The value of forecasts: Experimental evidence from India

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Abstract

Unpredictable weather makes it challenging for households and firms to make optimal investment decisions. Technologies that reduce these risks are crucial for climate change adaptation. We experimentally evaluate one such technology – an accurate, localized, early monsoon onset forecast – in India, randomizing 250 villages into control, forecast, or insurance. The forecast changes farmers' beliefs about the coming growing season. In response, forecast farmers adapt their behavior along multiple margins, changing cultivated area, crop choice, farm input expenditure, and off-farm business. By enabling farmers to tailor their investments to coming weather, forecasts reduce farmers' risk exposure and increase aggregate welfare.

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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). This presents a critical challenge for households and firms, as uncertainty about upcoming climatic conditions makes it difficult to optimally invest in income-generating activities. This challenge is fundamental to agriculture, as farmers must make on- and off-farm input decisions before weather – a key but stochastic determinant of farm output – is realized. Weather risk in agriculture is particularly acute in low-income countries, where farmers have limited access to risk-coping technologies such as insurance (Cole and Xiong, 2017) and are expected to bear the brunt of climate change (Carleton et al., 2022; Hultgren et al., 2025).

Technologies that help households and firms tailor their investments to the weather, thereby reducing their risk exposure and improving overall well-being, could therefore be an enormously valuable form of climate change adaptation (Carleton et al., 2024). Localized long-range (or "seasonal") forecasts, which provide information about broad climatic conditions well in advance, are a promising technology in this vein. In theory, and in contrast to short-range (e.g., day- or week-ahead) forecasts, long-range forecasts enable households and firms to tailor their investment decisions to the upcoming season. These forecasts are particularly promising in agriculture, where farmers require advance information to make non-marginal adjustments to key farm inputs and to decide how much to invest in off-farm activities (Gine et al., 2015).[1] While these forecasts could enable substantial behavior change (FAO, 2019), their use is not widespread, because forecast information is a public good, under-provided by the private market (Stiglitz, 1999), because forecast dissemination in low-income countries has traditionally been poor (Yegbemey and Egah, 2021), and because producing a seasonal forecast that is accurate enough to impact agricultural decisions is an extremely challenging climate science problem (Mase and Prokopy, 2014; Wang et al., 2015; Rosenzweig and Udry, 2019).

In this paper, we use a cluster-randomized experiment to estimate the causal effects of a novel long-range forecast of the onset of the Indian Summer Monsoon, produced by the Potsdam Institute for Climate Research (Stolbova et al., 2016). We conduct our experiment in Telangana, India, where farmers are highly dependent on the monsoon. Reliance on monsoon rains is far from unique to Telangana: nearly two-thirds of the global population lives in monsoonal climates (Wang et al., 2021), whose weather patterns are expected to become more variable under climate change (Katzenberger et al., 2021; Prabhu and Chitale, 2024). Monsoonal regions are characterized by a rainy season where the bulk of farm production occurs and a less-productive dry season. We use 25 years of historical data from India to demonstrate that the *timing* of the onset of the monsoon, even holding total rainfall fixed, has meaningful impacts on agricultural production: delayed monsoon onset reduces crop yields on average and for cash crops in particular.

[1] While research on short-range forecasts documents some benefits to farmers (Fosu et al., 2018; Fabregas et al., 2019; Rudder and Viviano, 2024; Surendra et al., 2024, 2025), these forecasts cannot inform key seasonal decisions like crop choice or land use.

The forecast we use has a series of advantages: it is extremely accurate, contains agriculturally-relevant information, and can be provided to farmers well in advance of the monsoon's arrival, making it an improvement over previously-available onset forecasts.[2] Released about 40 days before monsoon onset, the forecast arrives early enough for farmers to make non-marginal changes in key farm inputs such as land use and crop choice (Gine et al., 2015), as well as deciding how much to engage in non-agricultural business – two key climate adaptation strategies. This forecast has particular accuracy over Telangana: in this region, the forecasted onset date was accurate to within one week in each of the past 10 years prior to our experiment, and validation exercises suggest it has an overall accuracy of approximately 73%. For forecast dissemination, we partner with the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), a respected international organization based in India, to ensure that farmers view the forecast as credible.

We randomize 250 villages in Telangana into a control group, a group that is offered the forecast, and a group that is offered a monsoon onset index insurance product (modeled on Mobarak and Rosenzweig, 2014), which serves as a benchmark. The forecast reduces risk by providing farmers with information about the quality of the upcoming growing season, allowing farmers to tailor investments to the coming weather conditions. In contrast, insurance – the canonical risk-coping instrument – enables farmers to shift consumption across states of the world but provides no information about the upcoming season, making it a useful comparison. We sample 5-10 farmers per village, and all farmers in a village receive the same treatment.

We ask and answer four main research questions, summarizing our main results in Figures 4 and 5. First, does the forecast change farmers' beliefs about monsoon onset? Farmers update their beliefs in response to our forecast. After receiving the information, farmers in forecast villages have posterior beliefs about the monsoon onset date that are 26% (p-value 0.031) closer to the forecasted onset date than farmers in control villages.

Second, how do farmers adapt their agricultural input decisions in light of the forecast, and does this translate into changes in farm output? To generate predictions, we develop a simple theoretical model which shows that farmers' behavioral responses to a forecast should depend on their prior belief about monsoon onset timing.[3] In order to take the theory to data, we pre-specified heterogeneous treatment effects by farmers' prior beliefs about monsoon onset. In our main specification, we divide farmers by prior belief tercile into early-, middle-, and late-prior farmers – though our results are robust to using a linear interaction between priors and treatment and to alternative bins. Helpfully from a research perspective, the forecast in our study year was for an average monsoon, creating ideal conditions to estimate heterogeneity according to farmers' prior beliefs. Our historical analysis demonstrates that later monsoon onset is associated with worse agricultural outcomes, particularly for cash cropping. As a result, our theory predicts that

[2] The only widely available monsoon forecast in this setting is from the Indian Meteorological Department (IMD), which predicts onset over Kerala—a region whose monsoon timing has been shown to be largely uncorrelated with the rest of India (Moron et al., 2017).

[3] In our data, we find substantial heterogeneity in farmer priors. Though location explains some of these differences, 46% of the total variation in mean prior remains after removing village fixed effects.

as compared to their control-group counterparts with similar priors: (i) early-prior forecast farmers who are told that the coming monsoon will be *later* (and therefore worse) than they expected should invest less in agriculture; (ii) middle-prior forecast farmers who are told that the coming monsoon will *align* with their expectations should not change their behavior; and (iii) late-prior forecast farmers who are told that the coming monsoon will be *earlier* (and therefore better) than they expected should increase overall farm investment and engage in more cash cropping. In all three cases, we expect the forecast to improve farmers' input decisions by enabling them to tailor their farm investments to the coming monsoon.

Our results are remarkably consistent with these predictions. Using a standardized agricultural investment index, we find that early-prior and late-prior farmers respond in opposite ways to the forecast (p-value on the difference: 0.000), which we confirm with a linear interaction between forecast and prior beliefs. We see suggestive evidence that early-prior farmers reduce investment by 0.08 SD relative to farmers with similar priors in the control group (p-value 0.256); we see no impact on middle-prior forecast farmers' investments; and late-prior forecast farmers increase agricultural investment by a standardized effect of 0.31 SD (p-value 0.001) relative to the control. Breaking the index into its constituent components, we find that the forecast leads early-prior farmers to meaningfully reduce land under cultivation (-22% of the control mean, p-value 0.003), with a point estimate suggesting an approximately 10% decline in farm expenditure (p-value 0.417). Middle-prior forecast farmers do not alter their investments. Late-prior forecast farmers considerably increase both land under cultivation (21%, p-value 0.061) and total expenditure (31%, p-value 0.017), and are 33% more likely to plant cash crops than control farmers with similar priors (p-value 0.005). We reject equality between early- and late-prior forecast farmers for land under cultivation (p-value 0.001), cash cropping (p-value 0.032), and total expenditure (p-value 0.019), confirmed in the linear specification. These results demonstrate that farmers tailor their investments to the forecast in ways that should make them better off: early-prior farmers avoid investing too much in agriculture during a worse-than-expected season, and late-prior farmers take advantage of a better-than-expected season by investing more than they would have otherwise.

On average, treatment effects on agricultural outputs should generally align with these on-farm investment changes, such that lower investments should reduce agricultural output, while higher investments should lead to increases in farm production. We find evidence that this is the case. Compared to control farmers with similar priors, early-prior forecast farmers have 25% lower agricultural output (p-value 0.039), with 22% lower market value (p-value 0.060), in line with these farmers' reduction in land under cultivation. Middle-prior forecast farmers experience no change in agricultural output, consistent with their (lack of) input response. While imprecisely estimated, late-prior forecast farmers increase their agricultural output by 22% (p-value 0.187), and the value of their output by 16% (p-value 0.348), which is also in line with their investment effects. We find significant differences between early- and late-prior forecast farmers for production (p-value 0.017; also significant in the linear specification) and value of production (p-value 0.056), highlighting meaningful heterogeneity in farm outcomes to the forecast by prior beliefs.

We find an incomplete mapping between agricultural inputs and farm profits. This is perhaps expected, as agriculture is inherently a stochastic process, and investments will not always map directly into profits (Rosenzweig and Udry, 2020). Though onset timing is an important determinant of crop yields, shocks during the growing season – such as extreme rainfall or drought – that are unrelated to the forecast can nonetheless disrupt farm profit. In our context, we find that early-prior forecast farmers have even lower farm profits (-\$400, or -40%, p-value 0.089) than would be implied by their input changes under a one-to-one mapping between inputs and profits. We see no statistically significant impacts on middle- or late-prior forecast farmers, and the late-prior forecast farmer point estimate in particular is quite close to zero (-\$65, or -6%, p-value 0.850). We investigate this further and find that heavy flooding – outside of the scope of the forecast – hit Telangana in early July (Business Line, 2022). Flood exposure is balanced across our treatment arms. In a non-prespecified exploration, we find a pattern of results that suggests that these shocks may have broken the correspondence between inputs and profits. We find much larger crop losses for late-prior forecast farmers than for early-prior forecast farmers, consistent with the former group planting more valuable crops. Using a counterfactual measure of farm profits which accounts for these losses, or restricting the sample to the 46% of farmers who were *not* affected by floods, we see farm profit reductions for early-prior forecast farmers, small impacts for middle-prior forecast farmers, and farm profit increases for late-prior forecast farmers – more consistent with our observed input changes.

Third, how do farmers adapt their non-agricultural business activities in response to the forecast? In principle, farmers could use the forecast to decide how much off-farm work to engage in. Whether farmers should increase or decrease off-farm activity is ambiguous, and depends on whether off-farm work is complimentary to or substitutes for agriculture. Early-prior forecast farmers, who are told that the growing season will be later (i.e., worse) than expected, increase non-farm business operation by 43% (p-value 0.155), while late-prior forecast farmers, who are told that the growing season would be earlier (i.e., better) than expected, decrease business operation by 36% (p-value 0.222). This pattern is mirrored in non-agricultural investment and business profits. Early-prior forecast farmers increase investment by 17% (p-value 0.713), translating into an \$80 increase in business profits (p-value 0.293). In contrast, late-prior forecast farmers reduce business investments by 78% on average (p-value 0.073), with a corresponding reduction in business profits of \$44 (p-value 0.628). We reject equality between early- and late-prior forecast farmers for business operation (p-value 0.060), but not for non-agricultural investment (p-value 0.130) or business profits (p-value 0.268). In the linear specification, the interaction with prior beliefs is significant for all three outcomes. These patterns are consistent with forecast farmers treating non-agricultural businesses as a substitute for farming.

Fourth, how does the forecast ultimately impact farmer well-being? Theory predicts that forecasts should (weakly) increase welfare for *all* farmers, as accurate information allows everybody to tailor their on- and off-farm investments to the coming state regardless of their prior beliefs. We therefore estimate welfare impacts pooled across priors. We find that forecasts increase per-capita food consumption by 7% (p-value 0.040). While imprecise, our estimates imply asset value and net savings increase, but there is no change in livestock holdings or non-food consumption. We summarize these results in an index, estimating an overall welfare improvement of 0.06 SD (p-value 0.048). To put our results in context, though the precise components of the welfare indices differ across study, our welfare effect falls between that of emergency loans (Lane, 2024, 0.02 SD) and that of irrigation access (Jones et al., 2022, 0.11 SD).

As a final exercise, we compare the impacts of the forecast to those of index insurance. First, we replicate the well-established finding that index insurance leads farmers to increase investment (Karlan et al., 2014), and show that the magnitude of this effect is comparable to the (absolute) changes we observe in the forecast group. Therefore, the forecast, which can be provided at very low cost, has economically meaningful effects on farmer behavior that are on par with a widely used, but costly to implement, risk-coping tool. Second, we use this treatment arm to reiterate a key advantage of the forecast: it enables farmers to tailor their investments to the upcoming growing season, something insurance cannot do. Consistent with our model, we find that the increased investment in the insurance group is driven by early-prior farmers, who, had they instead received the forecast, would have been told that the coming season was worse than they were expecting and reduced their investments. In contrast, late-prior farmers, who would have been told that the coming season was better than expected by the forecast and therefore increased their investments, do not respond to the insurance treatment.

Taken together, our results demonstrate that long-range monsoon forecasts can help farmers cope with increasing weather risk in a changing climate. This study therefore makes three primary contributions. First, by demonstrating that forecasts enable farmers to tailor their on- and off-farm investments to the coming growing season, thus reducing risk and improving overall welfare, we contribute to a growing literature on climate change adaptation in low-income countries. Large climate adaptation gaps exist in poor countries, which are disproportionately exposed to climate change (Carleton and Hsiang, 2016; Hsiang et al., 2017; Hultgren et al., 2025). Though climate adaptation can take many forms, technologies which reduce risk, rather than shifting utility across states, may be particularly valuable and remain understudied (Carleton et al., 2024).[4] We show that forecasts effectively reduce risk for farmers, increasing welfare. While a small number of other studies have examined the role of risk reduction tools in the face of climate change such as irrigation (Jones et al., 2022) and flood-, drought-, or salinity-tolerant seeds (Emerick et al., 2016; Boucher et al., 2024; Patel, 2024), these past approaches (i) require farmers to adopt new technologies, which has proven difficult in low-income contexts (Duflo et al., 2008), and/or (ii) lock farmers in, reducing risk along a single margin alone (e.g., improving yields for rice, but not other crops). In contrast, forecasts address the fundamental challenge that farmers must make decisions before the weather is realized, allowing them to tailor a wide range of inputs to the state. We show that forecasts lead farmers to adapt in a variety of ways, both adjusting their agricultural investments and shifting

[4] As reviewed by Carleton et al. (2024), climate adaptation can take many forms, but adaptation approaches which directly reduce risk are relatively few and far between.

into non-agricultural work.

Second, our study contributes the first experimental evidence of the impact of an accurate, localized, long-range monsoon forecast on farmer behavior. The limited prior work on forecasts is mainly concentrated in the U.S., where trust in information systems is much higher (Gibson and Mullins, 2020; Shrader, 2023; Shrader et al., 2023; Downey et al., 2023), and/or studies short-range forecasts that only allow for more marginal adaptive responses (Fosu et al., 2018; Fabregas et al., 2019; Yegbemey et al., 2023; Rudder and Viviano, 2024 in agriculture, Molina and Rudik, 2023 for hurricanes, and Ahmad et al., 2023 for pollution). In contrast, we experimentally evaluate the impact of long-range forecasts in a population that is highly vulnerable to climate, and find that the forecast has substantial impacts on farmers' decision-making, raising welfare. In doing so, we build directly on work by Rosenzweig and Udry (2019), who use a farmer fixed-effect design to study the Indian Meterological Department's (IMD) forecast of monsoon rainfall *quantity*, and argue that while the IMD's forecast has remarkably low accuracy, accurate long-range forecasts of the monsoon would have the potential to generate very large welfare gains. In contrast, we causally identify the impact of an accurate forecast. Crucially, we also identify a key determinant of farmer responses to the forecast: prior beliefs.[5] We measure farmer priors over the upcoming monsoon's onset, and document that our treatment causes farmers to update their beliefs in the direction of the forecast. These changes in beliefs map directly to changes in both investments and outcomes by enabling farmers to tailor their behavior to the coming monsoon season. These findings demonstrate the value of considering prior beliefs in estimating the impacts of information.

Finally, we demonstrate that forecasts reduce farmers' exposure to weather risk, which has been linked to underinvestment in profitable technologies (Rosenzweig and Binswanger, 1993) and therefore to the agricultural productivity gap between low- and high-income countries (Donovan, 2021). This builds on the prior work in this area that been focused on addressing missing markets for insurance (Lybbert and Sumner, 2012; Karlan et al., 2014; Cole and Xiong, 2017; Carter et al., 2017) and credit (Lane, 2024). Forecasts require minimal financial infrastructure, can be distributed widely at low cost, and effectively change farmer behavior and improve well-being, making them a promising complement to standard agricultural risk-coping tools.

The remainder of this paper proceeds as follows. Section 2 describes the context, and shows the impact of monsoon onset on crop yields. Section 3 presents a theoretical model of farmer decision-making under risk. Section 4 describes our experimental design. Section 5 presents our results on beliefs, and Section 6 presents our results on agriculture, off-farm business and welfare. Section 7 compares forecasts to insurance. Section 8 concludes.

2 Research context

Two thirds of the global population, including most of India, lives in a monsoonal climate (Wang et al., 2021), characterized by an intense wet season during which most of the year's rain falls and

[5]In doing so, we add to a literature on the importance of environmental beliefs for decision-making, including Gine et al. (2015); Kala (2019); Zappalà (2023, 2024), and Patel (2024).

a dry season with limited precipitation. The main agricultural season takes place during the rainy season. Monsoon onset, which starts the rainy season, is highly variable (Appendix Figure H.1), and has historically been difficult to predict for both climate scientists and farmers.

2.1 Historical impacts of monsoon onset timing on agricultural yields

We first provide motivating evidence on 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 rainy-season (kharif) agriculture across India to show both that monsoon onset delays negatively impact crop production, even conditional on total rainfall.[6] These damaging impacts are substantially worse for cotton, a key cash crop in our setting, than for rice, a key staple crop.

We use district-level yield data across the country from the Indian Ministry of Agriculture and Farmers' Welfare and the ERA-5 daily gridded precipitation data from the European Centre for Medium Range Weather Forecasting Reanalysis data (Muñoz-Sabater et al., 2021) spanning 1997 to 2022 to estimate the historical effect of monsoon onset delay on crop yields during the kharif growing season.[7] We estimate a simple panel fixed effects regression:

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

where the outcome variable is log yield of cotton or rice in the kharif season for district d in year y, Onset_{dy} is standardized onset timing, Rainfall_{dy} is kharif rainfall quantity, α_d are district fixed effects, δ_t are year fixed effects, and ε_{dt} is an error term, clustered at the district level. We also present specifications where we use alternative functional forms for rainfall and/or include temperature, in order estimate the consequences of monsoon onset timing above and beyond these other climatic conditions. Table 1 presents the results. The identifying assumption – similar to that in a large literature on the impacts of weather on agricultural outcomes (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Hultgren et al., 2025) – is that, conditional on location- and time-specific fixed effects, monsoon onset timing is plausibly exogenous.

Later monsoon onset leads to lower district-level yields for both rice (Panel A, 1 to 1.7 percent decline per SD of onset delay) and cotton (Panel B, 2.6 to 4.3 percent decline per SD of onset delay). Importantly, the yield decline is 2.5 to 2.8 times larger for cotton than rice. To put these magnitudes in context, the impact of a 1 SD later monsoon is similar to that of a 1 SD change in total growing season precipitation for each crop. As the within-district SD of onset timing is approximately 1.5 weeks, a monsoon that arrives three weeks late would cause rice yields to fall by 2 to 3.4%,

[6] Moron and Robertson (2014) demonstrate that total kharif rainfall and monsoon onset timing are not highly correlated. Nevertheless, we include total rainfall controls in our regressions to confirm that onset timing is relevant for agriculture even holding rain fixed.

[7] Appendix B provides more detail about the data and estimation. We define monsoon onset following Moron and Robertson (2014), and, following Moron et al. (2017), we 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)	(4) log(Yield)	(5) log(Yield)
			Panel A: Rice		
Onset (SD)	-0.012***	-0.012***	-0.011***	-0.010***	-0.017***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
			Panel B: Cotton		
Onset (SD)	-0.034***	-0.029**	-0.029**	-0.026**	-0.043***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
Total Rainfall	No	Yes	Yes	Yes	No
(Total Rainfall)^2	No	No	No	Yes	No
Monthly Temperature	No	No	Yes	Yes	No
Monthly Rain and Temp. Bins	No	No	No	No	Yes
N(rice)	12491	12491	12491	12491	12491
N(cotton)	4556	4556	4556	4556	4556

Notes: This table presents the effect of monsoon onset timing on yields of rice (panel A) and cotton (panel B), estimated using Equation 1. The outcome in each column is kharif 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 and restrict the sample to monsoonal regions of India according to Moron and Robertson (2014). See Appendix B for more details on the data and sample. In Columns (2) and (3), we control for total precipitation over the main kharif growing season which runs from May to September. In Columns (3) and (4), we also control for average temperature in each month of the growing season. In Column (4), we add in a quadratic in precipitation. In Column (5), we control for monthly precipitation and the count of days in a series of temperature bins for each month of the main Kharif growing season. Standard errors are clustered by district. Significance: *** $p < 0.01$, ** $p < 0.05$, ** $p < 0.10$.

and cotton yields to fall by 5.2 to 8.6%. These results are robust across a series of specifications. Importantly, the findings are robust to controlling for total growing season precipitation (and its square), demonstrating that monsoon onset timing is important for agricultural outcomes, even while holding the amount of rainfall fixed.

These results have two main implications, which we take to the data from our experiment below. First, farmers who expect to face an earlier monsoon should increase their investments in agriculture. Second, farmers who expect to face an earlier monsoon ought to increase their investments in cash crops in particular.

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 improve welfare, because they enable farmers to materially alter investment decisions such as land use, crop mix, input expenditure, and non-farm activities in advance of the monsoon's arrival.

We deploy a new long-range forecast of localized monsoon onset described in Stolbova et al. (2016).[8] This 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. More specifically, the 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.[9] This forecast 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), in addition to changing off-farm investments. Backcasting over the past 10 years, this forecast was correct each year. When evaluated from 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.

Our monsoon onset forecast is distinct from (i) existing monsoon onset forecasts; (ii) forecasts of monsoon rainfall quantity; and (iii) short-range weather forecasts. First, this localized 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.[10] Moreover, the IMD forecast only

[8] See Appendix H for more details on monsoon forecasting.

[9] At the time of this writing, this methodology was being used to generate three monsoon onset forecasts for India: Telangana, central India, and Delhi.

[10] 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.

arrives two weeks in advance of the monsoon's onset, which also limits its usefulness relative to a longer-range forecast. Second, the forecast we use provides a highly accurate forecast of onset *timing*, and there exist no corresponding accurate monsoon rainfall *quantity* forecasts. The most widely-available existing national quantity forecast in India, produced by the IMD, is uncorrelated with actual rainfall in much of the country (Rosenzweig and Udry, 2019). Finally, the long-range monsoon forecast we employ is very different 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 input changes.[11]

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, compared to the national average of 46%, the sector provides only 15% of the Gross State Value Added, equal to the national average (Government of Telangana, 2020; Ministry of Agriculture and Farmers Welfare, 2023). 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 approximately 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. Farmers receive some government assistance, though both formal and informal insurance are far from full. 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 because of a lack of demand. Private insurance exists, but is severely underutilised. At baseline, only 0.75% of farmers in our sample had heard of rainfall insurance.

In the status quo, farmers' information about the weather is also limited. While 65% of farmers in our sample report having received some information about the upcoming Kharif season at baseline

[11] 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, and are not well-suited to forecasting beyond a short time window.

(conducted prior to planting in early May; see Figure 2), the reliability of their sources is unclear. Very few farmers rely on information from the government (7.4%) or extension services (7.3%) (Appendix Figure A.2). 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 risk, which we use to illustrate the effects of the monsoon forecasts and the insurance product. We provide extended model details in Appendix C. 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 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 $x > 0$.[12] 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.[13]

Farmer decisions The farmer's prior belief over the probability distribution of ϵ for the coming agricultural season is given by $G(\cdot)$. Farmers 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.

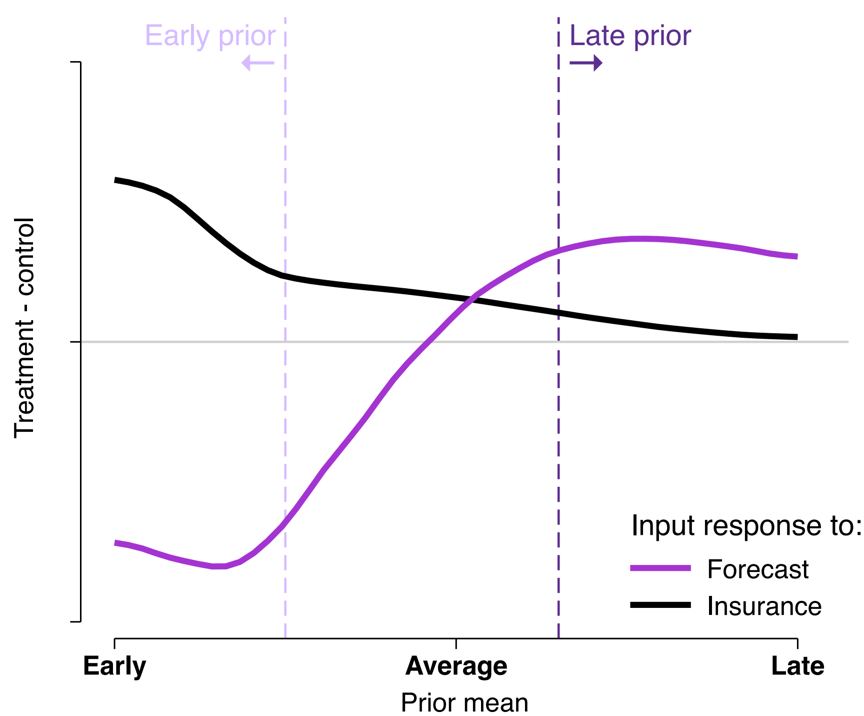
[12] For simplicity, we assume that monsoon onset is the only determinant of production and that output is monotonically decreasing in onset timing. While it is possible that extremely early rain could be detrimental to agricultural output, in general, delayed monsoons are associated with lower output, as shown by Amale et al. (2023) and confirmed by our own data in Section 2. 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). As we show in Section 2, monsoon onset timing matters for crop yields even holding rainfall quantity fixed.

[13] 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.

Appendix C.2 shows that the optimal investment is therefore a (weakly) increasing function of a farmer's beliefs on the realization of ϵ.[14] 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.

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



Notes: This figure plots the simulated relationship in our model between the treatment effect of forecasts and insurance on optimal investment and the farmer's prior. 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 when farmers believe the monsoon will arrive. 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 C.3 for simulation details.

Figure 1 illustrates the key results of the model, plotting the treatment effect of a forecast

[14]For extremely risk-averse farmers, investment will not respond to beliefs. For reasonable parameter values, however, this relationship will be strictly increasing.

(purple) on agricultural investment. This figure depicts responses to a forecast of an average monsoon.[15] In this case, the forecast tells farmers with early priors that the coming season will be later, and thus worse, than they expected. As a result, they reduce their investments. The forecast tells farmers with middle (and therefore correct) priors that the coming season will be in line with their expectations. They therefore do not change their investment behavior strongly. The forecast tells farmers with late priors that the coming season will be earlier, and thus better, than they expected. They therefore increase their investments. To account for this inherent heterogeneity, when we take this model to the data, we allow our estimated treatment effects to vary by terciles of prior belief, comparing forecast group farmers with early, middle, and late priors to their control group counterparts. While alternative specifications, including allowing priors to enter linearly, show similar results, our preferred approach is to allow treatment effects to vary non-parametrically. Note that in the event of an average forecast like that shown here, theory predicts that the *average* treatment effect of the forecast on investment across farmers of all prior types will be close to zero, as the positive and negative responses of late-prior and early-prior farmers will cancel each other out.

The model also predicts that welfare should (weakly) rise for all forecast farmers, regardless of prior beliefs. Early-prior farmer welfare is expected to rise because their returns to agriculture should go up relative to the control, while late-prior farmer welfare is expected to rise because they can reallocate money that would have gone to agricultural investment into other forms of profitable investments, such as non-agricultural business, assets (including livestock) or into savings, both of which can be consumed in the second period.

Finally, Figure 1 illustrates how responses to the forecast (purple) differ from those to an insurance product (shown in 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 coming weather – causes all farmers to weakly increase their investment in agriculture. In contrast, the forecast enables farmers to tailor their investments to the upcoming growing season realization. This highlights the different mechanisms behind the impacts of 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 impacts of forecasts. We randomized 250 villages (sampling 5-10 farmers each) in Telangana into either a forecast group (100 villages), a control group (100 villages), or an insurance group (50 villages) which serves as a benchmark for the effects of the forecast.

We sampled villages in two districts in Telangana, Medak and Mahabubnagar, and restricted

[15] Appendix Figure C.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.

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 and insurance being offered in our experiment.

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 E.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:

> *"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."*

This year's forecast was for an average monsoon, which is ideal from a research perspective, because it enables a high-powered test of our theory that farmer responses to the forecast should differ by their prior beliefs about monsoon onset.

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. In addition to being correct overall, the forecast was also extremely accurate in our study sample. Appendix Figure A.4 shows rainfall across the weather gauges we installed in our 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. We also document heavy rainfall in some areas during July, consistent with popular press reports of flooding during this time period (Business Line, 2022; The New Indian Express, 2022).

Insurance Our insurance product, intended to serve as a benchmark for the effect size of the forecast, 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 the ERA-5 reanalysis data described above, and following the approach of Moron and Robertson (2014) as shown in Appendix Figure H.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 (Moron and Robertson, 2014). These payout thresholds were set only using historical data, and were fully independent of the forecast.

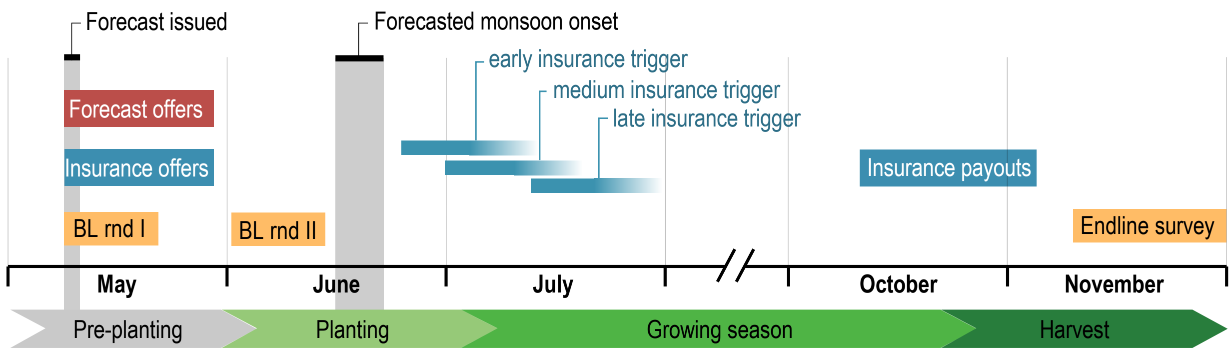
Farmers were informed that they would receive a low payout if the monsoon were 15-19 days late compared to the local "on time" onset date; a medium payout if the monsoon were 20-29 days late; and a large payout if the monsoon were 30 days late or later. The maximum payout was set to approximately $190 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).[16] Farmers in the insurance treatment arm received an information sheet covering these details (Appendix Figure E.2). As with the forecast product, we offered farmers this insurance product through a BDM mechanism in order 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.[17] We present takeup of the forecast and insurance product in Appendix Figure A.3 and Appendix Table A.5.

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

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

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.

Takeup is over 85 percent for both treatment groups.[18] The remaining farmers reported no interest in the product or declined to participate in the BDM.

Timeline Figure 2 presents the timeline for the experiment. We conducted our baseline survey in May 2022, timed such that we could deliver the forecast at the end of the survey, but still several weeks before monsoon (or the IMD 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 all households in June 2022, approximately two weeks after the initial baseline, where we collected data on farmer posterior beliefs about the monsoon. Finally, we conducted our endline survey in November 2022.

4.2 The importance of prior beliefs

Our theory implies that treatment effects should depend on farmers' prior beliefs about the onset of the coming monsoon. 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

[18] Appendix Figure A.3 and Appendix Table A.3 document that the later a farmer thinks the monsoon is likely to be, the more likely they are to purchase each product when offered.

around in light of their response. We gathered this information during both baseline round I and baseline round II to establish whether (and by how much) the forecast changed farmers' priors.

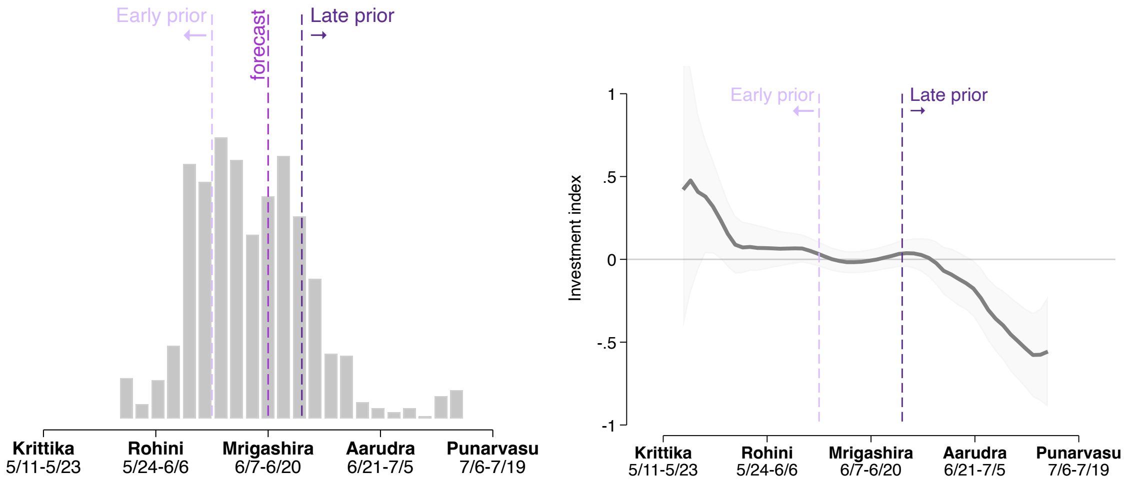
Figure 3 presents data on priors.[19] The left panel plots a histogram of the mean of each farmer's priors. The forecast, which was the same for all farmers in our experiment, is represented as a purple dashed vertical line. The forecast in the year of our study was for an average monsoon, close to the mean of the prior distribution. For the purposes of our analysis, we divide this distribution into terciles. Tercile 1, or early-prior farmers (to the left of the blue vertical line) expected an early monsoon; in the forecast arm, these farmers were told that the coming monsoon would be worse than expected. Tercile 2, or "middle prior" farmers (between the dashed vertical lines) expected an average monsoon; in the forecast arm, these farmers were told that the coming monsoon would align with their expectations. Finally, Tercile 3, or "late prior" farmers (to the right of the green vertical line) expected a late monsoon; in the forecast arm, these farmers were told that the coming monsoon would be better than they expected.[20] The right panel presents the relationship between agricultural investments (summarized in a standardized index described immediately below) and prior beliefs for control-group farmers only. In line with our historical analysis, we find that farmers who expect an earlier (i.e., better) monsoon invest more.[21]

[19] Though we do not have sharp predictions on the relationship between prior beliefs and farmer characteristics, we present these correlations in Appendix Table A.7. We find that households with heads residing in their birth village have later priors, while farmers with more landholdings have earlier priors.

[20] As we describe in Section 5, we use these prior terciles to estimate heterogeneous treatment effects according to farmer prior. Appendix A.10 shows that the results are robust to alternative prior definitions: linear priors or bins defined relative to the Mrigashira karte.

[21] Appendix Table A.6 breaks out each component of the index, and shows that later priors are associated with less land under cultivation, a lower probability of planting cash crops, and lower total input expenditure, consistent with farmers understanding that later monsoon onsets lower agricultural output as we show in Section 2.

Figure 3: Farmers' prior beliefs



Notes: This figure presents data on farmer priors over the timing of the onset of the 2022 monsoon, measured in kartes (a local approximately two-week-long unit of time). To elicit priors, we use the beans task described in Section 4. The left panel plots a histogram of the mean of each farmer's beliefs after removing strata fixed effects. The forecasted monsoon onset date is represented by the central bright purple dashed vertical line. The 2022 forecast was for an average monsoon, and the forecast lies close to the mean of the prior distribution. Dashed lines show the terciles of beliefs that we use in our analysis. Early-prior farmers (to the left of the light purple dashed line) expected an early monsoon, and would hear that the coming monsoon would be later (i.e., worse) than expected in the forecast treatment group. Middle-prior farmers (between the light and dark purple dashed lines) expected an average monsoon, and would hear that the coming monsoon would be as expected in the forecast treatment group. Finally, late-prior farmers (to the right of the dark purple dashed line) expected a late monsoon, and would hear that the coming monsoon would be earlier (i.e., better) than expected in the forecast group. The right panel shows the relationship between prior beliefs and an agricultural investment index (land cultivation, cash cropping, and total input expenditure) in the control group only, after removing strata fixed effects and baseline controls. As predicted by theory, the later a farmer's prior, the less they invest, because a later monsoon leads to worse agricultural outcomes (Section 2). Appendix Table A.6 presents regression results showing the relationship between prior terciles and the components of the investment index.

4.3 Agricultural, off-farm, and welfare outcomes

We collect detailed measurements of farmers' agricultural investment decisions and resulting farm outputs. We consider a number of choices that may be affected by our treatments, including the amount of land cultivated, crop mix, and expenditures on inputs such as labor, seeds, and fertilizer. 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. We aggregate these measures into a standardized agricultural investment index, made up of land under cultivation, cash cropping, and input expenditure. The primary farm production outcomes of interest are agricultural output, value of production, yield, and farm profits.

We also measure farmers' engagement in non-agricultural business. We collect data on whether a farmer operates a non-farm enterprise, how much money they invest in this enterprise, and business profits.[22]

Finally, we collect several measures of economic well-being. First, we measure per-capita spend-

[22] We collect off-farm business data over the last 30 days to increase recall, and scale these estimates to the length of the growing season for comparability with the agricultural outcomes.

ing on food and non-food consumption. Next, we capture the value of a farmers' assets and the number of livestock in their possession. Third, we measure savings and debts, both indicators of farmers' financial position.[23]

4.4 Experimental integrity

Attrition, descriptive statistics, and balance Before proceeding with main results, we test for differential attrition. 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. We do not see differential attrition between the forecast group an the control group.[24]

Appendix Table A.3 presents 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 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. Appendix Table A.4 further presents balance between the forecast and control group for each tercile of prior beliefs on the set of household characteristics from Appendix Table A.3.[25] Within each tercile, the forecast and control groups are similar. Household size is somewhat smaller for treated farmers with late priors. We include this in the set of LASSO baseline characteristics used in our analysis, described below.

Pre-registration This research was pre-registered at the AEA and the analysis plan was accepted via pre-results review at the *Journal of Development Economics.* Deviations are in general minor; the full list can be found in Appendix F. One change bears mentioning here, because it pertains to the main specification. In the pre-analysis plan, we proposed splitting our forecast treatment effects by priors, dividing farmers into two groups: those with early priors, for whom the forecast

[23]In addition to these standard welfare metrics, we consider impacts of our treatments on mental health, using the PHQ-8 screening tool, a standard and locally-validated depression metric (Bhat et al., 2022). We also measure migration by capturing how many individuals from the household migrated elsewhere over the cropping season and the value of remittances they sent home.

[24]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. Households in the insurance treatment arm are slightly more likely to answer all surveys. If anything, this would bias our insurance treatment effects downwards as we anticipate that those who do not respond are likely to have experienced worse outcomes.

[25]We omit the village-level characteristics, because priors are an individual characteristic, and omit the beliefs, because the terciles are defined using these belief data.

would be for a worse-than-expected monsoon, and those with late priors, for whom the forecast would be for a better-than-expected monsoon. However, because the forecast provides a range of dates, and because we collected priors in kartes, two-week windows of time, approximately 40% of the sample could neither be characterized as early- or late-prior farmers, as these farmers' priors fell within the forecasted date range. Therefore, we instead split the sample into terciles to define an early-prior group for whom the forecast would be for a worse-than-expected monsoon, a middle-prior group for whom the forecast would be for an as-expected monsoon, and a late-prior group for whom the forecast would be fore a better-than-expected monsoon. Because of this change, we discuss a specification where we linearly interact farmers' priors with the forecast treatment (Appendix A.9) throughout. We also create an alternative grouping where we classify farmers, as best we can, based on whether their prior falls before, within, or after the forecasted date range (Appendix A.10). Both of these approaches yield similar results to the early-, middle-, and late-prior specification we present in the main text.

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. Figure 4 plots posterior beliefs in the control group (gray) and in the treatment group (purple), measured in kartes (local approximately two-week measures of time). This figure also shows the forecast (the dashed line is centered on the midpoint of the karte; the shaded area shows the full karte). Among the forecast group, the distribution of posterior beliefs (solid purple) is meaningfully earlier, and therefore closer to the forecast. As predicted by theory, however, their beliefs do not collapse to the forecast itself, but rather land between the forecast and their no-forecast-counterfactual beliefs.

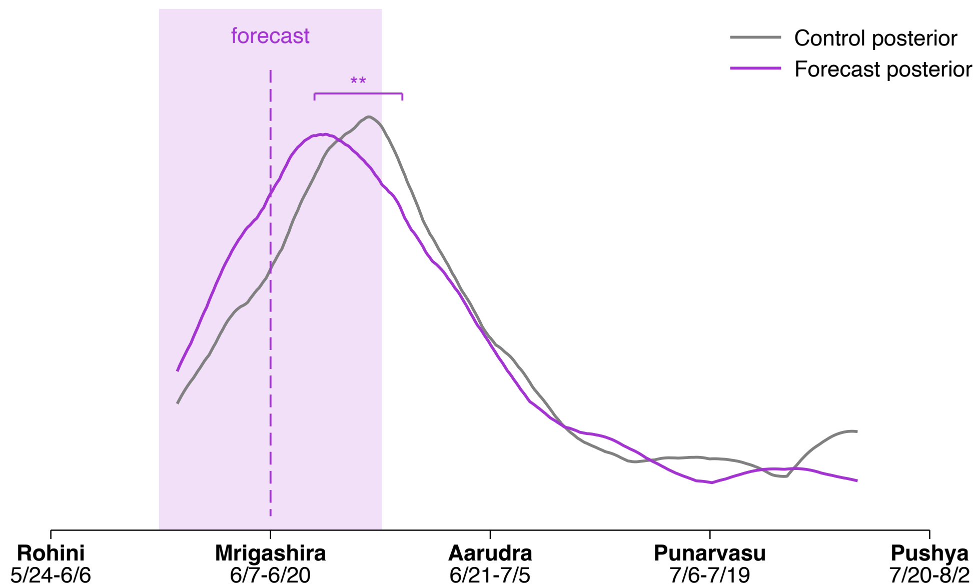
We formally test for impacts on beliefs by comparing households in the forecast treatment group with those in the control and insurance groups. Since the insurance group did not receive the forecast, it serves as a placebo. Specifically, we estimate:

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

where Y_{iv} are measures of beliefs for household i in village v: the absolute difference between the posterior and the forecast, the absolute difference between the posterior and the prior, and a Kolmogorov-Smirnov test statistic for the difference between the posterior and prior distributions. 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 by village.[26]

[26] Because takeup of the forecast and insurance products was not 100% (as documented in Appendix Figure A.3 and Appendix Table A.5, we present IV versions of all of the results in Section 5 in Appendix G.5, where we instrument for forecast (insurance) takeup with an indicator for being in a forecast (insurance) village. As expected, our estimated magnitudes increase somewhat, and significance is broadly unchanged.

Figure 4: Distribution of posterior beliefs



Notes: This figure plots posterior beliefs over this year's monsoon onset, measured in kartes (a local unit of time that is approximately two weeks long), and elicited via the beans tasked described in Section 4. We plot the mean of each farmer's posterior distribution. 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, after removing strata fixed effects but adding back the grand mean. The vertical purple dashed line and shaded area indicate 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 -0.197 and p-value 0.031 without controlling for prior beliefs, coefficient -0.195 and p-value 0.033 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 on statistical significance. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2 presents the results. We find that the absolute difference between the forecast and the posterior is 26% (p-value 0.031) 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, p-value 0.012, Column 2) and in the Komolgorov-Smirnov test (11% lower than control, p-value 0.062, 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.

Willingness-to-pay We find that farmers' willingness to pay (WTP) for both forecasts and insurance is low, though WTP for both forecasts and our insurance product – which provides \$190 in case the monsoon is delayed by 30 days or more – is very similar (Appendix Figure A.5). We interpret these results with 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.

Table 2: Effect of the forecast and insurance on beliefs

	(1) $\lvert$ posterior $-$ forecast $\rvert$	(2) $\lvert$ posterior $-$ prior $\rvert$	(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 G.15.

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 nobody 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.).

6 Forecast effects on agriculture, off-farm business, and welfare

In this section, we discuss the treatment effects of the forecast on agriculture, off-farm business and welfare (which we compare to those of insurance in Section 7). Because our theory predicts that the effect of the forecast on farmer behavior will differ depending on a farmer's prior, our main specification for estimating treatment effects on agricultural inputs, farm outputs, and off-farm business is:

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

where $[\text{Prior bin} = \text{b}]_i$ are indicators which divide farmers into terciles (early, middle, and late) on the basis of their priors.[27] We categorize all farmers as having early, middle, or late priors; For

[27] Figure 3 demonstrates that these bins are meaningfully related to investment in the control group. We show that our results are robust to a specification that is linear in priors (Appendix A.9) and to an alternative grouping that defines news relative to the forecasted karte (Appendix A.10). We also present continuous treatment effects on our summary agricultural investment index in Figure 6.

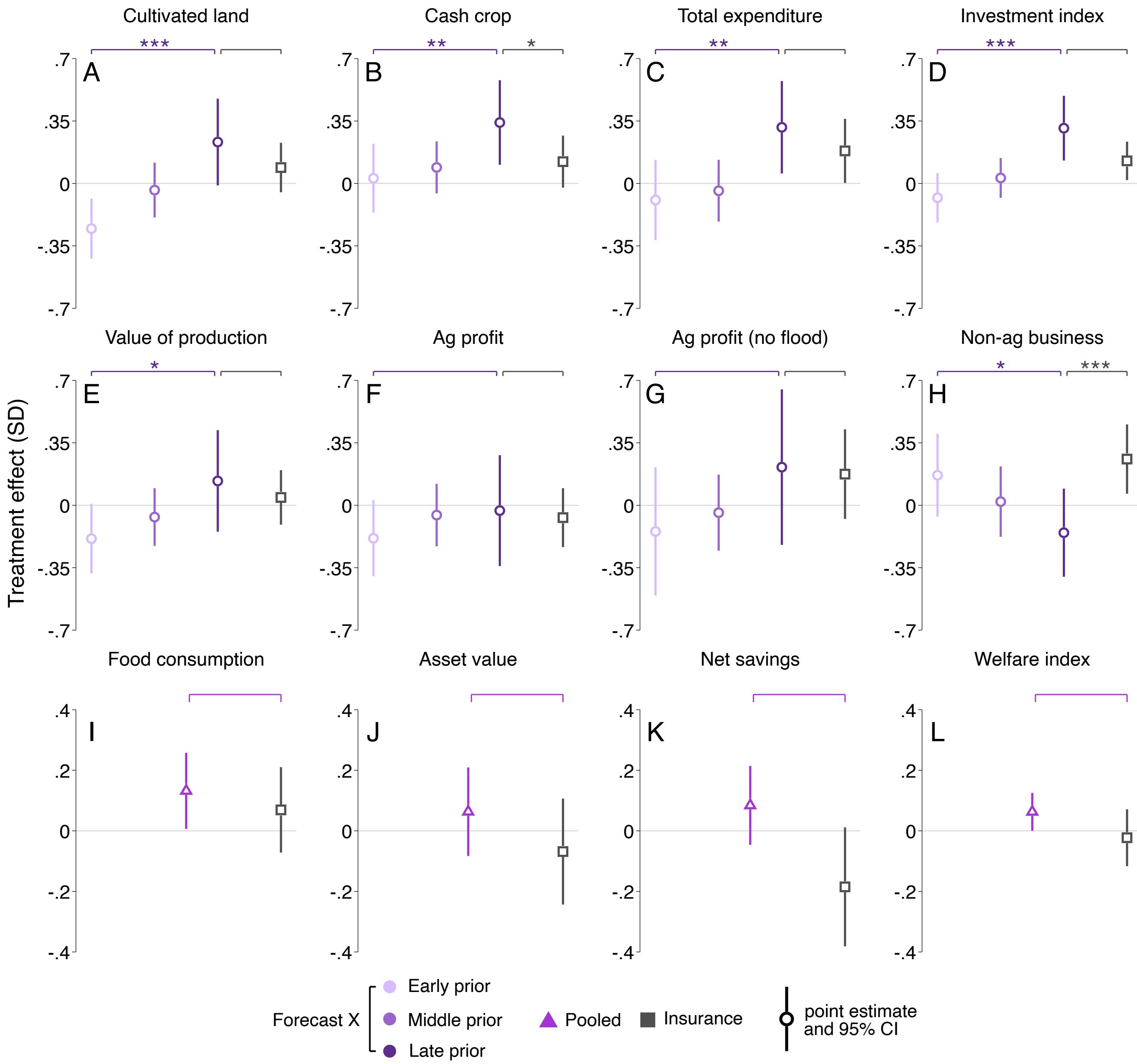
early-prior farmers, the forecast is for a later (and thus worse) monsoon than expected. For middle-prior farmers, the forecast is for an as-expected monsoon. For late-prior farmers, the forecast is for an earlier (and thus better) monsoon than expected. In all cases, our estimates compare treated farmers to control-group counterparts with similar priors. All other variables are as defined in Equation (3) above.[28] In Appendix A.8, we present results pooling all forecast farmers regardless of prior beliefs, estimated using Equation (3). As predicted by theory, these treatment effects tend to aggregate to zero across our main agricultural input, farm output, and off-farm business outcomes, as they average over negative and positive treatment effects.

The realized forecast predicted an average monsoon, close to the mean of farmer beliefs (Figure 3). Based on our theoretical model and historical yield data, we expect early-prior forecast farmers to reduce agricultural investment, middle-prior forecast farmers to make no major changes, and late-prior forecast farmers to increase investment. While higher investment should generally lead to greater yields and profits, agricultural outcomes are inherently variable, and we should not necessarily expect a one-to-one relationship between inputs and outputs (Rosenzweig and Udry, 2020; McCullough et al., 2020; Suri and Udry, 2022). The effect of the forecast on off-farm enterprises is theoretically ambiguous, depending on whether these activities serve as complements or substitutes to farming. Overall, because the forecast helps all farmers to tailor their on- and off-farm decisions to the coming monsoon season, theory predicts a (weak) improvement in overall welfare. In keeping with this theoretical prediction, we estimate pooled treatment effects of the forecast on welfare using Equation (3).

We summarize these results in Figure 5 (standardizing all effects for comparability across outcomes). Our results are remarkably consistent with our theoretical predictions. As compared with control-group farmers with similar priors, early-prior forecast farmers (light purple circle) reduce farm inputs and increase off-farm investment; middle-prior forecast farmers (middle purple circle) broadly see no change; and late-prior forecast farmers (dark purple circle) increase farm inputs and decrease non-agricultural business. While some of the individual point estimates for early-, middle-, and late-prior forecast farmers are not statistically significant, the difference in treatment effects for early- vs. late-prior forecast farmers is almost always different from zero (which is corroborated by the continuous-prior specification shown in Appendix A.10). Welfare rises on average in the forecast treatment arm (bright purple triangle).

[28]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 agricultural investment choices, agricultural productivity measures, off-farm business, and welfare measures.

Figure 5: Summary of main results



Notes: This figure summarizes our main results. All effects are in standard deviations. The top row plots agricultural inputs; the middle row plots farm outputs and non-farm business; and the bottom row plots welfare outcomes. In the top three rows, we present treatment effects of the forecast by tercile of prior beliefs. For early-prior farmers (light purple) the forecast was for a later (and thus worse) than expected monsoon. For middle-prior farmers (middle purple), the forecast was for an as-expected monsoon. For late-prior farmers (dark purple), the forecast was for an earlier (and thus better) than expected monsoon. We compare forecast farmers in each group to their control-group couterparts with similar priors. In the bottom row, we present pooled effects of the forecast (bright purple triangle) and insurance (gray square). Coefficients and 95% confidence intervals are plotted for the forecast and insurance treatments, estimated using Equation (4) in the top two rows, where we interact the forecast treatment with the prior belief terciles. Regressions in these two rows include prior tercile fixed effects. In the bottom row, we estimate coefficients and 95% confidence intervals using Equation (3). Regressions in all rows include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Overbraces indicate the significance level of tests for equality between coefficients. Dark purple overbraces show tests between early- and late-prior forecast farmers; gray overbraces show tests between late-prior farmers and insurance; and bright purple overbraces show tests between pooled forecasts and insurance. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.1 Effects on agriculture

Land and crop choice Table 3 presents the impact of our treatments on land use and crop choice, and shows evidence in support of our theory. Early-prior forecast farmers (who were told the monsoon would be worse than expected) *reduce* land under cultivation by 22% (p-value 0.003) of the control mean, and were 31% (p-value 0.053) less likely to add a crop type from last year to this year.[29] While they were also less likely to change crops, this effect is not statistically significant (p-value 0.319). Middle-prior forecast farmers (who were told the monsoon would be better than expected) do not change their land under cultivation (point estimate of -3.3%, p-value 0.838), or their crop choices.

In contrast, late-prior forecast farmers (who were told the monsoon would be better than expected) *increase* land under cultivation by 21% (p-value 0.061). They were also 17 percentage points more likely to grow a cash crop (p-value 0.005), 13 percentage points more likely to have changed a crop compared to last year (p-value 0.041), and 14 percentage points more likely to have added a new crop type compared to last year (p-value 0.062), all compared to control group farmers with similar priors. We find no evidence that these farmers replaced a previous-year crop with something else, suggesting the changes we see reflect new crops being added to the mix, rather than substitution.

We find differences between early- and late-prior forecast farmers 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) we confirm this heterogeneity in a linear specification (Appendix Table A.13). These results are consistent with the forecast enabling tailored investments: farmers in this treatment group adjusted their crop mix to match their updated expectations about the upcoming season.

[29] 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 × Early Prior	-0.475***	0.015	-0.053	-0.113*	0.012
	(0.161)	(0.049)	(0.053)	(0.059)	(0.045)
Forecast × Middle Prior	-0.070	0.045	0.043	0.011	0.014
	(0.147)	(0.037)	(0.051)	(0.047)	(0.038)
Forecast × Late Prior	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 Early	0.031	1.000	1.000	0.272	1.000
q-val Middle	1.000	1.000	1.000	1.000	1.000
q-val Late	0.067	0.046	0.066	0.067	0.161
q-val Insurance	0.293	0.265	0.373	0.373	0.684
Test Early=Late	0.001	0.032	0.023	0.004	0.830
Test Insur. = Late	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). Early, Middle, and Late Prior indicate the prior tercile for a respondent. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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 Kharif season of the experiment than in the prior season. Added Crop is an indicator for planting at least one additional crop in Kharif season of the experiment compared to the prior season. Sub Crop is an indicator for planting at least one fewer crop in the Kharif season of the experiment than in the prior season. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 G.16 presents an IV analogue.

Farm inputs Table 4 measures the impact of our treatments on agricultural input expenditures. Point estimates for early-prior forecast farmers (who were told that the monsoon would be worse than expected) suggest that these farmers reduced their input expenditures, though somewhat less than they reduced land under cultivation.[30] The point estimate implies that early-prior forecast farmers reduced their total expenditures by 9% (p-value 0.417). This decline is driven by roughly proportional decreases in spending on fertilizer, seeds, and labor. We find no effects on middle-prior forecast farmers (who were told that the monsoon would be as expected). However, late-prior forecast farmers (who were told that the monsoon would be better than expected) increase their investments substantially, with total expenditures increasing by 31% of the control mean (p-value 0.017), driven by statistically significant changes in fertilizer and labor expenditure, and positive but imprecise impacts on seed spending. We reject equality between early- and late-prior fore-

[30] Appendix Table G.6 contains treatment effects on per-acre input use. Broadly, we find an increase in total per-acre inputs for early-prior forecast farmers. This is consistent with early-prior forecast farmers decreasing land area cultivated by 22% but total inputs by 10%. We do not find changes in per-acre input use for middle- or late-prior forecast farmers.

cast farmers on total spending (p-value 0.019), corroborated by the continuous-prior specification (Appendix Table A.14).[31]

We also create an overall farm investment index from outcomes in Table 3 (land cultivation and cash cropping) and Table 4 (total input expenditure). While imprecise, the point estimate for early-prior forecast farmers suggests that these farmers reduced investment by 0.08 standard deviations (p-value 0.256). We find no impacts on middle-prior forecast farmers, with a standardized treatment effect on the investment index of 0.03 SD (p-value 0.588). However, late-prior forecast farmers increased investments by 0.31 SD effect (p-value 0.001). We reject equality between early- and late-prior forecast farmers (p-value 0.000), confirmed in the linear specification (Appendix Table A.14). These results suggest that forecast allow farmers to make better input decisions by tailoring their farm investments to the coming monsoon.

Table 4: Effect of the forecast and insurance on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast ×	-30.93	-0.68	-42.36	-130.18	-0.08
Early Prior	(42.19)	(2.61)	(85.27)	(160.55)	(0.07)
Forecast ×	-28.94	-2.01	-44.45	-57.46	0.03
Middle Prior	(39.38)	(1.60)	(67.61)	(123.98)	(0.06)
Forecast ×	96.40*	2.20	263.23**	441.92**	0.31***
Late Prior	(55.61)	(3.35)	(105.20)	(185.41)	(0.09)
Insurance	95.98**	-0.93	109.85*	256.27**	0.13**
	(42.81)	(1.34)	(63.63)	(128.57)	(0.05)
q-val Early	1.000	1.000	1.000	1.000	
q-val Middle	1.000	1.000	1.000	1.000	
q-val Late	0.077	0.147	0.049	0.049	
q-val Insurance	0.265	0.437	0.265	0.265	
Test Early=Late	0.058	0.493	0.026	0.019	0.000
Test Insur. = Late	0.994	0.368	0.204	0.373	0.065
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs, estimated using Equation (4). Early, Middle, and Late Prior indicate the prior tercile for a respondent. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, 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. We exclude it from the MHT correction as it is a composite of three outcomes already included. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 G.17.

[31] We also reject equality between early- and late-prior forecast farmers for fertilizer expenditure (p-value 0.058) and labor expenditure (p-value 0.026); using the continuous specification, we estimate significant heterogeneity on labor, but not fertilizer.

Agricultural output Table 5 presents effects on three measures of agricultural production: total crop output in kilograms, the value of this production, and crop yield per hectare.[32] Our forecast treatment effects follow the broad pattern we documented for agricultural inputs. Early-prior forecast farmers (who received a forecast of a worse-than-expected monsoon) reduced agricultural output, including a 25% (p-value 0.039) decline in production and a 22% (p-value 0.060) decline in crop market value — consistent with having reduced land area and total expenditures. We see no impacts on yields – consistent with land and production falling by approximately the same amount. We find close to zero effects for middle-prior forecast farmers (who received a forecast of an as-expected monsoon), who did not change farm inputs. Though both are imprecisely estimated, we find that late-prior forecast farmers (who received a forecast of a better-than-expected monsoon) increased agricultural output by 22% (p-value 0.187) and the market value of production by 16% (p-value 0.348) — following from their increases in cultivated land, input expenditure, and the probability of cash cropping. We see no meaningful changes in yield, suggesting changes output are likely due to expansions or contractions of in production rather than intensification. Yet again, we reject equality between early- and late-prior forecast farmers on both production (p-value 0.017) and the market value of production (p-value 0.056); the linear specification finds heterogeneity by priors in production only (Appendix Table A.15).

Agricultural profits Agricultural profits should generally align with on-farm investments, such that higher (lower) investments should lead to higher (lower) profits on average. Table 6 presents impacts of the forecast on agricultural profits. We find that early-prior forecast farmers have meaningfully lower farm profits (−\$401, p-value 0.089) than their counterparts in the control group. This is a more substantial decrease than their input changes would imply. We do not find statistically significant impacts on profits for either middle- or late-prior forecast farmers. Though both point estimates are negative, the effect for late-prior forecast farmers is quite close to zero (−\$64, p-value 0.850). Moreover, we find no difference between early- and late-prior forecast farmers here or in the linear specification (Appendix Table A.16).

The fact that changes in investments did not perfectly translate into change in agricultural profits suggests that some farmers may have been negatively affected by a shock that was unrelated to monsoon onset timing (and thus to the forecast). Indeed, Telangana was hit by heavy flooding in early July (Business Line, 2022; The New Indian Express, 2022). While the likelihood of flood exposure is balanced between treatment and control (Appendix Table A.25), because late-prior forecast farmers spent more on inputs and farmed more valuable crops, the same flood may have led to greater losses among this group than in the control. We conduct a (non-pre-specified) analysis of these shocks in the remainder of Table 6. While none of the resulting estimates are statistically different from zero, their pattern is informative. First, early-prior forecast farmers saw relatively

[32] 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 local administrative data on market, or mandi, prices for Telangana (Allen and Atkin (2022); Kochhar and Song (2024)) during the year of our study.

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

	(1) Prod (Kg)	(2) Value Prod ($)	(3) Yield
Forecast × Early Prior	-16.90**	-534.76*	-6.59
	(8.17)	(284.81)	(4.35)
Forecast × Middle Prior	-10.75	-188.75	-0.73
	(7.50)	(235.57)	(3.61)
Forecast × Late Prior	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 Early	0.218	0.218	0.218
q-val Middle	0.839	1.000	1.000
q-val Late	1.000	1.000	1.000
q-val Insurance	1.000	1.000	1.000
Test Early=Late	0.017	0.056	0.261
Test Insur. = Late	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). Early, Middle, and Late Prior indicate the prior tercile for a respondent. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted for all outcomes in Tables 5 and 6, except for Column (4) of Table 6, since it is a sub-sample analysis of Column (1). 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 G.18.

small crop losses (i.e., production that was lost to shocks, valued at district-median prices), with much larger damages for middle- and late-prior forecast farmers. Treating these losses as crop revenue in a counterfactual profit calculation, we find a pattern of treatment effects that is more in line with farmers' input adjustments: early-prior forecast farmers see a profit reduction, middle-prior forecast farmers see approximately no change, and late-prior forecast farmers see an increase. Finally, we estimate effects on realized agricultural profits only for the 46% of farmers who reported no losses from flooding or cyclones.[33] Again, we find evidence consistent with the input effects: early-prior forecast farmers see lower farm profits, there is virtually no change for middle-prior forecast farmers, and late-prior forecast farmer agricultural profits rise.

These results are consistent with the external validity point made in Rosenzweig and Udry (2020): agriculture is an inherently stochastic process. While the forecast appears to have led treatment farmers to make choices that would have been agronomically-appropriate on average, the occurrence of an orthogonal flood shock reduced profits for many of these farmers during our experiment. Nevertheless, Appendix Figure A.6 shows that farmers' self-reported trust in the

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

forecast increased substantially over the course of the growing season, demonstrating that farmers understand the distinction between monsoon onset and other growing season realizations.[34]

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

	(1) Ag Profit	(2) Loss	(3) Profit + Loss	(4) Ag Profit Non-Flood
Forecast × Early Prior	-401.08*	54.39	-296.60	-341.47
	(235.92)	(135.32)	(322.80)	(427.31)
Forecast × Middle Prior	-118.98	217.10*	99.46	-96.46
	(194.07)	(122.61)	(221.38)	(253.28)
Forecast × Late Prior	-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 Early	0.218	0.298	0.243	
q-val Middle	1.000	0.839	1.000	
q-val Late	1.000	1.000	1.000	
q-val Insurance	1.000	0.238	1.000	
Test Early=Late	0.400	0.411	0.338	0.222
Test Insur. = Late	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). Early, Middle, and Late Prior indicate the prior tercile for a respondent. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Ag Profit is the value of production (evaluated at district-median prices) less total expenditure. Loss is the value of reported crop losses (evaluated at district-median prices). Profit + 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. All outcomes are in USD. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted for all outcomes in Tables 5 and 6, except for Column (4) of this table, since it is a sub-sample analysis of Column (1). 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 G.19.

6.2 Effects on non-agricultural business

Table 7 presents the effects of the forecast on non-agricultural business. We find suggestive evidence that early-prior forecast farmers (who received a forecast of a worse-than-expected monsoon) engaged in more non-agricultural activity than their control counterparts, while late-prior forecast farmers (who received a forecast of a better-than-expected monsoon) engaged in less. While not statistically significant, the point estimates imply that early-prior forecast farmers were 42% (p-value 0.155) more likely than control to own a non-agricultural business, increased non-agricultural investment by 17% (p-value 0.713), and increased business profits by $80 ($p$-value 0.293). In contrast, we see suggestive evidence that late-prior forecast farmers were less likely to own a non-agricultural

[34] 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).

business (35%, p-value 0.222), reduced non-agricultural investment by more than 76% (p-value 0.073), and saw a \$44 decline in business profits (p-value 0.628). We reject equality between early- and late-prior forecast farmers on non-agricultural business ownership (p-value 0.060), but not on investment (p-value 0.130) or profits (p-value 0.268). In the linear specification, we find statistically significant prior heterogeneity on all three business outcomes (Appendix Table A.17). These results, which are in the opposite direction to our agricultural input findings, are consistent with farmers treating business as a substitute for agriculture.[35]

Table 7: Effect of the forecast and insurance on off-farm business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast × Early Prior	0.06	26.46	79.97
	(0.04)	(71.83)	(76.02)
Forecast × Middle Prior	0.01	6.48	17.15
	(0.03)	(58.60)	(48.16)
Forecast × Late Prior	-0.05	-122.57*	-43.70
	(0.04)	(68.34)	(90.32)
Insurance	0.09***	101.44	104.95*
	(0.03)	(63.15)	(55.11)
q-val Early	0.785	0.785	0.785
q-val Middle	1.000	1.000	1.000
q-val Late	0.287	0.282	0.502
q-val Insurance	0.029	0.078	0.061
Test Early=Late	0.060	0.130	0.268
Test Insur. = Late	0.007	0.002	0.151
Control Mean	0.14	157.98	165.51
Observations	1197	1199	1197

Notes: This table presents estimates of the treatment effects of forecasts and insurance on non-farm business activity estimated using Equation (4). Early, Middle, and Late Prior indicate the prior tercile for a respondent. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 G.21.

[35] In addition to estimates for non-agricultural business, in Appendix A, we present results for other income sources (Appendix Table A.23) and migration (Appendix Table A.24). Forecasts have no significant impacts on other income-generating activities, though we see evidence that early-prior forecast farmers saw reduced labor income – consistent with choosing not to work on others' farms in the face of a poor growing season. If anything, livestock income declines, consistent with (especially late-prior forecast) farmers selling fewer assets. Finally, we see that the forecast reduced the number of migrants that left the household. These reductions are concentrated among early- and late-prior forecast farmers, with the strongest effects on early-prior forecast households. To the extent that migrant labor depends on a good monsoon, a forecast of a worse-than-expected monsoon may have therefore depressed migration (Rosenzweig and Udry, 2020).

6.3 Effects on welfare

Finally, we measure impacts on farmer well-being in Table 8. Because theory predicts that forecasts should increase overall welfare for *all* farmers, we estimate pooled treatment effects of the forecast using Equation (3). Forecasts increase per-capita food consumption by 7% of the control mean (p-value 0.040), and we find no impacts on other consumption (point estimate of $-\$0.52$, p-value 0.523).[36] Though not statistically significant, forecasts raise asset value by 8% (p-value 0.397). We see no effect on livestock count. Forecasts increase savings net of debt by \$184 (p-value 0.206), compared to a control group mean of $-\$1{,}083$, largely driven by a decrease in debt, though these estimates are also imprecise.[37] We aggregate these economic well-being measures into an inverse-covariance weighted index, and estimate that forecasts raise overall well-being by 0.06 SD (p-value 0.048). This effect size is comparable to other welfare estimates. (Lane, 2024) estimate the welfare value of emergency loans at 0.02 standard deviations, while Jones et al. (2022) estimate the welfare value of irrigation access at 0.11 standard deviations.

Treatment effects on the index are largest for early-prior forecast farmers (0.14 SD, p-value 0.021), zero for middle-prior forecast farmers (0.00 SD, p-value 0.973), and weakly positive for late-prior forecast farmers (0.05 SD, p-value 0.375), consistent with responses to our forecast treatment having been concentrated in the early- and late-prior groups (Appendix Table A.28). Together, these results demonstrate that the forecast improved overall welfare.

Table 8: Effect of the forecast and insurance on economic well-being

	(1) Food cons	(2) Other cons	(3) Asset value	(4) Livestock	(5) Net savings	(6) Welfare index
Forecast	0.87**	-0.52	113.68	0.01	184.33	0.06**
	(0.42)	(0.82)	(134.09)	(0.02)	(145.68)	(0.03)
Insurance	0.46	1.92*	-123.01	0.01	-405.18*	-0.02
	(0.47)	(1.01)	(160.52)	(0.03)	(219.80)	(0.05)
q-val Forecast	0.249	0.945	0.945	0.945	0.701	
q-val Insurance	0.499	0.196	0.499	0.868	0.196	
Control Mean	13.22	9.93	1503.10	0.22	-1031.41	0.00
Observations	1201	1201	1201	1201	1129	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on economic well-being. The estimation follows Equation (3). All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Food cons is food consumption per household member in USD over the past 30 days. Other cons is non-food consumption (other than medical expenses). Asset value is the value of assets in USD. Livestock is the count of livestock in Tropical Livestock Units. Net savings is savings less outstanding debt in USD. Welfare index is an inverse covariance weighted index of the other five outcomes in the table. We exclude the index from the MHT correction as it is a composite of outcomes already included. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[36] Appendix Table A.27 shows that this effect rises to 9.7% in non-flooded villages. We present effects on further-disaggregated consumption categories in Appendix Table A.29.

[37] We provide additional results on household finances in Appendix Table A.30. We estimate impacts on mental health in Appendix Table A.31. We find no impact on overall mental health, though forecast farmers do report increases in poor appetite and/or overeating. We also find evidence of somewhat worse mental health for bad-news farmers, consistent with stress from learning bad news.

7 Forecasts vs. insurance

As a final exercise, we compare forecasts to insurance, the canonical risk-coping tool. This comparison (i) provides a benchmark for the effect sizes produced by the forecast, and (ii) sheds light on the mechanisms through which these two technologies work. Figure 5 summarizes the effects of insurance on twelve key outcomes.[38] Panels A through D demonstrate that insurance farmers increase agricultural investment overall, with effects that are slightly smaller in magnitude to the impacts of the forecast for late-prior farmers (and similar in absolute value to the impacts for early-prior farmers). These effects are in line with prior work on agricultural insurance (Karlan et al., 2014), demonstrating that forecasts have a meaningful impact on farmer decision-making.

The insurance arm also helps highlight the unique mechanism through which forecasts operate. As described in Section 3, the forecast reduces farmers' risk exposure by allowing them to better tailor their investments to the coming growing season. In contrast, the model shows that insurance allows farmers to shift consumption between states of the world, but does not provide information. While this should raise farmer welfare on average, it does not allow farmers to avoid losses by adjusting their investments to better align with expected weather conditions.

Figure 1 shows how predicted investment varies by farmers' priors under the forecast (purple) and insurance (black).[39] The model predicts that while we should see weakly increased investments for all farmers in the insurance group, these impacts will be largest among early-prior insurance farmers – those who would have received a forecast of a worse-than-expected monsoon – and smallest among late-prior insurance farmers – those who would have received a forecast of a better-than-expected monsoon. Intuitively, insurance allows early-prior farmers (who anticipate a good growing season) to meaningfully increase agricultural activity by protecting against downside risk. Insurance should also weakly raise investment among late-prior farmers, but as they expect worse growing conditions, these effects should be smaller.

Figure 6 presents an empirical test of these predictions, using the agricultural investment index as our key outcome of interest. As predicted, we find that early-prior insurance farmers invest more than the control, while late-prior insurance farmers do not change their investments.[40] These findings contrast sharply with the forecast, which helps to correct farmer beliefs by reducing investment among early-prior farmers and encouraging investment among late-prior farmers.[41]

We can also see evidence of this tailoring effect by comparing insurance and late-prior forecast farmers (who received a forecast of a better-than-expected monsoon). One notable difference in upfront investments between the two arms is that insurance farmers are meaningfully less likely

[38]These effects can be seen in tabular form in Tables 4, 5, 6, 7, and 8.

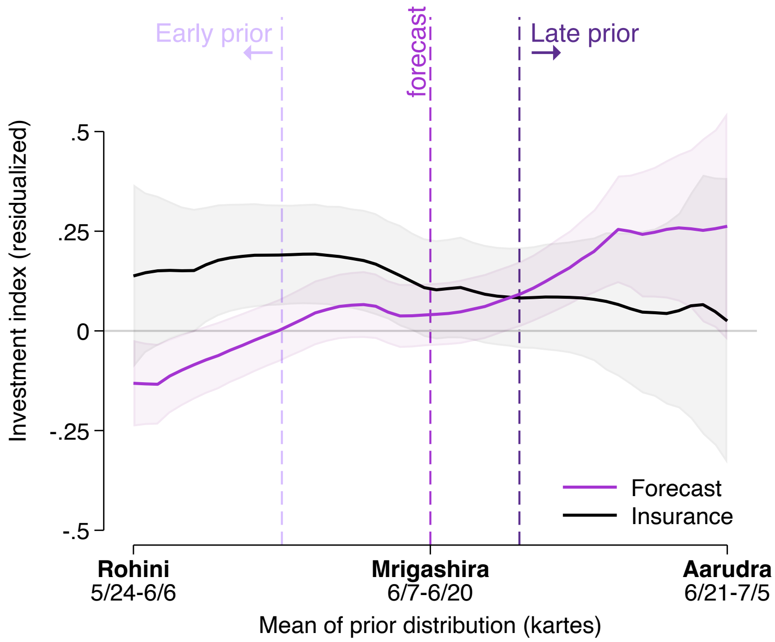
[39]To incorporate insurance, we model farmers as gaining a fixed amount of income if the realized state falls below some pre-determined threshold. See Appendix C for more details.

[40]Appendix Table A.26 reports effects of the insurance treatment by prior tercile on our core farm inputs.

[41]We broadly estimate that insurance did not appear to have large impacts on farmer well-being (Panels I – L). These results are consistent with prior work demonstrating that while insurance can be expected to improve welfare on average (Mobarak and Rosenzweig, 2014; Carter et al., 2017; Cole and Xiong, 2017), in any given year, farmers may see null, or even negative impacts (Karlan et al., 2014) – particularly if, as we discuss above, insurance induces investments from overly-optimistic farmers.

to change crops than late-prior forecast farmers, in keeping with the idea that insurance does not provide information that allows farmers to adjust their cropping decisions. We also show that insurance farmers *increased* off-farm investment (Panel H). This contrasts with late-prior forecast farmers, who instead reduced their non-farm investment, again highlighting that while insurance encourages greater overall investment, it does not allow for the kind of tailored decision-making that forecasts enable.[42]

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 the year prior to the experiment. 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 central bright purple dashed vertical line denotes the realized forecast (an average monsoon). The vertical light and dark purple dashed lines denote the terciles of this distribution.

8 Conclusion

In this paper, we provide evidence on the value of a promising new climate adaptation technology: forecasts. We use a cluster-randomized trial to study the causal impact of an accurate, localized forecast of the onset timing of the Indian Summer Monsoon, delivered well in advance of its arrival,

[42]The insurance arm also confirms that the discrepancy between agricultural inputs and outputs we document above is not unique to forecasts, but likely driven by exogenous weather shocks beyond what our two instruments – both focused on monsoon onset alone – were designed to address. Indeed, as with forecast farmers, we see a mismatch between agricultural inputs and farm output for the insurance group (Figure 5, Panels E and F). Despite increased investments, we see no change in (the value of) farm production or profits overall. However, among farmers reporting no flood or cyclone damages (Panel G), we see that insurance increased farm profits (though this is noisily measured).

on farmer well-being. Our simple theoretical model predicts that such a forecast will enable farmers to tailor their decisions to the coming monsoon season, and that these responses should depend on farmers' prior beliefs. Our estimated treatment effects confirm these predictions.

The forecast caused early-prior forecast farmers (who received a forecast of a worse-than-expected monsoon) to reduce agricultural inputs, had no impact on middle-prior forecast farmers (who received a forecast of an as-expected monsoon), and caused late-prior forecast farmers (who received a forecast of a better-than-expected monsoon) to increase farm inputs. In keeping with these input changes, we broadly see negative, close-to-zero, and positive point estimates on agricultural outcomes for these three groups, respectively. Turning to farm profits, while we find negative impacts for early-prior forecast farmers, we estimate close-to-zero effects for late-prior forecast 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 late-prior forecast group. Our results on non-agricultural business are the mirror-image of the impacts on agriculture, with positive effects for early-prior forecast farmers, and negative effects for late-prior forecast farmers. Finally, we find that the forecast increased welfare, with increases in food consumption, asset value, net savings, and an overall welfare index.

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. 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

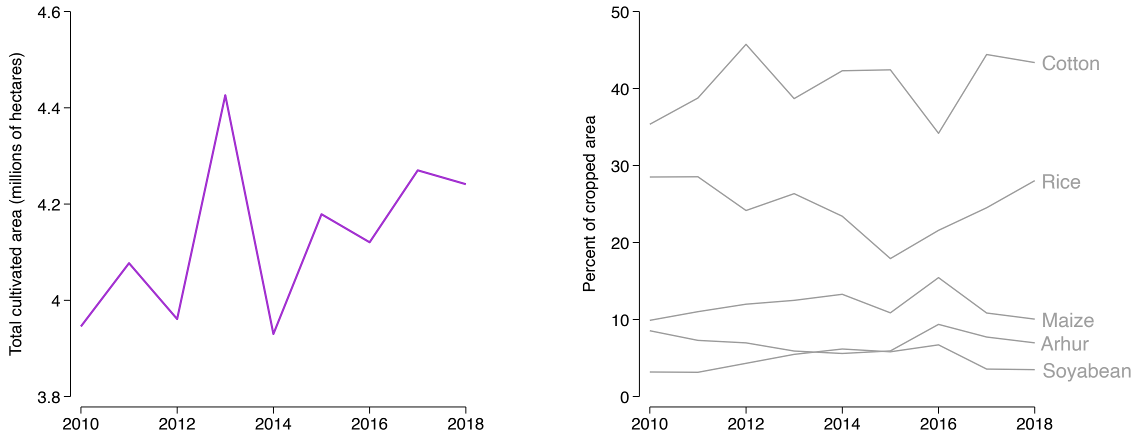
Fiona Burlig, Amir Jina, Erin M. Kelley, Gregory Lane, and Harshil Sahai

Contents

A Appendix tables and figures

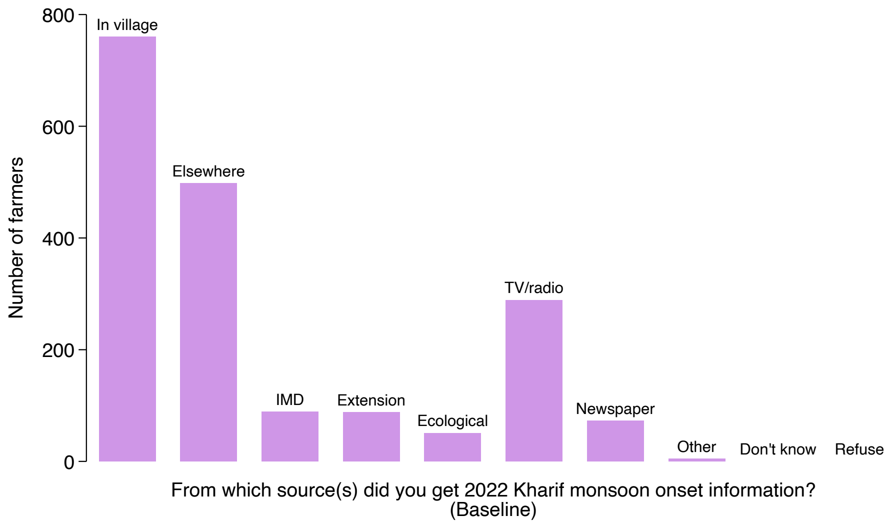
A.1 Context

Figure A.1: Variability of cultivation in Telangana



Notes: This figure presents statistics on the use of agricultural land in Telangana from 2010 to 2018, using data from the Ministry of Agriculture and Farmers' Welfare. The left panel shows total land under cultivation. The right panel shows the percent of agricultural land area cropped to the top five crops: cotton (the main cash crop), rice (the main staple crop), maize, arhartur, and soyabean.

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 kharif season studied in the experiment. 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.

A.2 Attrition and balance

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 forecast, insurance, and control

	(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	−0.13	0.06
	[2.52]	[2.35]	[2.07]	(0.18)	(0.20)	(0.20)
HH head age	47.99	47.48	46.43	−0.47	−1.47	1.08
	[12.31]	[11.67]	[11.78]	(0.92)	(1.20)	(1.20)
HH head educ	6.05	6.03	6.45	−0.05	0.34	−0.41
	[5.12]	[5.05]	[5.04]	(0.38)	(0.49)	(0.50)
# of plots	2.01	1.98	2.07	−0.03	0.07	−0.10
	[1.20]	[1.09]	[1.12]	(0.10)	(0.12)	(0.11)
Total land (ha)	2.71	2.32	2.54	−0.41	−0.19	−0.21
	[4.75]	[2.38]	[2.24]	(0.27)	(0.31)	(0.25)
Observations	472	481	247			
			Panel C: Beliefs about the monsoon			
2022 onset mean	4.89	4.84	4.86	−0.05	−0.02	−0.03
	[0.63]	[0.50]	[0.51]	(0.07)	(0.08)	(0.07)
2022 onset SD	0.98	0.89	0.90	−0.09**	−0.08*	−0.01
	[0.32]	[0.27]	[0.29]	(0.03)	(0.04)	(0.04)
Historical onset mean	4.84	4.82	4.96	−0.01	0.13*	−0.13**
	[0.56]	[0.49]	[0.46]	(0.06)	(0.07)	(0.06)
Historical onset SD	0.82	0.77	0.79	−0.05**	−0.04	−0.01
	[0.19]	[0.19]	[0.19]	(0.02)	(0.03)	(0.03)
Observations	472	481	247			

Notes: This table presents tests for 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. Columns (1) – (3) show means and [standard deviations]. The remaining columns present the pair-wise differences and (standard errors). Standard errors are clustered at the village level, and regressions control for strata fixed effects. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.4: Balance across forecast and control, by tercile of prior belief

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Early prior		**Middle prior**		**Late prior**		Difference		
	Control	Forecast	Control	Forecast	Control	Forecast	(2)-(1)	(4)-(3)	(6)-(5)
HH size	5.23	5.26	5.34	5.54	5.68	4.86	0.02	0.21	-0.84^{**}
	[2.62]	[2.19]	[2.30]	[2.58]	[2.70]	[2.01]	(0.28)	(0.24)	(0.35)
HH head age	46.18	47.38	49.21	47.47	48.61	47.70	1.37	−1.76	−1.11
	[12.48]	[12.20]	[12.14]	[11.02]	[12.13]	[12.20]	(1.51)	(1.33)	(1.78)
HH head educ	6.22	5.95	5.40	6.17	6.86	5.85	−0.40	0.73	−1.08
	[5.12]	[5.22]	[5.04]	[4.91]	[5.17]	[5.06]	(0.61)	(0.56)	(0.68)
# of plots	2.01	2.06	2.10	1.91	1.86	1.99	0.04	−0.20	0.10
	[1.17]	[1.12]	[1.31]	[1.04]	[1.02]	[1.15]	(0.16)	(0.14)	(0.20)
Total land (ha)	3.16	2.62	2.57	2.21	2.27	1.99	−0.63	−0.39	−0.28
	[7.22]	[2.62]	[2.53]	[2.12]	[2.50]	[2.40]	(0.57)	(0.27)	(0.38)
Observations	167	176	188	212	119	93			

Notes: This table presents tests for balance between forecast and control households within each tercile of prior beliefs. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. Columns (1) – (6) show means and [standard deviations]. The remaining columns present the pair-wise differences and (standard errors). Standard errors are clustered at the village level, and regressions control for strata fixed effects. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

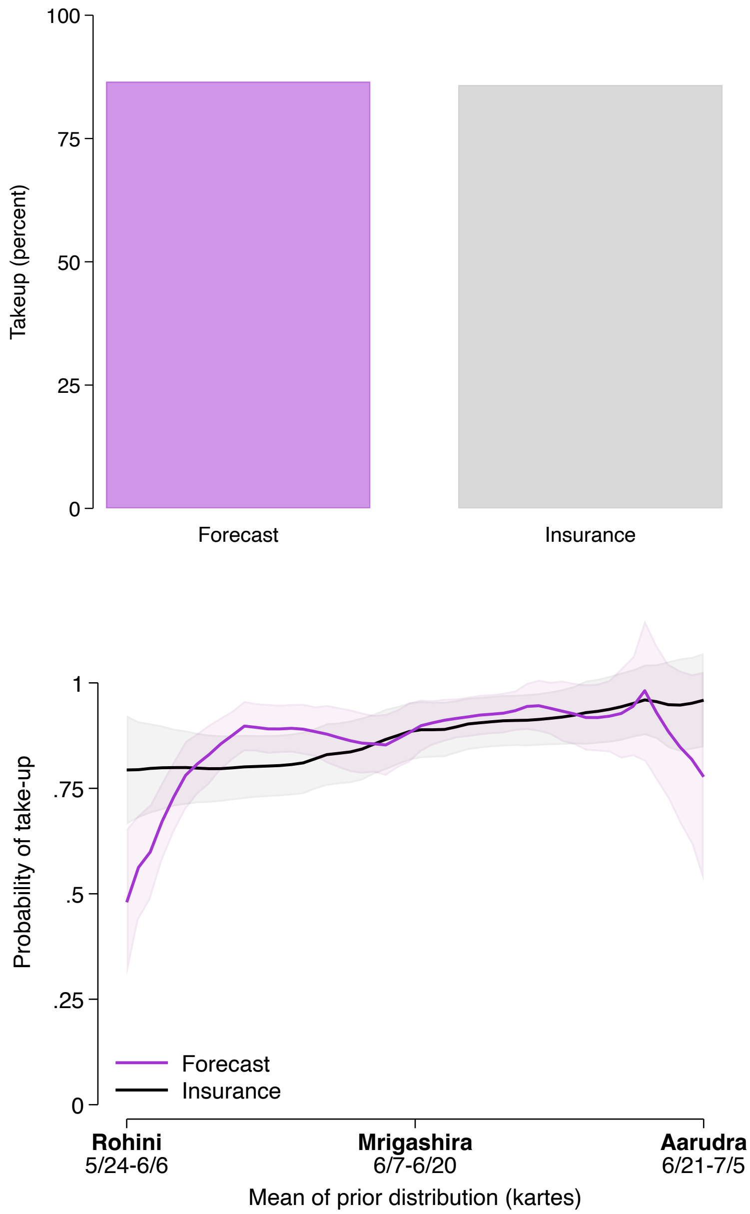
A.3 Takeup

Table A.5: 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 × Early Prior			0.820***	-0.004	0.003	0.022
			(0.043)	(0.007)	(0.003)	(0.017)
Forecast × Middle Prior			-0.000	0.891***	0.004	0.003
			(0.010)	(0.026)	(0.003)	(0.013)
Forecast × Late Prior			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 effect of offering the forecast and insurance treatments on takeup of those treatments. We produce Columns (1) and (2) by estimating Equation (3) with forecast takeup and insurance takeup as the outcome variables, 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. Early, Middle, and Late Prior indicate the prior tercile for a respondent. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions for Columns (3) to (6) also incldue prior tercile fixed effects. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

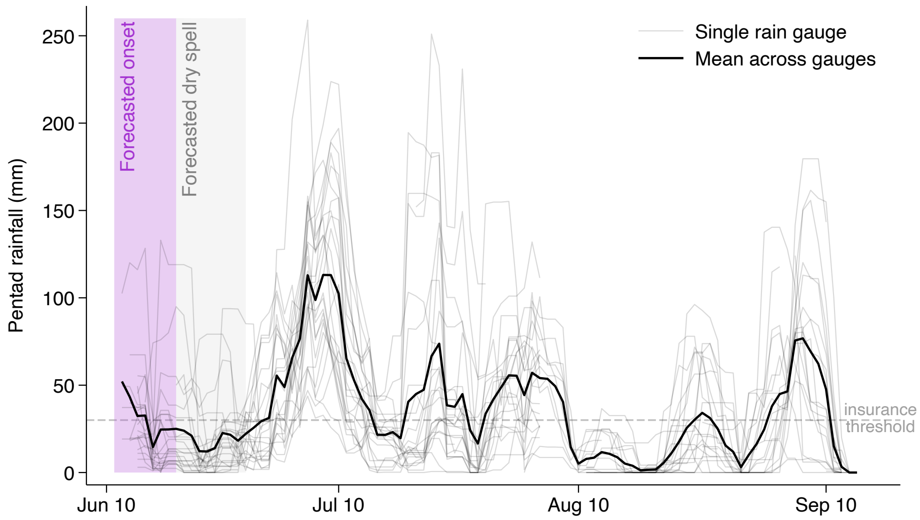
Figure A.3: Takeup of forecasts and insurance



Notes: This figure presents takeup of 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.

A.4 Forecast accuracy

Figure A.4: Rainfall realizations and forecast accuracy in our sample



Notes: This figure shows rainfall over our sample, measured at each of our 25 rain gauges (light gray lines). Following standard practice in climate science, each line plots rainfall amounts 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.

A.5 Beliefs

Table A.6: Association between control-group priors and agricultural investment

	(1) Land Ha.	(2) Cash Crop	(3) Total Exp.	(4) Invest Index
Middle	-0.200	-0.153***	-77.770	-0.175**
	(0.153)	(0.053)	(159.494)	(0.075)
Late	-0.347*	-0.168***	-303.730*	-0.238**
	(0.209)	(0.063)	(178.804)	(0.096)
Test Middle=Late	0.484	0.796	0.178	0.464
Early mean	2.29	0.59	1517.10	0.12
Observations	473	473	473	473

Notes: This table reports the relationship between control group prior beliefs and farm inputs. Land Ha. is land under cultivation in hectares, Cash Crop is an indicator for the farmer planting at least one cash crop, Total Exp. is the total amount spent on all inputs (in USD), and Invest Index is an inverse covariance weighted index of the previous four variables. We regress each outcome on indicators being Middle tercile (2nd) and Late tercile (3rd) of mean prior beliefs, with the Early tercile (1st) as the omitted category. Priors are elicited using the bean task described in Section 4. "Test Middle = Late" is the p-value on the test of equality between the two coefficients. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. The sample includes control-group farmers only. 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: 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 the village in which they currently reside. # 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 the kharif season prior to the experiment. 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.6 Belief spillovers

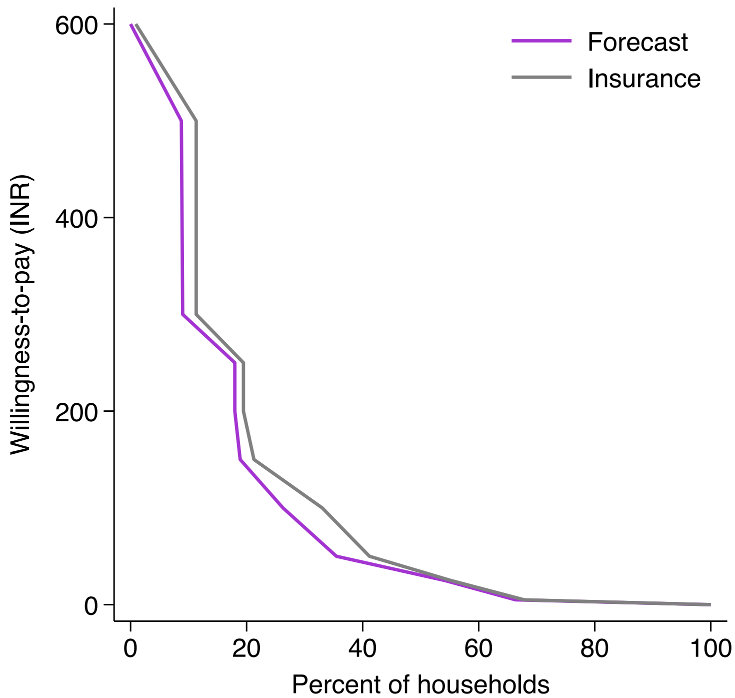
Table A.8: Effect of the forecast on untreated farmer beliefs (spillover sample)

	(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: This table presents the effect of information spillovers on beliefs. Forecast Village is an indicator for being an untreated farmer (i.e., 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 untreated farmers in control villages and in forecast villages. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.7 Willingness-to-pay

Figure A.5: 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 D. 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).

A.8 Pooled forecast treatment results

Table A.9: 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	0.302	0.245	0.340	0.340	0.646

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. 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. Sharpened q-values are adjusted across all outcomes in Tables A.9 and A.10 (except the index), 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 (pooled) and insurance on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast	-1.99	-0.77	24.38	26.48	0.04
	(29.19)	(1.54)	(50.20)	(95.44)	(0.05)
Insurance	97.60**	-0.94	113.49*	263.16**	0.13**
	(43.35)	(1.34)	(64.16)	(130.28)	(0.06)
q-val Forecast	1.000	1.000	1.000	1.000	
q-val Insurance	0.245	0.431	0.245	0.245	
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	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, 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 A.9 and A.10 (except the index), 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 (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. 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. "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 coefficients. Sharpened q-values are adjusted for all outcomes in Tables A.11 and A.12, except Column (4) in the latter table because it is a subsample analysis of Column (1). 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 (pooled) and insurance on agricultural profits

	(1) Ag Profit	(2) Loss	(3) Profit + 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 ($) is the value of production plus the value of crop losses, less total expenditure in USD. Ag Profit Non-Flood ($) is agricultural profits for the sample of households that did not report crop losses due to flooding or cyclones Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. "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 coefficients. Sharpened q-values are adjusted for all outcomes in Tables A.11 and A.12, except Column (4) in the latter table because it is a subsample analysis of Column (1). Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.9 Linear prior

Table A.13: Continuous prior: 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	-0.118	0.054*	0.021	-0.012	0.006
	(0.110)	(0.031)	(0.036)	(0.039)	(0.028)
Forecast X Prior	0.525**	0.093*	0.111*	0.149**	-0.003
	(0.214)	(0.048)	(0.058)	(0.060)	(0.045)
q-val Forecast X Prior	0.078	0.083	0.083	0.078	0.399
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 using a continuous prior. Forecast X Prior is an interaction between the forecast treatment and the farmer's prior, measured in kartes. Farmers with earlier priors are more optimistic about the coming growing season, and are told that the monsoon will be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with later priors are more pessimistic about the coming growing season, and are told that the monsoon will be earlier (i.e., better) than they expected in the forecast treatment arm. Both the base effect of the prior and an indicator for the insurance treatment are included in the main regression but are not reported. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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 Kharif season of the experiment than in the prior season. Added Crop is an indicator for planting at least one additional crop in Kharif season of the experiment compared to the prior season. Sub Crop is an indicator for planting at least one fewer crop in the Kharif season of the experiment than in the prior season. Sharpened q-values are adjusted across all outcomes in Tables A.13 and A.14 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.14: Continuous prior: Effect of the forecast and insurance on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast	-1.65	-0.81	25.14	27.40	0.04
	(29.07)	(1.53)	(49.85)	(94.70)	(0.04)
Forecast X Prior	64.26	1.09	201.72*	356.37**	0.22***
	(48.19)	(2.23)	(105.95)	(176.81)	(0.08)
q-val Forecast X Prior	0.094	0.306	0.072	0.072	
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs, using a continuous prior. Forecast X Prior is an interaction between the forecast treatment and the farmer's prior, measured in kartes. Farmers with earlier priors are more optimistic about the coming growing season, and are told that the monsoon will be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with later priors are more pessimistic about the coming growing season, and are told that the monsoon will be earlier (i.e., better) than they expected in the forecast treatment arm. Both the base effect of the prior and an indicator for the insurance treatment are included in the main regression but are not reported. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, 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. We exclude it from the MHT correction as it is a composite of three outcomes already included. Sharpened q-values are adjusted across all outcomes in Tables A.13 and A.14 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.15: Continuous prior: Effect of the forecast and insurance on agricultural output

	(1) Prod (Kg)	(2) Value Prod ($)	(3) Yield
Forecast	-8.39	-187.41	-2.95
	(5.35)	(194.68)	(2.77)
Forecast X Prior	19.31*	487.50	6.80
	(9.99)	(331.98)	(4.88)
q-val Forecast X Prior	0.339	0.339	0.339
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, using a continuous prior. Forecast X Prior is an interaction between the forecast treatment and the farmer's prior, measured in kartes. Farmers with earlier priors are more optimistic about the coming growing season, and are told that the monsoon will be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with later priors are more pessimistic about the coming growing season, and are told that the monsoon will be earlier (i.e., better) than they expected in the forecast treatment arm. Both the base effect of the prior and an indicator for the insurance treatment are included in the main regression but are not reported. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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. Sharpened q-values are adjusted for all outcomes in Tables A.15 and A.16, except Column (4) in the latter table because it is a subsample analysis of Column (1). Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.16: Continuous prior: Effect of the forecast and insurance on agricultural profit

	(1) Ag Profit	(2) Loss	(3) Profit + Loss	(4) Ag Profit Non-Flood
Forecast	-215.18	158.61*	-38.94	-125.33
	(161.21)	(90.28)	(193.18)	(250.34)
Forecast X Prior	112.20	176.31	263.27	481.60
	(271.58)	(127.98)	(332.96)	(451.75)
q-val Forecast X Prior	0.339	0.339	0.339	
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, using a continuous prior. Forecast X Prior is an interaction between the forecast treatment and the farmer's prior, measured in kartes. Farmers with earlier priors are more optimistic about the coming growing season, and are told that the monsoon will be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with later priors are more pessimistic about the coming growing season, and are told that the monsoon will be earlier (i.e., better) than they expected in the forecast treatment arm. Both the base effect of the prior and an indicator for the insurance treatment are included in the main regression but are not reported. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Ag Profit is the value of production (evaluated at district-median prices) less total expenditure. Loss is the value of reported crop losses (evaluated at district-median prices). Profit + 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. All outcomes are in USD. Sharpened q-values are adjusted for all outcomes in Tables A.15 and A.16, except Column (4) in the latter table because it is a subsample analysis of Column (1). Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.17: Continuous prior: Effect of the forecast and insurance on business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast	0.02	-11.80	28.18
	(0.02)	(41.32)	(40.93)
Forecast X Prior	-0.08**	-153.49**	-122.12*
	(0.04)	(68.57)	(72.29)
q-val Forecast X Prior	0.054	0.054	0.054
Control Mean	0.14	157.98	165.51
Observations	1197	1199	1197

Notes: This table presents estimates of the treatment effects of forecasts and insurance on non-farm business activity, using a continuous prior. Forecast X Prior is an interaction between the forecast treatment and the farmer's prior, measured in kartes. Farmers with earlier priors are more optimistic about the coming growing season, and are told that the monsoon will be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with later priors are more pessimistic about the coming growing season, and are told that the monsoon will be earlier (i.e., better) than they expected in the forecast treatment arm. Both the base effect of the prior and an indicator for the insurance treatment are included in the main regression but are not reported. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.10 Alternative prior bin definition

Table A.18: Alternative prior bins: 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 X Early Prior	-0.471***	0.012	-0.053	-0.114*	0.013
	(0.161)	(0.049)	(0.053)	(0.059)	(0.045)
Forecast X Middle Prior	0.046	0.059*	0.046	0.041	0.000
	(0.148)	(0.035)	(0.047)	(0.048)	(0.036)
Forecast X Late Prior	0.313	0.172*	0.176**	0.093	0.106*
	(0.322)	(0.089)	(0.078)	(0.097)	(0.064)
q-val Early	0.033	1.000	1.000	0.270	1.000
q-val Middle	1.000	1.000	1.000	1.000	1.000
q-val Late	0.211	0.188	0.188	0.211	0.188
Test Early = Late	0.031	0.103	0.014	0.059	0.231
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	1201.00	1201.00	1201.00	1201.00	1201.00

Notes: This table presents estimates of the treatment effects of forecasts and insurance on farmers' land use and cropping decisions, estimated using Equation (4), with alternative prior bins. Early, Middle, and Late indicate the prior classification for a respondent. Early-prior farmers were the most optimistic, with their prior belief falling before the Mrigashira karte, and were therefore told that the monsoon would be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with Middle Priors had average beliefs that fell within the forecasted karte, and were told that the monsoon would be as they expected in the forecast group. Late-prior farmers were the most pessimistic, with their prior belief falling after the forecasted karte, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast treatment arm. All regressions include an indicator for the insurance treatment, prior bin fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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 Kharif season of the experiment than in the prior season. Added Crop is an indicator for planting at least one additional crop in Kharif season of the experiment compared to the prior season. Sub Crop is an indicator for planting at least one fewer crop in the Kharif season of the experiment than in the prior season. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient. Sharpened q-values are adjusted across all outcomes in Tables A.18 and A.19 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.19: Alternative prior bins: Effect of the forecast and insurance on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast X Early Prior	-29.26	-0.68	-38.68	-123.59	-0.08
	(42.38)	(2.60)	(85.06)	(160.39)	(0.07)
Forecast X Middle Prior	-8.05	-0.91	6.16	24.79	0.08
	(38.76)	(1.73)	(62.35)	(116.18)	(0.06)
Forecast X Late Prior	105.54	0.41	285.64*	482.66*	0.29**
	(74.17)	(2.38)	(154.31)	(266.17)	(0.12)
q-val Early	1.000	1.000	1.000	1.000	
q-val Middle	1.000	1.000	1.000	1.000	
q-val Late	0.188	0.404	0.188	0.188	
Test Early = Late	0.113	0.758	0.070	0.052	0.008
Control Mean	372.803	7.221	761.958	1443.485	0.000
Observations	1201.00	1201.00	1201.00	1201.00	1201.00

Notes: This table presents estimates of the treatment effects of forecasts and insurance on inputs, estimated using Equation (4), with alternative prior bins. Early, Middle, and Late indicate the prior classification for a respondent. Early-prior farmers were the most optimistic, with their prior belief falling before the Mrigashira karte, and were therefore told that the monsoon would be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with Middle Priors had average beliefs that fell within the forecasted karte, and were told that the monsoon would be as they expected in the forecast group. Late-prior farmers were the most pessimistic, with their prior belief falling after the forecasted karte, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast treatment arm. All regressions include an indicator for the insurance treatment, prior bin fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, 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. We exclude it from the MHT correction as it is a composite of three outcomes already included. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient. Sharpened q-values are adjusted across all outcomes in Tables A.18 and A.19 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.20: Alternative prior bins: Effect of the forecast and insurance on agricultural output

	(1) Prod (Kg)	(2) Value Prod ($)	(3) Yield
Forecast X Early Prior	-16.47**	-534.36*	-6.53
	(8.16)	(285.02)	(4.36)
Forecast X Middle Prior	-5.44	-27.79	-1.06
	(7.07)	(253.72)	(3.31)
Forecast X Late Prior	12.86	101.66	1.40
	(14.91)	(405.50)	(7.01)
q-val Early	0.205	0.205	0.205
q-val Middle	1.000	1.000	1.000
q-val Late	1.000	1.000	1.000
Test Early = Late	0.082	0.191	0.321
Control Mean	66.906	2419.931	35.374
Observations	1201.00	1201.00	1170.00

Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural output, estimated using Equation (4), with alternative prior bins. Early, Middle, and Late indicate the prior classification for a respondent. Early-prior farmers were the most optimistic, with their prior belief falling before the Mrigashira karte, and were therefore told that the monsoon would be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with Middle Priors had average beliefs that fell within the forecasted karte, and were told that the monsoon would be as they expected in the forecast group. Late-prior farmers were the most pessimistic, with their prior belief falling after the forecasted karte, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast treatment arm. All regressions include an indicator for the insurance treatment, prior bin fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient. Sharpened q-values are adjusted for all outcomes in Tables A.20 and A.21, except Column (4) in the latter table because it is a subsample analysis of Column (1). Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.21: Alternative prior bins: Effect of the forecast and insurance on agricultural profit

	(1) Ag Profit	(2) Loss	(3) Profit + Loss	(4) Ag Profit Non-Flood
Forecast X Early Prior	-406.80*	49.00	-309.03	-337.57
	(235.93)	(134.99)	(322.30)	(426.30)
Forecast X Middle Prior	-46.22	235.75*	194.16	23.52
	(211.36)	(123.74)	(234.76)	(270.31)
Forecast X Late Prior	-385.77	78.34	-312.13	325.73
	(321.51)	(152.68)	(382.93)	(541.29)
q-val Early	0.205	0.314	0.253	
q-val Middle	1.000	0.520	1.000	
q-val Late	1.000	1.000	1.000	
Test Early = Late	0.957	0.880	0.995	0.341
Control Mean	970.624	661.068	1654.238	1052.591
Observations	1201.00	1201.00	1201.00	554.00

Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural profit and loss, estimated using Equation (4), with alternative prior bins. Early, Middle, and Late indicate the prior classification for a respondent. Early-prior farmers were the most optimistic, with their prior belief falling before the Mrigashira karte, and were therefore told that the monsoon would be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with Middle Priors had average beliefs that fell within the forecasted karte, and were told that the monsoon would be as they expected in the forecast group. Late-prior farmers were the most pessimistic, with their prior belief falling after the forecasted karte, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast treatment arm. All regressions include an indicator for the insurance treatment, prior bin fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Ag Profit is the value of production (evaluated at district-median prices) less total expenditure. Loss is the value of reported crop losses (evaluated at district-median prices). Profit + 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. All outcomes are in USD. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient. Sharpened q-values are adjusted for all outcomes in Tables A.20 and A.21, except Column (4) in the latter table because it is a subsample analysis of Column (1). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.22: Alternative prior bins: Effect of the forecast and insurance on business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast X Early Prior	0.06 (0.04)	29.23 (71.79)	81.71 (76.02)
Forecast X Middle Prior	0.01 (0.03)	1.63 (51.78)	42.95 (45.46)
Forecast X Late Prior	-0.10** (0.05)	-163.42* (83.97)	-175.73** (85.31)
q-val Early	0.736	0.736	0.736
q-val Middle	1.000	1.000	1.000
q-val Late	0.055	0.055	0.055
Test Early = Late	0.016	0.086	0.026
Control Mean	0.135	157.981	165.509
Observations	1197.00	1199.00	1197.00

Notes: This table presents estimates of the treatment effects of forecasts and insurance on non-farm business activity estimated using Equation (4), with alternative prior bins. Early, Middle, and Late indicate the prior classification for a respondent. Early-prior farmers were the most optimistic, with their prior belief falling before the Mrigashira karte, and were therefore told that the monsoon would be later (i.e., worse) than they expected in the forecast treatment arm. Farmers with Middle Priors had average beliefs that fell within the forecasted karte, and were told that the monsoon would be as they expected in the forecast group. Late-prior farmers were the most pessimistic, with their prior belief falling after the forecasted karte, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast treatment arm. All regressions include an indicator for the insurance treatment, prior bin fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient. Sharpened q-values are adjusted for all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.11 Income-generating activities and migration

Table A.23: Effect of the forecast and insurance on other income-generating activities

	Panel A: Forecast vs. Insurance		
	(1) Labor Inc.	(2) Livestock Inc.	(3) Remittance Inc.
Forecast	-44.45 (33.59)	-81.30 (70.69)	-2.77 (2.37)
Insurance	-29.11 (40.93)	-41.70 (113.22)	-5.72** (2.53)
q-val Forecast	0.338	0.338	0.338
q-val Insurance	0.907	0.907	0.079

	Panel B: Forecast Terciles		
Forecast × Early Prior	-114.22** (54.72)	-0.18 (100.40)	-1.37 (4.72)
Forecast × Middle Prior	7.33 (44.15)	-143.86 (101.26)	-2.10 (2.26)
Forecast × Late Prior	-20.22 (67.89)	-177.44 (129.70)	-6.79** (3.41)
q-val Early	0.126	1.000	1.000
q-val Middle	1.000	0.900	0.900
q-val Late	0.353	0.211	0.163
Test Early=Late	0.264	0.290	0.323
Insur. = Late	0.895	0.405	0.691
Control Mean	324.53	496.70	7.46
Observations	1199	125	1201

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 in the last 12 months, Livestock Inc. is income from selling livestock in the last 12 months, and Remittance Inc. is income from remittances received in past 30 days, all in USD. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions in Panel B also include prior tercile fixed effects. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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.24: Effect of the forecast and insurance on migration

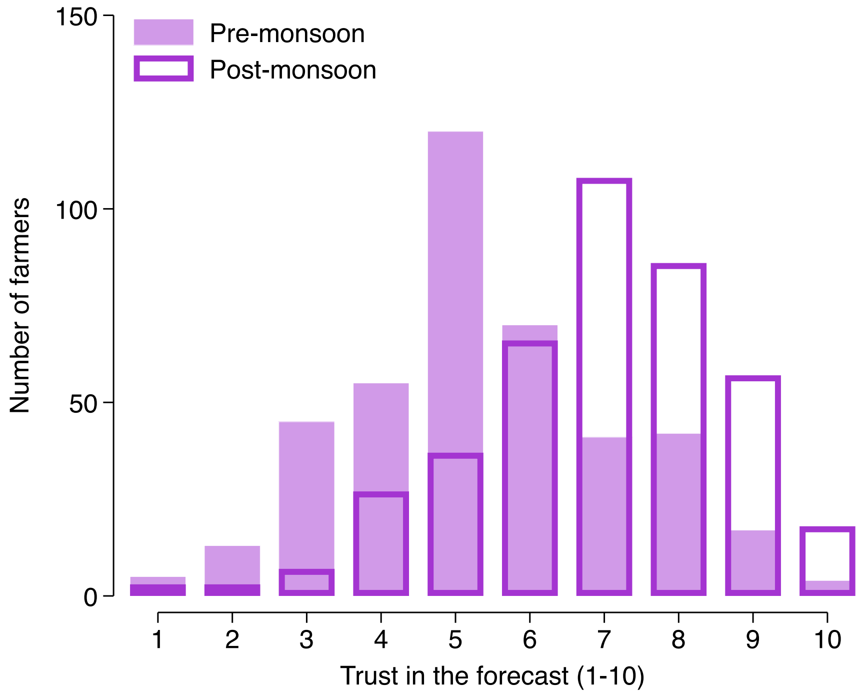
	Panel A: Forecast vs. Insurance			
	(1) Any Migrant	(2) Num Temp Mig.	(3) N. Female	(4) N. Male
Forecast	-0.03	-0.09**	-0.03**	-0.05*
	(0.02)	(0.04)	(0.01)	(0.03)
Insurance	-0.00	-0.08**	-0.04**	-0.04
	(0.03)	(0.04)	(0.02)	(0.03)
q-val Forecast	0.084	0.057	0.057	0.062
q-val Insurance	0.288	0.111	0.111	0.111

	Panel B: Forecast Terciles			
Forecast × Early Prior	-0.05	-0.15**	-0.06**	-0.08*
	(0.04)	(0.06)	(0.02)	(0.04)
Forecast × Middle Prior	-0.03	-0.04	-0.02	-0.02
	(0.03)	(0.05)	(0.02)	(0.04)
Forecast × Late Prior	0.00	-0.07	-0.02	-0.04
	(0.04)	(0.06)	(0.03)	(0.05)
q-val Early	0.074	0.037	0.037	0.037
q-val Middle	1.000	1.000	1.000	1.000
q-val Late	1.000	1.000	1.000	1.000
Test Early=Late	0.329	0.401	0.245	0.534
Insur. = Late	0.863	0.851	0.546	0.963
Control Mean	0.15	0.22	0.06	0.15
Observations	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 12 months. NḞemale and N. Male are the number of temporary female and male migrants, respectively. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions in Panel B also include prior tercile fixed effects. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.12 Trust

Figure A.6: Farmer trust in the forecast



Notes: This figure presents farmers' stated trust in the forecast, measured on a 1–10 scale. The solid histogram presents trust in the forecast when farmers received the information, while the hollow histogram presents trust after the monsoon had arrived. The sample includes only farmers in the forecast treatment group.

A.13 Shocks

Table A.25: Shock realizations across treatments

	Panel A: Forecast vs. Insurance				
	(1)	(2)	(3)	(4)	(5)
	Flood	Drought	Animal	Cyclone	Any
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 ×	-0.07	0.01	0.01	0.04	0.01
Early Prior	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)
Forecast ×	-0.05	0.00	0.05	0.04	0.05
Middle Prior	(0.04)	(0.02)	(0.03)	(0.05)	(0.06)
Forecast ×	0.03	0.03	0.01	-0.05	0.04
Late Prior	(0.06)	(0.03)	(0.05)	(0.07)	(0.06)
q-val Early	1.000	1.000	1.000	1.000	1.000
q-val Middle	1.000	1.000	1.000	1.000	1.000
q-val Late	1.000	1.000	1.000	1.000	1.000
Test Early=Late	0.184	0.505	0.929	0.208	0.674
Test Insur. = Late	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 a particular shock type. 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 losses from any of these four shocks. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions in Panel B also include prior tercile fixed effects. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.14 Insurance and prior beliefs

Table A.26: Effect of insurance on inputs by prior terciles

	(1) Land Ha.	(2) Cash Crop	(3) Total Inputs	(4) Invest Index
Insurance × Early Prior	0.486** (0.226)	0.023 (0.065)	415.311* (217.148)	0.172* (0.095)
Insurance × Middle Prior	0.110 (0.172)	0.092* (0.051)	274.439 (172.141)	0.157** (0.076)
Insurance × Late Prior	-0.073 (0.303)	0.048 (0.077)	59.705 (243.760)	0.017 (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 Late	1.000	1.000	1.000	
Test Early=Late	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 farm inputs by prior belief terciles. 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. We exclude it from the MHT correction as it is a composite of three outcomes already included. Early, Middle, and Late Priors indicate the prior tercile for a respondent. Those with Early Priors were the most optimistic. Farmers with Middle Priors had average (and thus correct) beliefs. Those with Late Priors were the most pessimistic. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Additionally, each regression also controls for the forecast treatment, with separate controls 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.15 Additional welfare results

Table A.27: Effect of the forecast and insurance on economic well-being, no flood shock

	(1)	(2)	(3)	(4)	(5)	(6)
	Food cons	Other cons	Asset value	Livestock	Net savings	Welfare index
Forecast	1.32**	-0.59	42.70	0.01	25.87	0.04
	(0.65)	(1.06)	(160.89)	(0.03)	(205.65)	(0.05)
Insurance	0.80	2.35	-55.39	-0.02	-779.87***	-0.06
	(0.75)	(1.88)	(229.95)	(0.05)	(275.25)	(0.06)
q-val Forecast	0.274	1.000	1.000	1.000	1.000	
q-val Insurance	0.618	0.618	0.913	0.913	0.025	
Control Mean	13.57	9.83	1546.97	0.19	-839.15	0.02
Observations	554	554	554	554	516	554

Notes: This table presents estimates of the treatment effects of forecasts and insurance on well-being, restricting the sample to those who did not report losses due to flooding or cyclones. The estimation follows Equation (3). Food cons is food consumption per household member in USD over the past 30 days. Other cons is non-food consumption (other than medical expenses). Asset value is the value of assets in USD. Livestock is the count of livestock in Tropical Livestock Units. Net savings is savings less outstanding debt in USD. Welfare index is an inverse covariance weighted index of the other five outcomes in the table. We exclude the index from the MHT correction, as it is a composite of outcomes already included. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. 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 A.28: Effect of the forecast and insurance on economic well-being by prior tercile

	(1) Food cons	(2) Other cons	(3) Asset value	(4) Livestock	(5) Net savings	(6) Welfare index
Forecast ×	0.32	-0.48	349.12	0.07*	372.18	0.14**
Early Prior	(0.65)	(1.45)	(264.89)	(0.04)	(252.96)	(0.06)
Forecast ×	1.19**	-0.80	29.35	-0.04	59.12	-0.00
Middle Prior	(0.53)	(0.97)	(153.43)	(0.03)	(228.47)	(0.04)
Forecast ×	1.14	-0.28	-135.55	0.02	121.49	0.05
Late Prior	(0.84)	(1.45)	(145.83)	(0.05)	(253.87)	(0.05)
Insurance	0.45	1.91*	-115.78	0.01	-406.54*	-0.02
	(0.47)	(1.00)	(158.47)	(0.03)	(217.24)	(0.05)
q-val Early	0.456	0.456	0.456	0.456	0.456	
q-val Middle	0.143	1.000	1.000	0.929	1.000	
q-val Late	1.000	1.000	1.000	1.000	1.000	
q-val Insurance	0.493	0.182	0.536	0.782	0.182	
Test Early=Late	0.413	0.917	0.094	0.466	0.515	0.288
Test Insur. = Late	0.449	0.147	0.906	0.840	0.064	0.285
Control Mean	13.22	9.93	1503.10	0.22	-1031.41	0.00
Observations	1201	1201	1201	1201	1129	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on well-being. The estimation follows Equation (4). Food cons is food consumption per household member in USD over the past 30 days. Other cons is non-food consumption (other than medical expenses). Asset value is the value of assets in USD. Livestock is the count of livestock in Tropical Livestock Units. Net savings is savings less outstanding debt in USD. Welfare index is an inverse covariance weighted index of the other five outcomes in the table. We exclude the index from the MHT correction, as it is a composite of outcomes already included. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include prior tercile fixed effects, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 A.29: Effect of the forecast and insurance on per-capita consumption (disaggregated)

	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 ×	0.16	0.05	-1.00***	0.11	0.03	1.36**	-0.28	-0.17	-1.76
Early Prior	(0.41)	(0.17)	(0.38)	(0.27)	(0.09)	(0.58)	(1.03)	(0.70)	(2.93)
Forecast ×	0.99***	0.15	-0.61*	-0.15	0.09	-0.76	0.01	-0.46	-0.76
Middle Prior	(0.38)	(0.14)	(0.36)	(0.22)	(0.08)	(0.48)	(0.84)	(0.44)	(2.24)
Forecast ×	0.84	0.48**	-0.30	-0.25	0.11	-0.28	-0.85	0.10	-0.81
Late Prior	(0.55)	(0.22)	(0.54)	(0.34)	(0.10)	(0.60)	(1.13)	(0.55)	(2.82)
q-val Early	1.000	1.000	0.085	1.000	1.000	0.085	1.000	1.000	1.000
q-val Middle	0.088	0.515	0.433	0.740	0.515	0.433	0.793	0.515	0.793
q-val Late	0.984	0.352	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Test Early=Late	0.298	0.105	0.273	0.384	0.513	0.041	0.693	0.761	0.807
Test Insur. = Late	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). Cereals is spending on rice, millet, suji, ragi, or any other grain. Milk is spending on dairy products. Tab / Alc is spending on tobacco or alcohol. 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 in USD spent per household member during the past 30 days, and are winsorized at the 5th and 95th percentile. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions in Panel B also include prior tercile fixed effects. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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.30: Effect of the forecast and insurance on household finances

	(1) Savings	(2) Took Loan	(3) Debt Out	(4) Missed Payment	(5) Farm Loan
	Panel A: Forecast vs. Insurance				
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 ×	-48.58	-0.07	-449.03*	-0.15*	-0.09*
Early Prior	(33.80)	(0.05)	(238.37)	(0.09)	(0.05)
Forecast ×	-0.84	-0.06	-47.90	-0.17*	-0.11**
Middle Prior	(31.62)	(0.05)	(206.16)	(0.09)	(0.05)
Forecast ×	19.67	-0.02	-30.84	0.02	-0.04
Late Prior	(41.86)	(0.07)	(256.32)	(0.14)	(0.07)
q-val Early	0.171	0.171	0.171	0.171	0.171
q-val Middle	0.644	0.266	0.644	0.176	0.176
q-val Late	1.000	1.000	1.000	1.000	1.000
Test Early=Late	0.163	0.583	0.258	0.254	0.567
Test Insur. = Late	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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions in Panel B also include prior tercile fixed effects. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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.31: Effect of the forecast and insurance on mental health

	Panel A: Forecast vs. Insurance								
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5	(6) Q6	(7) Q7	(8) Q8	(9) Norm
Forecast	0.04	-0.01	0.10	0.00	0.17**	0.10	-0.07	0.11	0.07
	(0.09)	(0.08)	(0.07)	(0.09)	(0.07)	(0.09)	(0.08)	(0.07)	(0.05)
Insurance	0.14	-0.17**	-0.11	-0.06	-0.03	0.03	0.14	0.03	-0.01
	(0.14)	(0.09)	(0.08)	(0.09)	(0.07)	(0.09)	(0.09)	(0.08)	(0.05)
q-val Forecast	0.868	0.868	0.654	0.868	0.207	0.704	0.800	0.654	0.654
q-val Insurance	0.956	0.627	0.698	1.000	1.000	1.000	0.698	1.000	1.000

	Panel B: Forecast Terciles								
Forecast × Early Prior	0.06	0.00	0.19	0.11	0.26**	0.06	-0.03	0.23**	0.14*
	(0.21)	(0.12)	(0.12)	(0.14)	(0.12)	(0.13)	(0.16)	(0.11)	(0.08)
Forecast × Middle Prior	-0.00	-0.05	0.10	-0.02	0.16**	0.11	-0.12	0.10	0.04
	(0.09)	(0.11)	(0.10)	(0.10)	(0.08)	(0.11)	(0.09)	(0.09)	(0.07)
Forecast × Late Prior	0.05	0.09	-0.06	-0.11	0.03	0.14	-0.00	-0.04	0.02
	(0.18)	(0.16)	(0.16)	(0.17)	(0.14)	(0.20)	(0.16)	(0.12)	(0.13)
q-val Early	1.000	1.000	0.264	0.725	0.210	1.000	1.000	0.210	0.210
q-val Middle	1.000	1.000	1.000	1.000	0.733	1.000	1.000	1.000	1.000
q-val Late	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Test Early=Late	0.981	0.670	0.218	0.310	0.175	0.739	0.916	0.106	0.420
Test Insur. = Late	0.606	0.120	0.779	0.785	0.678	0.605	0.362	0.582	0.887
Control Mean	1.56	0.97	0.73	1.29	0.47	0.67	0.66	0.50	-0.02
Observations	1201	1201	1201	1201	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts and insurance on mental health, estimated using Equations (3, panel A) and (4, panel B). We measure outcomes using the PhQ-8 screening tool, a standard and locally-validated depression metric (Bhat et al. (2022)). Outcomes for questions 1-8 are measured in the number of days in the past seven that the respondent agreed with the question prompt. Norm (column 9) is standardized PhQ-8 score. Q1 asked about having little pleasure in doing things, Q2 feeling depressed or hopeless, Q3 having trouble sleeping or sleeping too much, Q4 having little energy, Q5 having poor appetite or overeating, Q6 feeling bad about yourself or think you have little worth, Q7 trouble concentrating, and Q8 moving or speaking slowly so others do not notice. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Regressions in Panel B also include prior tercile fixed effects. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted across all outcomes in the table, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B Panel analysis: Additional details

This Appendix provides additional details about our data and sample construction for our historical analysis of the effect of monsoon onset timing on crop yields across India (described in Section 2).

Monsoon onset data Our precipitation data come from the European Centre for Medium-Range Weather Forecasting Reanalysis dataset (ERA5). To convert this precipitation information into data on monsoon onset at the grid-cell level, we follow Moron and Robertson (2014)'s definition: "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 false positives — cases when a wet spell is followed by drought — an onset date cannot be followed "by a 10-day dry spell (receiving less than 5 mm) in the following 30 d from the onset." We adjust the first-day rainfall threshold to from 1mm to 4mm, to better match the Indian context.

We construct district-level onset data by taking the area-weighted-average onset date of all pixels that lie (fully or partially) within each district. We standardize each district's onset dates according to the district-specific mean and variance of the onset.

Agriculture data We obtain district-level kharif season crop yield data from the Indian Ministry of Agriculture and Farmers' Welfare. Our data spans 1997–2022. We use 2011 Census of India district definitions. We focus our analysis on two major crops: rice, a key staple, and cotton, a key cash crop.

Defining monsoonal regions While most of India is characterized by monsoonal rainfall patterns, with little-to-no rain outside the main monsoon season, some regions have other rainfall patterns. We therefore restrict our analysis to the monsoonal regions of India. We follow the monsoonal regions outlined in Moron et al. (2017). To be conservative, we therefore exclude the states of Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Tripura, Jammu and Kashmir, and Tamil Nadu from our analysis.

C Model details

C.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.[43]

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:

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

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.

C.2 Optimal farmer investment and saving decisions

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

[43] 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:[44]

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

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

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

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:

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

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

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

with weights:

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

where the second equality comes from plugging in the FOC for savings in (C.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:

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

[44]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:

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

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:

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

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 (C.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.

C.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):

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

Production The technology is Cobb-Douglas in investment:

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

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

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

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:

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

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:

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

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

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

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

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

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

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

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

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

The parameters are set according to Table C.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 C.1: Parameters for model simulation

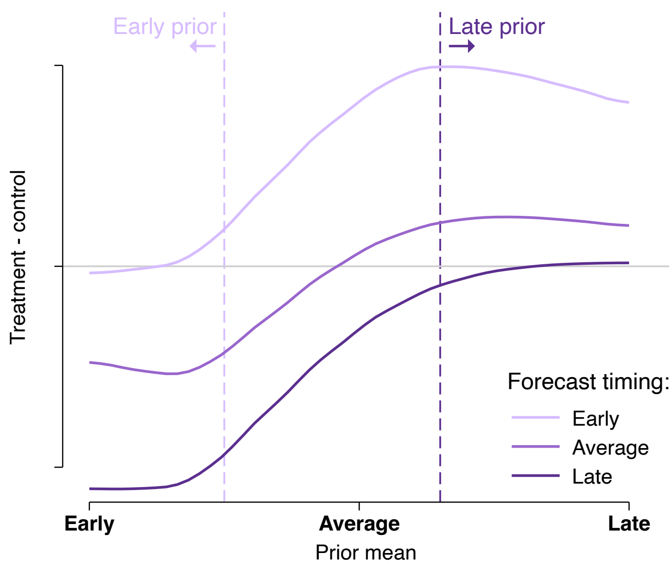
Parameter	Description	Value
Panel A: Utility Parameters		
r	Relative risk aversion	0.5
β	Discount factor	0.95
y	Starting wealth	5
p	Input price	1
Panel B: Production Parameters		
α	Production function curvature	0.6
$\bar{z}$	Max productivity	3
k	Scale parameter of productivity	2
Panel C: State Parameters		
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

Notes: This table presents the parameters used in our model simulation, as well as their assumed values (or range of values).

C.4 Model predictions for alternative forecast realizations

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



Notes: This figure plots the simulated relationship in our model between the treatment effect of forecasts on optimal investment and farmers' priors prior. 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 when farmers believe the monsoon will arrive. 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 light upper line; responses to an average forecast realization (as was the case in our empirical setting) are depicted by the central line; and responses to a late forecast realization are depicted in the dark bottom line.

D 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.

D.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.

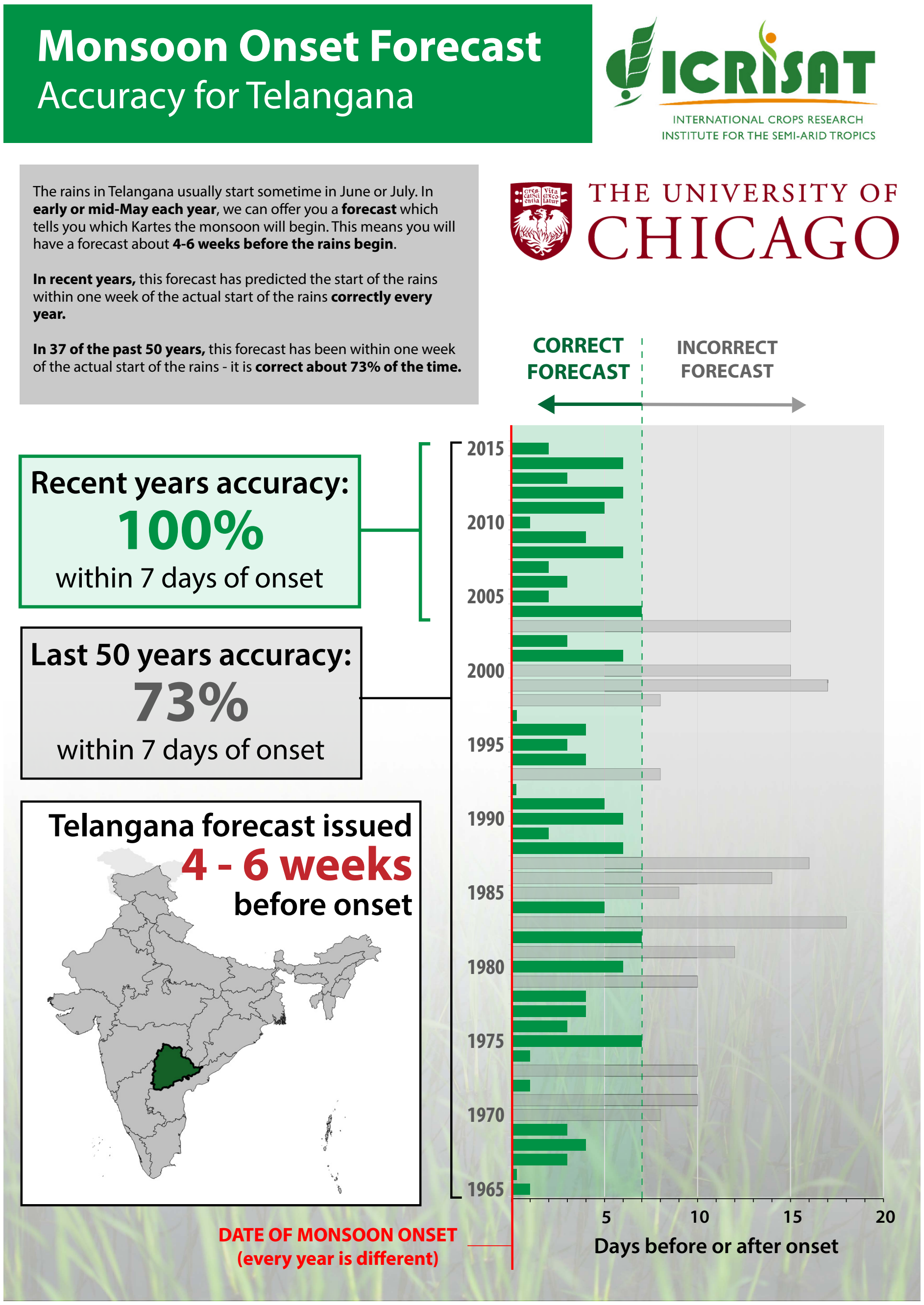
D.2 Distribution of BDM prices

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.

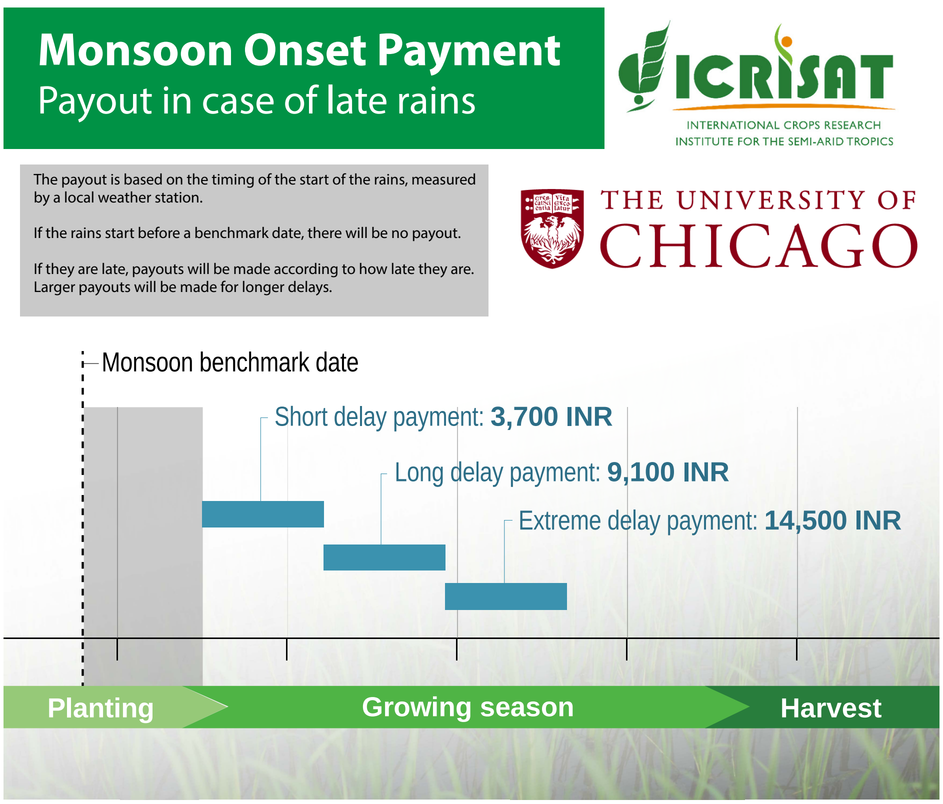
E Information sheets

Figure E.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 D. The information sheet was translated into Telugu before being presented to farmers.

Figure E.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 D. The information sheet was translated into Telugu before being presented to farmers.

F 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 G.6.

- **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 G.5 for completeness.

- **Outcome variables** We exclude medical spending from the construction of "other consumption", as it is unclear whether increased medical spending implies higher (e.g., households can afford to spend more money on treatment) or lower (e.g., households have negative health shocks that require expenditure) welfare.

- **Analysis.** For the correlations between WTP and prior beliefs (described in Section 5 and presented in Appendix Tables G.1, G.2, and G.3, 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 G.1 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 G.3, 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.

- **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.

- **Analysis.** We did not pre-specify the analysis on crop losses, profits net of losses, and profits for non-flood-affected farmers (Columns (2)–(6) of Table 6).

G Additional pre-specified results

G.1 Correlates of willingness-to-pay

Table G.1: 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 (26.242)	-17.142 (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 G.2: 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 G.3: 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. Prob mass of beans before individual 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: *** $p < 0.01$, * $p < 0.05$, ** $p < 0.10$.

G.2 Belief heterogeneity

Table G.4: Effect of the forecast on beliefs by prior strength

	(1) | posterior − forecast |	(2) | posterior − prior |	(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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G.3 Additional farm input results

Table G.5: 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 × Early Prior	-0.067	-72.159**	7.779
	(0.056)	(35.587)	(58.702)
Forecast × Middle Prior	0.001	-61.669**	26.606
	(0.052)	(30.567)	(42.893)
Forecast × Late Prior	0.056	51.839	207.148***
	(0.073)	(44.406)	(69.816)
Test Early=Late	0.158	0.027	0.032
Test Insur. = Late	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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.6: Effect of the forecast and insurance on inputs per acre

	Panel A: Forecast vs. Insurance			
	(1) Fert	(2) Seed	(3) Labor	(4) Total
Forecast	16.26*	-1.21	37.50*	89.76***
	(9.66)	(1.24)	(21.34)	(34.01)
Insurance	36.21**	-1.74	23.14	83.10**
	(14.32)	(1.23)	(23.12)	(39.87)
q-val Forecast	0.102	0.141	0.102	0.035
q-val Insurance	0.049	0.119	0.189	0.060

	Panel B: Forecast Terciles			
Forecast ×	19.24	-0.50	64.12*	120.87**
Early Prior	(15.62)	(1.63)	(37.51)	(60.37)
Forecast ×	9.24	-2.60*	25.98	63.54
Middle Prior	(13.05)	(1.38)	(27.07)	(42.84)
Forecast ×	22.22	0.37	13.63	90.65
Late Prior	(18.10)	(3.23)	(33.55)	(58.77)
q-val Early	0.213	0.411	0.213	0.213
q-val Middle	0.383	0.315	0.383	0.315
q-val Late	0.785	0.834	0.834	0.785
Test Early=Late	0.901	0.804	0.302	0.717
Test Insur. = Late	0.489	0.533	0.771	0.914
Control Mean	182.96	5.17	400.21	712.92
Observations	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, 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted across all outcomes in Tables 3 and 4, and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G.4 Heterogeneity

Table G.7: 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 × Early Prior	-0.461***	0.012	-0.053	-0.115*	0.011
	(0.160)	(0.050)	(0.053)	(0.059)	(0.045)
Forecast × Middle Prior	-0.110	0.050	0.046	0.026	0.023
	(0.142)	(0.038)	(0.051)	(0.048)	(0.038)
Forecast × Late Prior	0.429*	0.167***	0.125*	0.140**	0.013
	(0.241)	(0.060)	(0.065)	(0.071)	(0.053)
Forecast × Early Prior × Prior Str.	-0.007	-0.062	0.026	-0.125	-0.035
	(0.446)	(0.107)	(0.140)	(0.155)	(0.114)
Forecast × Middle Prior × Prior Str.	0.516	-0.057	0.015	-0.200	-0.056
	(0.512)	(0.126)	(0.162)	(0.138)	(0.137)
Forecast × Late Prior × 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. 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 G.8: Effect of the forecast on inputs by prior strength

	Panel A: Forecast × Prior Strength				
	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast	-2.98	-0.68	23.00	23.53	0.04
	(29.04)	(1.54)	(50.07)	(94.96)	(0.05)
Forecast × Prior Str.	15.06	-6.98	-71.80	-89.53	-0.02
	(72.62)	(4.45)	(148.38)	(257.03)	(0.12)
	Panel B: Forecast Terciles × Prior Strength				
Forecast × Early Prior	-31.44	-0.66	-44.81	-128.49	-0.08
	(41.68)	(2.59)	(84.94)	(158.38)	(0.07)
Forecast × Middle Prior	-32.95	-1.84	-61.51	-87.92	0.03
	(39.26)	(1.55)	(65.46)	(120.74)	(0.06)
Forecast × Late Prior	92.94*	1.73	255.04**	424.96**	0.30***
	(54.82)	(3.14)	(107.31)	(184.12)	(0.09)
Forecast × Early Prior × Prior Str.	40.98	-5.03	-231.91	-280.18	-0.16
	(104.37)	(7.98)	(203.98)	(375.62)	(0.17)
Forecast × Middle Prior × Prior Str.	93.91	-4.83	313.04	511.60	0.06
	(129.34)	(5.61)	(235.50)	(426.93)	(0.20)
Forecast × Late Prior × Prior Str.	18.20	-6.44	108.74	139.31	0.02
	(127.12)	(7.05)	(297.28)	(479.16)	(0.23)
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	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, 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. 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 G.9: 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 × Early Prior	-0.341	0.074	-0.019	-0.024	-0.040
	(0.215)	(0.061)	(0.077)	(0.083)	(0.056)
Forecast × Middle Prior	0.208	0.019	0.187*	0.196*	-0.025
	(0.354)	(0.093)	(0.112)	(0.114)	(0.085)
Forecast × Late Prior	0.317	0.152**	0.110*	0.116	0.036
	(0.227)	(0.065)	(0.064)	(0.075)	(0.056)
Forecast × Early Prior × Prior. - Fore.	-0.321	-0.101*	-0.061	-0.161*	0.088
	(0.225)	(0.061)	(0.088)	(0.089)	(0.064)
Forecast × Middle Prior × Prior. - Fore.	0.371	-0.031	0.183	0.235*	-0.051
	(0.371)	(0.108)	(0.132)	(0.133)	(0.095)
Forecast × Late Prior × 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. 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 G.10: Effect of the forecast on inputs by gap between forecast and prior

	Panel A: Forecast × Prior. - Fore.				
	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast	-4.81	-0.74	26.01	20.95	0.04
	(30.29)	(1.60)	(54.15)	(101.90)	(0.05)
Forecast × Diff. Prior and Forecast.	17.37 (27.33)	0.13 (1.08)	41.53 (60.93)	63.63 (99.75)	0.04 (0.05)
	Panel B: Forecast Terciles × Prior. - Fore.				
Forecast × Early Prior	29.77 (52.34)	3.98 (4.13)	112.44 (110.18)	135.61 (208.39)	0.02 (0.09)
Forecast × Middle Prior	30.34 (89.16)	2.62 (2.98)	10.51 (163.33)	63.37 (309.12)	0.10 (0.15)
Forecast × Late Prior	79.43 (59.33)	1.94 (3.42)	222.46** (104.88)	375.66* (192.17)	0.26*** (0.10)
Forecast × Early Prior × Prior. - Fore.	-119.13 (72.49)	-7.63** (3.55)	-288.84** (123.45)	-526.83** (222.91)	-0.20** (0.08)
Forecast × Middle Prior × Prior. - Fore.	77.93 (101.48)	5.77* (3.45)	74.61 (185.36)	164.96 (350.68)	0.10 (0.16)
Forecast × Late Prior × Prior. - Fore.	19.64 (35.55)	-1.19 (2.27)	123.51 (125.19)	155.68 (162.47)	0.05 (0.09)
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	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, 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. 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 G.11: 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*	-0.011	-0.041	-0.050	0.007
	(0.141)	(0.040)	(0.044)	(0.040)	(0.034)
Forecast ×	-0.099	-0.019	-0.030	-0.071	0.004
WTP	(0.122)	(0.039)	(0.050)	(0.045)	(0.036)
WTP	0.059	0.012	0.027	0.041	0.032
	(0.102)	(0.035)	(0.045)	(0.038)	(0.034)
	Panel B: Forecast Terciles × WTP				
Forecast ×	-0.776***	-0.005	-0.120	-0.128*	0.060
Early Prior	(0.253)	(0.066)	(0.075)	(0.072)	(0.053)
Forecast ×	-0.095	-0.075	-0.051	-0.061	0.020
Middle Prior	(0.194)	(0.054)	(0.065)	(0.057)	(0.052)
Forecast ×	0.371	0.119	0.027	0.071	-0.042
Late Prior	(0.304)	(0.084)	(0.082)	(0.077)	(0.074)
Forecast ×	0.019	-0.002	-0.052	-0.159*	0.032
Early Prior × WTP	(0.212)	(0.068)	(0.089)	(0.090)	(0.070)
Forecast ×	-0.202	-0.035	-0.013	-0.045	-0.013
Middle Prior × WTP	(0.150)	(0.049)	(0.052)	(0.054)	(0.042)
Forecast ×	0.105	0.048	0.098	-0.001	0.128*
Late Prior × WTP	(0.253)	(0.089)	(0.077)	(0.074)	(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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. 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 G.12: Effect of the forecast on inputs by WTP

	Panel A: Forecast × WTP				
	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast	-83.97**	0.54	-41.81	-173.16	-0.06
	(40.37)	(1.48)	(67.91)	(125.31)	(0.06)
Forecast × WTP	-37.17	0.57	21.13	20.26	-0.04
	(44.85)	(1.13)	(54.52)	(106.94)	(0.05)
WTP	71.06	-0.21	26.56	84.26	0.02
	(50.90)	(0.88)	(54.73)	(111.88)	(0.05)
	Panel B: Forecast Terciles × WTP				
Forecast × Early Prior	-192.75***	-1.04	-137.33	-512.87**	-0.20**
	(63.92)	(2.26)	(110.53)	(227.87)	(0.10)
Forecast × Middle Prior	-104.08**	-0.55	-151.49	-236.75	-0.11
	(52.38)	(1.26)	(100.33)	(177.16)	(0.09)
Forecast × Late Prior	69.64	3.65	233.37	312.29	0.25*
	(73.14)	(3.19)	(166.24)	(275.14)	(0.14)
Forecast × Early Prior × WTP	-192.03**	-0.55	-72.35	-176.68	0.02
	(80.10)	(1.69)	(108.93)	(222.45)	(0.10)
Forecast × Middle Prior × WTP	23.05	0.73	60.87	97.24	-0.07
	(42.54)	(1.06)	(69.13)	(119.79)	(0.07)
Forecast × Late Prior × WTP	48.91	2.87	143.45	247.85	0.08
	(67.11)	(2.56)	(168.71)	(259.90)	(0.12)
Control Mean	372.80	7.22	761.96	1443.49	0.00
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. Fert is the amount spend on fertilizer, Seeds the amount spent on seeds, 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. 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 G.13: 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 × Early Prior	-0.550***	-0.019	-0.054	-0.122*	0.039
	(0.196)	(0.055)	(0.067)	(0.069)	(0.052)
Forecast × Middle Prior	-0.112	0.037	0.030	-0.002	0.015
	(0.181)	(0.048)	(0.064)	(0.058)	(0.048)
Forecast × Late Prior	0.079	0.128*	0.133*	0.064	0.019
	(0.275)	(0.077)	(0.074)	(0.076)	(0.068)
Forecast × Early Prior × Risk Av.	0.225	0.084	0.012	0.041	-0.063
	(0.253)	(0.084)	(0.094)	(0.096)	(0.071)
Forecast × Middle Prior × Risk Av.	0.139	0.019	0.032	0.040	0.000
	(0.256)	(0.070)	(0.086)	(0.082)	(0.073)
Forecast × Late Prior × 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 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. Risk. Av. is the result of an incentivized risk game where higher values indicate the farmer is more risk averse. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.14: Effect of the forecast on inputs by risk aversion

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

	Panel B: Forecast Terciles × Risk Aversion				
Forecast × Early Prior	-9.19	-0.59	-28.95	-50.22	-0.13
	(49.82)	(2.90)	(114.18)	(217.35)	(0.08)
Forecast × Middle Prior	-74.39	-1.99	-133.95*	-265.44*	0.00
	(45.97)	(1.77)	(81.07)	(145.41)	(0.07)
Forecast × Late Prior	-4.80	4.93	136.45	141.04	0.18
	(61.58)	(4.85)	(118.52)	(200.18)	(0.12)
Forecast × Early Prior × Risk Av.	-46.18	-0.25	-30.52	-189.94	0.13
	(67.49)	(3.09)	(129.97)	(256.07)	(0.11)
Forecast × Middle Prior × Risk Av.	129.31*	0.14	247.32**	577.31***	0.08
	(67.24)	(2.58)	(114.44)	(214.05)	(0.10)
Forecast × Late Prior × Risk Av.	242.16**	-6.59	306.70	725.92**	0.31*
	(97.67)	(5.19)	(202.58)	(340.70)	(0.17)
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	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, 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. Risk. Av. is the result of an incentivized risk game. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G.5 Local average treatment effects

Table G.15: Effect of forecast and insurance takeup on beliefs

	(1) | posterior − forecast |	(2) | posterior − prior |	(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 takeup 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 G.16: 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
× Early Prior	(0.205)	(0.059)	(0.064)	(0.071)	(0.054)
Forecast takeup	-0.089	0.048	0.044	0.014	0.012
× Middle Prior	(0.164)	(0.042)	(0.057)	(0.053)	(0.042)
Forecast takeup	0.454*	0.176***	0.130*	0.160**	0.010
× Late Prior	(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 Early	0.039	1.000	1.000	0.246	1.000
q-val Middle	1.000	1.000	1.000	1.000	1.000
q-val Late	0.080	0.052	0.077	0.064	0.240
Test Early=Late	0.002	0.055	0.037	0.003	0.949
Test Insur. = Late	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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 G.17: Effect of forecast and insurance takeup on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast takeup	-40.13	-0.82	-55.57	-166.27	-0.10
× Early Prior	(51.97)	(3.18)	(104.29)	(197.03)	(0.09)
Forecast takeup	-32.44	-2.28	-51.50	-66.09	0.03
× Middle Prior	(44.04)	(1.80)	(75.96)	(139.22)	(0.06)
Forecast takeup	112.07*	2.29	289.85**	495.81**	0.32***
× Late Prior	(62.04)	(3.92)	(116.78)	(206.44)	(0.11)
Insurance takeup	112.03**	-1.06	128.06*	299.90**	0.15**
	(49.71)	(1.52)	(73.96)	(150.00)	(0.06)
q-val Early	1.000	1.000	1.000	1.000	
q-val Middle	1.000	1.000	1.000	1.000	
q-val Late	0.077	0.163	0.052	0.052	
Test Early=Late	0.053	0.535	0.031	0.020	0.001
Test Insur. = Late	1.000	0.410	0.231	0.403	0.138
Control Mean	372.80	7.22	761.96	1443.49	0.00
Observations	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, 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 G.18: 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
× Early Prior	(9.98)	(346.04)	(5.28)
Forecast takeup	-11.94	-199.74	-0.55
× Middle Prior	(8.53)	(264.44)	(4.05)
Forecast takeup	16.96	493.54	0.79
× Late Prior	(12.08)	(450.55)	(4.48)
Insurance takeup	3.03	156.65	-1.75
	(7.79)	(255.27)	(2.88)
q-val Early	0.209	0.209	0.209
q-val Middle	0.942	1.000	1.000
q-val Late	1.000	1.000	1.000
Test Early=Late	0.012	0.037	0.163
Test Insur. = Late	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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted for all outcomes in Tables G.18 and G.19, except Column (4) in the latter table because it is a subsample analysis of Column (1). Standard errors are clustered by village. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.19: Effect of forecast and insurance takeup on agricultural profits

	(1) Ag Profit	(2) Loss	(3) Profit + Loss	(4) Ag Profit Non-Flood
Forecast takeup	-484.34*	59.45	-360.30	-447.17
× Early Prior	(283.73)	(164.47)	(390.26)	(541.64)
Forecast takeup	-124.07	236.75*	112.99	-117.11
× Middle Prior	(218.77)	(137.60)	(249.83)	(277.83)
Forecast takeup	-33.63	208.87	180.70	593.43
× Late Prior	(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 Early	0.209	0.315	0.249	
q-val Middle	1.000	0.942	1.000	
q-val Late	1.000	1.000	1.000	
q-val Insurance				
Test Early=Late	0.322	0.496	0.322	0.208
Test Insur. = Late	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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. Sharpened q-values are adjusted for all outcomes in Tables G.18 and G.19, except Column (4) in the latter table because it is a subsample analysis of Column (1). Standard errors are clustered by village. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.20: effect of forecast and insurance takeup on business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast takeup	0.07	29.96	94.75
× Early Prior	(0.05)	(87.54)	(92.38)
Forecast takeup	0.01	9.04	21.71
× Middle Prior	(0.04)	(65.50)	(53.91)
Forecast takeup	-0.05	-124.09*	-33.86
× Late Prior	(0.05)	(72.10)	(98.27)
Insurance takeup	0.10***	116.49	119.14*
	(0.04)	(72.93)	(63.55)
q-val Early	0.844	0.844	0.844
q-val Middle	1.000	1.000	1.000
q-val Late	0.395	0.344	0.737
Test Early=Late	0.082	0.180	0.316
Test Insur. = Late	0.009	0.003	0.181
Control Mean	0.14	157.98	165.51
Observations	1197	1199	1197

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on business activity, 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. 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. Farmers with Early Priors were the most optimistic, and were told that the monsoon would be later (i.e., worse) than they expected in the forecast group. Farmers with Middle Priors had average beliefs, and were told that the monsoon would be as they expected in the forecast group. Farmers with Late Priors were the most pessimistic, and were told that the monsoon would be earlier (i.e., better) than they expected in the forecast group. All regressions include strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. "Test Early = Late" is the p-value on the test of equality between the first and third coefficient; "Test Insur. = Late" is the p-value for the test of equality between the third and fourth coefficients. 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 G.21: Effect of forecast and insurance takeup on economic well-being

	(1) Food cons	(2) Other cons	(3) Asset value	(4) Livestock	(5) Net savings	(6) Welfare index
Forecast takeup	0.38	-0.64	430.70	0.08*	421.96	0.17**
× Early Prior	(0.78)	(1.76)	(322.26)	(0.05)	(285.42)	(0.07)
Forecast takeup	1.34**	-0.90	37.70	-0.04	78.00	-0.00
× Middle Prior	(0.59)	(1.09)	(172.47)	(0.04)	(247.94)	(0.05)
Forecast takeup	1.27	-0.23	-140.86	0.01	159.19	0.05
× Late Prior	(0.93)	(1.57)	(160.93)	(0.06)	(285.52)	(0.06)
Insurance takeup	0.51	2.23*	-142.81	0.01	-465.43*	-0.03
	(0.53)	(1.14)	(180.83)	(0.03)	(245.98)	(0.05)
q-val Early	0.434	0.434	0.434	0.434	0.434	
q-val Middle	0.137	1.000	1.000	0.757	1.000	
q-val Late	1.000	1.000	1.000	1.000	1.000	
q-val Insurance						
Test Early=Late	0.438	0.853	0.102	0.350	0.545	0.236
Test Insur. = Late	0.450	0.135	0.992	0.973	0.053	0.282
Control Mean	13.22	9.93	1503.10	0.22	-1031.41	0.00
Observations	1201	1201	1201	1201	1129	1201

Notes: This table presents estimates of the treatment effects of forecast and insurance takeup on economic wellbeing, 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. Food cons is food consumption per household member in USD over the past 30 days. Other cons is non-food consumption (other than medical expenses). Asset value is the value of assets in USD. Livestock is the count of livestock in Tropical Livestock Units. Net savings is savings less outstanding debt in USD. Welfare index is an inverse covariance weighted index of the other five outcomes in the table. It has been excluded from the MHT correction as it is a composite of outcomes already included. 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 coefficients. 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

H Seasonal climate forecasts

Forecast time scales Forecasts can be made over a range of time-scales, including short-, medium-, and long-term forecasts. Short-term, or *weather*, forecasts, provide a prediction about precise weather conditions on a particular day, and are issued between one and fourteen days in advance.[45] Forecasts that provide information beyond this time horizon present information only about average conditions over a longer time period, rather than about an individual day. Medium-range forecasts are issued between 15 and 30 days in advance. Long-range, or *seasonal*, forecasts, which we study in this paper, provide information four or more weeks ahead. These forecasts also tend to provide information on longer time windows, with typical forecasts projecting climatic conditions over a month or entire season. Seasonal forecasts are particularly relevant for agriculture for two reasons. First, with long lead times, farmers can use these forecasts to make meaningful adjustments to key planting decisions, such as amount of land to cultivate and crop choice (Gine et al. (2015)). Second, seasonal forecasts provide information that is highly relevant to agricultural outcomes: climate over the full growing season.

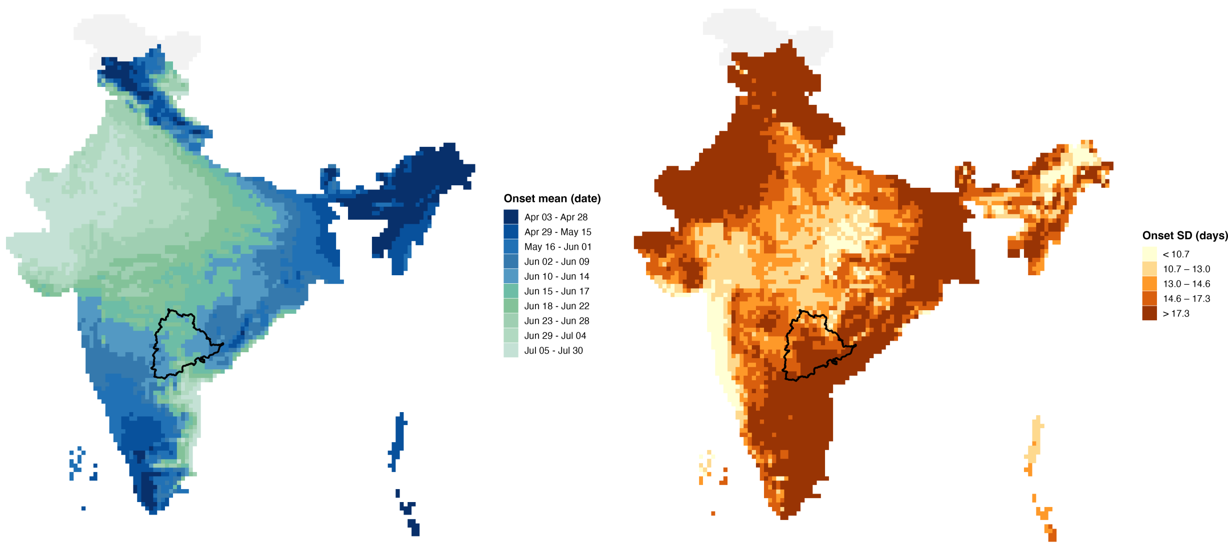
Existing monsoon forecasts Researchers have attempted to produce long-range forecasts of two key features of the Indian Summer Monsoon: rainfall quantity and monsoon onset timing. The Indian Meterological Department (IMD) produces a statistical forecast of the expected seasonal total rainfall quantity at the beginning of the monsoon each year. These forecasts 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 both little spatial coherence (Moron et al. (2017)) and little relevance to district- or state-level rainfall amounts. Put differently, 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 agriculture. 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)). More recently, the IMD has begun providing region-specific quantity forecasts. However, the accuracy of these forecasts is poor, rendering them of limited usefulness for farmer decision-making: Rosenzweig and Udry (2019) notes that these forecasts have a low ($\sim$0.2) or even negative correlation with realized rainfall over most of India.

In contrast, seasonal timing forecasts typically deal with the onset of the monsoon. While the monsoon arrives in early–mid June on average, variability in onset timing is high. Appendix

[45]The 14-day barrier is a physical limit, owing to the variability of the physical weather system.

Figure H.1 plots information about the monsoon onset over India, with Telangana outlined in black. IMD forecasts onset only over the south-western tip of the country — "monsoon onset over Kerala" (MOK)—which is not relevant for most of the country. Though MOK has been the subject of much of the research on onset timing and forecasting (e.g., Preenu et al., 2017), the monsoon does not progress smoothly northwards. Instead, monsoon rainfall frequently halts, and local false starts are common, such that MOK carries no more than a very limited 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 H.2, they show that there is virtually no signal value of MOK[46] in any region in India other than Kerala. Moreover, this forecast typically arrives 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).

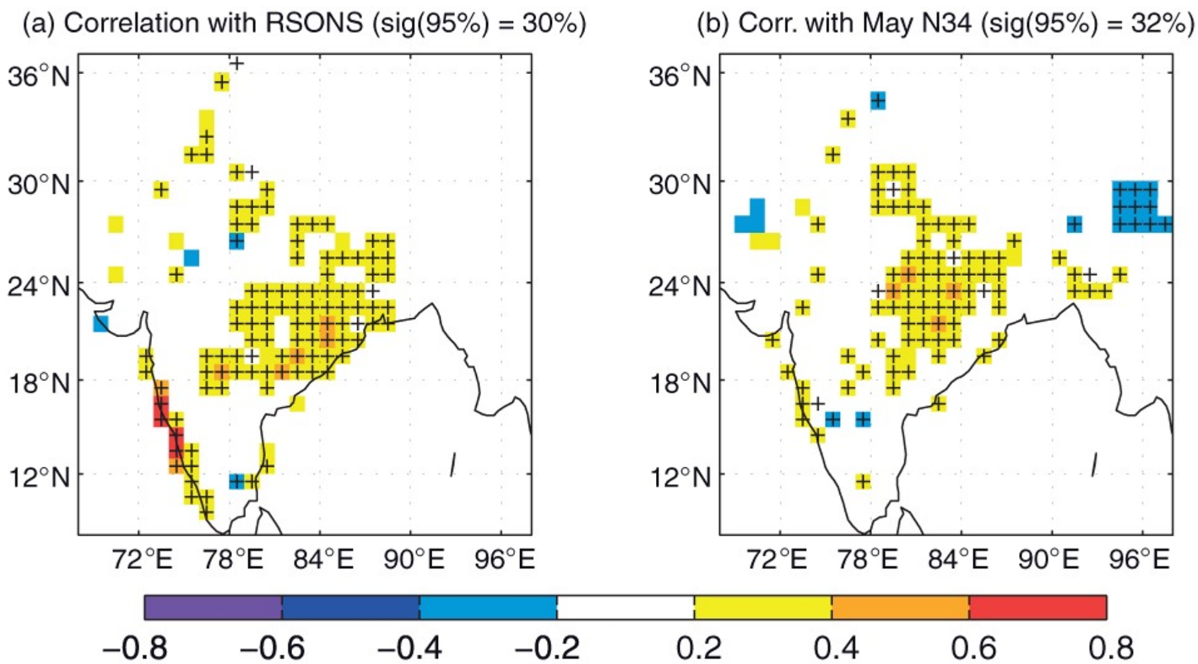
Figure H.1: Monsoon onset over India



Notes: The left panel shows the average monsoon onset day (in day-of-year) for the period 1940-2024 across India. The right panel shows the standard deviation of onset for the period 1940-2024. 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.

[46] 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 H.2: Monsoon onset over Kerala has limited predictive power elsewhere in India

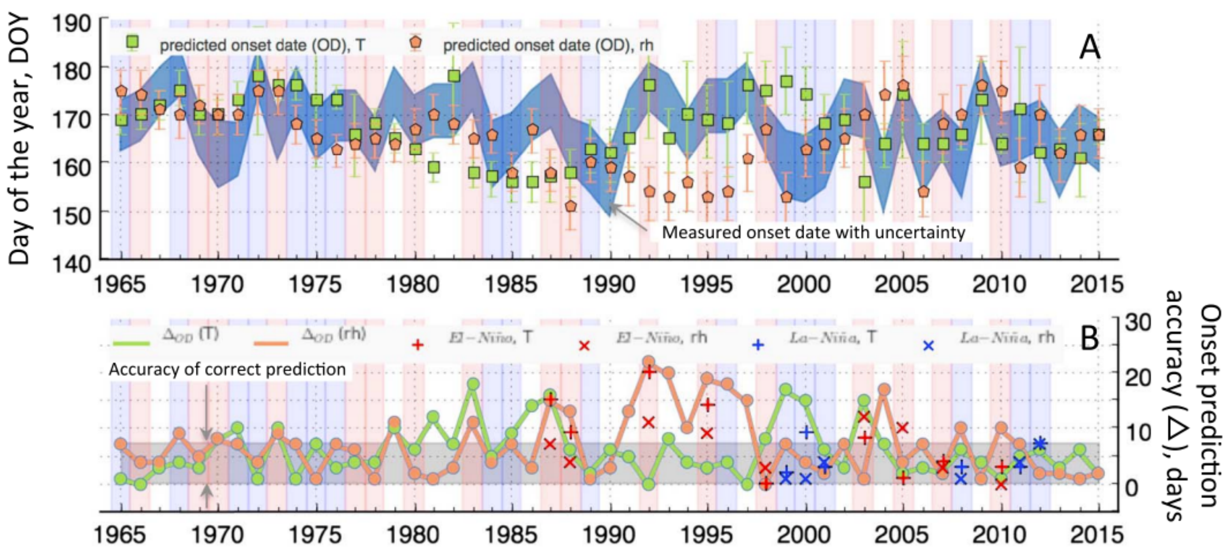


Notes: (a) Correlations between local-scale onset and the index of regional-scale onset (RSONS) defined in the text. (b) Correlations between local-scale onset and the Niño 3.4 SST index (N34) in May. Crosses indicate statistically significant correlations at the two-sided 95% level (see text). The value 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).

Our monsoon onset forecast We focus on onset forecasts for two main reasons. First, and most importantly, high-quality quantity forecasts are simply not available in our setting. In contrast, there exists such an accurate onset timing forecast. A new forecasting model model (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. The output from this forecast 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 forecast was "correct," defined as local onset falling within ±7 days of the predicted date, 73% of years in the sample.[47] Moreover, while MOK date is forecast only two weeks in advance of the average MOK date, the forecast we use is issued at least 35 days in advance of the average onset date in Telangana. Though high-quality, this forecast was not yet widely available to farmers who might benefit from the information.

[47]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.

Figure H.3: Our 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).

Second, farmers demand information on onset timing. Mobarak and Rosenzweig (2014) demonstrate that 40% of farmers purchase insurance against the risk of a *delayed monsoon onset* when randomly offered such a product. In our pilot, more than 60% of farmers stated that they would be willing to pay for a monsoon onset timing forecast. Finally, in a phone survey conducted by the Ministry of Agriculture and Farmers' Welfare in 2024, 88 percent of farmers reported that they would find a monsoon onset forecast, and 88 percent reported that they could use such a forecast for planting decisions.