Beliefs, forecasts, and investments: Experimental evidence from India

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

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Abstract

The world's 500 million smallholder farms are essential to the global economy, but face a fundamental challenge: farmers must commit to investment decisions before the weather – a key input to production – is realized. Farmers must therefore rely on their *beliefs* about inherently uncertain weather. In theory, a forecast that could align beliefs with actual realizations would enable farmers to improve their investments across multiple margins, but in practice, forecasts' effectiveness remains unknown. We use an RCT to document four new facts about farmer beliefs and forecasts. First, beliefs drive farmer behavior in the status quo. Second, farmers update their beliefs when given a high-quality, long-range forecast. Third, this forecast allows farmers to broadly re-optimize their investments, making adjustments both on and off the farm, which improves overall welfare. Fourth, farmer beliefs also impact their responses to a canonical agricultural policy instrument – insurance – underscoring the importance of aligning beliefs with realizations.

Keywords: beliefs; forecasts; agriculture; risk
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*Burlig: Harris School of Public Policy and Energy Policy Institute (EPIC), University of Chicago and NBER. Email: burlig@uchicago.edu. Jina: Harris School of Public Policy and EPIC, University of Chicago and NBER. Email: amirjina@uchicago.edu. Kelley: Harris School of Public Policy, University of Chicago. Email: erinmkelley@uchicago.edu. Lane: Harris School of Public Policy, University of Chicago and NBER. Email: laneg@uchicago.edu. Sahai: Kenneth C. Griffin Department of Economics, University of Chicago. Email: harshil@uchicago.edu. We are grateful to Vittorio Bassi, Susanna Berkouwer, Chris Blattman, Josh Dean, Kyle Emerick, Xavier Gine, Rachel Glennerster, Michael Greenstone, Faraz Hayat, Koichiro Ito, Kelsey Jack, Florence Kondylis, Michael Kremer, Jeremy Magruder, Craig McIntosh, Mushfiq Mobarak, Andrew Robertson, Mark Rosenzweig, Elena Surovyatkina, Catherine Wolfram, Brian Wright, and seminar participants at the Coase Project, the Paris School of Economics, London School of Economics, UCSD, EPIC Junior Workshop, Northwestern University, Princeton University, MIT, the UChicago Mini-Conference on Weather Advisory Services, the Yale Climate, Environment, and Economic Growth Conference, Y-RISE, and NBER Development for helpful comments and suggestions. We thank Manzoor Dar for excellent field support, Ramya Teeparthi for valuable project management, and Sanghwa Ahn, Anjani Balu, Alina Gafanova, Sam Hsu, Sarah Hussain, Mohit Negi, Meghna Singh, Prachi Shukla, Rathan Sudheer, and in particular Amrita Pal for outstanding research assistance. We thank the Becker Friedman Institute for Economics at the University of Chicago, J-PAL's Agricultural Technology Adoption Initiative and King Climate Action Initiative, and the World Bank for generously funding this project. This research has IRB approval from the University of Chicago (Protocol No. IRB20-1364), and is registered on the AEA RCT registry (Identification No. AEARCTR-0008846). All remaining errors are our own.

1 Introduction

Agricultural production is a major driver of the global economy. Around the world, more than 500 million smallholder farms produce approximately 30% of the planet's food. In low- and middle-income countries (LMICs), agriculture accounts for roughly 20% of GDP and employs approximately 40% of the workforce (The World Bank, 2025; FAO, 2023). Yet agriculture faces a fundamental challenge: it is highly dependent on the weather and farmers must commit to input choices before conditions are known. As a result, farmers must rely on their *beliefs* about inherently uncertain weather patterns. When these beliefs do not align with realized weather, the resulting mismatch between investment choices and growing conditions could meaningfully harm farmer welfare and impact the effectiveness of existing policy tools.

Given the importance of farmer beliefs, long-range weather forecasts – which provide information about the future growing season conditions well in advance – are a promising technology. By providing a signal about the future state, long-range forecasts are informative about the returns to a wide variety of inputs to production. As a result, these forecasts enable farmers to adjust their inputs across multiple margins, including both on- and off-farm activities. This contrasts with traditional agricultural interventions, which typically promote a single new technology or input. In addition, forecasts have the potential to be widely disseminated at very low cost. Though long-range forecasts appear promising in theory, we know little about how they influence beliefs and investments in practice. Moreover, there are reasons to think forecasts may not be effective in the developing world. First, as forecast dissemination in LMICs has traditionally been poor (Yegbemey and Egah, 2021), farmers may not believe information coming from a forecast, and may not know how to use the forecast to form beliefs. Even if a forecast does change farmer beliefs, farmers may not be able to update their investments accordingly if they face land, labor, or credit market constraints. Given that long-range forecasts are being widely promoted as a key climate adaptation tool for policymakers (FAO, 2019), understanding their real-world effectiveness is a first-order concern.

In this paper, we ask four main research questions. First, how do farmers' beliefs impact agricultural investment in the status quo? Second, can an accurate forecast shift farmer beliefs towards the true onset realization? Third, how does a forecast impact on- and off-farm investment and subsequent welfare? Fourth, how do beliefs shape farmers' responses to interventions beyond information?

To answer these questions, we collect novel data and run a randomized experiment to study farmer beliefs, behavior, and forecasts in the context of the Indian Summer Monsoon. As motivating evidence, we use historical data to demonstrate that the *timing* of the onset of the monsoon, even holding total rainfall fixed, has meaningful impacts on agricultural production. We therefore focus on beliefs about when the monsoon will arrive. We carry out our experiment and data collection in 250 villages across Telangana, with a sample of five farmers selected from each village. We elicit prior beliefs about the monsoon onset using a validated survey instrument (Gine et al., 2015). We then randomize villages into a control group, a group that is offered the forecast, and a group that is offered an index insurance product (modeled on Mobarak and Rosenzweig, 2014). This final group allows us to examine how beliefs shape responses to another canonical agricultural policy intervention. After randomization, we collect data on posterior beliefs, allowing us to assess the impact of the forecast on farmer beliefs. Finally, we conduct an extensive endline survey to measure the impacts of our treatments on investment behavior and welfare.

We disseminate a forecast of the timing of monsoon onset, designed specifically for Telangana, which is issued approximately 40 days in advance of the monsoon's arrival, and produced by the Potsdam Institute for Climate Research (Stolbova et al., 2016). This forecast has a series of advantages: it is extremely accurate, contains agriculturally-relevant information, and can be provided to farmers well in advance of planting, making it an improvement over previously-available onset forecasts.[1] 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 document four key results. First, we present descriptive evidence that beliefs drive farmers' behavior in the status quo. Although the average farmer's prior belief about monsoon timing is close to the actual arrival date, there is substantial heterogeneity across farmers, such that many farmers have beliefs that do not align with realized onset. Specifically, we find that some farmers expect the monsoon to arrive up to four weeks earlier than others.[2] This timing matters: historically, a three-week delay reduces rice yields by 2.7 to 4.5%, and cotton yields by 6.9 to 11.5%. These beliefs strongly correlate with farmers' choices. Farmers who expect an earlier monsoon, and thus a more favorable growing season, invest more on the farm. Conversely, those who expect a later monsoon, and thus a worse growing season, invest less. The magnitude is meaningful: moving from a 25th percentile prior belief to a 75th percentile prior belief is associated with an 0.14 SD reduction (p-value 0.01) in agricultural investment.

Second, we provide causal evidence that beliefs can be shifted closer to actual realizations when individuals receive an accurate forecast of future conditions. Farmers in forecast villages have posterior beliefs about monsoon onset timing that are 26% (p-value 0.031) closer to the realized onset date than farmers in control villages.

Third, we demonstrate that the forecast has meaningful impacts on farmer behavior and overall welfare. We begin by examining how farmers adapt their agricultural input decisions in light of the

[1]The only widely available long-range 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).

[2]Though location explains some of the variation in farmer priors, 46% of the total variation in mean prior remains after removing village fixed effects.

forecast. To generate predictions, we develop a simple theoretical model which shows that farmers' responses to a forecast should depend on their prior belief about monsoon onset timing. 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. A key test of our theory is whether early- and late-prior farmers respond differently to the forecast treatment. 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 *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 (weakly) improve farmers' input decisions by enabling them to tailor their farm investments to the coming monsoon, allowing them to reallocate their resources towards or away from agriculture as necessary.

Our results are very consistent with these predictions: 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. 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: <0.001), 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, with a noisy point estimate suggesting a substantial decline in farm expenditure. Middle-prior forecast farmers do not alter their investments. Late-prior forecast farmers considerably increase both land under cultivation and total expenditure, and are much more likely to plant cash crops than control farmers with similar priors. We reject equality between early- and late-prior forecast farmers for land under cultivation, cash cropping, and total expenditure, confirmed in the linear specification.

We find an incomplete mapping between changes in farm inputs, agricultural output, and farm profits. We do broadly find that early-prior forecast farmers have lower farm production and farm profits than their control-group counterparts, and we see increases in agricultural output (but not farm profits) for late-prior forecast farmers. However, the magnitudes of these effects are not in line with what we would anticipate given our observed changes in investment. As noted in Rosenzweig and Udry (2020), this pattern is not entirely unexpected, since outcomes depend both on individuals' ex-ante decisions and on random shocks. In our case, many villages in the experiment were heavily affected by flooding in early July (Business Line, 2022). When we restrict the analysis to farmers who were not impacted by the flood, the results align much more closely with the observed input effects: we see reductions in agricultural output and farm profits for early-prior forecast farmers, no effects for middle-prior forecast farmers; and positive effects for late-prior forecast farmers.

Forecasts differ from other information interventions because they provide early information that enables farmers to re-optimize across multiple margins, including off-farm investments, which we investigate next. 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. While only 14% of our sample own a non-agricultural enterprise, we find patterns that generally point in the opposite direction as our main results on agricultural investment, consistent with forecast farmers treating non-agricultural businesses as a substitute for farming. Indeed, 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.

Our theory predicts that individuals should update their beliefs and adjust their investment decisions accordingly – and this is what we find. What does this mean for welfare? We estimate welfare impacts pooled across priors, as accurate information should allow everybody to (weakly) tailor their on- and off-farm investments to the coming state, regardless of their prior beliefs. 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, the welfare effects we estimate are more than four times larger than those found for emergency loans (Lane, 2024, 0.02 SD) and slightly more than half as large as the impacts of a large-scale irrigation scheme (Jones et al., 2022, 0.11 SD). Forecasts thus generate comparable welfare gains to other programs designed to improve farmer well-being, but at dramatically lower cost.

Fourth and finally, we examine how beliefs shape not only farmers' investment decisions in the status quo, but also their responses to a canonical agricultural policy – index insurance. If beliefs affect how farmers' decisions change when they receive insurance, this suggests another margin along which forecasts, which align beliefs with actual realizations, could improve outcomes for farmers. We extend our theoretical model to show that the effects of insurance should vary based on farmers' priors. Consistent with the model, and despite the fact that the overall monsoon realization was average, we find that early- and middle-prior farmers who expect a relatively good or average growing season increase investment when they receive insurance, whereas late-prior farmers, who anticipate a relatively bad growing season, do not respond to the insurance treatment. These results suggest that aligning farmer beliefs with the coming realization could improve how they respond to insurance, increasing the returns to forecast dissemination.

This study makes two primary contributions. First, we contribute to the literature on beliefs and production by providing new evidence that (i) beliefs are correlated with investment behavior in the status quo; (ii) producers' beliefs can be aligned more closely with actual realizations; (iii) this in turn changes investments and outcomes; and (iv) beliefs meaningfully affect the impact of policy interventions. These results have implications for many of the 500 million smallholder farmers worldwide. Moreover, because many businesses in LMICs beyond farmers make decisions under uncertainty that depend on future outcomes, these findings can also potentially provide valuable insights on the role of beliefs and forecasts for a broader range of firms. To our knowledge, the only existing research on firms' beliefs comes from a small macroeconomics literature studying firms in high-income countries (Bloom et al., 2025; Coibion et al., 2018, 2019). The effects of beliefs and information in those settings are likely to differ substantially from those faced by small farms (and firms) in developing countries.[3] Finally, a small literature examines how beliefs *form* (Patel, 2024; Kala, 2019; Gine et al., 2015; Zappalà, 2023, 2024). In contrast, we take beliefs as given and complement this literature by examining how beliefs influence investment decisions and how responsive those beliefs are to information about future realizations.

Second, we contribute to an active literature on weather risk and climate change. While a small number of studies have examined the role of risk reduction tools in the face of climate change such as irrigation (Jones et al., 2022), agricultural advice about new inputs to use (Cole and Fernando, 2020), and climate-resistant 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). As countries seek effective climate adaptation strategies that reduce farmers' exposure to weather risk, long-range forecasts have emerged as a promising tool.[4] We show that forecasts lead farmers to adapt in a variety of ways, both adjusting

[3]While some research has examined household beliefs, particularly in the context of education (Jensen, 2010; Dizon-Ross, 2019). In contrast, we focus on how beliefs influence smallholder farmers' decisions about agricultural and non-agricultural investments.

[4]Large climate adaptation gaps exist in poor countries, which are disproportionately exposed to climate change

their agricultural investments and shifting into non-agricultural work, which ultimately improves welfare. Thus, we demonstrate that forecasts provide a unique solution to weather risk: they tackle the core problem that farmers must choose inputs before the weather is realized, providing information that lets them tailor a wide range of decisions – including whether to farm at all – to the coming state without having to adopt new technologies.

To the best of our knowledge, there is only one other paper that considers the impact of long range forecasts in a LMIC.[5] Rosenzweig and Udry (2019) use a farmer fixed-effect design to study the Indian Meteorological 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 experimentally identify the impact of an accurate forecast, and demonstrate that it improves welfare. Crucially, we also identify a key determinant of farmer responses to the forecast: prior beliefs. 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.

The remainder of this paper proceeds as follows. Section 2 provides motivating evidence that monsoon onset timing impacts agriculture in India. Section 3 presents a theoretical model of farmer decision-making under risk. Section 4 describes our experimental design and data. Section 5 presents our first result: beliefs impact investment in the status quo. Section 6 presents our second result: the forecast shifts beliefs. Section 7 presents our third result: the forecast impacts agriculture, off-farm business, and welfare. Section 8 presents our final result: beliefs impact farmers' responses to index insurance. Section 9 concludes.

2 Motivating evidence: Monsoon onset drives yields

We begin with motivating evidence that monsoon onset timing is critically important for Indian agriculture. Using historical data on rainy-season (kharif) agriculture across India, we show that monsoon onset delays negatively impact crop production, *even conditional* on total rainfall.[6] Moreover, we find that these damaging impacts are substantially worse for cotton, a key cash crop in our setting, than for rice, a key staple crop.

(Carleton and Hsiang, 2016; Hsiang et al., 2017; Hultgren et al., 2025). Though climate adaptation can take many forms, technologies like forecasts, which reduce risk, rather than shifting utility across states, may be particularly valuable and remain understudied (Carleton et al., 2024).

[5]While there exists limited prior work on forecasts, this 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, Song, 2023 in labor, 2023 for hurricanes, and Ahmad et al., 2023 for pollution).

[6]This builds on prior work, which 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 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.[8] 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%, 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.

[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).

[8] 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.

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: *** $p < 0.01$, ** $p < 0.05$, ** $p < 0.10$.

These results have two main implications. 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. These insights inform our empirical analysis.

3 Model

In this section, we present a simple two-period model of farmers' decision-making under risk. 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_k and a concave, risky agricultural production technology $f(x, \epsilon_k)$. In period two, farmers consume (c_2^k) from production and savings.

Production The output from this production technology is modified by the state of the world ϵ_k for $k \in \{1, ..., K\}$, where ϵ_k are ordered so that for any $k > m$ we have higher production and a greater marginal product: $f(x, \epsilon_k) > f(x, \epsilon_m)$ and $f'(x, \epsilon_k) > f'(x, \epsilon_m)$ for all $x > 0$.[9] There is no product at zero investment regardless of the state: $f(0, \epsilon_k) = 0$ for all k. 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.[10]

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:

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

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

Appendix C.2 shows that the optimal investment is therefore a (weakly) increasing function of a farmer's beliefs on the realization of ϵ.[11] 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*

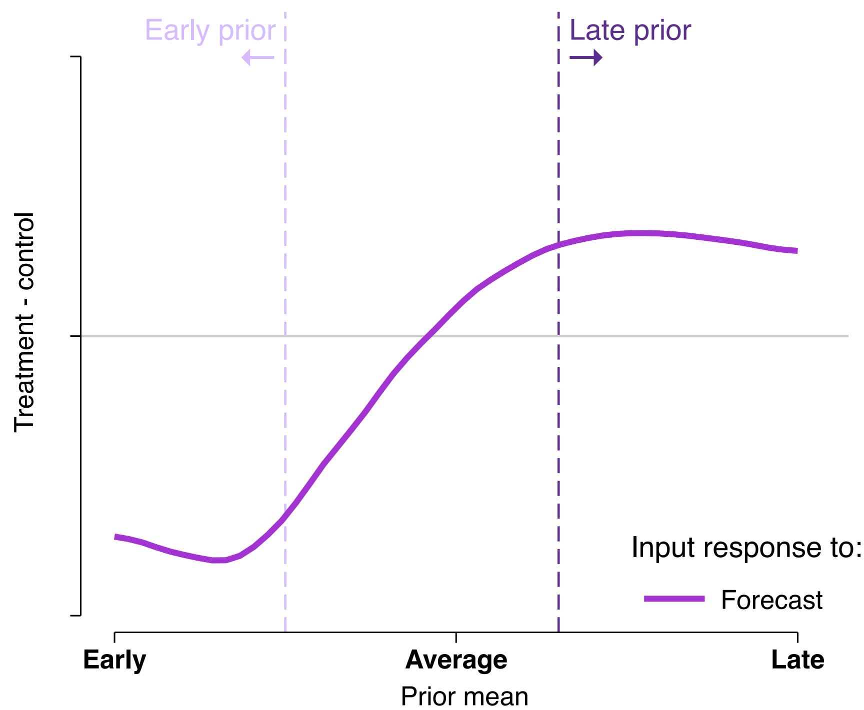
[9] For simplicity, we assume that monsoon onset is the only determinant of production and that output is monotonically decreasing in onset timing. While it is possible that extremely early rain could be detrimental to agricultural output, in general, delayed monsoons are associated with lower output, 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.

[10] 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. Similarly, the savings level s could also be interpreted as investment in income activities that are not (or less) dependent on the monsoon arrival.

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

such realization.

Figure 1: Investment choice with a forecast (model)



Notes: This figure plots the simulated relationship in our model between the treatment effect of forecasts 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 forecast in this simulation is for an average monsoon. The gray horizontal line is centered at zero. The x-axis reflects when farmers believe the monsoon will arrive. Our theory predicts that farmers with early priors will respond to an average forecast by reducing investment compared to the control; farmers with average priors should not respond; and farmers with late priors will respond by increasing investment relative to the control. See Appendix C.3 for simulation details.

Figure 1 illustrates the key results of the model, plotting the treatment effect of a forecast (purple) on agricultural investment. This figure depicts responses to a forecast of an average monsoon.[12] 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.

[12] 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.

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 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.

4 Experimental design and data

We conduct our experiment in Telangana. The state is home to 35 million people, but farm productivity remains low: while 55% of the labor force is employed in agriculture, the sector only provides 15% of Gross State Value Added (Government of Telangana, 2020; Ministry of Agriculture and Farmers Welfare, 2023). The majority of farms are small, with an average landholding of 1 hectare. Rice is the main staple crop, but Telangana also grows a number of important cash crops, including cotton.[13] Like much of central India, Telangana is dependent on the monsoon, with approximately 80% of total annual rainfall occurring during the monsoon season. While the monsoon arrives in early-mid June on average, monsoon onset is highly variable: between 1979 and 2019, the standard deviation of the onset date was approximately 20 days (Appendix Figure H.1). Farmers' access to high-quality weather information in Telangana is also limited: while 65% of farmers in our sample report having received some information about the coming Kharif season at baseline, the reliability of their sources is unclear, with less than 10% of farmers receiving their information from either the government or extension services, instead overwhelmingly relying on other farmers (Appendix Figure A.2).

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 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

[13] 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.

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 Our primary treatment is a long-range forecast of the timing of the onset of the Indian summer monsoon. We deploy a novel long-range forecast of localized monsoon onset, first described in Stolbova et al. (2016).[14]

This 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 elsewhere in the country (including our study area), 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, as the monsoon does not progress northwards from Kerala in a predictable manner. Moreover, the IMD forecast only arrives two weeks in advance of the monsoon's onset, which also limits its usefulness relative to a longer-range forecast. In contrast, our forecast provides accurate onset information over a key growing region, Telangana, and has been correct for ten out of the past ten years. Backcasting over 1965–2015, the forecast was correct 73% of the time. Moreover, our forecast is issued at least a month in advance, enabling farmers to substantively adjust key production decisions, such as crop choice, amount of land to put in production, and input use on this land (Gine et al., 2015), in addition to changing off-farm investments. Second, the forecast we use provides highly accurate information about onset *timing*, and there exists no corresponding localized accurate seasonal 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

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

the upcoming week or two, but cannot be used to make large-scale input changes.[15]

Farmers were told about the forecast using the following text, which is straightforward and easy for farmers to understand:

> *"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 received 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."*

The forecast in the year of our experiment 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 provided farmers with financial protection against a late monsoon. Though weather risk is a substantial concern for agriculture in the state, during the time of our experiment, there was no state-subsidized crop insurance program, and while private insurance

[15] 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.

exists, it is not widespread: at baseline, less than 1% of farmers in our sample had heard of rainfall insurance.

We modeled our rainfall insurance 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.[16] 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 20 percent of the average farmer's agricultural revenues (Ministry of Statistics and Programme Implementation, Government of India, 2013).[17] 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.[18] We present takeup of the forecast and insurance product in Appendix Figure A.3 and Appendix Table A.5. Takeup is over 85 percent for both treatment groups.[19] 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 the monsoon (or the IMD forecast) arrived. Households in the forecast and insurance villages were offered their respective products. For forecast farmers, 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.

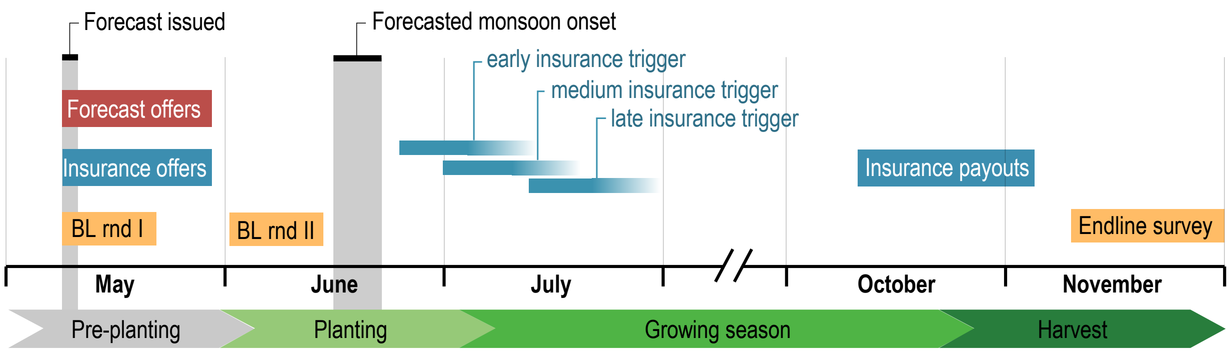
[16]We define a village-specific "on time" monsoon onset date based on the average monsoon onset date in that location, using the ERA-5 reanalysis data described above, and following the approach of Moron and Robertson (2014) as shown in Appendix Figure H.1. We installed rain gauges close to each village (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).

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

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

[19]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.

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.

4.2 Data

Beliefs 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 Gine et al. (2015). We first asked them to place the beans according to the historical distribution for the past 10 years, where we told farmers to think of each bean as representing one year's monsoon. Once the historical distribution was laid out on the table in front of the farmer, we asked them to consider whether they believed the monsoon would arrive on time, early, or late in the coming year. We then asked how they would like to move the beans around in light of their response. We gathered this information during both baseline round I and baseline round II to establish whether (and by how much) the forecast changed farmers' beliefs.

Agricultural, off-farm, and welfare outcomes At endline, we collect detailed measurements of farmers' agricultural investments including the amount of land cultivated, crop mix, and expenditures on inputs such as labor, seeds, and fertilizer. For crop choice, we are interested in whether farmers 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 are agricultural output, and farm profits. We also measure farmers' engagement in non-agricultural business, and focus on whether a farmer operates a non-farm enterprise, and business investments/profits.[20] Finally, we collect several measures of economic well-being, including per-capita spending on food and non-food consumption; the value of a farmers' assets and the number

[20] 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.

of livestock in their possession; and savings and debts.[21]

4.3 Experimental integrity

Attrition, descriptive statistics, and balance 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.[22]

Appendix Table A.3 presents descriptive statistics and balance checks. As expected, villages are similar between groups on a variety of characteristics. They contain approximately 400 households, 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 have 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, and 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.[23] 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.

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 is 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 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

[21]In addition to these standard welfare metrics, we consider impacts of our treatments on mental health, using the PHQ-8 depression screening tool (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.

[22]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.

[23]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.

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 Result I: Beliefs impact investment in the status quo

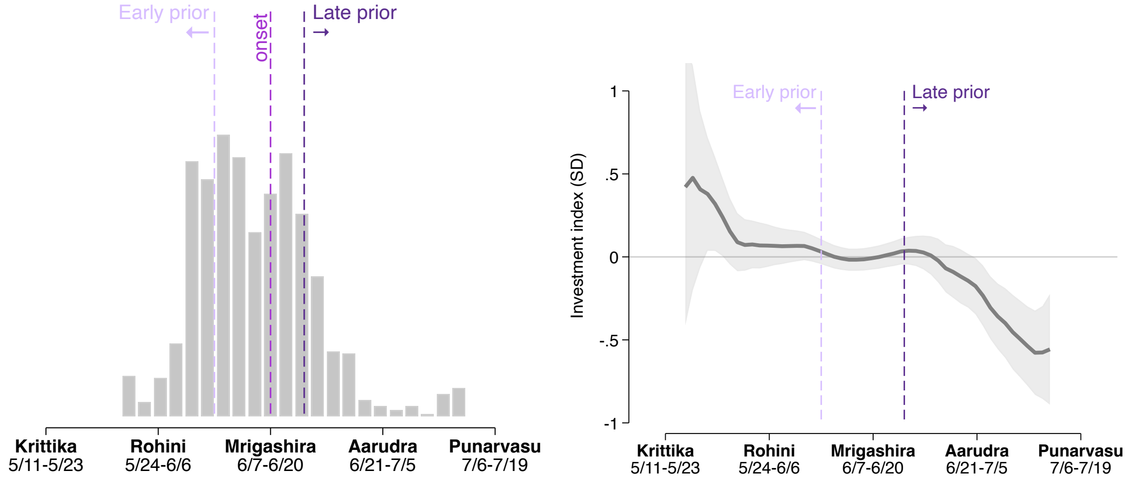
We begin by testing how beliefs affect investment in the status quo. Figure 3 presents our data on prior beliefs, measured in kartes (approximately two-week units of time).[24] The left panel plots a histogram of the mean of each farmer's priors. Realized onset, which was the same for all farmers in our experiment, is represented as a bright purple dashed vertical line. The study year had an average monsoon, close to the mean of the prior distribution. We divide the prior belief distribution into terciles (Appendix A.10 shows that the results are robust to alternative prior definitions). Tercile 1, or early-prior farmers (to the left of the light purple vertical line) expected an early monsoon. Tercile 2, or "middle prior" farmers (between the dashed vertical lines) expected an average monsoon. Finally, Tercile 3, or "late prior" farmers (to the right of the dark purple vertical line) expected a late monsoon.

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.[25] The magnitude is meaningful: moving from a 25th percentile prior to a 75th percentile prior is associated with an 0.14 SD reduction (p-value 0.01) in agricultural investment.

[24] While belief formation is not the focus of our experiment, as 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.

[25] 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: Beliefs impact investment



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 realized monsoon onset date is represented by the central bright purple dashed vertical line. 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. Middle-prior farmers (between the light and dark purple dashed lines) expected an average monsoon. Finally, late-prior farmers (to the right of the dark purple dashed line) expected a late monsoon. 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.

6 Result II: The forecast changes beliefs

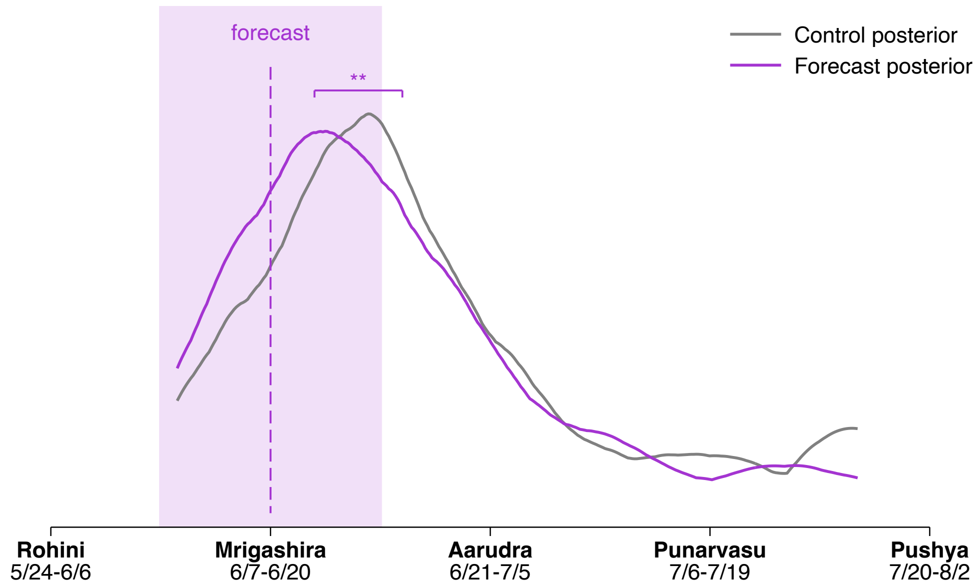
Impact on beliefs Next, we turn to the impact of forecasts. We begin by testing whether farmers' beliefs about monsoon onset change in response to the forecast. Figure 4 plots posterior beliefs in the control group (gray) and in the treatment group (purple). This figure also shows the forecast: the dashed line is centered on the midpoint of the karte, and the shaded area shows the full karte. Among the forecast group, the distribution of posterior beliefs is meaningfully earlier, and therefore closer to both the forecast and the realized onset date. Consistent with our theory, in which farmers are Bayesian updating, however, beliefs among forecast-group farmers 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 posterior, the absolute difference between the posterior and the realized onset date, and the absolute difference between the posterior

Figure 4: The effect of the forecast on 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

and the forecasted onset date. 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]

Table 2 presents the results. In Column (1), we show that the forecast changed farmer beliefs: farmers in the forecast group have earlier posteriors (-0.197 kartes, p-value 0.031) than farmers in the control group. As we show in Figure 4, the forecast was earlier than control farmers' posteriors, so the sign on this estimate suggests that farmers updated in the direction of the forecast. To more formally test this, Columns (2) and (3) show that the absolute difference between the posterior and the onset and the absolute difference between the posterior and the forecast fall in the forecast group, a reduction of 26% (p-value 0.031).[27] The point estimates in Columns (2) and (3) are

[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 the IV versions of our results 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.

[27]Appendix Table G.4 presents results for two additional directional outcomes: the absolute difference between posterior and prior, Kolmogorov–Smirnov test statistic for the difference between a respondent's prior distribution

Table 2: Effect of the forecast and insurance on beliefs

	(1) posterior	(2) | posterior − onset |	(3) | posterior − forecast |
Forecast	-0.197**	-0.180**	-0.180**
	(0.092)	(0.083)	(0.083)
Insurance	-0.019	-0.024	-0.024
	(0.109)	(0.096)	(0.096)
Control Mean	5.60	0.70	0.70
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 is the respondents posterior belief about the monsoon onset date. |posterior - onset| is the absolute difference between a respondent's posterior and actual monsoon onset date. |posterior - forecast| is the absolute difference between a respondent's posterior and the forecast date for the monsoon onset. 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.17.

identical because the forecast was identical to the realized onset date. The insurance group, which got no information, serves as a useful placebo. Reassuringly, we find strong evidence across all three columns that the insurance treatment did not affect 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 forecasts and insurance – 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 disseminated within the village, farmers may offer a lower price in the BDM game compared to their true valuation.

Information spillovers Finally, we check whether our forecast treatment caused any spillover effects on beliefs. To do so, we compare monsoon beliefs from a sample of untreated farmers living in treated villages (where some farmers received our forecast) to a similar spillover sample in control villages (where nobody did). Appendix Table A.8 shows no evidence of information spillovers.[28] 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.).

and their posterior distribution. Both suggest farmers updated in the direction of the forecast, and are statistically significant at the 5 and 10 percent levels, respectively.

[28]Our measured spillover effects on the precise onset timing are noisy, though if anything we see *later* posteriors in the spillover group, inconsistent with the forecast having been earlier than most control farmers' posteriors. We precisely estimate a null spillover effect on the likelihood that the monsoon will arrive on time.

7 Result III: The forecast impacts agriculture, off-farm business, and welfare

We present the treatment effects of the forecast on agriculture, off-farm business and welfare. Our theory predicts that the effect of the forecast on farmer behavior will differ depending on a farmer's prior, and we categorize all farmers as having early, middle, or late priors. Our main specification for estimating treatment effects on agricultural inputs, farm outputs, and off-farm business is:

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

where $[\text{Prior bin} = \text{b}]_i$ are indicators which divide farmers into terciles (early, middle, and late) on the basis of their priors.[29] In all cases, our estimates compare treated farmers to control-group counterparts with similar priors. Our main coefficients of interest are β_1, β_2, and β_3. Our theory predicts that early- and late-prior farmers should respond differently to the forecast. Therefore, as a key test of the model, we test for equality between β_1 and β_3. All other variables are as defined in Equation (3) above, except X_{iv} also includes a control for being in the insurance treatment group.[30]

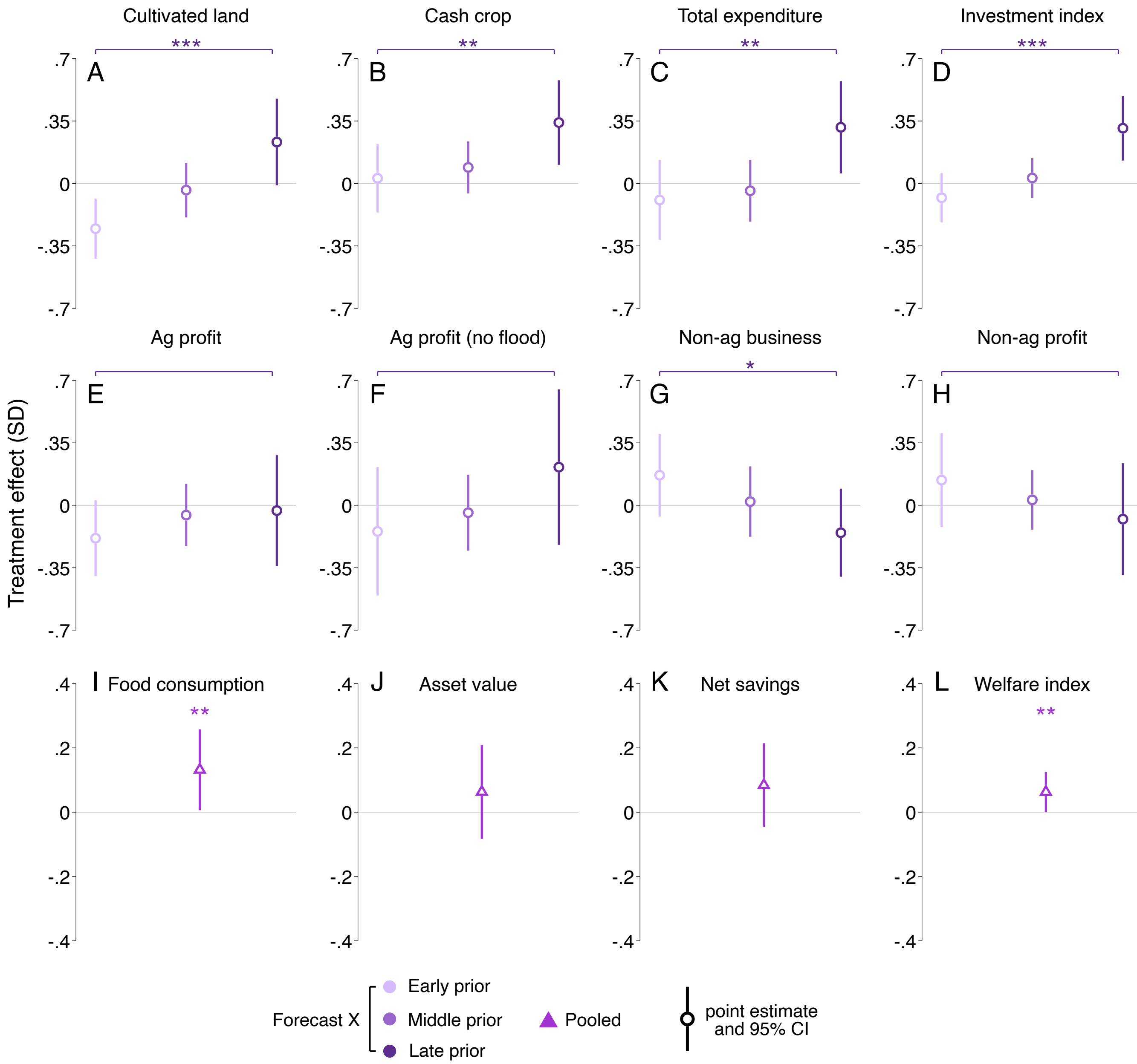
The realized forecast predicted an average monsoon, close to the mean of farmer beliefs (Figure 3). For early-prior farmers, this means that the forecast is for a later (and thus worse) monsoon than expected. For middle-prior farmers, the forecast is for an as-expected monsoon. For late-prior farmers, the forecast is for an earlier (and thus better) monsoon than expected. We therefore 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 (see Figure 1).[31] While higher agricultural investment should generally lead to greater yields and farm 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, and depends on whether these activities serve as complements or substitutes to farming. Finally, 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,

[29] 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.

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

[31] 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 because the forecast was for an average monsoon.

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 profits (for the full sample and the non-flooded sample only) and non-farm business ownership and profits; and the bottom row plots welfare outcomes. In the top two 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 counterparts with similar priors. Coefficients and 95% confidence intervals are plotted for the forecast treatment, estimated using Equation (4), 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 present pooled effects of the forecast (bright purple triangle). Here, we estimate coefficients and 95% confidence intervals using Equation (3). Regressions in all rows include an indicator for the insurance treatment, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors are clustered at the village level. In the top two rows, purple overbraces indicate the significance level on a test for equality between early- and late-prior forecast farmers. In the bottom row, stars indicate the significance level of the forecast coefficient. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 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).

7.1 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.[32] 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.

[32] 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 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*** (0.161)	0.015 (0.049)	-0.053 (0.053)	-0.113* (0.059)	0.012 (0.045)
Forecast × Middle Prior	-0.070 (0.147)	0.045 (0.037)	0.043 (0.051)	0.011 (0.047)	0.014 (0.038)
Forecast × Late Prior	0.435* (0.233)	0.171*** (0.061)	0.130** (0.064)	0.135* (0.072)	0.027 (0.054)
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
Test Early=Late	0.001	0.032	0.023	0.004	0.830
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, 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, a fixed effect for the insurance treatment arm, 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 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.18 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.[33] 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 forecast farmers on total spending (p-value 0.019), corroborated by the continuous-prior specification (Appendix Table A.14). These results provide further evidence that forecasts allow farmers to tailor

[33] Appendix Table G.7 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.

their input decisions to the coming monsoon. [34]

Finally, we 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 <0.001), confirmed in the linear specification (Appendix Table A.14). These results suggest that forecasts allow farmers to make better input decisions by tailoring their farm investments to the coming monsoon.

Table 4: Effect of the forecast on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast × Early Prior	-30.93	-0.68	-42.36	-130.18	-0.08
	(42.19)	(2.61)	(85.27)	(160.55)	(0.07)
Forecast × Middle Prior	-28.94	-2.01	-44.45	-57.46	0.03
	(39.38)	(1.60)	(67.61)	(123.98)	(0.06)
Forecast × Late Prior	96.40*	2.20	263.23**	441.92**	0.31***
	(55.61)	(3.35)	(105.20)	(185.41)	(0.09)
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	
Test Early=Late	0.058	0.493	0.026	0.019	0.000
Control Mean	373	7	762	1443	0
Observations	1201	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts 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, a fixed effect for the insurance treatment arm, and baseline controls chosen by double-selection LASSO. Fert is the amount spent 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 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.19.

Agricultural output and farm profits Table 5 presents effects on agricultural output (in kg) and farm profits.[35] Consistent with the inherently stochastic nature of agriculture (Rosenzweig and

[34] 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.

[35] In Appendix Table G.8, we present impacts on the value of agricultural production, which shows similar patterns. We use district median prices to value production in constructing profits, 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.,

Udry, 2020), we find that our input effects translated imperfectly into output and profit effects. Early-prior forecast farmers (who received a forecast of a worse-than-expected monsoon) reduced agricultural production by 25% (p-value 0.039) and farm profits by \$401 (p-value 0.089), larger declines than would have been implied by their input reductions alone. We see no effect on farm output or profits for middle-prior farmers (whose prior was confirmed by the forecast, and who did not change their input behavior). We find suggestive evidence of a 22% increase in agricultural output for late-prior farmers (who received a forecast of a better-than-expected monsoon), but this is not statistically different from zero, and we estimate a very noisy null result on farm profits for this group. We reject equality between early- and late-prior forecast farmers on production (p-value 0.017, confirmed in the linear specification in Appendix Table **??**) but not on farm profits.

Table 5: Effect of the forecast on agricultural output

	(1) Ag Prod (Kg)	(2) Ag Profit	(3) Ag Prod Non-Flood (Kg)	(4) Ag Profit Non-Flood
Forecast × Early Prior	-16.90**	-401.08*	-16.62	-341.47
	(8.17)	(235.92)	(17.07)	(427.31)
Forecast × Middle Prior	-10.75	-118.98	-8.08	-96.46
	(7.50)	(194.07)	(10.55)	(253.28)
Forecast × Late Prior	14.52	-64.98	42.39**	498.33
	(11.00)	(344.39)	(18.09)	(518.06)
q-val Early	0.084	0.084		
q-val Middle	0.437	0.437		
q-val Late	0.598	0.740		
Test Early=Late	0.017	0.400	0.018	0.222
Control Mean	66.91	970.62	74.80	1052.59
Observations	1201	1201	554	554

Notes: This table presents estimates of the treatment effects of forecasts on agricultural output and profit, 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, a fixed effect for the insurance treatment arm, and baseline controls chosen by double-selection LASSO. Ag Prod (Kg) is total agricultural production in kilograms. Ag Profit is the value of production in USD (evaluated at district-median prices) less total expenditure. Ag Prod Non-Flood (Kg) is the total agriculture production in kilograms for the sample of households that did not report crop losses due to flooding or cyclones. Ag Profit Non-Flood is agricultural profits in USD for the sample of households that did not report crop losses due to flooding or cyclones. "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 except for Column (3) and (4) since these are just sub-sample analyses. 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.20.

These results are consistent with some farmers having been impacted 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.22), because late-prior forecast farmers spent more on inputs and farmed more valuable crops, the same flood may have led

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.

to greater losses among this group than in the control. We conduct a (non-pre-specified) analysis of these shocks in the third and fourth columns of Table 5: we estimate effects on production and agricultural profits *only* for the 46% of farmers who reported no losses from flooding or cyclones.[36] Despite cutting the sample substantially, we find evidence that is much more consistent with the input effects: early-prior forecast farmers see both lower agricultural production (22% decline, p-value 0.330) and farm profits (-$341, p-value 0.424), there is virtually no change for middle-prior forecast farmers, and there is a meaningful increase in late-prior forecast farmer production (57%, p-value 0.019) and agricultural profits ($493, p-value 0.336). We continue to reject equality between early- and late-prior farmers on production (p-value 0.018) but not profits (p-value 0.222). Thus, 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 agricultural output and farm profits for many of these farmers during our experiment.[37]

7.2 Effects on non-agricultural business

Table 6 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 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.16). These results, which are in the opposite direction to our agricultural input findings, are consistent with farmers treating business as a substitute for agriculture.[38]

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

[37] Appendix Figure A.6 shows that farmers' self-reported trust in the forecast increased substantially over the course of the growing season, demonstrating that farmers understand the distinction between monsoon onset and other growing season realizations. 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).

[38] In addition to estimates for non-agricultural business, in Appendix A, we present results for other income sources (Appendix Table A.21). Forecasts have no significant impacts on other income-generating activities, including migration, 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.

Table 6: Effect of the forecast 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)
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
Test Early=Late	0.060	0.130	0.268
Control Mean	0.14	157.98	165.51
Observations	1197	1199	1197

Notes: This table presents estimates of the treatment effects of forecasts 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, a fixed effect for the insurance treatment arm, 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We present an IV analogue in Appendix Table G.22.

7.3 Effects on welfare

Finally, we measure impacts on farmer well-being in Table 7. Because theory predicts that forecasts should (weakly) increase overall welfare for *all* farmers, regardless of prior, 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).[39] 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.[40] 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 from studies whose interventions were substantially more expensive. 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.

[39] Appendix Table A.24 shows that this effect rises to 9.7% in non-flooded villages. We present effects on further-disaggregated consumption categories in Appendix Table A.26.

[40] We provide additional results on household finances in Appendix Table A.27. We estimate impacts on mental health in Appendix Table A.28. 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.

If anything, treatment effects on our welfare 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.25). Taken together, these results demonstrate that the forecast improved overall welfare, in a manner consistent with theory.

Table 7: Effect of the forecast 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)
q-val Forecast	0.249	0.945	0.945	0.945	0.701	
Control Mean	13.22	9.93	1503.10	0.22	-1031.41	0.00
Observations	1201	1201	1201	1201	1129	1201

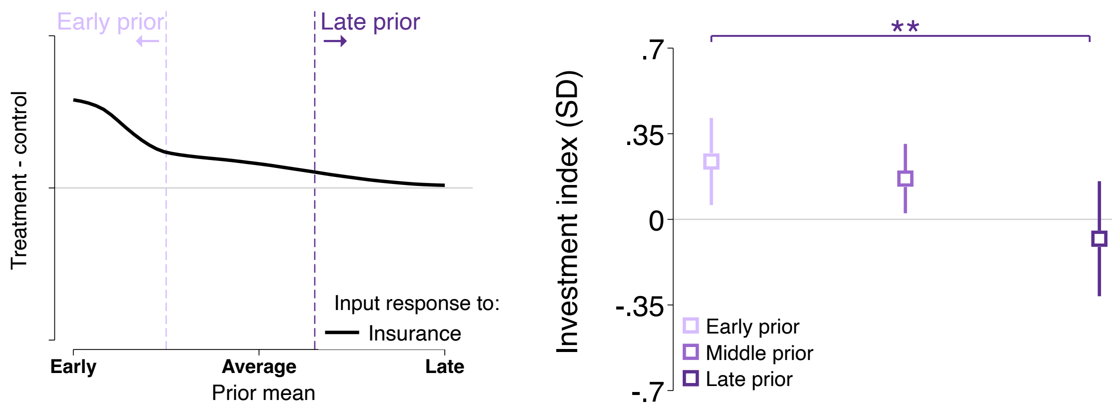
Notes: This table presents estimates of the treatment effects of forecasts on economic well-being. The estimation follows Equation (3). All regressions include strata fixed effects, enumerator fixed effects, a fixed effect for the insurance treatment arm, and baseline controls chosen by double-selection 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

8 Result IV: Beliefs impact farmer responses to index insurance

As a final exercise, we examine how beliefs shape not only farmers' investment decisions in the status quo, but also their responses to a canonical agricultural policy – index insurance. If beliefs affect how farmers interact with insurance, this suggests another margin along which forecasts – which align beliefs with actual realizations – could improve outcomes for farmers. We extend the model outlined in Section 3 to incorporate insurance, modeling farmers as gaining a fixed amount of income if the realized state falls below some pre-determined threshold (see Appendix C for details). The left panel of Figure 6 presents the key prediction: while we should see weakly increased investments for all farmers in the insurance group, these impacts will be largest among early-prior insurance farmers and smallest among late-prior insurance farmers. 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.

The right panel of of Figure 6 takes these predictions to data, plotting the treatment effect of insurance on our agricultural investment index for farmers with early, middle, and late priors. The results line up very well with our theoretical prediction: early- and middle-prior insurance farmers, who expect the growing season to be better-than-average or average, respond to the insurance

Figure 6: Investment choice with insurance (model and empirics)



Notes: This figure plots the relationship between the treatment effect of insurance on investments and farmers' prior beliefs. The left panel presents the simulated relationship in our model between the treatment effect of 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 gray horizontal line is centered at zero. The x-axis reflects when farmers believe the monsoon will arrive. Our theory predicts that farmers with early priors will respond to an insurance product by increasing investment compared to the control, farmers with middle priors will exhibit a more muted response, and farmers with late priors will not respond. See Appendix C.3 for simulation details. The right panel plots realized treatment effects on the investment index, measured in SD, estimated using a modified version of Equation (4) where rather than interacting the forecast offer with prior bins, we interact the insurance offer with prior bins. The regression includes an indicator for the forecast treatment, strata fixed effects, enumerator fixed effects, and baseline controls chosen by double-selection LASSO. Standard errors are clustered by village. The overbrace indicates the significance level of the test for equality between the early- and late-prior coefficients. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

treatment by increasing their investment by 0.24 SD (p-value 0.009) and 0.17 SD (p-value 0.021), respectively.[41] However, late-prior insurance farmers, who expect a worse-than-average growing season, do not change their investments (-0.08 SD, p-value 0.510).[42]

These results demonstrate that farmers' beliefs matter, not only for determining status quo investments or for driving the response to the forecast, but also for the effectiveness of core agricultural support policies. This has two key implications. First, these findings underscore the importance of aligning farmers' beliefs with the coming realization, as a mismatch can lead to both welfare reductions in the status quo and less-than-ideal responses to policy (e.g., if farmers expect a worse growing season than what actually occurs, they may respond to insurance by doing nothing instead of increasing their farming activity). This increases the value of an accurate forecast that can improve the alignment between farmers' beliefs and realizations. Second, these results suggest that it may be valuable to collect data on beliefs when researchers are evaluating agricultural policy. If, for example, demand for index insurance is found to be low, this may be because farmers believe the coming season will be poor, rather than something fundamentally unappealing about the technology; data on beliefs can allow researchers to test this hypothesis.

[41] Appendix Table A.23 reports results in tabular form and presents effects on individual index components.

[42] In Appendix A.8 and Appendix A.15, we present effects of insurance on our main outcomes. We find that insurance leads to increases in both farm and off-farm investment, but find limited evidence for changes in farm outputs or welfare, likely because farmers in the insurance group were disproportionately affected by flooding.

9 Conclusion

Agricultural production is central to the economies of low- and middle-income countries. Yet, the world's farmers face the central challenge of deciding on inputs before the weather, a key determinant of output, is realized. As a result, farmers are reliant on their beliefs to make decisions. In this paper, we use a cluster-randomized trial to document several new facts about the importance of farmer beliefs about the weather in agricultural production. First, beliefs about monsoon onset timing drive investment behavior in the status quo. Second, a high-quality, long-range forecast of monsoon onset timing moves farmer beliefs. Third, in response to this forecast, farmers make meaningful changes in both on- and off-farm investment, which translates to overall welfare gains. Fourth, beliefs impact farmer responses to a canonical policy instrument: index insurance. These findings highlight the value of aligning beliefs with coming realizations.

Moreover, our findings demonstrate that forecasts are a useful tool for helping farmers to cope with a variable climate, 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 meteorological, 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).

References

Ahmad, Husnain F., Matthew Gibson, Fatiq Nadeem, Sanval Nasim, and Arman Rezaee (2023): "Forecasts: Consumption, production, and behavioral responses," Working paper.

Allen, Treb and David Atkin (2022): "Volatility and the gains from trade," *Econometrica*, 90 (5), 2053–2092.

Amale, Hardeep Singh, Pratap Singh Birthal, and Digvijay Singh Negi (2023): "Delayed monsoon, irrigation and crop yields," *Agricultural Economics*, 54 (1), 77–94.

Anderson, Michael L. (2008): "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training projects," *Journal of the American Statistical Association*, 103 (484), 1481–1495.

Becker, Gordon M., Morris H. DeGroot, and Jacob Marschak (1964): "Measuring utility by a single-response sequential method," *Behavioral Science*, 9 (3), 262–232.

Berkouwer, Susanna B. and Joshua T. Dean (2022): "Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households," *American Economic Review*, 112 (10), 3291–3330.

Bhat, Bhargav, Jonathan de Quidt, Johannes Haushofer, Vikram H. Patel, Gautam Rao, Frank Schilbach, and Pierre-Luc P. Vautrey (2022): "The long-run effects of psychotherapy on depression, beliefs, and economic outcomes," NBER working paper No. 30011.

Bloom, Nicholas, Mihai A. Codreanu, and Robert A. Fletcher (2025): "Rationalizing Firm Forecasts," NBER Working paper.

Boucher, Stephen R., Michael R. Carter, Jon Einar Flatnes, Travis J. Lybbert, Jonathan G. Malacarne, Paswel P. Marenya, and Laura A. Paul (2024): "Bundling Genetic and Financial Technologies for More Resilient and Productive Small-Scale Farmers in Africa," *The Economic Journal*, 134 (662), 2321–2350.

Business Line (2022): "Floods in Telangana severely impact infrastructure, says post-event analysis," .

Carleton, Tamma, Esther Duflo, B. Kelsey Jack, and Guglielmo Zappalà (2024): "Adaptation to Climate Change," in *Handbook of the Economics of Climate Change*, ed. by Lint Barrage and Solomon Hsiang, Elsevier, chap. 4.

Carleton, Tamma A. and Solomon M. Hsiang (2016): "Social and economic impacts of climate," *Science*, 353 (6304), aad9837.

Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar (2018): "How Do Firms Form Their Expectations? New Survey Evidence," *American Economic Review*, 108 (9), 2671–2713.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele (2019): "Inflation Expectations and Firm Decisions: New Causal Evidence*," *The Quarterly Journal of Economics*, 135 (1), 165–219.

Cole, Shawn A. and A. Nilesh Fernando (2020): "'Mobile'izing agricultural advice: Technology adoption, diffusion, and sustainability," Working paper.

COP28 Presidency (2023): "COP28 partnership announces food innovation priorities for investment and scaling," .

Das, Sukanta Kumar, Sanjib Kumar Deb, CM Kishtawal, and Pradip Kumar Pal (2015): "Validation of seasonal forecast of Indian summer monsoon rainfall," *Pure and Applied Geophysics*, 172 (6), 1699–1716.

Deschênes, Olivier and Michael Greenstone (2007): "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather," *American Economic Review*, 97 (1), 354–385.

Dizon-Ross, Rebecca (2019): "Parents' Beliefs about Their Children's Academic Ability: Implications for Educational Investments," *American Economic Review*, 109 (8), 2728–65.

Downey, Mitch, Nelson Lind, and Jeffrey G. Shrader (2023): "Adjusting to rain before it falls," *Management Science*, 69 (12), 7151–7882.

Duflo, Esther, Michael Kremer, and Jonathan Robinson (2008): "How high are rates of return to fertilizer? Evidence from field experiments in Kenya," *American Economic Review*, 98 (2), 482–488.

Emerick, Kyle, Alain de Janvry, Elisabeth Sadoulet, and Manzoor H. Dar (2016): "Technological innovations, downside risk, and the modernization of agriculture," *American Economic Review*, 106 (6), 1537–1561.

Fabregas, Raissa, Michael Kremer, Matthew Lowes, Robert On, and Guilia Zane (2019): "SMS-extension and farmer behavior: Lessons from six RCTs in East Africa," Working paper.

FAO (2019): "Handbook on climate information for farming communities – What farmers need and what is available," Rome, Italy.

FAO (2023): "Small family farmers produce a third of the world's food," https://www.fao.org/newsroom/detail/Small-family-farmers-produce-a-third-of-the-world-s-food/en, accessed: YYYY-MM-DD.

Fosu, Mathias, Dean Karlan, Shashidhara Kolavalli, and Christopher Udry (2018): "Disseminating innovative resources and technologies to smallholders in Ghana (DIRTS)," .

Gibson, Matthew and Jamie T. Mullins (2020): "Climate Risk and Beliefs in New York Floodplains," *Journal of the Association of Environmental and Resource Economists*, 7 (6), 1069–1111.

Gine, Xavier, Robert M. Townsend, and James Vickery (2015): "Forecasting when it matters: Evidence from semi-arid India," Working paper.

Government of Telangana (2020): "Socioeconomic Outlook," .

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, Kate Larsen, and Trevor Houser (2017): "Estimating economic damage from climate change in the United States," *Science*, 356 (6345), 1362–1369.

Hultgren, Andrew, Tamma Carleton, Michael Delgado, Diana R. Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Amir Jina, Robert E. Kopp, Steven B. Malevich, Kelly E. McCusker, Terin Mayer, Ishan Nath, James Rising, Ashwin Rode, and Jiacan Yuan (2025): "Climate change impacts on global agriculture accounting for adaptation," Working paper.

Jensen, Robert (2010): "The (Perceived) Returns to Education and the Demand for Schooling*," *The Quarterly Journal of Economics*, 125 (2), 515–548.

Jones, Maria, Florence Kondylis, John Loeser, and Jeremy Magruder (2022): "Factor market failures and the adoption of irrigation in Rwanda," *American Economic Review*, 112 (7), 2316–2352.

Kala, Namrata (2019): "Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture," Working paper.

Kirtman, Ben P, Dughong Min, Johnna M Infanti, James L Kinter, Daniel A Paolino, Qin Zhang, Huug Van Den Dool, Suranjana Saha, Malaquias Pena Mendez, Emily Becker, et al. (2014): "The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction," *Bulletin of the American Meteorological Society*, 95 (4), 585–601.

Kochhar, Rajat and Ruozi Song (2024): "Does market power in agricultural markets hinder farmer climate change adaptation?" Working paper.

Lane, Gregory (2024): "Adapting to floods with guaranteed credit: Evidence from Bangladesh," *Econometrica*.

McCullough, Ellen B., Julianne D. Quinn, Andrew M. Simons, Leslie J. Verteramo, and Joshua Woodard (2020): "Modeling climate smart soil health investments in sub-Saharan Africa," Working paper.

Ministry of Agriculture and Farmers Welfare (2023): "Lok Sabha Starred Question No. 228," .

Ministry of Statistics and Programme Implementation, Government of India (2013): "Situation assessment survey of agricultural households," National Sample Survey, 70th round.

Mobarak, Ahmed Mushfiq and Mark Rosenzweig (2014): "Risk, insurance and wages in general equilibrium," NBER working paper No. 19811.

Molina, Renato and Ivan Rudik (2023): "The social value of hurricane forecasts," Working paper.

Moron, Vincent and Andrew W Robertson (2014): "Interannual variability of Indian summer monsoon rainfall onset date at local scale," *International Journal of Climatology*, 34 (4), 1050–1061.

Moron, Vincent, Andrew W Robertson, and DS Pai (2017): "On the spatial coherence of sub-seasonal to seasonal Indian rainfall anomalies," *Climate Dynamics*, 49 (9-10), 3403–3423.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda, Clément Albergel, Gabriele Arduini, Gianpaolo Balsamo, Souhail Boussetta, Margarita Choulga, Shaun Harrigan, Hans Hersbach, et al. (2021): "ERA5-Land: A state-of-the-art global reanalysis dataset for land applications," *Earth System Science Data Discussions*, 1–50.

Patel, Dev (2024): "Environmental beliefs and adaptation to climate change," Working paper.

Preenu, PN, PV Joseph, and PK Dineshkumar (2017): "Variability of the date of monsoon onset over Kerala (India) of the period 1870–2014 and its relation to sea surface temperature," *Journal of Earth System Science*, 126 (5), 76.

Rajeevan, M, DS Pai, R Anil Kumar, and B Lal (2007): "New statistical models for long-range forecasting of southwest monsoon rainfall over India," *Climate Dynamics*, 28 (7-8), 813–828.

Rosenzweig, Mark and Christopher R Udry (2019): "Assessing the benefits of long-run weather Forecasting for the rural poor: Farmer investments and worker migration in a dynamic equilibrium model," NBER working paper No. 25894.

Rosenzweig, Mark R and Christopher Udry (2020): "External Validity in a Stochastic World: Evidence from Low-Income Countries," *The Review of Economic Studies*, 87 (1), 343–381.

Rudder, Jess and Davide Viviano (2024): "Learning from Weather Forecasts and Short-Run Adaptation: Evidence from an At-Scale Experiment," Working Paper.

Schlenker, Wolfram and Michael J. Roberts (2009): "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 106 (37), 15594–15598.

Shrader, Jeffrey G. (2023): "Improving climate damage estimates by accounting for adaptation," Working paper.

Shrader, Jeffrey G., Laura Bakkensen, and Derek Lemoine (2023): "Fatal errors: The mortality value of accurate weather forecasts," NBER working paper No. 31361.

Song, Yuqi (2023): "The value of weather forecasts: Labor responses to accurate and inaccurate temperature forecasts in China," Working paper.

Stolbova, Veronika, Elena Surovyatkina, Bodo Bookhagen, and Jürgen Kurths (2016): "Tipping elements of the Indian monsoon: Prediction of onset and withdrawal," *Geophysical Research Letters*, 43 (8), 3982–3990.

Suri, Tavneet and Christopher Udry (2022): "Agricultural Technology in Africa," *Journal of Economic Perspectives*, 36 (1), 33–56.

The New Indian Express (2022): "Telangana floods: Godavari in spate, houses collapse, streets turn into streams," .

The World Bank (2025): "Our World in Data," https://ourworldindata.org/, accessed: YYYY-MM-DD.

Yegbemey, Rosaine N, Gunther Bensch, and Colin Vance (2023): "Weather information and agricultural outcomes: Evidence from a pilot field experiment in Benin," *World Development*, 167, 106178.

Yegbemey, Rosaine N. and Janvier Egah (2021): "Reaching out to smallholder farmers in developing countries with climate services: A literature review of current information delivery channels," *Climate Services*, 23, 100253.

Zappalà, Guglielmo (2023): "Drought exposure and accuracy: Motivated reasoning in climate change beliefs," *Environmental and Resource Economics*, 85, 649–672.

——— (2024): "Adapting to climate change accounting for individual beliefs," *Journal of Development Economics*, 169 (103289).

Beliefs, forecasts, and investments: Experimental evidence from India

Online appendix

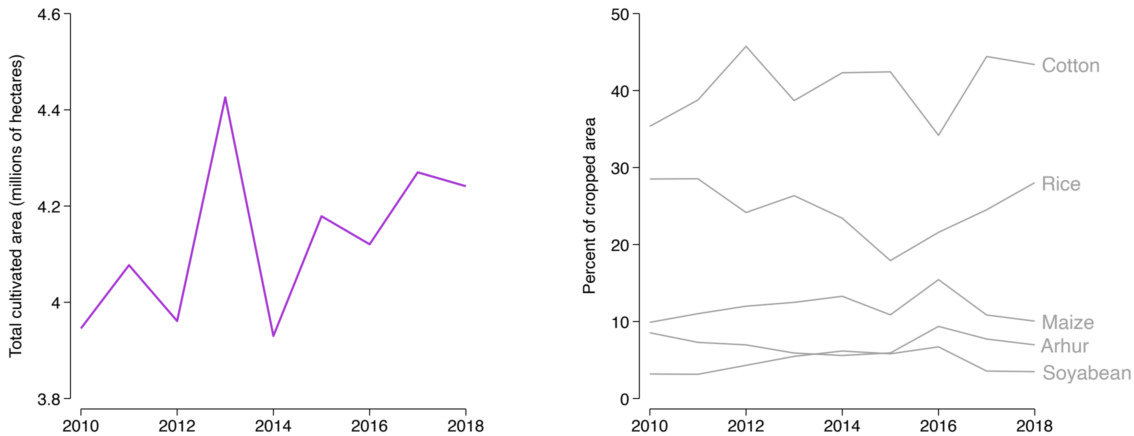
Fiona Burlig, Amir Jina, Erin M. Kelley, Gregory Lane, and Harshil Sahai

Contents

A Appendix tables and figures

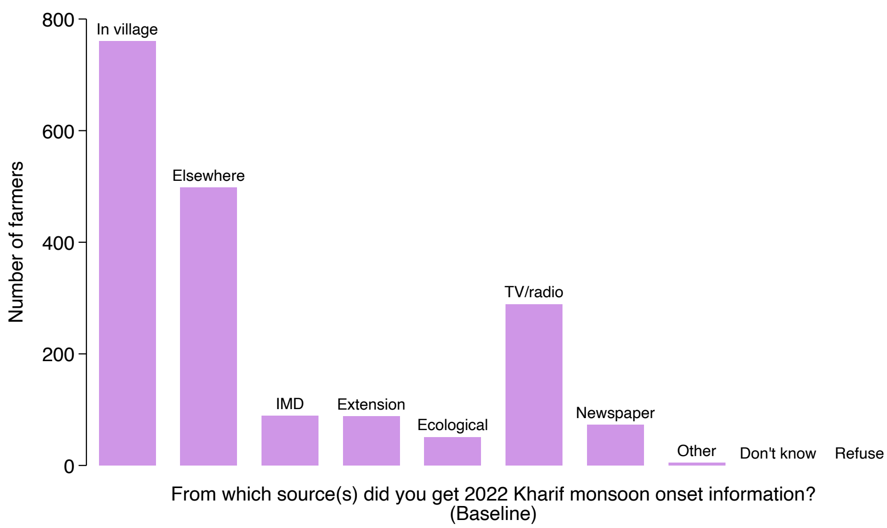
A.1 Context

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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

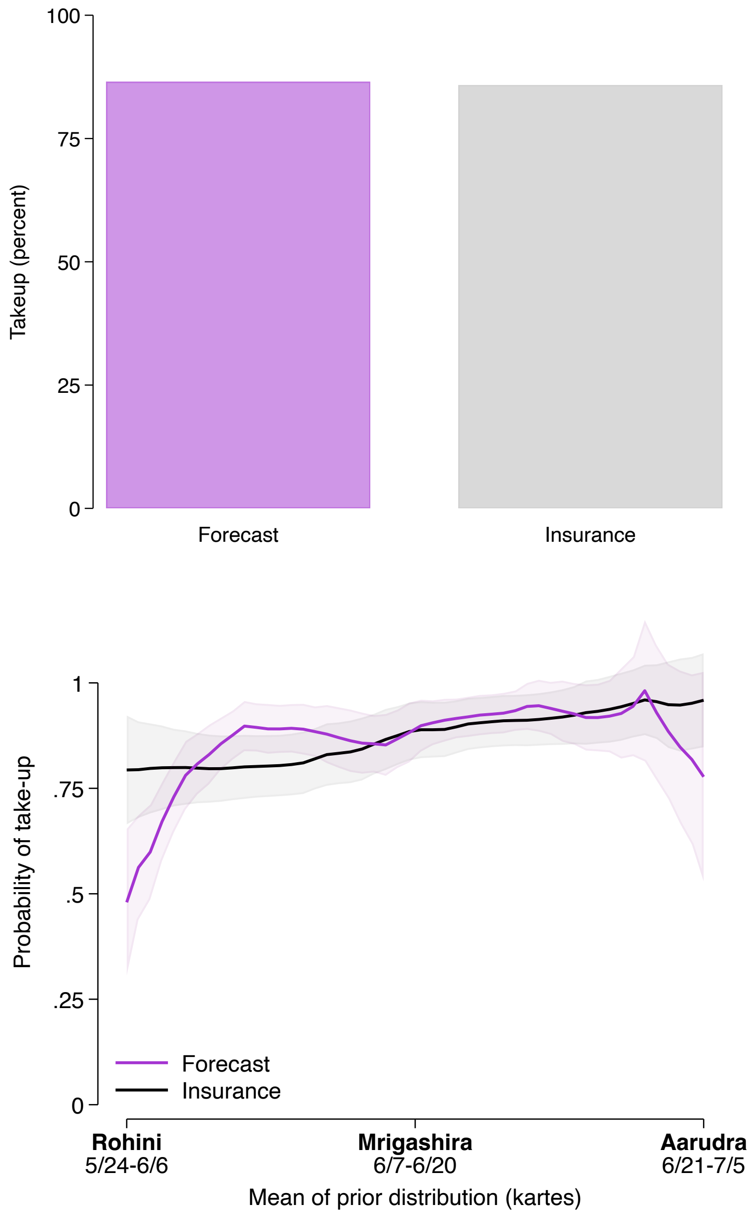
A.3 Takeup

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 include prior tercile fixed effects. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

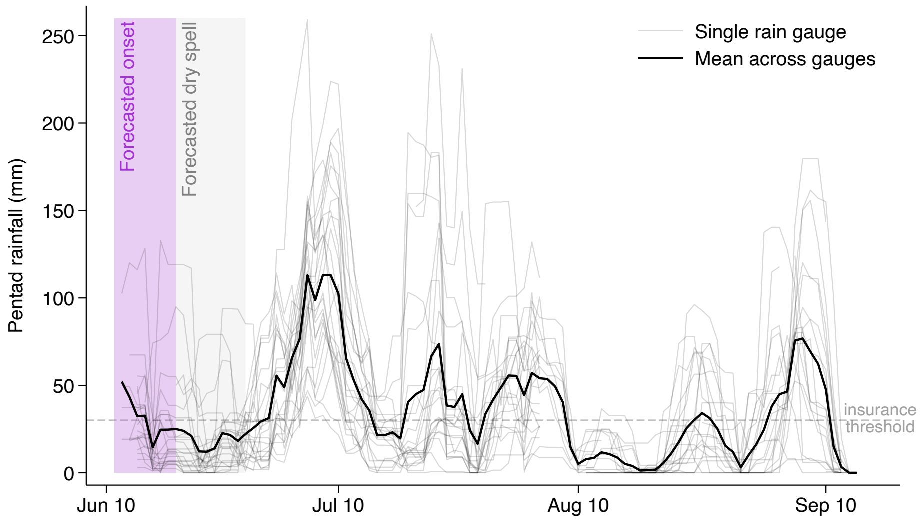
Figure A.3: Takeup of forecasts and insurance



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				0.225**				
(1/0)				(0.091)				
# of plots					-0.018			
					(0.019)			
Total land (ha)						-0.011**		
						(0.005)		
Cash crops 2021							-0.035	
(1/0)							(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

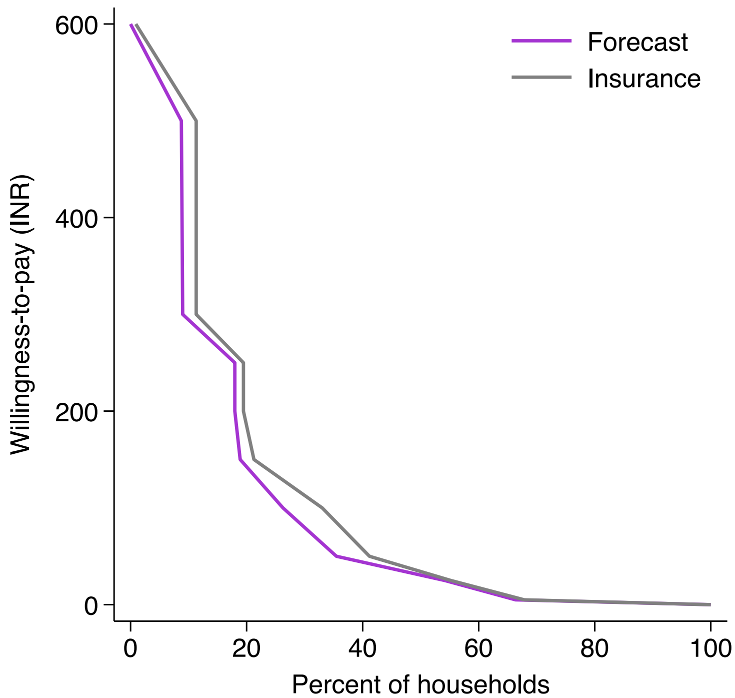
Table A.8: Effect of the forecast on untreated farmer beliefs (spillover sample)

	(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 (3). 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
	(29.18)	(1.54)	(50.18)	(95.40)	(0.05)
Insurance	97.60**	-0.94	113.49*	263.16**	0.13**
	(43.33)	(1.34)	(64.13)	(130.22)	(0.06)
q-val Forecast	1.000	1.000	1.000	1.000	
q-val Insurance	0.244	0.431	0.244	0.244	
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 (3). 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 production and profits

	(1) Ag Prod (Kg)	(2) Ag Profit	(3) Ag Prod Non-Flood (Kg)	(4) Ag Profit Non-Flood
Forecast	-8.55	-213.20	-3.65	-114.66
	(5.32)	(160.64)	(9.19)	(237.23)
Insurance	2.55	-146.68	25.50**	402.92
	(6.80)	(183.47)	(12.88)	(297.66)
q-val Forecast	0.227	0.227		
q-val Insurance	1.000	1.000		
Control Mean	66.91	970.62	66.91	970.62
Observations	1201	1201	554	554

Notes: This table presents estimates of the treatment effects of forecasts and insurance on agricultural output, estimated using Equation (3). Ag Prod (Kg) is total agricultural production in kilograms. Ag Profit ($) is the value of production (evaluated at district-median prices) less total expenditure in USD. Ag Prod Non-Flood (Kg) is total agricultural production for the sample of households that did not report crop losses due to flooding or cyclones. Ag Profit Non-Flood ($) 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 except Columns (3) and (4) because they are a subsample analysis of Column (1) and (2). 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 off-farm business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast	0.01	-13.36	26.93
	(0.02)	(42.66)	(41.46)
Insurance	0.09***	99.33	103.06*
	(0.03)	(63.06)	(55.59)
q-val Forecast	1.000	1.000	1.000
q-val Insurance	0.032	0.084	0.069
Control Mean	0.14	157.98	165.51
Observations	1197	1199	1197

Notes: This table presents estimates of the treatment effects of forecasts on non-farm business activity estimated using Equation (3). 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. "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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We present an IV analogue in Appendix Table G.22.

A.9 Linear prior

Table A.13: Continuous prior: Effect of the forecast 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	0.070	0.072	0.072	0.070	0.308
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 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 on inputs

	(1) Fert	(2) Seed	(3) Labor	(4) Total	(5) Invest Index
Forecast	-1.65	-0.81	25.14	27.40	0.04
	(29.05)	(1.53)	(49.83)	(94.66)	(0.04)
Forecast X Prior	64.26	1.09	201.72*	356.37**	0.22***
	(48.17)	(2.23)	(105.91)	(176.73)	(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 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 on agricultural output

	(1) Prod (Kg)	(2) Ag Profit	(3) Ag Prod Non-Flood (Kg)	(4) Ag Profit Non-Flood
Forecast	-8.39	-215.18	-3.82	-125.33
	(5.35)	(161.21)	(9.81)	(250.34)
Forecast X Prior	19.31*	112.20	37.73**	481.60
	(9.99)	(271.58)	(18.92)	(451.75)
q-val Forecast X Prior	0.267	0.267		
Control Mean	66.91	970.62	74.80	1052.59
Observations	1201	1201	554	554

Notes: This table presents estimates of the treatment effects of forecasts 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 Prod (Kg) is total agricultural production in kilograms. Ag Profit is the value of production (evaluated at district-median prices) less total expenditure. Prod Non-Flood (Kg) is the total agriculture production in kilograms for the sample of households that did not report crop losses due to flooding or cyclones. Ag Profit Non-Flood is agricultural profits for the sample of households that did not report crop losses due to flooding or cyclones. Sharpened q-values are adjusted for all outcomes except Columns (3) and (4) because they are subsample analysis of Column (1) and (2). 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 on business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast	0.02	-11.80	28.18
	(0.02)	(41.30)	(40.92)
Forecast X Prior	-0.08**	-153.49**	-122.12*
	(0.04)	(68.54)	(72.26)
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 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.17: Alternative prior bins: Effect of the forecast 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*** (0.161)	0.012 (0.049)	-0.053 (0.053)	-0.114* (0.059)	0.013 (0.045)
Forecast X Middle Prior	0.046 (0.148)	0.059* (0.035)	0.046 (0.047)	0.041 (0.048)	0.000 (0.036)
Forecast X Late Prior	0.313 (0.322)	0.172* (0.089)	0.176** (0.078)	0.093 (0.097)	0.106* (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	1201	1201	1201	1201

Notes: This table presents estimates of the treatment effects of forecasts 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.17 and A.18 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.18: Alternative prior bins: Effect of the forecast 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	372.80	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 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.17 and A.18 (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 on agricultural output

	(1) Prod (Kg)	(2) Ag Profit	(3) Prod Non-Flood (Kg)	(4) Ag Profit Non-Flood
Forecast X Early Prior	-16.47**	-406.80*	-14.68	-337.57
	(8.16)	(235.93)	(16.93)	(426.30)
Forecast X Middle Prior	-5.44	-46.22	-0.10	23.52
	(7.07)	(211.36)	(9.70)	(270.31)
Forecast X Late Prior	12.86	-385.77	51.77*	325.73
	(14.91)	(321.51)	(26.63)	(541.29)
q-val Early	0.093	0.093		
q-val Middle	1.000	1.000		
q-val Late	0.635	0.635		
Test Early = Late	0.082	0.957	0.035	0.341
Control Mean	66.91	970.62	74.80	1052.59
Observations	1201	1201	554	554

Notes: This table presents estimates of the treatment effects of forecasts 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 Prod (Kg) is total agricultural production in kilograms. Ag Profit is the value of production (evaluated at district-median prices) less total expenditure. Prod Non-Flood (Kg) is the total agriculture production in kilograms for the sample of households that did not report crop losses due to flooding or cyclones. Ag Profit Non-Flood is agricultural profits for the sample of households that did not report crop losses due to flooding or cyclones. Sharpened q-values are adjusted for all outcomes except Columns (3) and (4) because they are subsample analysis of Column (1) and (2). "Test Early = Late" is the p-value on the test of equality between the first and third coefficient. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.20: Alternative prior bins: Effect of the forecast on business activity

	(1) Non-Ag Bus.	(2) Non-Ag Invest	(3) Bus Profit
Forecast X Early Prior	0.06	29.23	81.71
	(0.04)	(71.79)	(76.02)
Forecast X Middle Prior	0.01	1.63	42.95
	(0.03)	(51.78)	(45.46)
Forecast X Late Prior	-0.10**	-163.42*	-175.73**
	(0.05)	(83.97)	(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	0.14	157.98	165.51
Observations	1197	1199	1197

Notes: This table presents estimates of the treatment effects of forecasts 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.21: Effect of the forecast and insurance on other income-generating activities

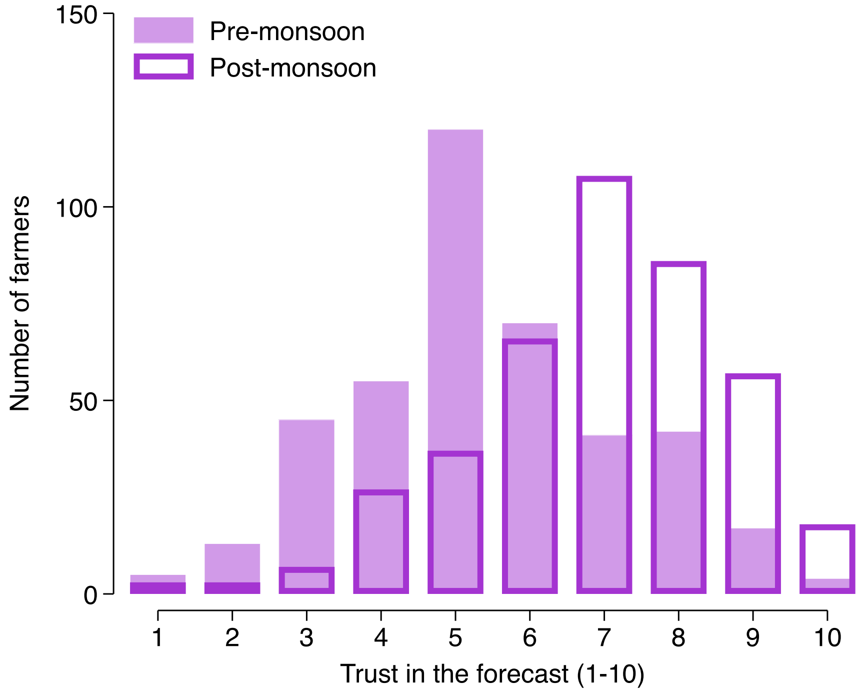
	Panel A: Forecast vs. Insurance			
	(1) Labor Inc.	(2) Livestock Inc.	(3) Migrant	(4) Remittance Inc.
Forecast	-44.45	-23.71*	-0.03	-2.77
	(33.59)	(12.21)	(0.02)	(2.37)
Insurance	-29.11	-17.48	-0.00	-5.72**
	(40.93)	(12.32)	(0.03)	(2.53)
q-val Forecast	0.265	0.265	0.265	0.265
q-val Insurance	0.467	0.306	0.808	0.108

	Panel B: Forecast Terciles			
Forecast × Early Prior	-114.22**	-24.34	-0.05	-1.37
	(54.72)	(22.36)	(0.04)	(4.72)
Forecast × Middle Prior	7.33	-34.33**	-0.03	-2.10
	(44.15)	(15.61)	(0.03)	(2.26)
Forecast × Late Prior	-20.22	0.83	0.00	-6.79**
	(67.89)	(21.40)	(0.04)	(3.41)
q-val Early	0.174	0.383	0.326	0.585
q-val Middle	0.785	0.127	0.492	0.551
q-val Late	1.000	1.000	1.000	0.229
Test Early=Late	0.264	0.413	0.329	0.323
Insur. = Late	0.895	0.415	0.863	0.691
Control Mean	324.53	55.89	0.15	7.46
Observations	1199	1201	1201	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, Migrant is an indicator for any migrant having left the household in the past 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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.22: Shock realizations across treatments

Panel A: Forecast vs. Insurance

	(1) Flood	(2) Drought	(3) Animal	(4) Cyclone	(5) 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

	(1) Flood	(2) Drought	(3) Animal	(4) Cyclone	(5) Any
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	0.504	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.23: Effect of insurance on inputs by prior terciles

	(1) Land (Ha.)	(2) Cash Crop	(3) Total Inputs	(4) Invest Index
Insurance × Early Prior	0.639*** (0.218)	0.054 (0.061)	481.370** (214.734)	0.237*** (0.091)
Insurance × Middle Prior	0.112 (0.160)	0.098** (0.049)	317.589** (161.788)	0.167** (0.072)
Insurance × Late Prior	-0.263 (0.289)	-0.000 (0.073)	-86.297 (235.796)	-0.079 (0.120)
q-val Insure Early	0.011	0.142	0.026	
q-val Insure Middle	0.193	0.081	0.081	
q-val Insure Late	1.000	1.000	1.000	
Test Early=Late	0.011	0.549	0.057	0.030
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.24: Effect of the forecast and insurance on economic well-being, no flood shock

	(1) Food cons	(2) Other cons	(3) Asset value	(4) Livestock	(5) Net savings	(6) 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.25: 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)	(264.78)	(0.04)	(252.85)	(0.06)
Forecast ×	1.19**	-0.80	29.35	-0.04	59.12	-0.00
Middle Prior	(0.53)	(0.97)	(153.37)	(0.03)	(228.37)	(0.04)
Forecast ×	1.14	-0.28	-135.55	0.02	121.49	0.05
Late Prior	(0.84)	(1.45)	(145.77)	(0.05)	(253.75)	(0.05)
Insurance	0.45	1.91*	-115.78	0.01	-406.54*	-0.02
	(0.47)	(1.00)	(158.40)	(0.03)	(217.14)	(0.05)
q-val Early	0.455	0.455	0.455	0.455	0.455	
q-val Middle	0.143	1.000	1.000	0.928	1.000	
q-val Late	1.000	1.000	1.000	1.000	1.000	
q-val Insurance	0.492	0.182	0.536	0.782	0.182	
Test Early=Late	0.412	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.26: 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	0.133	0.212	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)	(0.43)	(2.24)
Forecast ×	0.84	0.48**	-0.30	-0.25	0.11	-0.28	-0.85	0.10	-0.81
Late Prior	(0.54)	(0.22)	(0.54)	(0.34)	(0.10)	(0.60)	(1.13)	(0.55)	(2.82)
q-val Early	1.000	1.000	0.084	1.000	1.000	0.084	1.000	1.000	1.000
q-val Middle	0.088	0.514	0.432	0.740	0.514	0.432	0.792	0.514	0.792
q-val Late	0.982	0.350	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Test Early=Late	0.297	0.104	0.272	0.383	0.513	0.041	0.693	0.761	0.807
Test Insur. = Late	0.208	0.112	0.909	0.206	0.923	0.276	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.27: Effect of the forecast and insurance on household finances

	Panel A: Forecast vs. Insurance				
	(1) Savings	(2) Took Loan	(3) Debt Out	(4) Missed Payment	(5) Farm Loan
Forecast	-14.28	-0.06	-193.13	-0.11*	-0.09**
	(23.94)	(0.04)	(137.96)	(0.06)	(0.04)
Insurance	-48.12**	0.18***	374.72*	-0.01	0.18***
	(21.52)	(0.04)	(206.98)	(0.06)	(0.04)
q-val Forecast	0.254	0.175	0.194	0.175	0.085
q-val Insurance	0.027	0.001	0.045	0.211	0.001

	Panel B: Forecast Terciles				
Forecast × Early Prior	-48.58	-0.07	-449.03*	-0.15*	-0.09*
	(33.78)	(0.05)	(238.27)	(0.09)	(0.05)
Forecast × Middle Prior	-0.84	-0.06	-47.90	-0.17*	-0.11**
	(31.61)	(0.05)	(206.07)	(0.09)	(0.05)
Forecast × Late Prior	19.67	-0.02	-30.84	0.02	-0.04
	(41.85)	(0.07)	(256.21)	(0.14)	(0.07)
q-val Early	0.171	0.171	0.171	0.171	0.171
q-val Middle	0.644	0.265	0.644	0.176	0.176
q-val Late	1.000	1.000	1.000	1.000	1.000
Test Early=Late	0.163	0.582	0.258	0.254	0.566
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.28: 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	0.867	0.867	0.653	0.867	0.207	0.703	0.799	0.653	0.653
q-val Insurance	0.955	0.625	0.696	1.000	1.000	1.000	0.696	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)	(0.15)	(0.16)	(0.17)	(0.14)	(0.20)	(0.16)	(0.12)	(0.13)
q-val Early	1.000	1.000	0.264	0.724	0.210	1.000	1.000	0.210	0.210
q-val Middle	1.000	1.000	1.000	1.000	0.730	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	0.174	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_k and a concave, risky agricultural production technology $f(x, \epsilon_k)$. In the period two, farmers consume (c_2^k) from production and savings.

Production The output from this production technology is modified by the state of the world ϵ_k for $k \in \{1, ..., K\}$, where ϵ_k are ordered so that for any $k > m$ we have higher production and a greater marginal product: $f(x, \epsilon_k) > f(x, \epsilon_m)$ and $f'(x, \epsilon_k) > f'(x, \epsilon_m)$ for all $x > 0$. There is no product at zero investment regardless of the state: $f(0, \epsilon_k) = 0$ for all k. 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:

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

where $u(\cdot)$ is a concave utility function, c_1 is first period consumption, c_2^k is second period consumption in state k, $g(\epsilon_k)$ 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:

$$\mathbf{E}[u'(c_2)] = \sum_k u'(c_2^k, \epsilon_k) g(\epsilon_k) \tag{C.3}$$

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:

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

with weights:

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

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_k for higher k. 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:

$$c_2^k = f(x, \epsilon_k) + s + b \cdot 1\{\epsilon_k \in K_I\},$$

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^k increases from the payouts, causing $u'(c_2^k)$ to fall by concavity the weights; for high states, c_2^k is unchanged; on net, $\mathbf{E}[u'(c_2^k)]$ falls. Thus, the weights $w(c_2^k, \epsilon_k)$ in (C.6) will fall for low states (because $u'(c_2^k)$ falls) and rise for high states (because $\mathbf{E}[u'(c_2^k)]$ 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:

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

The scale parameter h 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:

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

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:

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

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

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

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

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

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

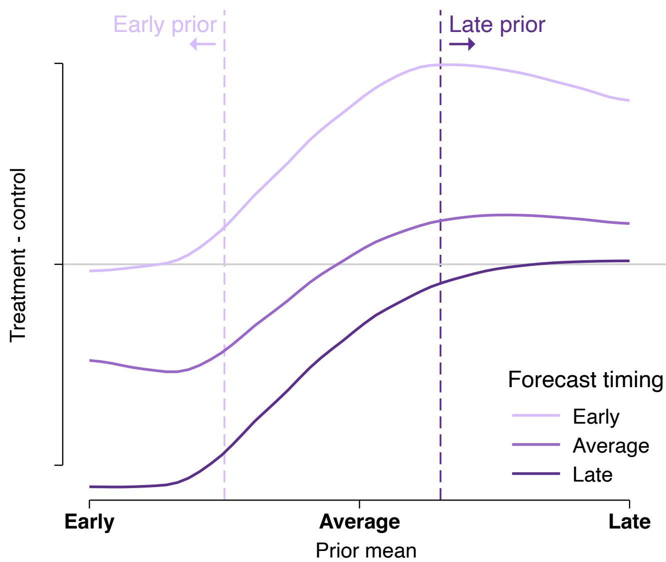
Parameter	Description	Value
Panel A: Utility Parameters		
r	Relative risk aversion	0.5
β	Discount factor	0.95
y	Starting wealth	5
p	Input price	1
Panel B: Production Parameters		
α	Production function curvature	0.6
$\bar{z}$	Max productivity	3
h	Scale parameter of productivity	2
Panel C: State Parameters		
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_K	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. The y-axis represents the difference between farmers who receive a treatment and those who do not. The gray 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.

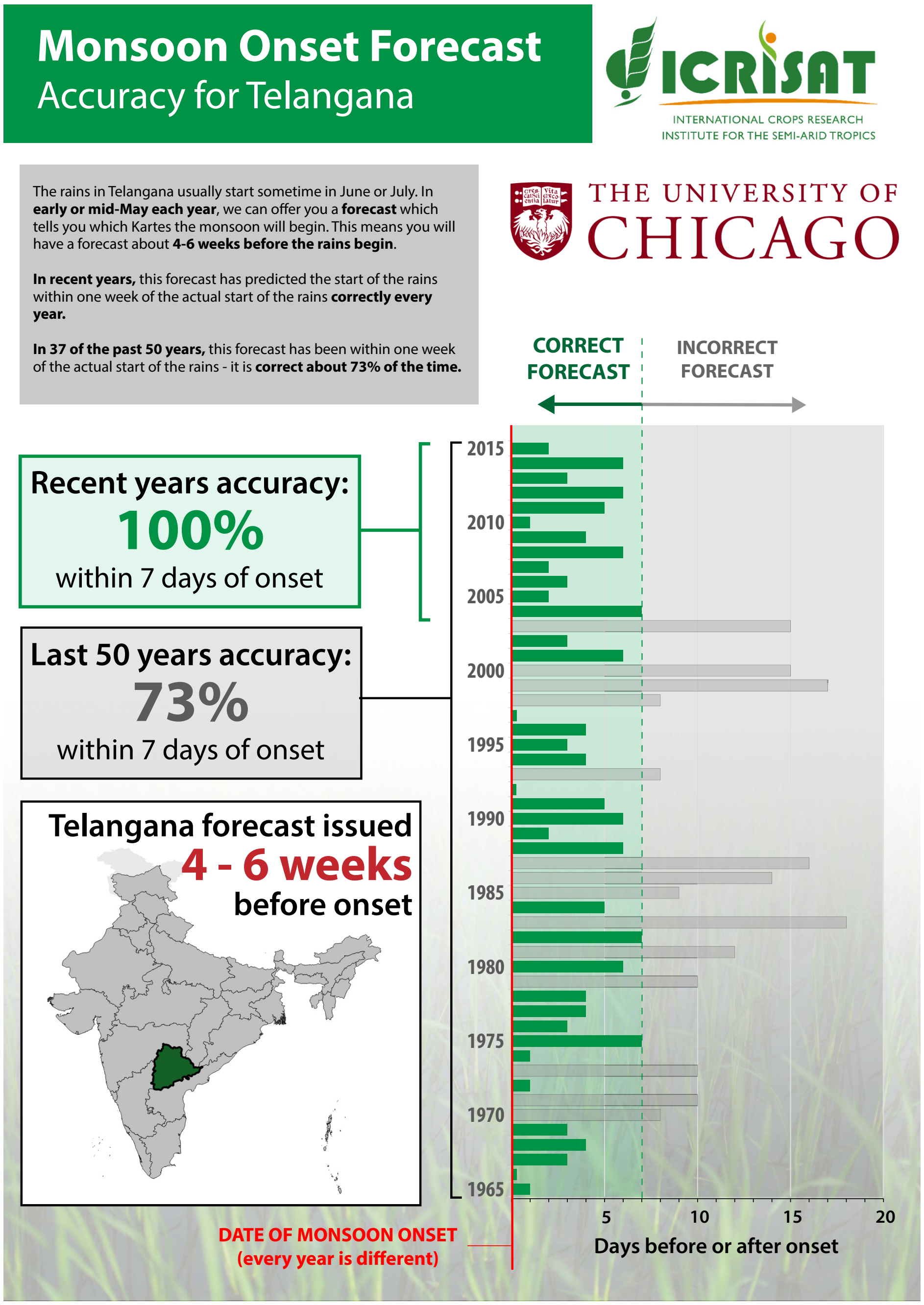
D.2 Distribution of BDM prices

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.

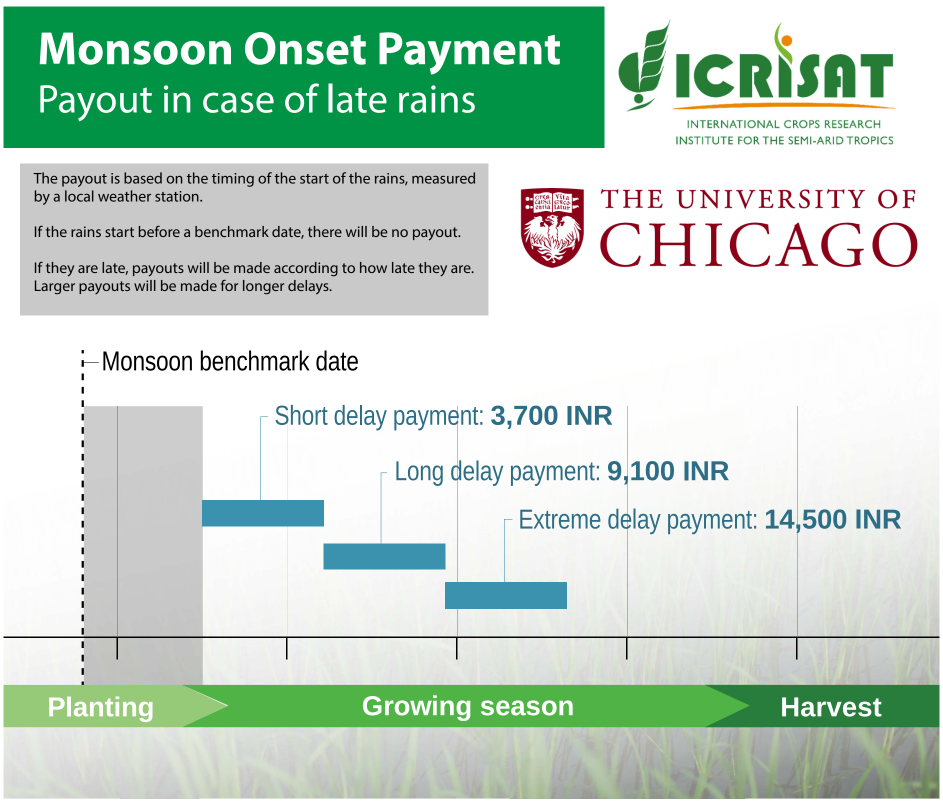
E Information sheets

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.** In addition to our pre-specified belief outcomes, we add the absolute value of the difference between the posterior and the forecast, since this provides a test of whether farmers are responding to the forecast itself.

- **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.7.

- **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.6 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.

- **Outcome variables.** In addition to our pre-specified variables on *ex post* well-being, we add a welfare index to Table 7. As with the investment index, this is complementary to the q-value approach to dealing with multiple hypotheses, serving as a single summary measure of *ex post* welfare. An advantage of the index over the FWER correction is that this index accounts for changes in the *direction* of different measures of welfare, while the FWER approach only considers p-values irrespective of sign.

- **Analysis.** For the correlations between WTP and prior beliefs (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 5).

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	-17.142				
	(26.210)	(115.197)				
Std. Prior2		13.634				
		(48.210)				
| Share Before On Time Cutoff − 0.5 |			-92.939*			
			(50.524)			
| Share Before Early Cutoff − 0.5|				-31.460		
				(63.363)		
|Prior − Vg. Historical|					17.368	
					(24.260)	
Risk Aversion						-2.722
						(1.945)
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 (16.442)
Std Prior 3rd Tercile	4.115 (20.843)
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 (69.010)			
Prob mass of beans before individual ontime cutoff		1.055 (37.277)		
Prob mass of beans before individual early cutoff			-75.258 (74.662)	
Risk Preference - higher is more risk averse				-3.867 (4.613)
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 Additional belief results

Table G.4: Effect of the forecast on beliefs (additional outcomes)

	(1) $\lvert$ posterior $-$ prior $\rvert$	(2) K-S Stat
Forecast	-0.239**	-0.050*
	(0.094)	(0.027)
Insurance	-0.095	-0.020
	(0.111)	(0.032)
Control Mean	0.89	0.44
Observations	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 - prior| is the absolute difference between a respondent's posterior belief and the respondent's prior belief. 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.5: Effect of the forecast on beliefs by prior strength

	(1) posterior	(2) | posterior − onset |	(3) | posterior − forecast |
Forecast	-0.172*	-0.163**	-0.163**
	(0.091)	(0.083)	(0.083)
Stdv of Prior × Forecast	-0.131	-0.211	-0.211
	(0.211)	(0.185)	(0.185)
Stdv of Prior Distribution	0.306**	0.239**	0.239**
	(0.127)	(0.107)	(0.107)
Control Mean	5.60	0.70	0.70
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 is the respondent's posterior belief about the monsoon arrival date. |posterior - onset| is the absolute difference between a respondent's prior and the actual arrival of the monsoon. |posterior - forecast| is the absolute difference between a respondent's posterior and the forecast date for the monsoon onset. 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 results

Table G.6: 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)	(22.831)	(33.006)
Insurance	0.024	33.839	78.034*
	(0.046)	(28.866)	(41.622)
	Panel B: Forecast Terciles		
Forecast × Early Prior	-0.067	-72.159**	7.779
	(0.056)	(35.572)	(58.677)
Forecast × Middle Prior	0.001	-61.669**	26.606
	(0.052)	(30.554)	(42.875)
Forecast × Late Prior	0.056	51.839	207.148***
	(0.073)	(44.387)	(69.787)
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.7: 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***
	(9.65)	(1.24)	(21.33)	(34.00)
Insurance	36.21**	-1.74	23.14	83.10**
	(14.31)	(1.23)	(23.11)	(39.85)
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 × Early Prior	19.24	-0.50	64.12*	120.87**
	(15.61)	(1.63)	(37.49)	(60.34)
Forecast × Middle Prior	9.24	-2.60*	25.98	63.54
	(13.04)	(1.38)	(27.06)	(42.82)
Forecast × Late Prior	22.22	0.37	13.63	90.65
	(18.09)	(3.23)	(33.54)	(58.74)
q-val Early	0.213	0.410	0.213	0.213
q-val Middle	0.382	0.314	0.382	0.314
q-val Late	0.784	0.834	0.834	0.784
Test Early=Late	0.901	0.804	0.302	0.716
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 and 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 alternative measures of agriculture output

	(1) Value Prod ($)	(2) Yield	(3) Loss ($)
Forecast × Early Prior	-534.76*	-6.59	54.39
	(284.81)	(4.35)	(135.32)
Forecast × Middle Prior	-188.75	-0.73	217.10*
	(235.57)	(3.61)	(122.61)
Forecast × Late Prior	390.05	-0.49	207.89
	(415.47)	(4.12)	(149.61)
Insurance	125.42	-1.66	195.48**
	(222.97)	(2.59)	(91.02)
q-val Early	0.321	0.321	0.525
q-val Middle	1.000	1.000	0.444
q-val Late	1.000	1.000	1.000
q-val Insurance	1.000	1.000	0.147
Test Early=Late	0.056	0.261	0.411
Test Insur. = Late	0.519	0.776	0.935
Control Mean	2419.93	35.37	661.07
Observations	1201	1170	1201

Notes: This table presents estimates of the treatment effects of forecasts on agricultural output 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, a fixed effect for the insurance treatment arm, and baseline controls chosen by double-selection LASSO. Value Prod is the value of agriculture production (evaluated at district-median prices). Yield is the the amount of output (in Kg) divided by the total area planted. Loss is the value of reported crop losses (evaluated at district-median prices). "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 this table. Standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G.4 Heterogeneity

Table G.9: 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.10: 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
	(29.03)	(1.54)	(50.04)	(94.92)	(0.05)
Forecast × Prior Str.	15.06	-6.98	-71.80	-89.53	-0.02
	(72.59)	(4.44)	(148.31)	(256.92)	(0.12)
	Panel B: Forecast Terciles × Prior Strength				
Forecast × Early Prior	-31.44	-0.66	-44.81	-128.49	-0.08
	(41.66)	(2.59)	(84.90)	(158.31)	(0.07)
Forecast × Middle Prior	-32.95	-1.84	-61.51	-87.92	0.03
	(39.24)	(1.55)	(65.43)	(120.69)	(0.06)
Forecast × Late Prior	92.94*	1.73	255.04**	424.96**	0.30***
	(54.80)	(3.14)	(107.26)	(184.04)	(0.09)
Forecast × Early Prior × Prior Str.	40.98	-5.03	-231.91	-280.18	-0.16
	(104.33)	(7.97)	(203.89)	(375.46)	(0.17)
Forecast × Middle Prior × Prior Str.	93.91	-4.83	313.04	511.60	0.06
	(129.28)	(5.61)	(235.40)	(426.74)	(0.20)
Forecast × Late Prior × Prior Str.	18.20	-6.44	108.74	139.31	0.02
	(127.06)	(7.05)	(297.15)	(478.95)	(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.11: 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.12: 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
	(30.28)	(1.60)	(54.12)	(101.85)	(0.05)
Forecast × Diff. Prior and Forecast.	17.37	0.13	41.53	63.63	0.04
	(27.31)	(1.07)	(60.90)	(99.71)	(0.05)
	Panel B: Forecast Terciles × Prior. - Fore.				
Forecast × Early Prior	30.12	3.92	112.92	136.33	0.02
	(52.38)	(4.13)	(110.26)	(208.47)	(0.09)
Forecast × Middle Prior	31.27	2.53	11.75	65.24	0.10
	(89.15)	(2.99)	(163.22)	(308.92)	(0.15)
Forecast × Late Prior	79.01	2.01	221.89**	374.79*	0.26***
	(59.44)	(3.72)	(104.57)	(191.72)	(0.10)
Forecast × Early Prior × Prior. - Fore.	-119.42*	-7.58**	-289.23**	-527.42**	-0.20**
	(72.44)	(3.55)	(123.56)	(223.07)	(0.08)
Forecast × Middle Prior × Prior. - Fore.	79.05	5.68	76.10	167.22	0.10
	(101.45)	(3.46)	(185.20)	(350.43)	(0.16)
Forecast × Late Prior × Prior. - Fore.	18.58	-1.10	122.09	153.53	0.05
	(35.85)	(2.22)	(125.26)	(162.68)	(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.13: 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 × WTP	-0.099 (0.122)	-0.019 (0.039)	-0.030 (0.050)	-0.071 (0.045)	0.004 (0.036)
WTP	0.059	0.012	0.027	0.041	0.032
	(0.102)	(0.035)	(0.045)	(0.038)	(0.034)
	Panel B: Forecast Terciles × WTP				
Forecast × Early Prior	-0.776*** (0.253)	-0.005 (0.066)	-0.120 (0.075)	-0.128* (0.072)	0.060 (0.053)
Forecast × Middle Prior	-0.095 (0.194)	-0.075 (0.054)	-0.051 (0.065)	-0.061 (0.057)	0.020 (0.052)
Forecast × Late Prior	0.371 (0.304)	0.119 (0.084)	0.027 (0.082)	0.071 (0.077)	-0.042 (0.074)
Forecast × Early Prior × WTP	0.019 (0.212)	-0.002 (0.068)	-0.052 (0.089)	-0.159* (0.090)	0.032 (0.070)
Forecast × Middle Prior × WTP	-0.202 (0.150)	-0.035 (0.049)	-0.013 (0.052)	-0.045 (0.054)	-0.013 (0.042)
Forecast × Late Prior × WTP	0.105 (0.253)	0.048 (0.089)	0.098 (0.077)	-0.001 (0.074)	0.128* (0.070)
Control Mean	2.12	0.51	0.57	0.36	0.39
Observations	655	655	655	655	655

Notes: This table presents estimates of the treatment effects of forecasts on farmers' land use and cropping decisions by WTP. Land (Ha.) is area cultivated, measured in hectares. Cash Crop is an indicator for the farmer planting at least one cash crop. Changed Crop is an indicator for planting a different crop mix in the 2022 Kharif season than the farmer planted during the 2021 Kharif season. Added Crop is an indicator for planting an additional crop in 2022 as compared to 2021. Sub Crop is an indicator for removing a crop in 2022 as compared to 2021. 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.14: 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
	(40.34)	(1.48)	(67.86)	(125.20)	(0.06)
Forecast × WTP	-37.17	0.57	21.13	20.26	-0.04
	(44.81)	(1.13)	(54.48)	(106.85)	(0.05)
WTP	71.06	-0.21	26.56	84.26	0.02
	(50.86)	(0.88)	(54.69)	(111.79)	(0.05)

	Panel B: Forecast Terciles × WTP				
Forecast × Early Prior	-192.75***	-1.04	-137.33	-512.87**	-0.21**
	(63.87)	(2.25)	(110.44)	(227.69)	(0.11)
Forecast × Middle Prior	-104.08**	-0.55	-151.49	-236.75	-0.12
	(52.34)	(1.26)	(100.25)	(177.02)	(0.09)
Forecast × Late Prior	69.64	3.65	233.37	312.29	0.26*
	(73.09)	(3.19)	(166.11)	(274.92)	(0.14)
Forecast × Early Prior × WTP	-192.03**	-0.55	-72.35	-176.68	-0.02
	(80.03)	(1.69)	(108.84)	(222.27)	(0.10)
Forecast × Middle Prior × WTP	23.05	0.73	60.87	97.24	-0.06
	(42.51)	(1.06)	(69.08)	(119.70)	(0.07)
Forecast × Late Prior × WTP	48.91	2.87	143.45	247.85	0.07
	(67.06)	(2.56)	(168.58)	(259.69)	(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.15: 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.16: 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
	(36.35)	(1.77)	(61.57)	(119.07)	(0.06)
Forecast × Risk Av.	96.15*	-2.03	107.77	258.64	0.16*
	(52.31)	(2.16)	(88.54)	(172.49)	(0.08)
	Panel B: Forecast Terciles × Risk Aversion				
Forecast × Early Prior	-9.19	-0.59	-28.95	-50.22	-0.13
	(49.80)	(2.89)	(114.13)	(217.25)	(0.08)
Forecast × Middle Prior	-74.39	-1.99	-133.95*	-265.44*	0.00
	(45.95)	(1.77)	(81.03)	(145.35)	(0.07)
Forecast × Late Prior	-4.80	4.93	136.45	141.04	0.18
	(61.55)	(4.85)	(118.47)	(200.10)	(0.12)
Forecast × Early Prior × Risk Av.	-46.18	-0.25	-30.52	-189.94	0.13
	(67.47)	(3.09)	(129.91)	(255.96)	(0.11)
Forecast × Middle Prior × Risk Av.	129.31*	0.14	247.32**	577.31***	0.08
	(67.22)	(2.58)	(114.39)	(213.96)	(0.10)
Forecast × Late Prior × Risk Av.	242.16**	-6.59	306.70	725.92**	0.31*
	(97.63)	(5.19)	(202.49)	(340.55)	(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.17: 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.18: 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 G.18 and G.19 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.19: 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	(51.95)	(3.18)	(104.24)	(196.94)	(0.09)
Forecast takeup	-32.44	-2.28	-51.50	-66.09	0.03
× Middle Prior	(44.02)	(1.80)	(75.93)	(139.16)	(0.06)
Forecast takeup	112.07*	2.29	289.85**	495.81**	0.32***
× Late Prior	(62.02)	(3.92)	(116.73)	(206.35)	(0.11)
Insurance takeup	112.03**	-1.06	128.06*	299.90**	0.15**
	(49.69)	(1.52)	(73.93)	(149.94)	(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	0.402	0.137
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 G.18 and G.19 (except the index), and standard errors are clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.20: Effect of forecast and insurance takeup on agricultural output

	(1) Ag Prod (Kg)	(2) Ag Profit	(3) Ag Prod Non-Flood (Kg)	(4) Ag Profit Non-Flood
Forecast takeup	-20.83**	-484.34*	-21.97	-447.17
× Early Prior	(9.98)	(283.73)	(21.86)	(541.64)
Forecast takeup	-11.94	-124.07	-9.44	-117.11
× Middle Prior	(8.53)	(218.77)	(11.51)	(277.83)
Forecast takeup	16.96	-33.63	49.50**	593.43
× Late Prior	(12.08)	(377.11)	(21.25)	(590.37)
Insurance takeup	3.03	-164.23	34.68**	561.19
	(7.79)	(207.59)	(17.06)	(419.67)
q-val Early	0.080	0.080		
q-val Middle	0.478	0.478		
q-val Late	0.473	0.868		
Test Early=Late	0.012	0.322	0.021	0.208
Test Insur. = Late	0.262	0.731	0.551	0.962
Control Mean	66.91	970.62	66.91	970.62
Observations	1201	1201	554	554

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. Ag Prod (Kg) is total agricultural production in kilograms. Ag Profit is the total value of production in USD minus the value of expenses. Ag Prod Non-Flood (Kg) is the total agriculture production in kilogram among the sample of households that did not report crop losses due to flooding or cyclones. Ag Profit Non-Flood is total agricultural profits in USD 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 the table except for columns (3) and (4) as these are just sub-samples of the first two columns. Standard errors are clustered by village. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.21: 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
$\times$ Early Prior	(0.05)	(87.50)	(92.34)
Forecast takeup	0.01	9.04	21.71
$\times$ Middle Prior	(0.04)	(65.47)	(53.89)
Forecast takeup	-0.05	-124.09*	-33.86
$\times$ Late Prior	(0.05)	(72.07)	(98.23)
Insurance takeup	0.10***	116.49	119.14*
	(0.04)	(72.89)	(63.53)
q-val Early	0.843	0.843	0.843
q-val Middle	1.000	1.000	1.000
q-val Late	0.394	0.343	0.736
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.22: 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)	(322.13)	(0.05)	(285.29)	(0.07)
Forecast takeup	1.34**	-0.90	37.70	-0.04	78.00	-0.00
× Middle Prior	(0.59)	(1.09)	(172.40)	(0.04)	(247.82)	(0.05)
Forecast takeup	1.27	-0.23	-140.86	0.01	159.19	0.05
× Late Prior	(0.93)	(1.57)	(160.86)	(0.06)	(285.39)	(0.06)
Insurance takeup	0.51	2.23*	-142.81	0.01	-465.43*	-0.03
	(0.53)	(1.14)	(180.75)	(0.03)	(245.87)	(0.05)
q-val Early	0.433	0.433	0.433	0.433	0.433	
q-val Middle	0.137	1.000	1.000	0.756	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	0.235
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.

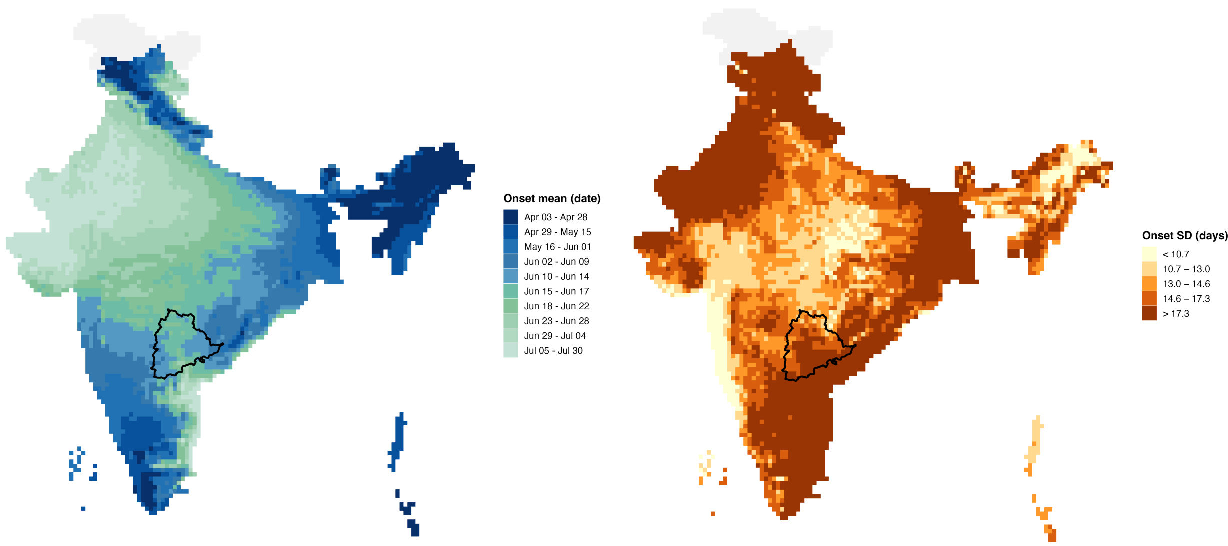
Existing monsoon forecasts Researchers have attempted to produce long-range forecasts of two key features of the Indian Summer Monsoon: rainfall quantity and monsoon onset timing. The Indian Meteoroligcal Department (IMD) produces a statistical forecast of the expected seasonal total rainfall quantity 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).

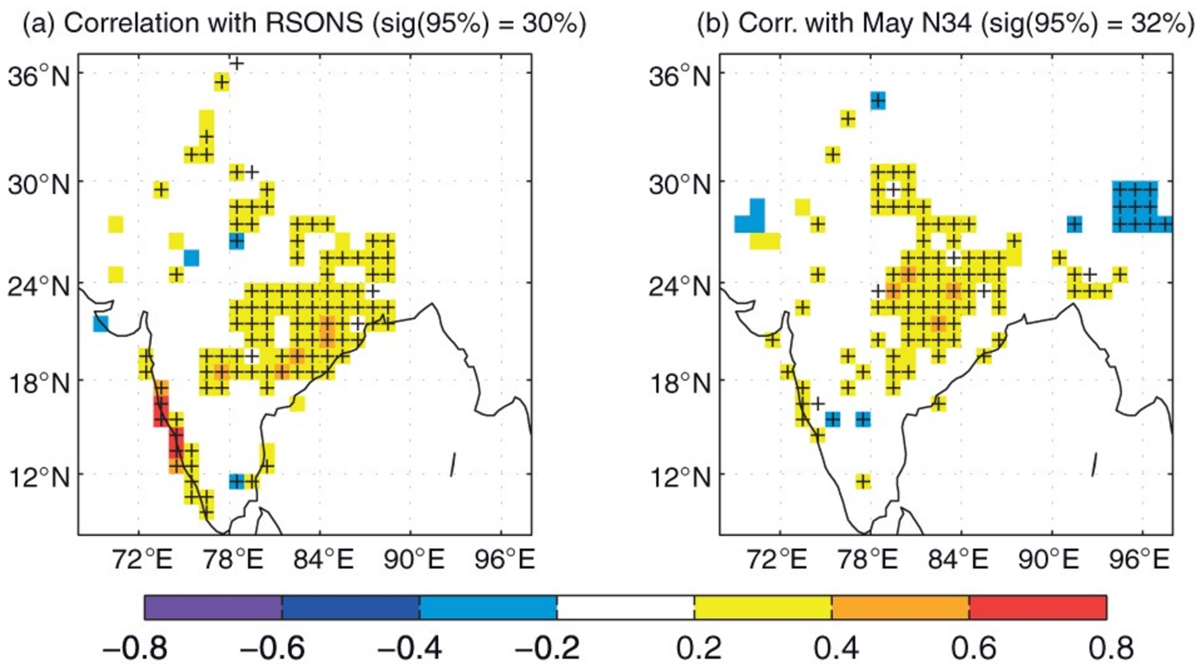
Figure H.1: Monsoon onset over India



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

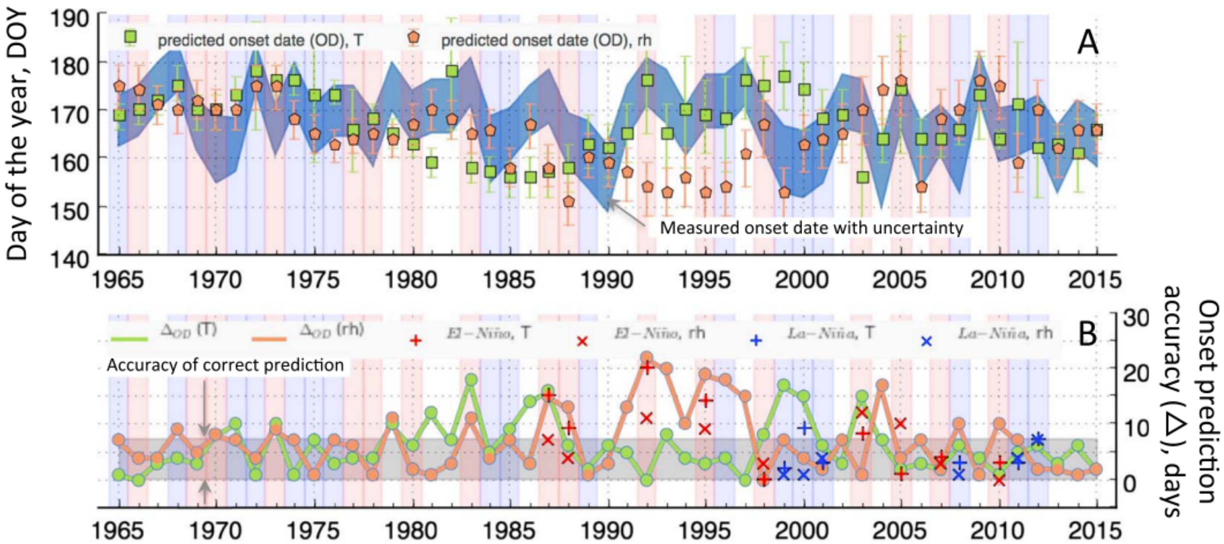


Notes: (a) Correlations between local-scale onset and the index of regional-scale onset (RSONS) defined in the text. (b) Correlations between local-scale onset and the Niño 3.4 SST index (N34) in May. Crosses indicate statistically significant correlations at the two-sided 95% level (see text). The value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