insurance offer village as an instrument for forecast or insurance takeup. Net savings is savings less outstanding debt in USD. Non-Ag Bus. is a dummy for owning a non-agricultural business. Non-Ag Invest is investment outside of agriculture in USD. Bus Profit is business profit in USD. Cons per cap is consumption per household member in USD. PhQ is the standardized score of the PHQ-9 screening tool; higher values are worse. Bins 1–3 indicate the prior tercile for a respondent. Prior bin 1 were the most optimistic, and received bad news. Prior bin 2 had their beliefs more or less confirmed, receiving neutral news. Prior bin 3 received good news. "Test Tercile 1 = 3" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Ter. 3" is the p-value for the test of equality between the third and fourth coefficient. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

E Seasonal climate forecasts

There are two aspects of the Indian Summer Monsoon (ISM) that researchers have attempted to forecast: quantity and timing. The ideal seasonal forecast for an Indian farmer would provide local-level information on the timing (onset) *and* quantity of monsoon rainfall with enough advance notice (e.g., greater than a month) to make decisions about labor and crop inputs. However, from the point of view of the forecaster, timing and quantity are two distinct physical questions and the state of knowledge on each has progressed independently. In the current project proposal, we utilize a timing forecast for reasons explained in the paragraphs below. Before discussing the exact details of that forecast, we provide some general background on the state of monsoon seasonal forecasts that are currently available.

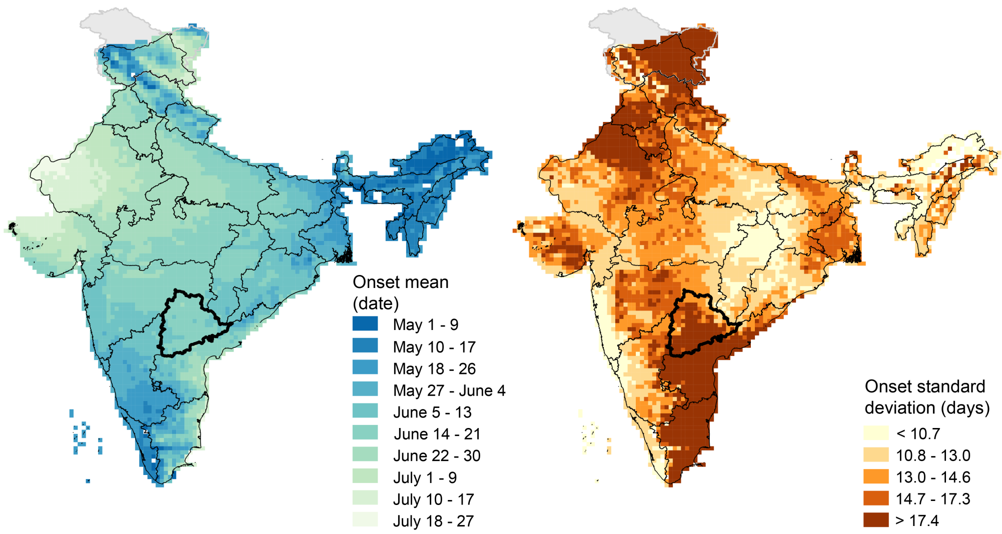
First, we note that there are a range of timescales over which forecasts can be made. In this project, we will focus on longer-term, or seasonal, forecasts, as these are important for large, *pre-season* input decisions. Short-term forecasting, or weather forecasts, typically range from next day to 14-day forecasts of exact weather conditions on a particular day. The accuracy of these forecasts diminishes with time, and the 14-day barrier is a physical limit on how far in advance exact conditions can be predicted. We assume farmers have access to these forecasts, as provided by the Indian Meteorological Department (IMD). Forecasts that attempt to provide information beyond this time horizon present information only about average conditions over a longer period of time than an individual day. Medium-range forecasts extend from 15 to under 30 days, and longer-range or seasonal forecasts attempt to provide information anywhere from 4 weeks to months in advance. The periods about which a forecast are made also tend to be longer, with some typical forecasts projecting changes over an entire month or season (e.g., a "rainier than average month").

Seasonal quantity forecasts have typically been one of the main areas of focus of the IMD which provides forecasts of the expected seasonal total rainfall each year at the beginning of the ISM. These forecasts, many statistical in nature, have traditionally focused on the All-India Rainfall Index (AIRI) (Rajeevan et al. (2007)). One of the most persistent criticisms of the AIRI forecasts is that the AIRI is itself a meaningless spatial average describing a phenomenon that has little spatial coherence (Moron et al. (2017)) and has little relevance to district- or state-level rainfall amounts. In simpler terms, an IMD forecast of "normal" monsoon rainfall amounts indicates nothing about rainfall amounts for a specific farmer in a specific location, rendering it useful for climate science but less useful for development or agricultural policy. More recently the IMD has provided quantity forecasts of particular regions, however, the accuracy is notably of limited use for individual household level decision. IMD's statistical quantity forecasts for large regional areas of India were found to have a low correlation with actual realized rainfall; Rosenzweig and Udry (2019) noted a low ($\sim$0.2) or negative correlation in most of their sample locations. One surprising fact noted by Rosenzweig and Udry (2019) is that despite this low forecast accuracy, it does apparently lead to some changes of behavior among institutional investors. IMD and other agencies have also begun some experiments with dynamical (i.e., physics-based) models of the monsoon, but such forecasts similarly aim to forecast AIRI, rendering them uninformative for local decisions, though they do show some skill nationally (Das et al. (2015)).

Seasonal timing forecasts typically deal with the "onset" of the monsoon. While the monsoon arrives in early–mid June on average, uncertainty over monsoon onset is high: between 1979 and 2019, the standard deviation of the onset date was approximately 20 days. Appendix Figure E.1 plots information about the monsoon onset over India, with Telangana outlined in black. IMD forecasts the onset only over one part of the country— 'monsoon onset over Kerala" (MOK)— which is not relevant for most of the country, and forecasts with only two weeks of advance notice. There is no local IMD monsoon onset forecast, and MOK has been the subject of much of the research on onset timing and forecasting (e.g., Preenu et al., 2017). Crucially, for the current study, the monsoon does not progress smoothly northwards - it frequently halts, and local false starts are common, implying that MOK carries no signal for a farmer in parts of India outside of a narrow strip of coastal Kerala. Moron and Robertson (2014) define local agronomic onset and demonstrate the correlation between MOK and local onset over India. In Appendix Figure E.2, they show that there is virtually no signal value of MOK[44] in any region in India other than Kerala.

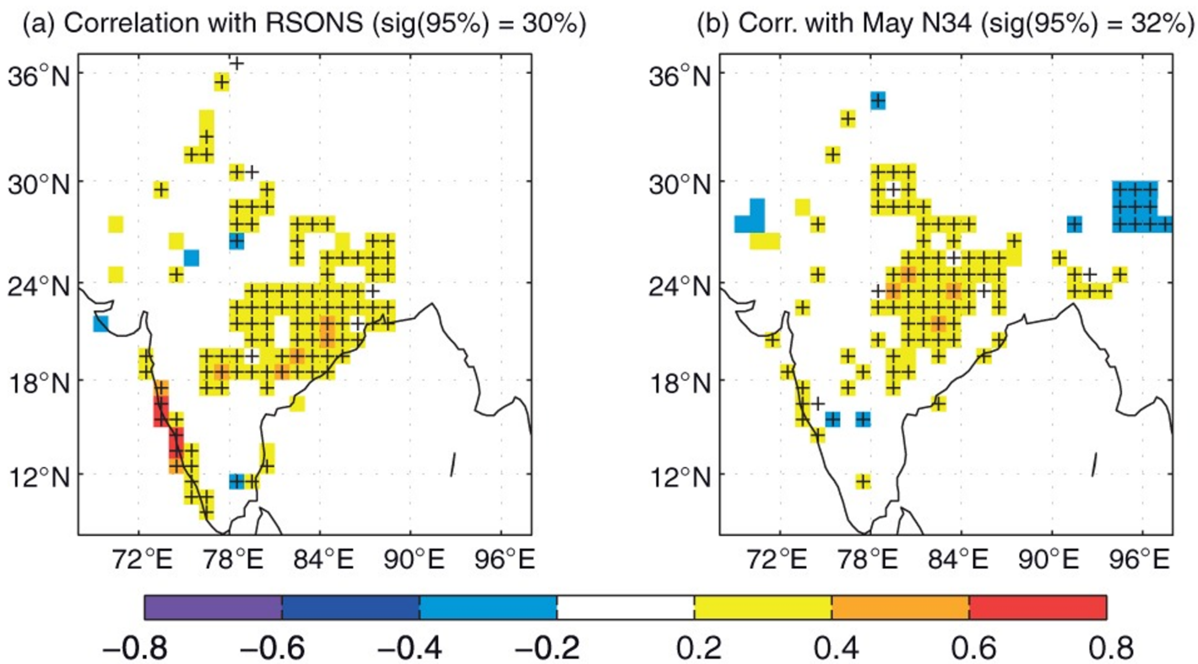
[44]In the paper, the authors define regional-scale monsoon onset (RSONS) as a summary measure of a number of onset indices over Kerala, which has a correlation of 0.92 with MOK (Moron and Robertson, 2014).

Figure E.1: Monsoon onset over India



Notes: The left panel shows the average monsoon onset day (in day-of-year) for the period 1979-2019 across India. The right panel shows the standard deviation of onset for the period 1979-2019. Local onset timing is derived following Moron and Robertson (2014), and captures the timing of the first wet spell of the season that is sufficient to wet the topsoil enough to plant crops and is not immediately followed by a dry spell (in which case it is known as a “false start”). In both panels, grid cells are 0.25 degrees. Telangana, the location of our experiment, is highlighted with a thick black border.

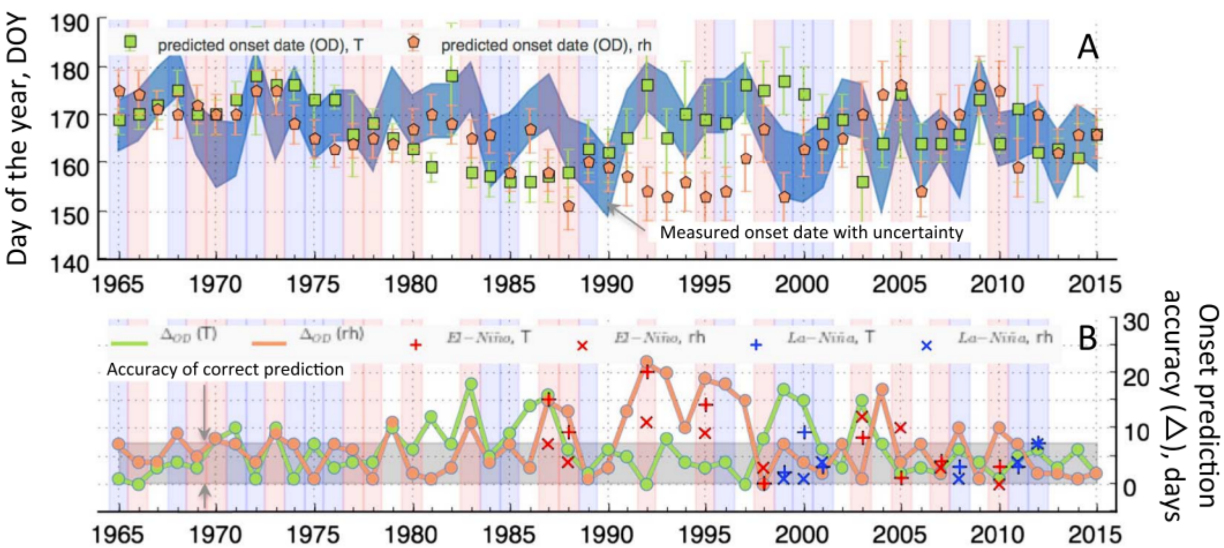
Figure E.2: Monsoon onset over Kerala has limited predictive power elsewhere in India



Notes: (a) Correlations between local-scale onset and the index of regional-scale onset (RSONS) defined in the text. (b) Correlations between local-scale onset and the Niño 3.4 SST index (N34) in May. Crosses indicate statistically significant correlations at the two-sided 95% level (see text). The value in parenthesis gives the fraction of significant grid boxes at the two-sided 95% level of significance according to a random-phase test. *Reproduced from* Moron and Robertson (2014).

In the present study, we focus on onset forecasts for two reasons. First, there is clear demand for information on timing: Mobarak and Rosenzweig (2014) demonstrate that onset timing is a key risk in farmers' decisions, with 40% of farmers opting to insure against the risk of a *delayed monsoon onset* when randomly offered such a product. Second, there has been a clearly dominant innovation in local onset forecasting, while there is no quantity forecast at local scales that is less uninformative than is currently available. A new model developed by the Potsdam Institute for Climate Impact Research (PIK) (Stolbova et al., 2016) uses observations of climate variables in the months leading up to the beginning of the monsoon to predict the timing of the onset of the monsoon up to one month in advance for a specific region of India and identifies a method for expanding this to other local regions. This forecast substantially outperforms the IMD forecasts that were analysed in Mobarak and Rosenzweig (2014), but is not yet widely available to farmers who might benefit from the information. The output from the PIK model is a probability distribution of potential onset dates of the monsoon for a range of states over the Eastern Ghats with particular accuracy over Telangana. When evaluated for onset dates from 1965-2015, this new scheme was "correct", defined

Figure E.3: The PIK forecast is accurate



Notes: Monsoon OD and prediction based on temperature (green) and relative humidity (orange) and measured (dark blue) (a) Onset date (OD) validated against NCEP/NCAR data. Red and light blue shading indicates positive ENSO (El Niño) and negative ENSO (La Niña) years. (b) Also shown is the difference between the real onset and predicted dates in days. Grey shading indicates range of 7 days, within the prediction is considered accurate (absolute value of the difference between the real onset date in a given year and the predicted onset date). *Reproduced from panels A and B of* Stolbova et al. (2016).

as local onset falling within ±7 days of the predicted date, 73% of years in the sample.[45] Moreover, while MOK date is forecast only two weeks in advance of the average MOK date, the PIK forecast is issued 35 days in advance of the average onset date in Telangana.

[45]Stolbova et al. (2016) also predicts withdrawal dates with 8 weeks lead-time and shows 84% of years falling within ±10 days of the actual withdrawal date.

F Panel analysis of effect of onset timing on crop yields

This section describes a supplementary observational analysis used to support two main implications of the paper's findings:

1. An earlier monsoon is beneficial for crops
2. A later monsoon harms cash crops (e.g., cotton) more than staples (e.g., rice)

We describe the data and analysis used to explore these two implications at a national level in India.

F.1 Data

Precipitation Data We use the European Centre for Medium Range Weather Forecasting (ECMWF) Reanalysis dataset (ERA5) to obtain daily precipitation data. We convert data from UTC to local time by implementing standard time zones. We are aware of the existing bias in ERA-5 rainfall dataset that leads to overestimation of monsoon precipitation in some parts of India and underestimation in other regions (Mahto and Mishra, 2019). In the methodology section we discuss how we attempt to overcome this.

Agriculture data Crop data are obtained from the Ministry of Agriculture and Farmers Welfare in India. The dataset contains district-wise, season-wise production, harvested area (in ha) of each crop, and corresponding yield. Outcomes are available for a number of seasons – kharif, rabi, whole year, winter, autumn and summer – and we focus on the Kharif season. We use data from 2001-2018 and aggregate districts at the level of the 2001 Census of India.

We cannot be sure that each observation is assigned to the right season, since summer, autumn and winter seasons are hard to interpret. However, they only constitute approximately 12% of all observations, and we choose to drop these from the data. Many district-crop-season panels are not balanced, and we include an additional specification that only takes a subset with balanced district-crop-season panel observations.

F.2 Methods

F.2.1 Monsoon onset definition

The India Meteorological Department (IMD) annually reports an official monsoon onset date that mostly reflects the start of the raining season over Kerala. As we focus on district-level effects of the monsoon onset variation and the onsets do not happen simultaneously over the country, we need to define local onsets for each region. While there is no unified definition of local monsoon onset and withdrawal in the literature, we chose to define them according to Moron and Robertson (2014).

Monsoon onset is defined as "the first wet day ($\geq$ 1 mm) of the first 5-day wet sequence from April 1st that receives at least the 5-day wet spell interannual mean in April – October for that pixel". To avoid cases when a wet spell is followed by drought, the onset cannot be followed "by a 10-day dry spell (receiving less than 5 mm) in the following 30 d from the onset." As the main specification, we use the original definition of onset but increase the first day threshold from 1mm to 4mm. This is due to the fact that Moron and Robertson (2014) used a different dataset, which is not publicly available. We decided to tune parameters in their algorithm and used produced various other newly defined onsets as robustness checks. We use this 4mm definition to produce figure E.1. We now state the algorithm in detail:

0: Denote a unique observation as p_{idy} for pixel i on day d in year y with units of mm per day.

I: For all April-October observations check if they can potentially be "the first wet day" observations: check if $p_{idy} \geq 4$. Denote them $p^*_{i^*d^*y^*}$.[46]

II: For each potential "first wet day" check if the subsequent 5-day wet sequence "receives at least the climatological 5-day wet spell amount": check if

$$\sum_{k=0}^{4} p^*_{i^*,d^*+k,y^*} \geq \frac{1}{N} \sum_{y}^{Y} \sum_{d=Apr,1}^{D=Oct,27} \sum_{k=0}^{4} p_{i^*,d+k,y},$$

where N is the number of all day-year pairs. In other words, for each pixel, we check if 5-day wet spell is greater or equal than the average 5-day April-October spell in all years.

III: For each potential "first wet day" check if the subsequent wet spell is not interrupted by a 10-day dry spell (receiving less than 5 mm) in the following 30 days from the onset: check if

$$\min_{j \in \{0,\dots 20\}} \sum_{k=0}^{9} p^*_{i^*,d^*+k+j,y^*} \geq 5$$

IV: Choose a subset of observations $p^*_{i^*d^*y^*}$ for which inequalities from *Step II* and *Step III* hold. Now, for each year-pixel pair we can take its own subset and we denote monsoon onset as the smallest d among this subset. If the subset is empty, we say that monsoon is not defined.

[46] The asterisk denotes a constant, not a parameter.

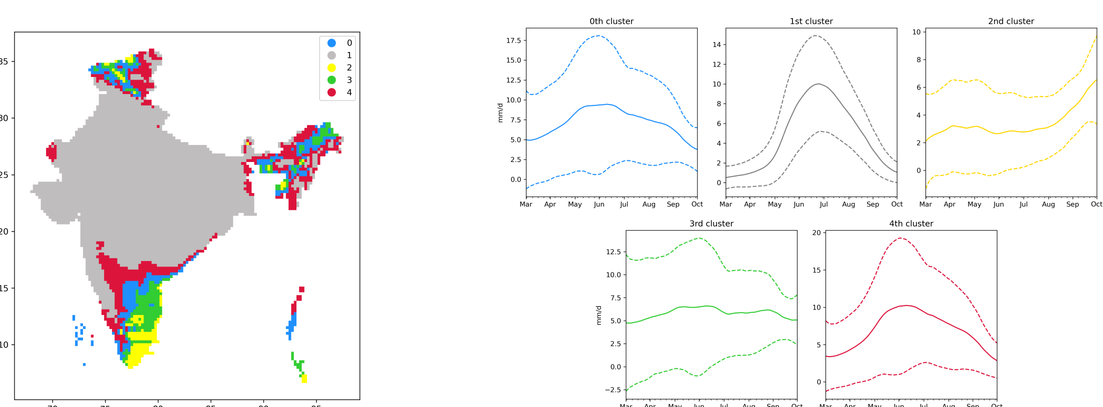
Finally, we align onset dates with agricultural data that is on district level. To do so, we calculate area-weighted averages of dates in pixels that intersect, fully or partially, with each district. For the following analysis, each district's onset date is standardized according to the district-specific mean and variance of the onset.

F.2.2 Regions clustering

In so-called monsoonal regions we expect no rainfall in pre- and post-monsoonal periods. However, the rest of the regions may have various patterns ranging from almost no rainfall throughout the year to constant heavy rains. This results in the need to distinguish between monsoonal regions and non-monsoonal regions. We use k-means clustering of low-pass filtered daily mean precipitations EOFs to categorize these differences from the precipitation data.

We first apply a low-pass recursive first-order filter with a cutoff of $\frac{1}{30}$ to gridded daily precipitation data. We use the Butterworth filter, but monsoonal area is mostly robust to the choice of a filter. Second, we standardize filtered data to zero mean and unit variance. Third, we find a leading empirical orthogonal function (EOF) for standardised filtered data for each pixel. Finally, we run a standard k-means clustering algorithm on these data. We use 5 clusters following Moron et al. (2017) but monsoonal area is mostly robust if we decrease the number of clusters. Figure F.1 shows results of k-means clustering on a grid level and the low-passed averaged rainfall of all points inside the cluster (in mm/d) with ± 1 standard deviation. Based on these patterns, we decide to treat either grey areas or grey and red areas as monsoonal.

Figure F.1: Results of k-means clustering



Notes: Left panel shows the results of the k-means clustering of Indian rainfall regimes into 5 different clusters . Right panels show the average rainfall pattern during the Kharif season for these clusters, with the strong seasonal pattern in rainfall seen only for the red and grey clusters.

F.2.3 Econometric strategy

We restrict our analysis to rice and cotton, which represent the most common staple crop and cash crop, respectively, in our experimental data. We estimate the following equation:

$$Log(yield_{it}) = \beta Onset_{it} + \alpha_i + \theta_j \times \gamma_t + \varepsilon_{it},$$

where $Log(yield_{it})$ is the logged yield of either rice or cotton in district i and year t, $Onset_{it}$ is the standardized onset date of a monsoon in district i and year t during the Kharif season, α_i are district fixed effects and $\theta_j \times \gamma_t$ are state-specific time trends for state j in year t. As a straightforward robustness check we use year fixed effects instead of state-specific time trends. Standardizing onset dates allows us to measure the effect of a relatively early or late onset in each district and to control for district-specific interannual variance of onsets. Thus, β will measure the relationship between one standard deviation in onset date and percentage change of harvested area.

F.3 Results

Table **??** shows the results for the effect of monsoon onset on yields for rice (panel A) and cotton (panel B). We note two main conclusions. First, we observe that a later monsoon negatively affects yields of both crops – a one standard deviation later monsoon onset within a district leads to, in column (3), a negative coefficient estimated in each panel. Second, a one standard deviation later monsoon negatively affects cotton approximate 2-3 times as badly as it does rice. This latter result lends support to our experimental finding that an onset that is earlier than expected will lead to farmers switching towards cotton, a notable cash crop.

G Becker et al. (1964) appendix

To elicit WTP for the given product, we use a Becker et al. (1964) (BDM) mechanism. We explain a two-step procedure to the household. In the first step, the household states their WTP. Then, the enumerator reveals an INR value written on the tablet. If the value listed on the tablet is above the household's stated WTP, the household does not get to purchase the product and their cash is returned. If the value is below the household's WTP, the household purchases the product and the cash goes to the enumerator. 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 (e.g., a bar of soap). Therefore, any misunderstanding about the process will be resolved before the BDM procedure for the product of interest (i.e., the forecast or insurance) is started.

G.1 Methodological overview

The BDM mechanism 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 Berkouwer and Dean (2022):

1. Prior to the baseline visit, we assign each participant a random BDM price drawn from either the forecast or insurance distribution of BDM prices (described below).

2. Each enumerator is then given a sealed envelope that contains that BDM price (in INR) 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 places the sealed envelope so that participant can see it.

4. Beginning with a starting price of INR 500 for both the forecast and insurance, 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 envelope said the price was INR 500, would you choose to purchase the forecast / insurance?

   i. If yes: If the envelope said the price was INR 1,000, would you choose to purchase the forecast / insurance?

      A. If yes: If the envelope said the price was INR 1,500, would you choose to purchase the forecast / insurance?

         - Etc.

      B. If no: If the envelope said the price was INR 1,250 would you choose to purchase the forecast / insurance?

         - Etc.

   ii. If no: If the envelope said the price was INR 250, would you choose to purchase the forecast / insurance?

      A. If yes: If the envelope said the price was INR 375, would you choose to purchase the forecast / insurance?

         - Etc.

      B. If no: If the envelope said the price was INR 125, would you choose to purchase the forecast / insurance?

         - Etc.

At the end of this process, the enumerator confirms that the participant fully understands their decision and the consequences of once the envelope is opened. They then ask that the participant retrieves the agreed upon amount in cash and place the bank notes next to the envelope containing the price. Finally, they will allow the participant a final chance to change their mind before the envelope is opened.

5. Once the participant has confirmed the price and has placed the cash, the participant and the enumerator together open the envelope and reveal the price.

6. If the participant's maximum WTP is lower than the BDM price in the envelope, the participant will not be able to purchase the forecast / insurance and will instead take back their cash.

7. If the participant's maximum WTP is at least as high as the BDM price in the envelope, the participant purchases the forecast / insurance, paying the price that was written inside the envelope out of their cash.

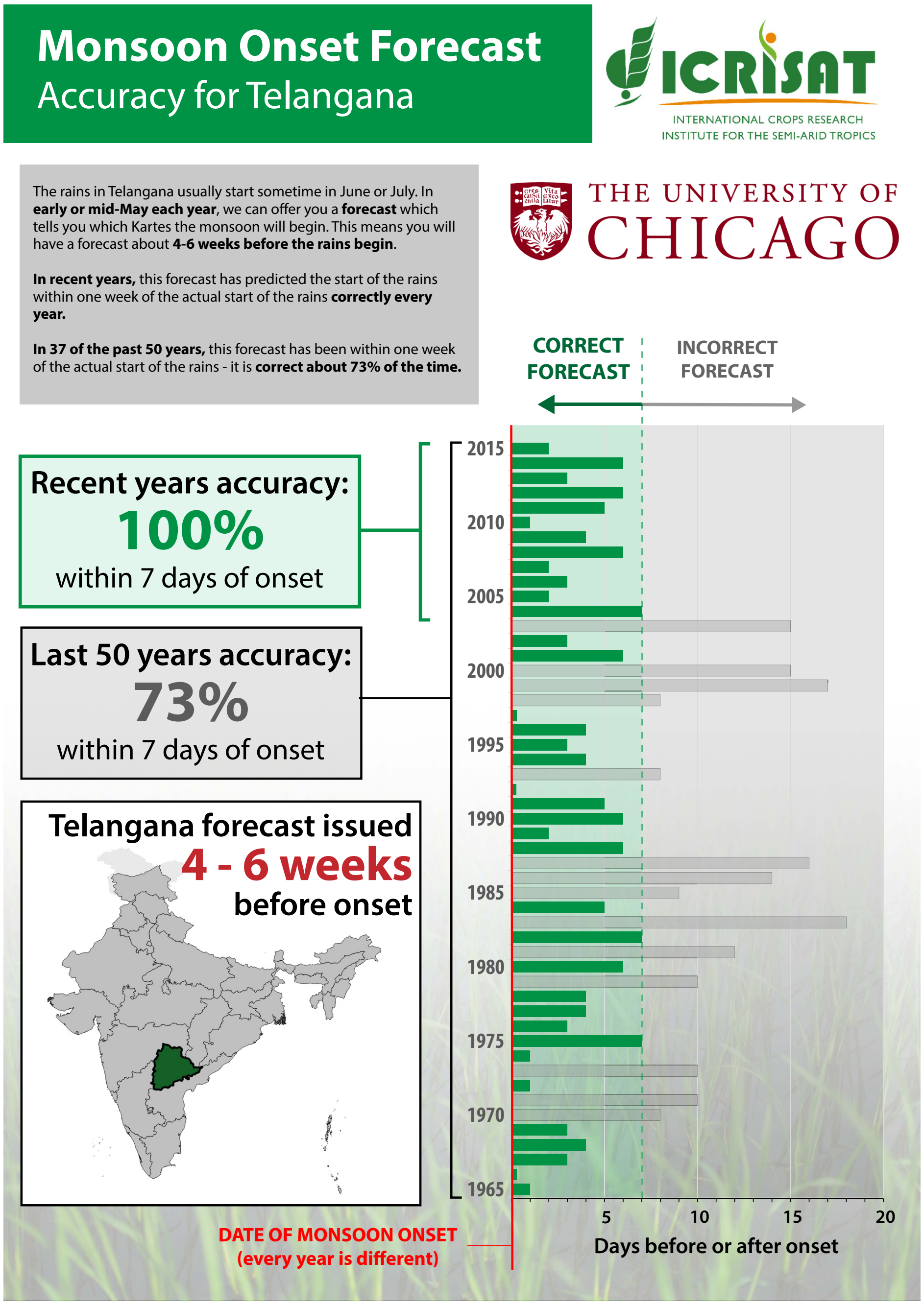
G.2 Distribution of BDM prices

We set the distribution of BDM price draws to low values so that nearly all farmers with positive willingness to pay will ultimately purchase the forecast or insurance product. In this way, we will increase power by maximizing adoption of each product without compromising the incentive compatibility of the BDM procedure. To this end, neither the participants nor the enumerators will be informed about the underlying price distribution. We choose the following distributions for each product:

- For the forecast product, 95% of participants will receive a price of zero while the remaining 5% of prices will be drawn from a uniform distribution ranging from 1 to 100 INR.
- For the insurance product, 95% of participants will receive a price of zero while the remaining 5% of prices will be drawn from a uniform distribution ranging from 1 to 100 INR.

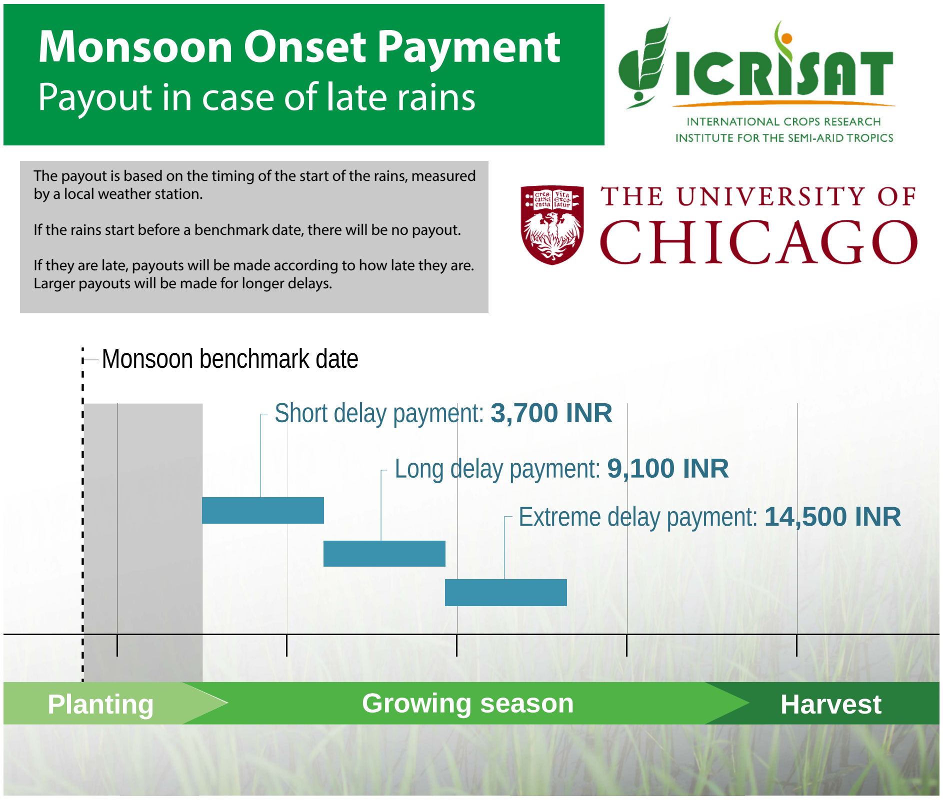
H Information sheets

Figure H.1: Forecast information sheet



Notes: We provided farmers with this information sheet about the forecast when offering them the product through the BDM mechanism described in Section 4 and Appendix G.

Figure H.2: Insurance information sheet



Notes: We provided farmers with this information sheet about the insurance product when offering them the product through the BDM mechanism described in Section 4 and Appendix G.