The value of forecasts: Experimental evidence from developing-country agriculture

Pre-analysis plan

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Abstract

Climate risk is a key driver of low agricultural productivity in poor countries. We use a cluster-randomized trial to evaluate a novel risk-mitigation approach: long-range forecasts that provide information about the onset of the Indian summer monsoon well in advance of its arrival. In contrast to traditional approaches that allow farmers to cope with risk *ex post*, this new *ex ante* technology provides accurate information at least one month in advance of the monsoon's arrival, enabling farmers to alter cropping choices and other up front input decisions. Moreover, forecasts have the potential to be disseminated cheaply, even at scale. We assign 250 villages to one of three groups: a control group; a group that is given an opportunity to purchase the forecast; and a group that is offered insurance. This design allows us to investigate farmers' willingness-to-pay for forecasts; measure how forecasts affect farmer beliefs, up-front investments, and welfare; and study how these effects compare to the canonical *ex post* loss mitigation tool: weather-based index insurance.

Keywords: Risk; forecasts; agriculture; climate

JEL Codes: D81; D25; O12; O13; Q12; Q54

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1 Introduction

Approximately 65% of the world's working poor depend on agriculture for their livelihoods (Castaneda et al. (2010)). Agricultural production is sensitive to highly variable climatic conditions. When faced with this type of risk, in the absence of full insurance, farmers make fewer profitable investments (Rosenzweig and Binswanger (1993)), exacerbating the gap in agricultural productivity between the developed and developing world (Donovan (2021)).[1] Reducing the negative consequences of agricultural risk is therefore of first-order economic importance.

Agricultural risk can be addressed in two ways: *ex ante* — with interventions that reduce farmers' exposure to risk — or *ex post* — with interventions to reduce the consequences of negative shocks. Prior efforts have largely focused on *ex post* coping strategies. While formal index insurance can improve outcomes substantially (Karlan et al. (2014)), demand is very low, even at actuarily fair rates (Cole and Xiong (2017)), and substantial subsidies are required to increase take-up (Mobarak and Rosenzweig (2014)). A small body of work has focused on *ex ante* interventions, documenting the potential of new agricultural production technologies to improve outcomes in the presence of climate risk (Emerick et al. (2016); Jones et al. (2022)). However, adoption of profitable technologies remains low among farmers in the developing world (Duflo, Kremer, and Robinson (2008); Jack (2011)), in part because introducing novel technologies can be costly.

In this project, we use a randomized controlled trial to evaluate a new *ex ante* approach to improving farmer welfare: accurate long-range forecasts that provide information about the onset of the Indian summer monsoon well in advance of its arrival.[2] Monsoon forecasts are promising for four main reasons. First, farmers have inaccurate beliefs about the monsoon's onset (Gine, Townsend, and Vickery (2015)) and there is clear demand for accurate information, with farmers frequently turning to unvalidated traditional sources such as astrologers and ecological signals (Acharya (2011)).[3] Second, forecasts can be delivered at low cost (e.g. via SMS) and farmers have been shown to respond to digital extension services

[1] In addition to the negative productivity consequences of uninsured risk, Carleton (2017) demonstrates that negative weather realizations can lead to farmer bankruptcy and even suicide.

[2] India is a useful setting for this research: 70–90 percent of total annual rainfall occurs during the during the short monsoon season and the variability of both timing and quantity is large and unpredictable (Kumar et al., 2013). Moreover, climate change is making these rains increasingly variable, increasing India's susceptibility to crop losses (Auffhammer and Carleton (2018)). We expect our results to be applicable outside of India as well, with relevance for the more than one-third of the global population that lives in the Asian monsoon region (Gadgil and Kumar (2006)).

[3] Monsoon onset is important because it marks the timing of transition between the dry season and the planting period, and informs farmers about the duration of the coming agricultural season. As a result, the monsoon onset date is particularly important for many upfront investment decisions in agriculture.

(Fabregas et al. (2019); Cole and Fernando (2020)) and information about market conditions (Aker (2010); Allen (2014)). Third, unlike short-run weather forecasts, which allow for marginal behavior adjustments only, this long-range monsoon forecast can lead to non-marginal changes in agricultural investments, because it provides information that affects the entire growing season delivered well in advance of the monsoon's arrival. In response, farmers can substantially adjust their production processes. Finally, in theory, a perfect forecast would completely eliminate weather risk.

Despite the large potential benefits of accurate monsoon forecasts, their usefulness has been limited by their limited accuracy. Though the monsoon's onset is extremely important for the Indian economy (Rosenzweig and Udry (2019)), its climatology is complex, which has made modeling and skillful forecasting difficult (Webster (2006); Wang et al. (2015)). The Indian government's own forecast, produced by the Indian Meterological Department (IMD), generates predictions about monsoon onset over Kerala, where the monsoon first arrives in India. However, this is poorly correlated with onset in India's agricultural regions, limiting this forecast's usefulness for farmers (Moron, Robertson, and Pai (2017)). The IMD does produce more specialized regional forecasts, but they have remarkably low skill: in much of the country, they are negatively correlated with rainfall realizations (Rosenzweig and Udry (2019)).

In contrast to these existing forecasts, we employ a novel, extremely accurate forecast, developed in Stolbova et al. (2016) and maintained by the Potsdam Institute for Climate Impact Research (PIK).[4] This forecast has two main benefits over previous approaches. First, PIK provides an accurate forecast over the Eastern Ghats. The forecast has particular skill over Telangana, the site of our experiment. In addition to the forecast's effectiveness in the state — the forecasted onset date has been accurate to within one week in each of the past 10 years — we selected Telangana because the state is home to 35 million people and is heavily dependent on the Indian summer monsoon: 55 percent of its workforce is employed in agriculture. The second advantage of the PIK forecast is that it can be delivered to farmers approximately 40 days in advance of monsoon onset, which is substantially earlier than the IMD's forecast, allowing farmers to make early decisions about key inputs such as crops, planting time, labor supply, and fertilizer purchases.

We conducted a series of focus group discussions and a pilot in Telangana during the 2021 Kharif growing season. Due to COVID-19 in India, this pilot was entirely phone-based. Nevertheless, this enabled us to test the logistics of forecast dissemination, and provided

[4]The PIK forecast relies on recent improvements in weather modeling (e.g. Rajeevan et al. (2007)), and statistically identifies a "tipping point" that is relevant for rainfall onset in a particular location, rather than across the entire sub-continent. We describe this forecast in more detail in Section 2 and Appendix A below.

useful information about the status quo. In particular, we found that farmers' monsoon onset information is limited and inaccurate, with existing sources reporting the correct onset date only 16 percent of the time. Farmers also expressed substantial demand for our forecast product, with 64 percent of respondents stating that they would be willing to purchase a similar forecast in 2022. Finally, we see suggestive evidence that the forecast led farmers to update their beliefs about the monsoon: the average expected onset date shifted towards the forecast. Taken together, these data suggest that forecasts have substantial potential in this setting. From an implementation perspective, we learned that farmers understood the language we used to convey the forecast. In focus group discussions, farmers revealed that the credibility of the forecast is important. In order to ensure that our forecast is trustworthy, we are partnering with the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), a well-respected Hyderabad-based NGO, to disseminate the forecast.

We use our novel long-range monsoon forecast to answer a series of key research questions, informed by a theoretical model of decision-making under risk. What is farmer willingness-to-pay (WTP) for a forecast of the monsoon's onset date? How does such a forecast impact farmer beliefs? How does a forecast affect up-front investments such as crop choice, area planted, and fertilizer use? Do these impacts translate changes in key outcomes such as yields, off-farm labor, consumption expenditure, and migration? How do forecasts compare to and interact with the canonical *ex post* loss mitigation tool: weather-based index insurance?

To answer our research questions, we have designed a cluster-randomized trial. We will implement this experiment in 250 villages in Telangana in partnership with ICRISAT. We randomize villages into three different groups: a control group; a group that receives a forecast offer; and a group that receives an insurance offer. We plan to sample 5 to 10 households per village to survey and treat, if applicable. We will use the Becker, DeGroot, and Marschak (1964) mechanism (henceforth "BDM mechanism") to measure the demand for weather forecasts and insurance, and randomization into offers to measure their impacts on farmer decisions and economic outcomes. We will estimate how these forecasts impact farmer beliefs, up-front investments, yields, and profits. We also measure farmers' WTP for these forecasts to evaluate their cost-effectiveness.

This study makes three main contributions. First, we build on a broad literature in development economics on approaches to coping with agricultural risk by contributing a novel *ex ante* approach. Next, we provide the first experimental evidence on the impacts of long-range forecasts on farmer outcomes. Finally, we contribute to agricultural policy in the developing world.

We first study a novel approach for reducing weather risk in developing-country agriculture. Prior research has focused largely on *ex post* approaches that help farmers cope with risk. Insurance, which allows farmers to smooth risk across states of the world, is the most prominent of these approaches. The benefits of insurance, including greater investment in profitable inputs, have been well documented (e.g. Karlan et al. (2014); Cole and Xiong (2017)). However, formal insurance markets are absent or incomplete in many parts of the world. Where these markets do exist, demand remains low at actuarily fair prices, requiring large subsidies to induce take-up (Mobarak and Rosenzweig (2014); Jensen and Barrett (2017); Carter et al. (2017)). More recently, Casaburi and Willis (2018) finds that adjusting the timing of the insurance premium can improve take-up, however this arrangement requires a credible mechanism to collect payments after the fact even when there is no payout (e.g. monopsony buyer). In the absence of insurance markets, Lane (2020) demonstrates that guaranteed credit generates similar benefits, however this product requires an strong micro-finance infrastructure that may be missing in many locations.

Our research builds on the smaller body of work that explores the benefits of *ex ante* approaches through the adoption of high performing seed varieties and irrigation technologies (Emerick et al. (2016); Jones et al. (2022)) by exploring the benefits of a novel intervention — accurate long-range monsoon forecasts. These forecasts are an appealing *ex ante* tool for tackling risk, above and beyond existing approaches. Unlike improved seeds, forecasts allow farmers to decide whether to plant at all, what to plant, and how to adjust inputs across crops, creating more opportunities for optimization. Unlike the short-run weather forecasts sometimes provided as part of agricultural extension programs (e.g. Fabregas et al. (2019)), these long-range onset forecasts provide farmers with information far enough in advance of the growing season for the farmers to substantially alter their planting and other input decisions. Finally, they have potential to be significantly more cost-effective than the other *ex ante* technology options. These features combine to make long-range monsoon forecasts a product with high potential to improve farmer welfare.

Second, this study provides the first experimental evidence on the effects of long-range monsoon forecasts on farmer welfare. Using panel data from 6 Indian villages, Rosenzweig and Udry (2019) show that skillful forecasts can lead farmers to change their behavior. They study the Indian government forecast, which has remarkably little skill over much of the country, limiting its ability to improve farmer well-being at scale. Our project builds on this work by using a randomized controlled trial in 250 villages to experimentally evaluate the impacts of highly-accurate long-range monsoon forecasts. These forecasts are a substantial improvement over farmers' status quo information, including the IMD's forecasts. Finally, this project has the potential to make a substantial contribution to agricultural policy in countries that rely on the monsoon. If we find that forecasts are effective at improving farmer welfare, and are more cost-effective to administer than insurance programs, governments can switch their focus to a whole new set of interventions for farmers. This is especially relevant in light of the large-scale investments that governments have made to support small-scale farmers in low-income countries. Between 1950 and 1980, governments invested heavily in public-sector crop insurance programs. In the 1990s, governments switched to promoting insurance schemes offered by the private commercial sector, backed often by government financial support (Mahul and Stutley (2010)). Governments have also used mechanisms to stabilize input and output prices including marketing boards, quotas, price support mechanism, input subsidies, and other mechanisms. Governments could use cost-effective monsoon forecasts to supplement or even substitute away from costly existing approaches.

The remainder of this pre-analysis plan proceeds as follows. Section 2 provides relevant details about the research setting, including insights from our pilot. Section 3 presents a simple theoretical model of farmer decision-making under risk. Section 4 describes our experimental design. Section 5 discusses the data we will collect over the course of our experiment. Section 6 presents our planned analysis, including a detailed outline of our regression specifications. Section 7 concludes.

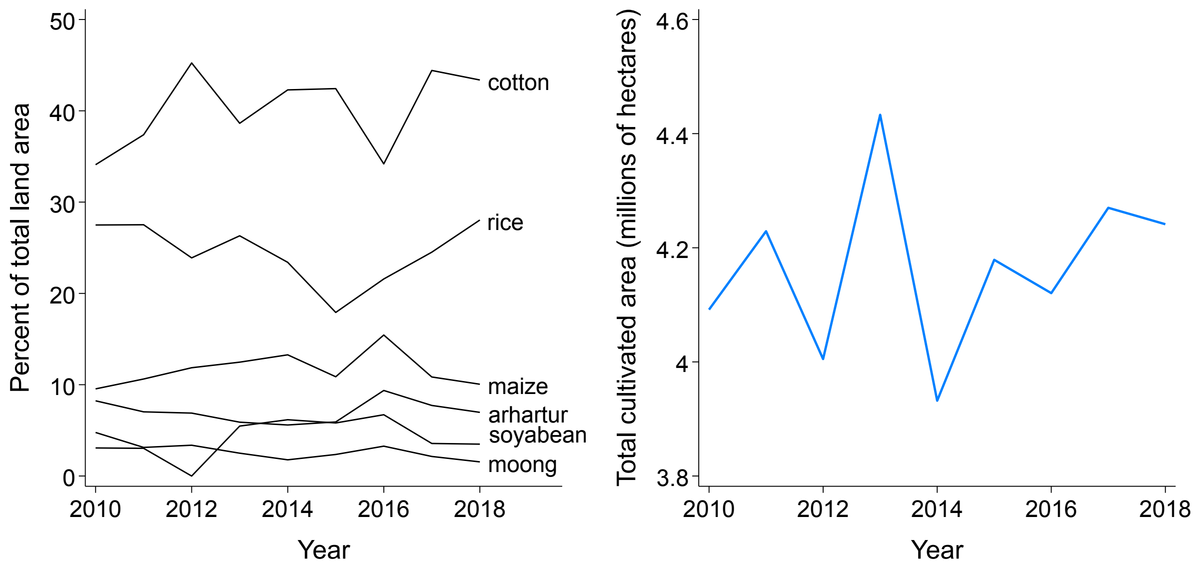
2 Research context

2.1 Agriculture in Telangana

Our study will take place in Telangana, India. The state is home to 35 million people, and agricultural productivity per worker is remarkably low. While 55% of the labor force is employed in agriculture, the sector provides only approximately 15% of the Gross State Value Added (Government of Telangana (2020)). The majority of farms are small, with the average landholding being 1 hectare. Rice is the main staple crop in the state, but Telangana also grows a number of important cash crops. The amount of land dedicated to each crop fluctuates substantially from year to year, with the total planted area recorded in the state between 2010 and 2018 showing a range of approximately 0.5 million hectares, about 10% of the average, between max and min. Figure 1 plots the area planted of the top five crops by cropped area in Telangana.

Telangana, like much of central India, is dependent on the monsoon for agriculture with about 80% of the total annual rainfall occurring in the monsoon months from June to September. The fluctuations in cropped area shown in Figure 1 are likely in part driven by the onset of the monsoon. While the monsoon arrives in early–mid June on average, uncertainty over monsoon onset is high in Telangana: between 1979 and 2019, the standard deviation of the

Figure 1: Planted area over time, top five crops in Telangana

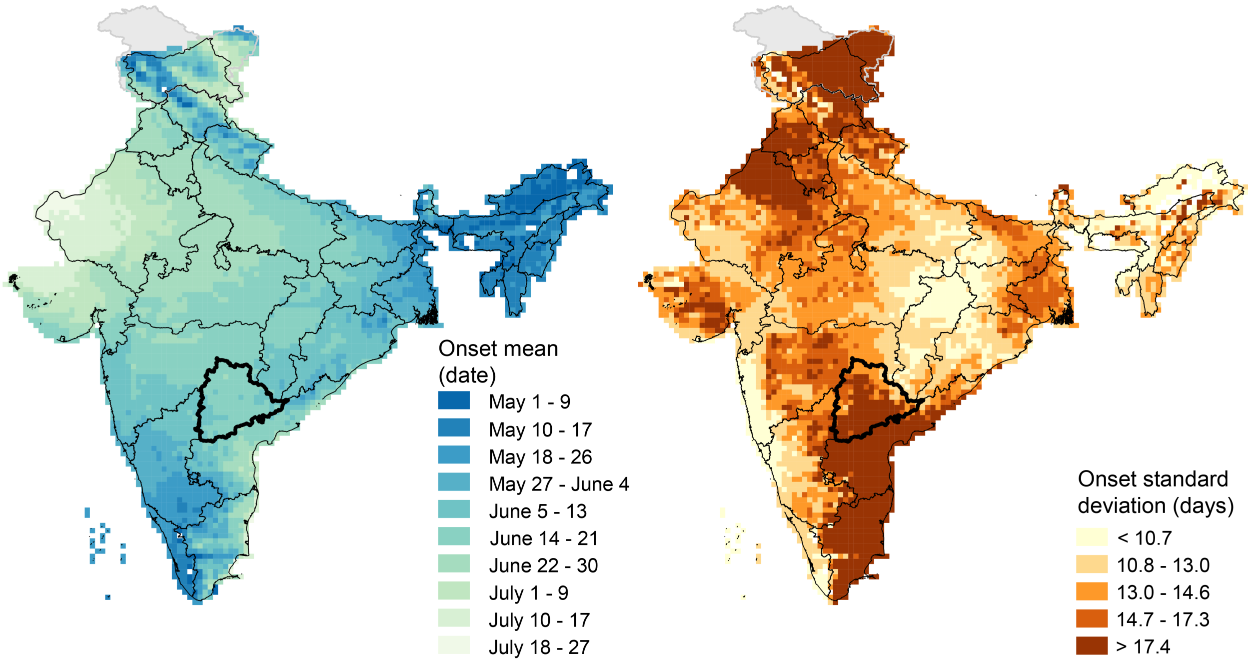


Notes: The left panel shows the proportion of total area planted for top five crops (by cropped area) across 2010-2018 in Telangana. The crops shown are restricted to crops grown either in the Kharif season or crops classified as "whole year" crops. The right panel shows the total planted area recorded in Telangana from 2010-2018. Data from the Centre for Monitoring the Indian Economy (CMIE).

onset date was approximately 20 days. Figure 2 plots information about the monsoon onset over India, with Telangana highlighted in black.

Weather risk is a substantial concern for agriculture in the state, as it rests in one of the most variable areas of the monsoonal region of India. Both formal and informal methods to smooth risk exist in Telangana. The Government of Telangana, through its *Rythu Bandhu* scheme, provides farmers with a number of pre-season incentives. Primary among these is the unconditional cash transfer of INR 5,000 for each acre planted for each season (Government of Telangana (2020)). This scheme also provides access to credit for small and marginal farmers to spend on inputs including seeds and fertilizers. An associated scheme, *Rythu Bima* provides subsidized health and life insurance to farmers in order to smooth idiosyncratic shocks to household income. One notable national crop insurance program, Pradhan Mantri Fasal Bima Yojana (PMFBY), has ceased to operate in the state. This is due to a change in the requirements of involuntary insurance to all agricultural loan-holders to a fully voluntary program. Private insurance exists, but is underutilised.

Figure 2: Monsoon onset over India



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

2.2 Forecasting the monsoon

We study a novel *ex ante* approach to reducing agricultural risk: long-range monsoon onset forecasts. These forecasts have the potential to substantially improve farmer welfare, because they enable farmers to materially alter their planting and other *ex ante* input decisions. We rely on a novel long-range forecast of the monsoon's onset produced by PIK, and described in Stolbova et al. (2016).[5] This forecast uses climate data from the months leading up to the beginning of the monsoon to predict the timing of the monsoon's onset over specific regions of India, including Telangana.[6] The PIK model produces a probability distribution of potential onset dates, which can be summarized as a likely onset date range, making it easy for farmers to understand. The forecast is issued at least a month in advance of the monsoon onset, enabling farmers to substantively adjust their production decisions. Backcasting over the past 10 years, the PIK forecast was correct each year. When evaluated from 1965–2015,

[5]See Appendix A for more details on monsoon forecasting.

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

the forecast was correct for 73% of the years in the sample.[7] This forecast is not yet widely available to farmers, leaving us with a unique opportunity to evaluate its impacts. In the remainder of this section, we explain why we prefer the PIK forecast to (i) existing monsoon onset forecasts; (ii) forecasts of monsoon rainfall quantity; and (iii) short-range weather forecasts.

2.2.1 Existing monsoon onset forecasts

The PIK forecast represents a significant improvement over existing monsoon onset information. The IMD produces a monsoon onset forecast. However, unlike PIK, the IMD forecasts the monsoon's onset over Kerala — the first arrival location of the Indian summer monsoon. The IMD does not produce any other regional onset forecasts. However, the monsoon does not progress northwards from Kerala in a predictable manner — meaning that onset over Kerala carries little signal about onset timing over the rest of the country. 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. Even if the IMD forecast were to contain useful information for India's agricultural regions, it arrives only two weeks in advance of the monsoon's onset, which limits its usefulness relative to the PIK forecast. The PIK forecast both arrives well in advance of the monsoon's onset, and produces a forecast that is relevant to India's farmers, making it superior to the IMD's onset forecast.

2.2.2 Monsoon rainfall quantity forecasts

Researchers have attempted to forecast two features of the Indian Summer Monsoon: quantity and timing. In this project, we focus on onset timing forecasts for two key reasons. First, while PIK provides a highly accurate forecast of onset timing, there exists no corresponding accurate monsoon rainfall quantity forecast. The most widely-available existing quantity forecast in India, produced by the IMD, is negatively correlated with actual rainfall in much of the country (Rosenzweig and Udry (2019)). In contrast, the PIK onset forecast is highly accurate over Telangana. Second, monsoon onset is a key determinant of agricultural outcomes in India. Mobarak and Rosenzweig (2014) demonstrate that farmers are willing to pay for insurance against a delayed onset (albeit at subsidized prices). This implies that onset timing matters for farmers. We therefore use the accurate PIK onset forecast in this study.

[7] Appendix Figure A.2 reproduces the main summary of the PIK forecast's accuracy.

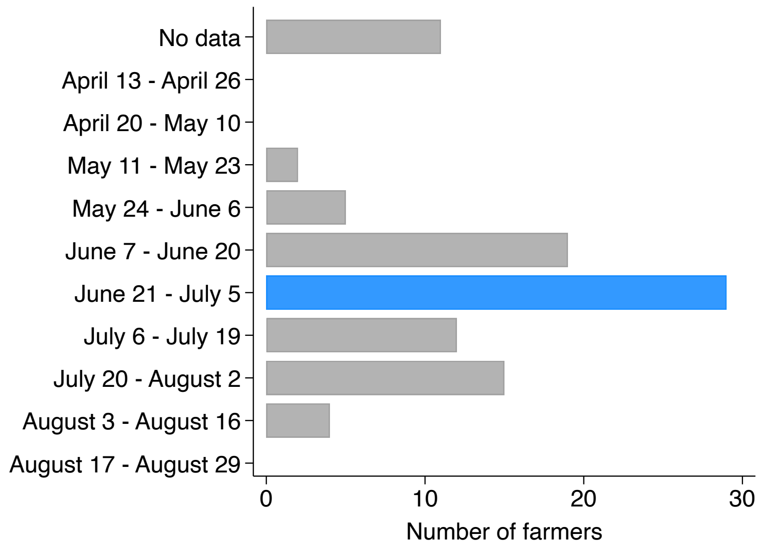
2.2.3 Weather forecasts

The PIK monsoon forecast is an example of a long-range seasonal climate forecast. These forecasts aim to predict conditions that will realize in the distant future. This is distinct from the more common short-run "weather forecasts" that aim to predict exact weather conditions at a specific point in the upcoming week or two. Seasonal climate forecasts are a relatively new innovation (see Kirtman et al. (2014) for a review), and are typically based physics models of the climate system linked to slower-moving conditions. In contrast, weather forecasts use deterministic, numerical simulations of weather variables based on current conditions. Weather forecasting techniques, therefore, are not well-suited to forecasting beyond a short time window. This means that while a weather forecast can allow farmers to make short-run adjustments to planting or sowing times, unlike seasonal climate forecats, they do not enable large-scale changes to up front inputs, such as planting new crops or ordering new inputs well in advance. By providing monsoon onset information at least a month in advance, the PIK forecast is therefore distinct from previous weather information that has been provided to farmers (e.g. Fabregas et al. (2019)).

2.3 Pilot

We conducted a pilot in the 2021 Kharif season to test the logistics of forecast dissemination and to understand farmer demand for a monsoon onset forecast. During our pilot, we offered farmers a choice between a monsoon onset forecast and a forecast of monsoon rainfall quantity. Farmers weakly preferred information on monsoon onset. Given that this is also substantially easier to predict, we are conducting our experiment with the onset forecast. While we had hoped to conduct this pilot in person, the COVID-19 situation in Telangana during this time period required us to work over the phone instead. We conducted surveys with 95 farmers before and after the monsoon's arrival. At the end of the baseline survey, we provided each farmer with a forecast, using the following text: "This year's forecast says the monsoon is likely to start over Telangana between June 24 and July 2, 2021. There may be a limited amount of pre-monsoon rainfall between 12-19 June. The continuous monsoon rainfall is expected after July 2." We also sent each farmer an SMS with the forecast information. This forecast was accurate: a range from June 24 to July 2 was predicted and the onset occurred on June 24, two weeks after the normal onset date of June 10 in the state (see Figure 2) (PIK (2021)). PIK also predicted that around the normal onset date, Telangana would see a "false start" of the monsoon, which also occurred and then rainfall ceased until June 24. Moreover, Figure 3 shows that at endline, the modal farmer in our pilot reported that the monsoon arrived during our forecasted window.

Figure 3: Pilot data – Reported monsoon onset dates



Notes: This figure plots the distribution of reported monsoon onset dates in our pilot data. Farmers reported monsoon onset dates in Kartes, a local unit of time measurement, approximately two weeks in length. The PIK forecast predicted that the monsoon would arrive during the bar highlighted in blue.

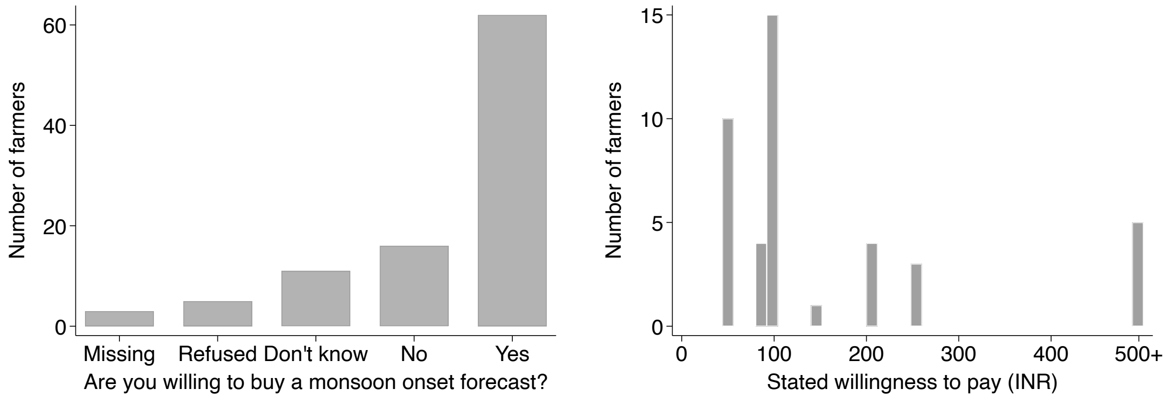
The pilot yielded three key findings. First, in the status quo, farmers do not have access to accurate information about the onset of the monsoon. The most popular sources of monsoon information farmers used were the TV/radio (25 percent of reported forecasts); astrologers (22 percent); and other farmers in the village (19 percent). Farmers reported that their existing sources of forecast information reported the correct kartes (June 21 – July 5) only 16 percent of the time. Neither astrologers nor other farmers in the village ever offered this date range.

Second, farmers demonstrated substantial demand for our forecast product. At endline, we told farmers that we could offer them a forecast for the 2022 Kharif season. We asked how much they would be willing to pay for such a forecast. Figure 4 shows that the majority of farmers (64 percent) reported being willing to purchase the forecasts, at prices ranging from Rs 50 to Rs 1,500.

Third, we find suggestive evidence that farmers updated their beliefs in response to our forecast. At both baseline and endline, we asked farmers when they expected the monsoon to arrive.[8] Between the baseline and endline survey, the distribution of farmers' beliefs about

[8]At endline, we also asked farmers when the monsoon actually arrived. Farmers responded differently to these two questions, suggesting that they understood the distinction.

Figure 4: Pilot data – Farmer willingness-to-pay for a monsoon onset forecast



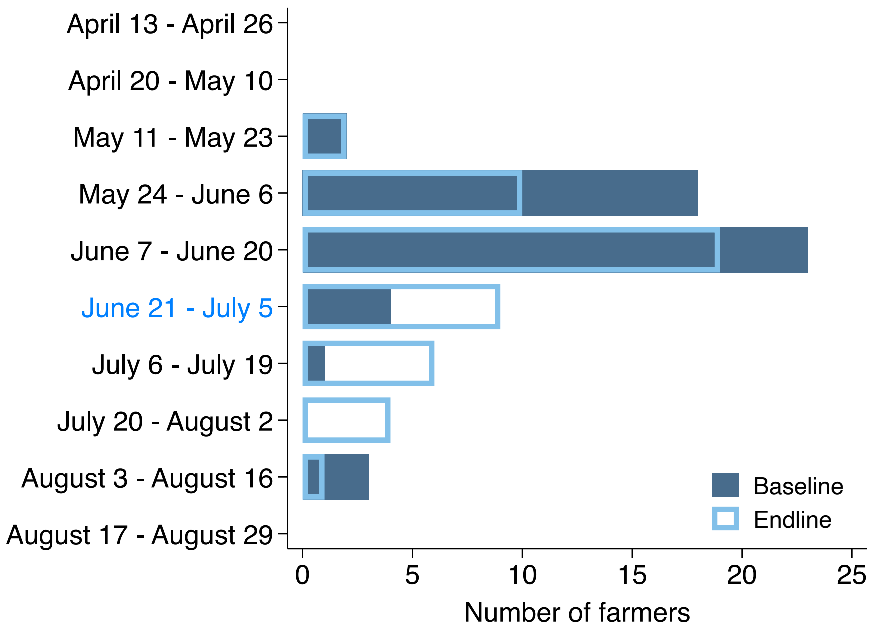
Notes: This figure plots results from our Kharif 2021 pilot. The left panel shows that the majority of farmers stated in the endline that they would be willing to purchase an onset timing forecast for the 2022 Kharif season. The right panel shows the distribution of prices farmers stated that they would be willing to pay for the forecast. One farmer reported being willing to pay INR 1,500; in this plot, we top-code this value to 500.

the monsoon onset moved substantially closer towards our forecast – and, consequently, towards the true onset date. Figure 5 shows farmer beliefs at baseline and endline, with a clear shift towards our forecasted arrival date between June 24 and July 2 (covered by the bar highlighted in blue).

2.4 Implementing partner

We partner with ICRISAT. ICRISAT is an international NGO, headquartered in Hyderabad, Telangana. 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 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 such a well-regarded institution is critical for this project's success, as it will lend important credibility to the forecasts for farmers who are encountering this information for the first time.

Figure 5: Pilot data – Farmers update beliefs towards the forecasted onset date



Notes: This figure plots when farmers expected the monsoon to arrive, measured both at baseline (solid navy) and at endline (hollow blue). Between these periods, farmers updated their beliefs towards the forecasted kartis (June 21 – July 5, denoted by blue text). This figure only includes data for the farmers who answered this question both at baseline and at endline.

3 Model

In this section we present a simple model of farmers' decision-making under uncertainty that incorporates forecasts and insurance.[9] We limit the model to examine input choice for a single crop as this is sufficient to illustrate the important implications of the monsoon forecast. We acknowledge that crop choice itself may be an important adjustment that is not fully captured in the model below. Should this margin indeed prove to be significant, we will expand the model to include a first stage crop choice problem which will nest the following continuous input choice problem. However, the primary intuition of the model — that a monsoon forecast allows farmers to re-optimize investments to better reflect future state probabilities — remains the same.

Farmer's decision-making process Suppose that the state denoted by ϵ is binary i.e. $\epsilon \in \{0, 1\}$, where 0 corresponds to late onset of rainfall (the "bad" state) and 1 corresponds to early onset of rainfall (the "good" state). The state is unobserved at the time when the

[9] Appendix B contains further details on the model.

decision is to be made. The farmer has a prior probability of s_0 that it will rain early. Therefore the farmer solves the following problem:

$$\begin{aligned} V(\theta, s_0) = \max_{c,l} \quad & s_0 u(c|\epsilon = 1) + (1 - s_0) u(c|\epsilon = 0) \\ \text{s.t.} \quad & c = y - w \cdot l + p \cdot g(l, \epsilon) \\ & y \geq w \cdot l \end{aligned} \tag{1}$$

where $u(c)$ denotes utility derived from consumption c. Non-farm income is denoted by y, input costs are w, and level inputs given by l, output function by $g(l, \epsilon)$, and price of output by p. Further, $\theta = (y, w, p, g)$. The first constraint defines total consumption, and the second budget constraint limits input investment.[10]

The farmer can then solve for the optimal level of inputs l^*. Making standard assumptions on the production function $g(\cdot)$, we can show that l^* is increasing in the prior probability the farmer has for the good state s_0. That is, if the farmer believes the good state is more likely, they will be more willing to invest more because these investments will have higher returns. The full model we present in this section does not have a simple closed-form solution. As a result, we generate predictions via simulation. For this simulation, we assume farmers have isoelastic utility, such that $u(c) = \frac{c^{1-r}-1}{1-r}$, and a Cobb-Douglas production function, $g(l, \epsilon) = (A + \epsilon) l^{\alpha}$.[11]

Figure 6 shows results from the baseline simulation of how the optimal level of input use changes as the farmer's priors for an early monsoon increases (s_0). As expected, if the farmer thinks an early monsoon is more likely, they will invest more into inputs in crop production.

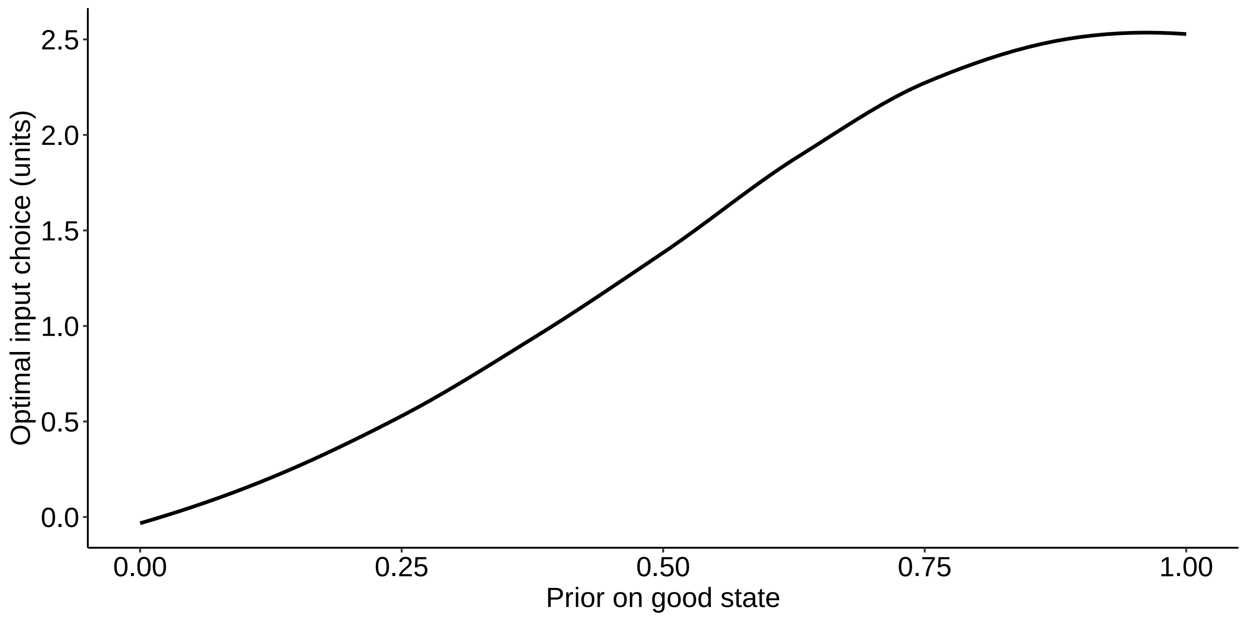
Forecasts We now introduce the opportunity for the farmer to purchase a near perfect forecast of the state.[12] If the forecast predicts that there will be a early monsoon, then the farmer will solve the above problem for $\epsilon = 1$), which yields value $V(\theta, 1)$. Likewise, if the forecast predicts that there will be a late monsoon, then the individual solves the above problem for $\epsilon = 0$), which yields value $V(\theta, 0)$. However, at the point of purchase the individual does not know what the forecast will be and so the gross value of this option is an expected value using their prior belief:

[10]For simplicity, we ignore credit constraints.

[11]For the results presented here, we set $r = 0.5$; $\alpha = 0.5$; $A = 0.1$; $\epsilon = 10$; $y = 5$; $w = 2$; $p = 2$; and $b = 5$.

[12]We can extend this problem to a setting where forecasts are not perfect, but instead have imperfect predictive power or "skill." To do this, we define the forecast skill as the probability of ϵ being equal to $\tilde{\epsilon}$ conditional on the realization of ϵ i.e. the forecast skill $Pr(\tilde{\epsilon} = \epsilon|\epsilon)$. In this case, farmers will solve an adjusted input problem where their weight on the outcome probabilities have shifted from their prior towards the forecast prediction. The value of this imperfect forecast to the farmer will be increasing in its predictive power, but the general predictions remain qualitatively similar.

Figure 6: Optimal input choice as a function of a farmer's prior



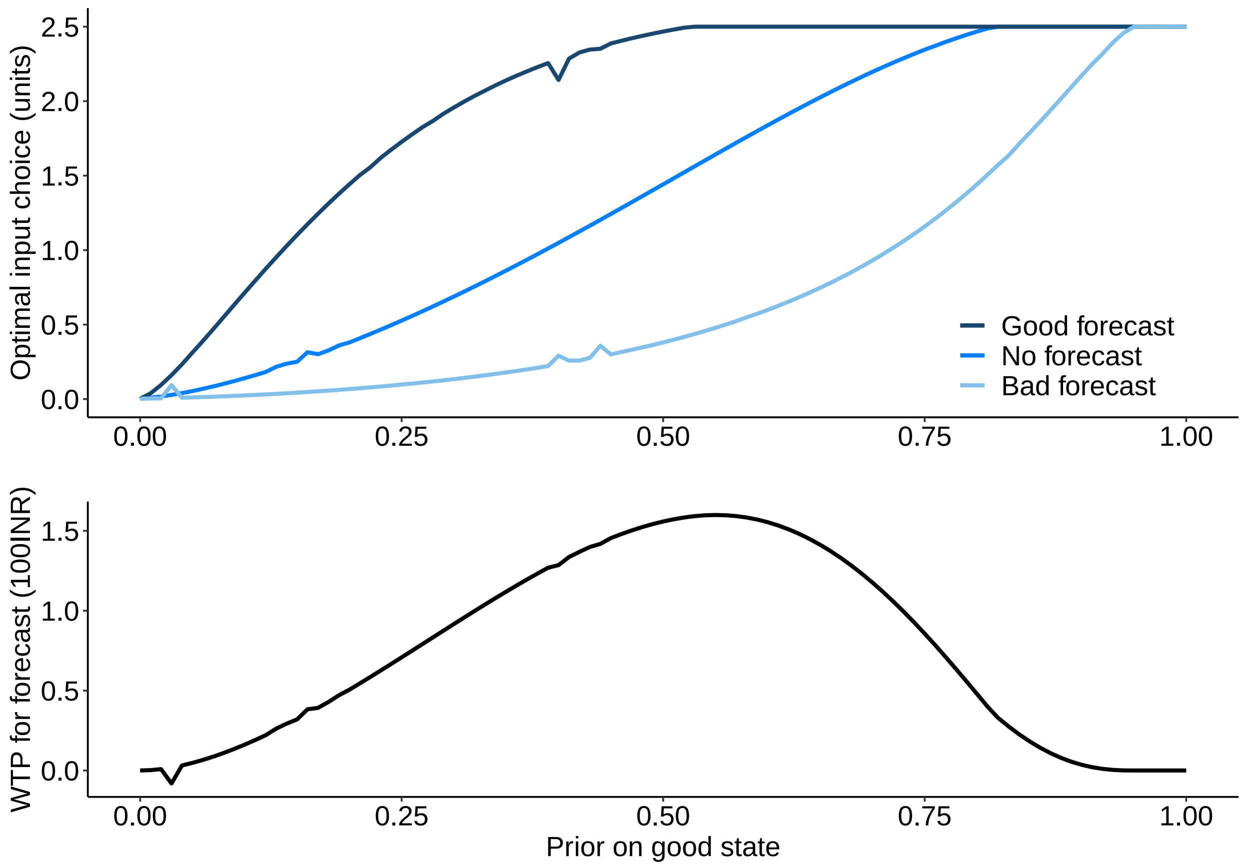
Notes: This figure plots the relationship between optimal input choice (modeled here as labor) and the farmer's prior that the good state of the world will be realized.

$$\bar{V}(\theta, s_0) = s_0 V(\theta, 1) + (1 - s_0)V(\theta, 0) \tag{2}$$

The willingness to pay for the forecast is therefore the difference between this expected value $\bar{V}(\theta, s_0)$ and the baseline value without forecasts $V(\theta, s_0)$. There are two types of gains from forecasts: the gain from information to optimize correctly and the gain from smoothing consumption across states.

Figure 7 plots two important simulation results from the model. The left panel plots the relationship between the farmer's prior of a good monsoon and their optimal investment choice with no forecast (as in figure 6), with a good forecast, and a bad forecast. As expected, the farmer will invest more when they receive a good forecast and less when they receive a bad one relative to the no forecast baseline. These adjustments are also most pronounced when the farmer has the most uncertainty about the monsoon. The right panel shows that the relationship between the strength of a farmer's prior and their willingness to pay for a forecast is non-monotonic: forecasts are most valuable when the farmer is the least certain. This result follows from the fact that farmers adjust their input allocation the most when they are most uncertain, which in turn causes the value of the forecast to be large.

Figure 7: Priors and forecasts



Notes: This figure plots simulation results from our model of forecasts with a skill level of 0.8. The top panel shows the relationship between a farmer's prior and the optimal input allocation with no forecast, a good forecast, and a bad forecast. The bottom panel shows the relationship between a farmer's prior and their willingness to pay for a forecast.

Insurance We now introduce the option for the farmer to purchase rainfall index insurance[13]. Now, the farmer's problem can be written as:

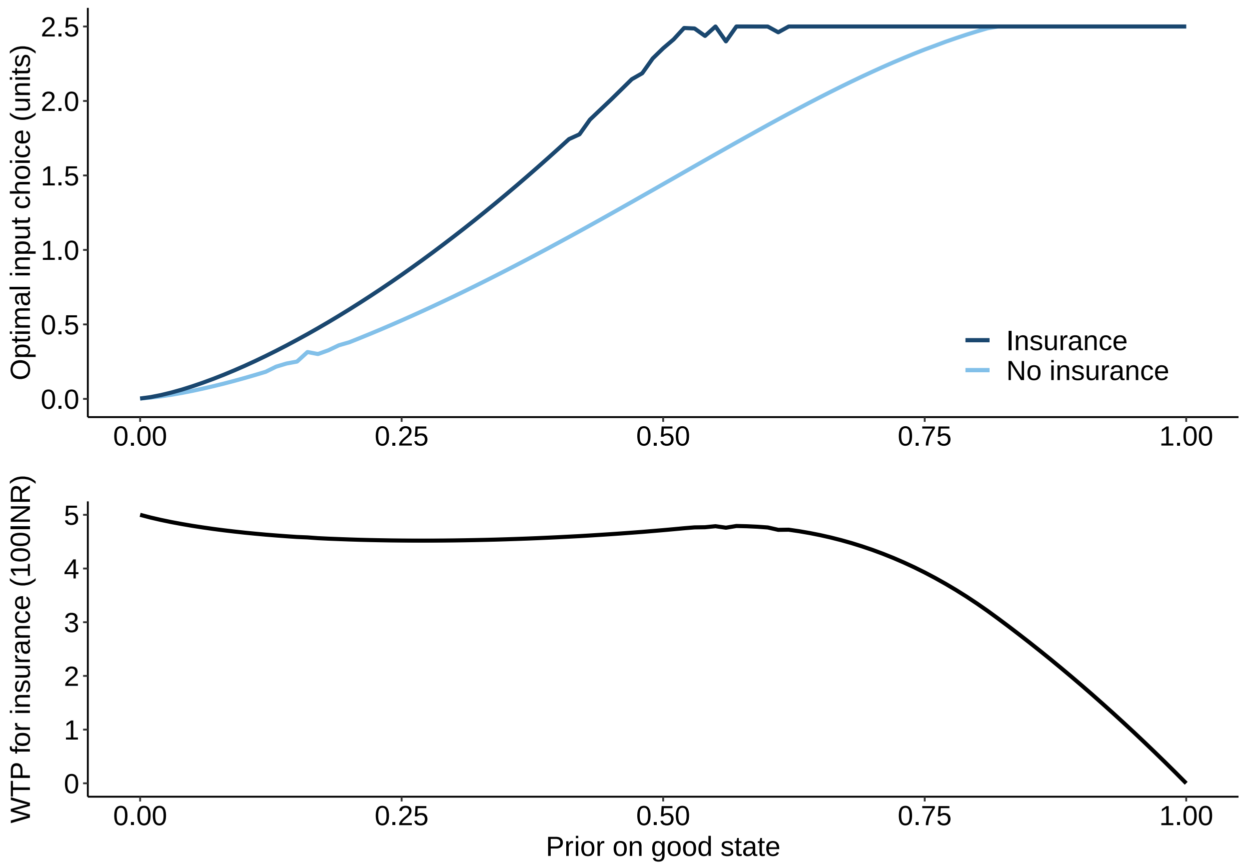
$$\begin{aligned} V(\theta, s_0, b) = \max_{c,l} \quad & s_0 u(c|\epsilon = 1) + (1 - s_0) u(c|\epsilon = 0) \\ \text{s.t.} \quad & c = y - w \cdot l + p \cdot g(l, \epsilon) + \mathbb{1}\{\epsilon = 0\} \cdot b \\ & y \geq w \cdot l \end{aligned} \tag{3}$$

where b denotes the insurance payout. The farmer's willingness to pay for insurance is then, as above, the difference between the value of the problem with the insurance coverage $V(\theta, s_0, b)$ and the baseline value $V(\theta, s_0, 0)$. Insurance delivers two benefits: smoothing from the ability to take more risk and invest more due to a bad-state payout, and the mechanical

[13]The farmer only receives compensation in the states where there is a delayed monsoon regardless of their own production outcome.

loosening of the bad-state budget constraint which expands the investment frontier. We reproduce the standard result that, in the presence of insurance, a farmer will invest more in up-front inputs.

Figure 8: Priors and insurance



Notes: This figure plots simulation results from our model of insurance. The top panel shows how optimal input investment vary over the farmer's prior both with and without insurance. The bottom panel plots willingness to pay for insurance over the farmer's prior.

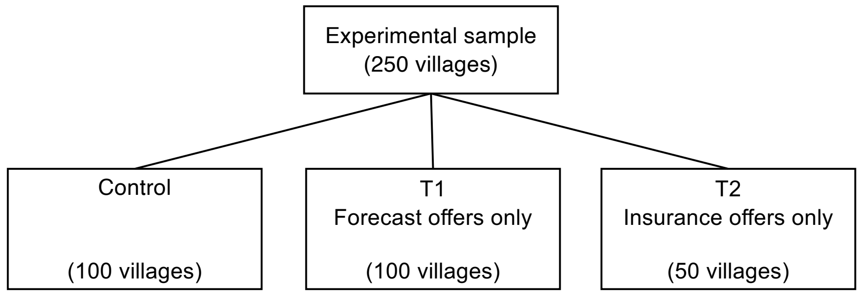
The left panel of Figure 8 plots this result from our simulation over the farmer's priors on a good monsoon. As with forecasts, the input adjustment is highest when farmers have the most uncertainty about the monsoon. The right panel plots the farmer's willingness to pay for insurance over their priors on the good state. The willingness to pay for insurance reflects the twin benefits insurances conveys: risk reduction and an increase in expected income. In the extreme when farmers are certain that there will be a late monsoon, the value of insurance is equal to its payout in the bad state. If farmers become less certain a bad state will occur, the expected value of this payout falls. However, simultaneously the risk reduction benefits increase as farmers will now benefit from increased investment. Together, these two effects largely balance out, keeping the value of insurance roughly constant for farmers with low to uncertain priors. Finally, the value insurance falls for farmers who think a good monsoon is likely. This arises because both the expected income from the insurance payment and the risk reduction benefits are small for farmers who think the bad state is unlikely.

4 Experimental design

Informed by our theoretical framework, we have designed a randomized controlled trial to estimate farmers' willingness to pay for and benefits of forecasts and insurance. We will randomize 250 villages (sampling 5-10 farmers each) in Telangana into one of two treatment arms and a control group. We put 100 villages in the control group, 100 villages in T1, and 50 villages in T2 to maximize statistical power for the forecast treatment, and because the insurance arm is more expensive than the forecast arm. We will sample villages throughout Telangana. We will restrict the sample by excluding villages with high penetration of irrigation, based on data from ICRISAT and the 2011 Indian Census, as these villages are already insulated from the variability of the monsoon. We will also draw our sample with a distance buffer between villages, to prevent across-village information sharing. To increase statistical power and ensure balance, we will stratify our randomization by district and select characteristics from the 2011 Census. We will then sample households within each village for inclusion in our survey.

Figure 9 presents a diagram of the experimental design. In the first treatment group (T1), we provide farmers with the option to purchase a forecast only. Comparing T1 to control identifies the impact of forecasts relative to the control group. In the second treatment group (T2), we provide farmers with the option to purchase an index insurance product only. Comparing T2 to T1 identifies the impact of insurance relative to the forecast group, and allows us to benchmark the impact of forecast relative to another well known risk-mitigation technology.

Figure 9: Experimental design



Notes: This figure shows the design for our cluster-randomized experiment, which includes a control arm and three treatment arms. In all villages, we will sample 5-10 farmers to participate in our survey and (if applicable) treatments. Farmers in T1 will be offered the opportunity to purchase a forecast. Farmers in T2 will be offered the opportunity to purchase an insurance contract.

Forecasts The monsoon forecast that our field NGO partner will offer to farmers comes from Stolbova et al. (2016). Appendix A provides more detail on this forecast. Farmers will be told about the forecast using the following text: "In late May/early June each year, we can offer you a forecast which tells you which Kartis [an approximately two-week local time step] the monsoon will arrive in. We offered you a sample of this product this year. 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 will return in the next two weeks to provide you the with the forecasted onset Kartis." We will offer farmers this forecast through a BDM mechanism to elicit farmer willingness-to-pay, which we describe in more detail below.

If a farmer purchases a forecast, approximately one week after the baseline survey, a field worker from our partner NGO will return to him with the forecast, which will be delivered with the following text: "This year's forecast says the monsoon is likely to start over Telangana between [approximately two week date range]. There may be a limited amount of pre-monsoon rainfall between [approximately one week range]. The continuous monsoon rainfall is expected after [date]." Farmers in our pilot expressed interest in receiving the forecast information via SMS, so after visiting the farmers in person to deliver this information, our partner NGO will also send an SMS with the same text. We validated the forecast language in our pilot. Farmers reported being willing to pay for a monsoon onset forecast, and updated their beliefs about monsoon onset towards the forecasted date. See Section 2.3 for further details.

Insurance Our insurance product will provide farmers with financial protection against a late monsoon, and will be implemented by our NGO field partner to increase the credibility of the product. We model this product directly on Mobarak and Rosenzweig (2014): farmers receive a sliding-scale payout at harvest time if the monsoon onset is delayed, and not otherwise. We will define a village-specific "on time" monsoon onset date based on the average monsoon onset date in that location, using reanalysis data from the ECMWF ERA-5 (Muñoz-Sabater et al. (2021)), and following the approach of Moron and Robertson (2014), as shown in Figure 2. We consider the monsoon as having officially started when our rain gauges accumulate at least 30mm of rainfall (Mobarak and Rosenzweig (2014)).[14] Around monsoon onset, a field team member will place rain gauges in each village well before the monsoon begins. In the approximately 3 weeks before and after the forecasted monsoon onset date, a field staff member will travel to each village on a daily basis to measure the amount of rainfall. They will take a photo of the rain gauge each day and send it to the research team, and we will verify a monsoon trigger. These monitoring visits will end as soon as the monsoon has begun in a given village.

Our NGO partner will inform farmers that they will receive a low payout if the monsoon is 15-20 days late compared to the local "on time" onset date; a medium payout if the monsoon is 20-30 days late; and a large payout if the monsoon is 30 days late or later. The maximum payout is set to approximately $190 USD, which will cover approximately 20 percent of the average farmer's agricultural revenues (MOSPI (2013)). 30 days after the on time onset date, the NGO will send a message to each farmer informing him about the monsoon onset and therefore payout: either the monsoon was on time, and they will not receive a payout this year; or the monsoon was [number] days late, and they will be paid [INR amount] at harvest time. Finally, at harvest time, farmers in villages where payouts were triggered will be revisited by a member of the NGO's field staff who will deliver their payouts. We will offer farmers this insurance product through a BDM mechanism to elicit willingness-to-pay, which we describe in more detail below.

Eliciting WTP We will use the Becker, DeGroot, and Marschak (BDM) mechanism to measure willingness to pay for forecasts and insurance during the baseline survey. We explain the general BDM process below; for more detail about the procedure see Appendix C.

To elicit WTP for the given product, we explain a two-step procedure to the household. In the first step, the household will state their willingness to pay and physically place the money on a table between the interviewee and the enumerator. Then, the enumerator opens

[14]This metric avoids monsoon "false starts"; accumulation of this amount is sufficient to wet the topsoil, which serves as a useful agronomic benchmark of onset.

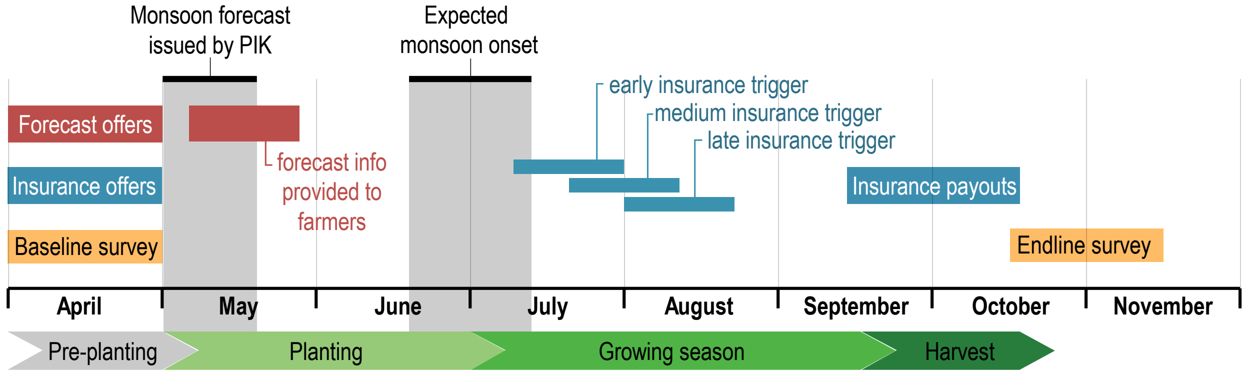
a sealed envelope containing a slip of paper with an INR value written on it. If the value listed on the paper is above the household's stated WTP, the household does not get to purchase the product and their cash is returned. If the paper value is below the household's WTP, the household purchases the 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 will play 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.[15]

We will skew 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. The underlying distribution will be unknown to farmers, meaning that they will not have any incentive to bid strategically. In this way we will maximize power by ensuring high take-up of each product without compromising incentive compatibility. Prices will be randomly assigned to each participant prior to the baseline visit. The field coordinator will then seal each price in the envelopes so that enumerators will not be aware of the price their households were allocated.

Timeline Figure 10 presents the planned timeline for the experiment. We will begin by conducting baseline surveys in April and early May 2022. Forecast and insurance offers will be made during this same visit to households in T1 and T2 villages. PIK typically releases its monsoon forecast in the first two weeks of May. Once this forecast is available, we will return to T1 villages to provide farmers with forecasts, and send accompanying SMS messages. The monsoon typically arrives in late June or early July. The early, medium, and late insurance trigger occur 15, 20, and 30 days after local onset, respectively. We will provide applicable insurance payments to farmers during the harvest, between late September and early October. Finally, we will conduct our endline survey after harvest, likely in November.

[15] In the control group where neither the forecast or insurance product are offered, we will instead offer households the opportunity to buy a bar of soap at a randomly chosen fixed price. This take-it-or-leave-it (TIOLI) offer will allow us to map an analogous demand curve for the bar of soap using this alternative method. We will compare the BDM derived demand curve to the TIOLI demand curve for the soap in order to confirm that both methods produce similar results.

Figure 10: Experimental timeline



Notes: This figure presents the planned timeline of our experiment in relation to the agricultural cycle. We expect to run the experiment during the 2022 Kharif season. We will implement the baseline survey, and provide treatment offers, in April. We will provide the monsoon forecast to farmers in May, in advance of expected onset between June and July. Insurance payouts will be triggered by monsoon onset timing, and insurance payouts will occur in September/October. Finally, we will conduct our endline survey in October/November.

Statistical power We have conducted power calculations to ensure that our design is capable of detecting reasonably sized treatment effects. All power calculations are based on a hypothesis test with a 5% significance level, using a sample of 1,250 households in 250 village clusters.[16] As described above, 100 villages will be offered forecasts, and 50 villages will be offered insurance. We assume ICCs between 0 and 0.20.

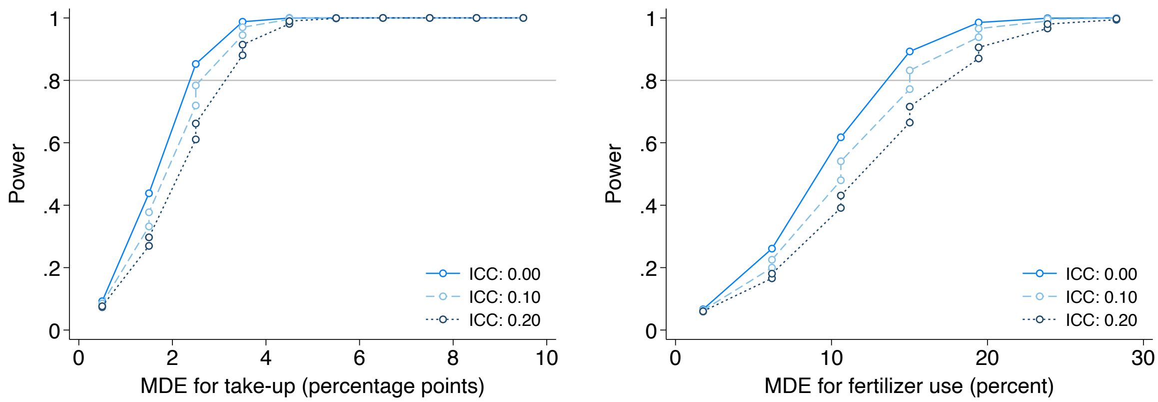
To inform these power calculations, we use the mean (0.0234) and standard deviation (0.144) of formal insurance take-up from Mobarak and Rosenzweig (2014), which also surveyed farmers in southern India. We expect a similar share of our farmers to have previously purchased rainfall insurance (though in our own pilot of 96 farmers, we found that 0 people had done so). Given that our forecast is novel and not currently available to the public, 0 people will have access in the status quo.

We are powered to 80% for MDEs above 3 percentage points. This is a reasonable effect size: Mobarak and Rosenzweig (2014) find that approximately 40 percent of households took up insurance when it was offered for a price. While our RCT will eventually provide conditional cash transfers and forecasts to farmers at a minimal price, and we therefore expect take-up to be close to 100%, this power calculation is informative about how precisely we will be able to trace out the demand curve. We are well-powered to measure WTP.

We also present a power calculation for input use, benchmarked to Emerick et al. (2016), which also worked with Indian farmers. A key input in Indian agriculture is fertilizer. We

[16] If anything, this is conservative, as we expect to sample between 5 and 10 households per village.

Figure 11: Power calculations



Notes: This figure shows the results of power calculations. The left panel plots power calculations for take-up of our forecast and insurance products, informed using data on insurance take-up from Mobarak and Rosenzweig (2014), which ran in a similar context. The right panel plots power calculations for treatment effects on input use, benchmarked using data on fertilizer use among Indian farmers from Emerick et al. (2016). Since we employ a cluster-randomized design, we present power calculations under three assumed intra-cluster correlation coefficients: 0, 0.1, and 0.2. In both cases, our design is powered to detect reasonably-sized treatment effects.

therefore use data on fertilizer to inform this power calculation. Fertilizer use in the control group in this sample has a mean of 56.6 kg. To conduct power calculations on these data, we residualize by regressing fertilizer use on district fixed effects, land holdings, household head education and age, whether the household has a thatched roof and/or latrine, and whether the household has a BPL card. We will collect similar data in our study and choose controls accordingly. The residualized SD is 46.

We are powered to detect effects of at least 15 percent. We assume 100% take-up for these calculations, which is reasonable because we will be providing the insurance and forecast products for free. These MDEs are in the range of estimates detected by previous agricultural experiments (e.g. Emerick et al. (2016) finds a treatment effect of approximately 10 percent), and are likely conservative, because we will collect baseline data and be able to employ an econometrically efficient ANCOVA specification. Taken together, these power calculations support our study design.

5 Data collection and survey instruments

5.1 Main outcomes

5.1.1 Main outcomes: Willingness-to-pay

BDM As described above, we will use the BDM mechanism to elicit farmers' willingness to pay for the forecast at baseline.

Stated preference During the endline survey, we will elicit a stated-preference measure of WTP by describing the forecast, and asking whether each farmer would be willing to buy such a forecast for the 2023 Kharif season, and if so, how much they would be willing to pay for the forecast.

5.1.2 Main outcomes: Beliefs

Beliefs - coarse measurement We ask farmers which Karte the monsoon has to start in for them to consider it early/late/on-time. We then ask what crops they would plant if the monsoon were on time, and whether/how they would change their crop choices if the monsoon were to arrive early/late. This will help us benchmark any responses that we see to forecasts to farmers' ex-ante intentions. Similarly, we ask about the share of their land they cultivate when the monsoon arrives on time, and whether they would increase or decrease this allocation if the monsoon were to arrive late/early. Finally, we ask about whether they would increase or decrease the amount of fertilizer they apply if the monsoon were to arrive early/late.

In addition to these hypothetical questions, we ask farmers when the monsoon started last year, whether they considered this early/late/on-time, and whether they expect the monsoon to arrive early/late/on-time this coming agricultural season.

Beliefs - granular measurement We ask farmers when the monsoon has arrived in the past 10 years, and elicit their subjective probability distribution of when it will arrive this year. To do this, we provide the farmers with 10 beans to distribute across kartes within a year, following Cole and Xiong (2017). In the case of the historical distribution, we tell farmers to think of each bean as representing one year's monsoon. Once the historical distribution is laid out on the table in front of the farmer, we ask them to consider whether they believe the monsoon will arrive early or late in the coming year. We then ask how they would like to move the beans around in light of their response. We gather this information at baseline and midline to establish whether (and by how much) the forecast changes farmers' priors.

5.1.3 Main outcomes: *Ex ante* outcomes

Agricultural activity We hypothesize that farmers who receive forecasts and/or insurance could change which plots they cultivate; which crops they choose to plant; and/or the inputs they apply to these crops. We measure these outcomes as follows.

We ask farmers how many plots they own and cultivate (including which plots they rent out and rent in). For each plot we ask the farmer to describe the plot; list the size of the plot; how they obtained the plot; whether it was cultivated, rented or left fallow last year; and which crops were cultivated overall, during the Kharif season and during the Rabi season. We also ask farmers what share of the plot they allocate to each crop.

Next, we ask farmers about inputs: seeds and fertilizer. For each input, we ask how much they apply across all plots, which plots receive that input, and the share they apply to each plot. This allows us to compute inputs per land area. This does not provide a measure of inputs by crop, which we determined was too complicated for farmers to report.

To capture labor investments, we ask who in the household worked on each plot. For each plot-worker combination, we then ask the number of days they worked on land preparation and sowing; activities involved during crop growth; and harvesting. We also ask whether any temporary workers were hired to assist on the farm, the activities they engaged in, the number of workers assigned to this task, the number of days they allocated to that task, and how much they were paid.

5.1.4 Main outcomes: *Ex post* outcomes

Agricultural activity In addition to the *ex ante* agricultural outcomes described above, we also measure *ex post* outcomes. In particular, for each plot, we ask how much of each crop they harvested. We then ask the amount of the harvested crop that is sold, consumed, spoiled, and slated for future sale.

Consumption We ask respondents to report total consumption expenditure across three categories:

1. "Frequent" (within the last 7 days): cereals (rice, suji/rawa), milk, and tobacco
2. "Infrequent" (within the last 30 days): meat (eggs, chicken, goat, fish), and mobile phone charges

3. "Rare" (within the last 5 months): clothing, medicine/doctor, and celebrations

We can also scale and aggregate these measures to produce a single measure of average consumption per day. This will allow us to measure whether forecasts and/or insurance increase farm households' consumption.

Assets We construct an asset index using the following procedure. We first ask respondents whether or not they own individual items across a list of assets. We then assign the asset index as the first component of the PCA score for this set of dummy variables. The set includes the following 10 items: TV, bicycle, motorbike, house, electricity, telephone/mobile phone, computer, sewing machine, thresher, and bullock cart. This will allow us to measure whether forecasts and/or insurance increase farm households' assets, and whether the effect of the forecast varies by owned assets.

Income generating activities In addition to the agricultural income described above, farmers may receive non-agricultural income. To capture this, we ask respondents which types of income generating activities they currently pursue, including non-farm business, wage employment and agriculture and livestock. For non-farm business, we ask when the households' largest business was created, the type of business, the revenue and profits they earned, and who in the household works there. For wage employment, we ask whether the farmer was engaged in any paid employment on/off the farm not including self-employment, the amount of time they worked, and the wage they earned. We repeat the wage question for other adults within the household. We also ask respondents about the current stock of livestock, and profits from livestock over the previous 12 months.

Household finance Similarly, we expect that forecasts and/or insurance may impact overall household finances. We ask farmers about how much money they have in savings, if any. We then ask if they have taken any loans, the amount, and whether they have any outstanding balance. Finally we ask about whether they received any pension/government transfers/insurance money or lottery; the amount they received from these sources; and whether they received any money from a relative/friend (including remittances) and the total value of these transfers.

5.2 Heterogeneity

As we describe in Section 6 below, we test for heterogeneous treatment effects along a series of dimensions.

5.2.1 Priors

Our theory predicts that priors are an important determinant of heterogeneity in this setting; we measure priors as described above. We also use these prior metrics to calculate the distance between these priors and relevant benchmarks (e.g. historical averages, posteriors, and the forecast itself).

5.2.2 Risk and time preferences

As described in Section 3 above, risk preferences play an important role in the take-up and impact of forecasts and insurance. We measure risk preferences (risk aversion) with multiple price list decision tasks (adapted from Holt and Laury (2002)). We estimate time preferences (discount factors) by adapting the Andreoni and Sprenger (2012) convex time budget (CTB) method, following Gine, Townsend, and Vickery (2015).

5.3 Secondary survey outcomes

In addition to the main outcomes and dimensions of heterogeneity described above, we are interested in conducting secondary analysis on several additional measures. We are not directly pre-specifying the analyses on these additional outcomes.

5.3.1 Summary statistics

Forecasts and insurance exposure We want to measure farmers' exposure to the types of products that we are working with in this experiment. To this end, we ask farmers whether they have heard about different insurance schemes (not including rainfall insurance). For each one, we then ask whether they have purchased it in the past, and whether they have received a payout. For rainfall insurance specifically, we ask a more detailed set of questions. These include whether they have heard about rainfall insurance, who they heard it from, the most recent year (and karte) of purchase, who they purchased from, the amount paid, whether it was tied to a specific crop, how much it payed out, and whether they intend to purchase it this coming Kharif season.

Similarly, we want to know farmers' exposure to forecasts. We ask whether they have ever received information about when the monsoon would start in previous Kharif seasons, and the most recent year (and karte) they heard it in, from whom they received this information, which source of information they relied on the most, and how accurate the information was. We also repeat these same questions for this coming Kharif season.

5.3.2 Additional outcomes

Migration Forecasts may impact whether household members decide to work on the farm or migrate. We ask households at baseline whether anyone in the household intends to migrate, when and for what reasons. At endline, we ask about whether anyone did migrate in the past year, why, and whether they intend to return.

Mental health Farmer suicides have been linked to agricultural outcomes in India (Carleton (2017)). To establish whether forecasts improve mental health, we measure farmers' depression levels using the standard PHQ-9 questionnaire.

Intra-household bargaining To understand who controls household finances, we ask a series of 6 questions (four from the DHS, adapted from the DHS to our agricultural context). These questions help identify whether the benefits from forecasts accrue primarily to the man or the woman, and whether norms around who should control household finances are impacted.

5.3.3 Additional heterogeneity

Shocks Shocks may mediate the impact of forecasts. To assess this possibility we ask farmers whether they experienced a variety of shocks in the last year. Forecasts may help households avoid negative coping strategies. We ask farmers about whether or not they engaged in a series of coping strategies.

6 Hypotheses and analysis

We will estimate four main sets of results, guided by our theoretical model. We will begin with "first stage" estimates of take-up and the demand curve. Next, we estimate belief effects: how did the forecast change priors? Third, we compute treatment effects on *ex ante* outcomes – input decisions farmers make – and *ex post* outcomes – results realized at the end of the growing season.

6.1 Willingness-to-pay and consumer surplus

We first describe how we will estimate WTP and consumer surplus. While these are outcomes of interest, we consider them secondary to the changes in *ex ante* input decisions and *ex post* welfare outcomes.

We run a BDM mechanism to elicit respondents' willingness to pay for forecasts, which we use for two purposes. First, we can map out the demand curve for forecasts by plotting the share of farmers who are willing to purchase a forecast at or above a given price. We can do the same for insurance.

By integrating below these empirical demand curves, we can project the welfare gains (consumer surplus) from forecast and insurance distribution:

$$\int \text{Forecast takeup}_{iv}(\text{price}) \ \partial\text{price}$$

$$\int \text{Insurance takeup}_{iv}(\text{price}) \ \partial\text{price}$$

These estimates can be compared to the costs of providing each to understand the net gains from counterfactual government policy of free or subsidized forecast/insurance distribution.

Similarly, we run a BDM exercise to elicit willingness to pay for insurance. By tracing out the demand curve for both products, we can see whether the demand for the two products differs.

Prior strength Our theoretical model suggests that a farmer's WTP will depend on the strength of his prior belief about the monsoon onset. We measure the strength of these priors in three ways, using data from our baseline survey. First, we compute the standard deviation of the prior distribution from the farmer's bean task. With this approach to measuring priors, we expect the heterogeneity to be monotonic in prior strength, so we incorporate this into our analysis as follows:

$$\text{Forecast WTP}_{iv} = \beta_0 + \beta_1 \text{Prior Strength}_{iv} + \gamma \mathbf{X}_{iv} + \eta_{iv}$$

Across all specifications in this section, we use double-selection LASSO to select controls for precision and we control for baseline measures of our outcomes when they are available through an ANCOVA specification. $\mathbf{X}_{iv}$ includes these controls and strata fixed effects. η_{iv} is an error term. For this and all other regressions in Section 6, we cluster our standard errors at the village level due to the clustered nature of our design. Our model predicts that, the weaker a farmer's prior is, the higher his WTP should be. In addition to this linear specification, we will also estimate a version where we divide prior strength into bins to accommodate nonlinearity. We plan to largely present these results graphically, but we will also include regression estimates for completeness and formal statistical tests.

Our other two measures of prior strength compute the probability that the coming monsoon will be a good year, comparing the farmer's bean task to (i) his own good vs. bad cutoff or (ii) the average cutoff in his village.[17] We expect the impact of these measures on WTP to be non-monotonic, so we incorporate them into Specification 1 as follows:

$$\text{Forecast WTP}_{iv} = \beta_0 + \beta_1 \text{Prior share}_{iv} + \beta_2 \text{Prior share}_{iv}^2 + \gamma \mathbf{X}_{iv} + \eta_{iv}$$

We define Prior share$_{iv}$ in the two ways described above, and allow for non-linearities using the squared term. Our model predicts that WTP (and thus observed takeup conditional on price) should be lower when priors are stronger (either for the good or the bad state), and higher when priors are closer to uniform. We will also explore other ways of parameterizing the prior strength, designed to best account for non-monotonicity in WTP. We will use our observed data to inform these approaches.

As a complement to this prior strength approach, we also estimate heterogeneous effects by a measure of farmers' ex-ante "sophistication." We compute the (absolute) difference between a farmers' prior and the mean historical onset date:[18]

$$\text{Forecast WTP}_{iv} = \beta_0 + \beta_1 |\text{Prior}_{iv} - \text{Historical mean}_{iv}| + \gamma \mathbf{X}_{iv} + \eta_{iv}$$

The effects of this measure of sophistication may be ambiguous. On one hand, farmers that are farther from the mean may be less sophisticated and value information less ($\beta_1 < 0$). On the other hand, farmers that are far from the mean may benefit the most from the information ($\beta_1 > 0$).

Finally, our theory also predicts a monotonic relationship between likelihood of a good year and insurance demand. We test this empirically as follows:

$$\text{Insurance WTP}_{iv} = \beta_0 + \text{Prior share}_{iv} + \gamma \mathbf{X}_{iv} + \eta_{iv}$$

We predict that insurance WTP will weakly fall as the farmer's belief in the good state rises.

[17] We will define a "good monsoon" as one that comes either early or on time, per the (average) farmer's definition of these cutoffs.

[18] We use this as a measure of sophistication because we expect the historical mean to be the best information available to the farmer at the time of our baseline survey. We conduct our baseline before the arrival of the PIK forecast, which is well before other forecasts (e.g. the IMD's own forecast) is delivered.

Risk preferences Similarly, our model predicts that risk aversion should impact farmers' WTP for forecasts and insurance. The more risk averse the farmer is, the more likely he should be to purchase insurance. The prediction is ambiguous for forecasts, following the classic Blair and Romano (1988) result. Again, we plan to present the main BDM results graphically. We can incorporate risk into our formal tests as follows:

$$\text{Forecast WTP}_{iv} = \beta_0 + \beta_1 \text{Risk aversion}_{iv} + \gamma \mathbf{X}_{iv} + \eta_{iv}$$
$$\text{Insurance WTP}_{iv} = \beta_0 + \beta_1 \text{Risk aversion}_{iv} + \gamma \mathbf{X}_{iv} + \eta_{iv}$$

We define Risk aversion$_{iv}$ as the share of lotteries a farmer chose to participate in the risk preference game.

6.2 Impact on beliefs

The "first stage" effect of a forecast should be to update a farmer's beliefs about monsoon onset. We test for this by comparing prior beliefs elicited at baseline with posterior beliefs measured at midline in the treatment groups compared with the control group. We expect that the forecast will lead farmers to update their beliefs towards our information. To empirically test the extent of this updating, we estimate the impact of forecasts on farmers' beliefs. We use several measures of belief change. For each outcome, we use the following regression specification:

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

where Forecast offer$_v$ is an indicator for being in a forecast offer village. We use two outcome variables which compare farmers' posteriors to their priors: the absolute value of the difference between the mean of the posterior and mean of the prior distribution; and the Komolgorov-Smirnov test statistic for the difference between the empirical CDF of the posterior and the empirical CDF of the prior, which is the absolute value of the maximum pointwise vertical difference between the CDFs. Finally, we then compare farmers' posteriors to the forecasted onset date by using the absolute value of the difference between the mean of the posterior distribution and the onset date as the outcome variable. For each of these outcomes, we use the beans task described in Section 5 as our measure of farmers' prior and posterior distributions. We expect that forecasts will move farmers' beliefs towards the forecasted onset date.

The above specification estimates the ITT effect of a forecast offer. However, it is possible that not every farmer who is offered a forecast will purchase one. To estimate the LATE of the forecast on beliefs, we will estimate the following two-stage least squares model:

$$\begin{aligned}\text{Forecast take-up}_{iv} &= \gamma_0 + \gamma_1 \text{Forecast offer}_v + \delta \mathbf{X}_{iv} + \nu_{iv} \\ Y_{iv} &= \beta_0 + \beta_1 \widehat{\text{Forecast take-up}}_{iv} + \delta \mathbf{X}_{iv} + \eta_{iv}\end{aligned}$$

We instrument for forecast take-up with being in an offer village. We expect these effects to be stronger than our ITT estimates.

Prior strength We expect the effects of the forecast on beliefs to depend on the strength of the farmer's prior belief. We allow for this in an interacted model:

$$\text{Y}_{iv} = \beta_0 + \beta_1 \text{Forecast offer}_v + \beta_2 \text{Forecast offer}_v \cdot \text{Prior strength}_{iv} + \gamma \mathbf{X}_{iv} + \eta_{iv}$$

We will test for heterogeneity by prior strength using the same definitions described previously. We expect that β_2 will be negative as farmers with stronger priors will update their beliefs less strongly when given the forecast.

6.3 *Ex ante* outcomes

Next, we estimate treatment effects on *ex ante* outcomes: farmers' input decisions farmers. Our theory predicts that these decisions should respond to both the forecast and insurance treatments. We test for impacts on several outcomes: area planted, labor use per area, fertilizer use per area, and crop choice. For crop choice, we use both an indicator for whether a farmer changed their crop choice compared with what they reported planning to plant at baseline and an indicator for a cash crop as outcomes. Our regression is as follows:

$$Y_{iv} = \delta_0 + \delta_1 \text{Insurance takeup}_{iv} + \delta_2 \text{Forecast takeup}_{iv} + \gamma \mathbf{X}_{iv} + \varepsilon_{iv}$$

Where Y_{iv} are the outcomes described above. We expect $\delta_1 > 0$ because insurance covers some of the downside risk the farmers face, thereby encouraging additional investment. The sign on δ_2 is ambiguous and will depend on whether the forecast provides good or bad news relative to the farmers prior (which we detail in later specifications). As above, we can use a farmer's village-based treatment assignment as an instrument for take-up if noncompliance is high.

Good vs. bad forecasts Our theory predicts that farmers' input decisions should respond differently depending on whether the forecast provides "good" or "bad" news. To test for this, we estimate separate treatment effects based on the directional difference between the forecast and a farmer's prior. Though we do not randomize the forecast information, by our experimental design, there should be an equal proportion of farmers who receive good news in the treatment group as those who *would have* received good news, but ended up in the control group (and same for bad news). Therefore, our experiment still provides useful variation to estimate these effects, unless all farmers have the same prior. Based on our pilot, we expect this to be unlikely. We estimate the following specification (ignoring insurance for simplicity):

$$\begin{aligned} Y_{iv} = \delta_0 &+ \delta_1 \text{Forecast takeup}_{iv} + \delta_2 \text{Good news}_{iv} \\ &+ \delta_3 \text{Forecast takeup}_{iv} \times \text{Good news}_{iv} + \gamma \mathbf{X}_{iv} + \varepsilon_{iv} \end{aligned}$$

where we define Good news_{iv} as the forecast informing a farmer that the monsoon will be on time or early, based either on the farmer's own threshold or the average threshold in his village.

Heterogeneous treatment effects We estimate heterogeneity in treatment effects on a number of farmer characteristics as well as WTP. First, we estimate heterogeneity by four forecast-related characteristics: prior strength, risk aversion, the absolute difference between a farmer's prior and his posterior, and the absolute difference between the prior and the forecast itself. Interactions are included as follows:

$$\begin{aligned} Y_{iv} = \delta_0 &+ \delta_1 \text{Insurance takeup}_{iv} + \delta_2 \text{Forecast takeup}_{iv} \\ &+ \delta_3 \text{Forecast takeup}_{iv} \times \text{Characteristic}_{iv} + \delta_4 \text{Insurance takeup}_{iv} \times \text{Characteristic}_{iv} \\ &+ \delta_5 \text{Characteristic}_{iv} + \gamma \mathbf{X}_{iv} + \varepsilon_{iv} \end{aligned}$$

We anticipate that farmer ex-ante responses will be weaker for those with stronger priors, larger for more risk averse farmers, larger for farmers who updated their beliefs the most, and larger for those whose priors were farthest from the forecast.

Next, we measure heterogeneity by a farmer's willingness to pay for the forecast, to measure whether there is selection on gains. Because of our BDM approach, we will only observe willingness to pay for farmers in treated villages, so we interpret these results with caution. Nevertheless, they are potentially revealing. To estimate this, we simply estimate:

$$\begin{aligned} Y_{iv} = &\delta_0 + \delta_1 \text{Insurance takeup}_{iv} + \delta_2 \text{Forecast takeup}_{iv} \\ &+ \delta_3 \text{Forecast takeup}_{iv} \times \text{WTP}_{iv} + \delta_4 \text{Insurance takeup}_{iv} \times \text{WTP}_{iv} \\ &+ \delta_5 \text{WTP}_{iv} + \gamma \mathbf{X}_{iv} + \varepsilon_{iv} \end{aligned}$$

6.4 *Ex post* outcomes

Finally, we estimate treatment effects on outcomes that are realized at harvest. Our predictions for these outcomes are less sharp than in the above sections, as these outcomes will depend on actual rainfall realizations as well as farmers' *ex ante* decisions. We measure impacts on two main sets of *ex post* outcomes: total harvest, yield, and value of crop sales; and household finances and consumption expenditure. As secondary outcomes, we also measure the amount of off-farm work conducted by the household, as well as migration. Finally, we will compute the impacts of exposure to the forecast treatment on stated WTP, collected at endline. If funding allows, we will also plan to conduct a revealed preference WTP follow-up in Spring 2023, but for budgetary reasons, we are currently only including a one-year version of the project in this PAP. We describe how we measure these outcomes in Section 5 above. To estimate treatment effects, we use the same regression specifications, including the heterogeneous treatment effect regressions, as in Section 6.3, but with new outcome variables. For brevity, we do not present these specifications again here.

7 Conclusion

In this project, we study a novel approach for reducing climate risk for farmers in developing countries: long-range monsoon forecasts that provide information about the onset of the monsoon at least one month in advance of its arrival. In contrast to standard tools that help farmers cope with risk *ex post*, such as weather-based index insurance, forecasts are an *ex ante* risk mitigation tool. In the status quo, farmers have limited and inaccurate information about the monsoon's onset, and have high demand for better information. In theory, an accurate forecast enables farmers to optimize their up-front planting and input decisions with respect to the coming growing season's monsoon, rendering it very valuable. Unlike insurance or other financial instruments, forecasts require limited infrastructure to supply to farmers: the information can be disseminated using existing networks of extension agents and/or via SMS messages. Recent advances in climate science have also made monsoon forecast extremely accurate (Stolbova et al. (2016); Potsdam Institute for Climate Impact Research (2021)). The forecast we use in this study provides information about the monsoon's onset over Telangana, and its predictions have been correct in each of the past 10 years.

We propose a cluster-randomized trial that randomizes villages into one of three groups: a control group, a group that is offered an opportunity to purchase the forecast, and a group that is offered an opportunity to purchase index insurance. This research design enables us to measure farmers' willingness-to-pay for forecasts using the Becker, DeGroot, and Marschak (1964) mechanism; to estimate the impacts of the forecast on up-front investment decisions such as crop choice, fertilizer, and planting time; and the impact of forecasts on ex post outcomes like yields, profits, and household consumption. Finally, we can benchmark the impacts of forecasts against index insurance.

We expect this project to make a significant contribution to the literature on the impact of risk-mitigation technologies, and agricultural policy in the developing world. Approximately one-third of the global population lives in the Asian monsoon region, where this type of forecast could substantially improve agricultural outcomes at low cost.

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Appendix for:

The value of forecasts: Experimental evidence from developing country agriculture

A Seasonal climate forecasts

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

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

Seasonal quantity forecasts have typically been one of the main areas of focus of the IMD which provides forecasts of the expected seasonal total rainfall each year at the beginning of the ISM. These forecasts, many statistical in nature, have traditionally focused on the All-

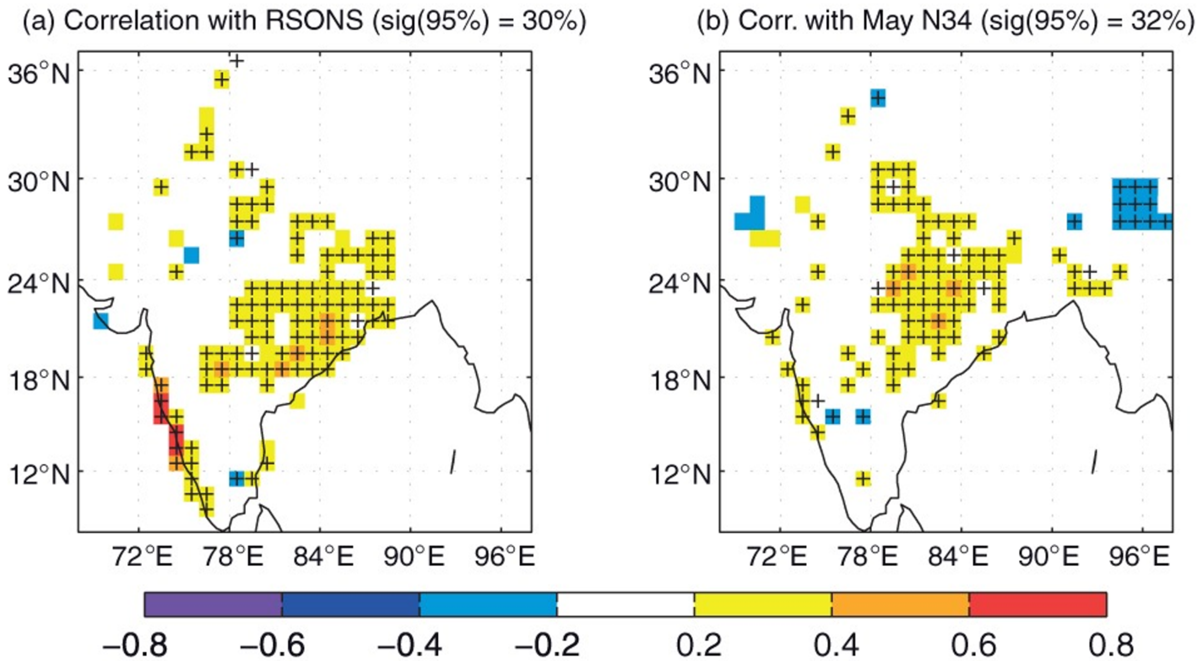
India Rainfall Index (AIRI) (Rajeevan et al. (2007)). One of the most persistent criticisms of the AIRI forecasts is that the AIRI is itself a meaningless spatial average describing a phenomenon that has little spatial coherence (Moron, Robertson, and Pai (2017)) and has little relevance to district-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

Seasonal timing forecasts typically deal with the "onset" of the monsoon. IMD forecasts and measures the onset only over one part of the country— 'monsoon onset over Kerala" (MOK)—which is not relevant for most of the country, and forecasts with only two weeks of advance notice. There is no local IMD monsoon onset forecast, and MOK has been the subject of much of the research on onset timing and forecasting (e.g. Preenu, Joseph, and Dineshkumar, 2017). Crucially, for the current study, the monsoon does not progress smoothly northwards - it frequently halts, and local false starts are common, implying that MOK carries no signal for a farmer in parts of India outside of a narrow strip of coastal Kerala. Moron and Robertson (2014) define local agronomic onset and demonstrate the correlation between MOK and local onset over India. In Figure A.1, they show that there is virtually no signal value of MOK[19] in any region in India other than Kerala.

In the present study, we focus on onset forecasts for two reasons. First, there is clear demand for information on timing: Mobarak and Rosenzweig (2014) demonstrate that onset

[19] 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).

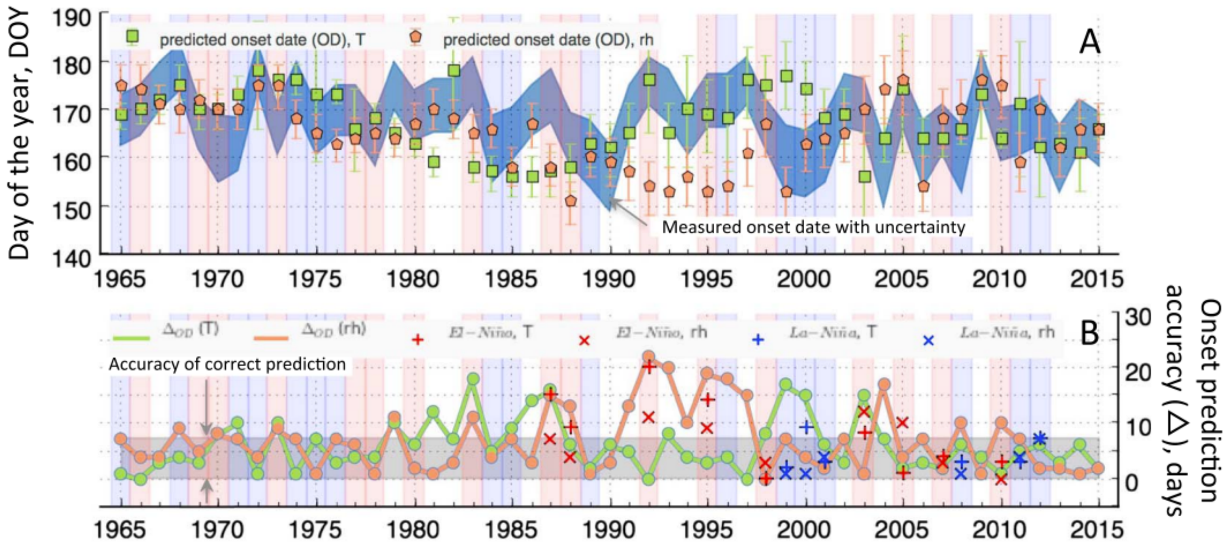
Figure A.1: Monsoon onset over Kerala has limited predictive power elsewhere in India



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).

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

Figure A.2: The PIK forecast is accurate



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

"correct", defined as local onset falling within ±7 days of the predicted date, 73% of years in the sample.[20] Figure Moreover, while MOK date is forecast only two weeks in advance of the average MOK date, the PIK forecast is issued 35 days in advance of the average onset date in Telangana.

B Model details

In this section we present more details on the model describing the value that forecasts provide farmers.

B.1 Farmer's decision-making process: Perfect forecasts

Suppose that the state denoted by ϵ is binary i.e. $\epsilon \in \{0, 1\}$, where 0 corresponds to late onset of rainfall and 1 corresponds to early onset of rainfall. The state is unobserved at

[20]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.

the time when the decision is to be made. Consider the case where the farmer has a prior probability of s_0 that it will rain early. This implies the following model:

$$\begin{aligned} V(\theta, s_0, \eta) = \max_{c,l} \quad & s_0 u(c, \eta | \epsilon = 1) + (1 - s_0) u(c, \eta | \epsilon = 0) \\ \text{s.t.} \quad & c = y - w \cdot l + p \cdot g(l, \epsilon) \\ & y = w \cdot l \end{aligned} \tag{B.1}$$

where $u(c, \eta)$ denotes utility defined over consumption c and unobserved heterogeneity η.[21] Non-farm income is denoted by y, wage by w, labor hired by l, output function by $g(l, \epsilon)$, and price of output by p. Further, $\theta = (y, w, p, g)$. The first budget constraint limits consumption, and the second budget constraint limits labor investment below initial wealth (this assumes no credit markets).

The problem can be solved for $l^*(s_0, \eta, \theta)$. Using implicit function theorem and assuming that $g(l, 1) > g(l, 0)$ and $\frac{\partial g(l,0)}{\partial l} < \frac{\partial g(l,1)}{\partial l}$ for all values of l, gives us that l^* is increasing in s_0.[22] That is if the output is point-wise higher in labor for early onset versus late onset, then a higher prior probability of rainfall is associated with hiring of more labor.

Now suppose the individual is offered a forecast of the state at price q. For simplicity, assume that the prediction is perfect. If the forecast predicts that $\epsilon = 1$, then the individual solves $V(\theta, 1, \eta)$ and if the forecast predicts that $\epsilon = 0$, then the individual solves $V(\theta, 0, \eta)$. At the point of purchase the individual does not know whether the given forecast will be $\epsilon = 1$ or $\epsilon = 0$ and so the gross value of this option is:

$$\bar{V}(\theta, s_0, \eta) = s_0 V(\theta, 1, \eta) + (1 - s_0) V(\theta, 0, \eta) \tag{B.2}$$

where we have assumed that the individual uses his prior distribution to assess the probability that the forecast will predict $\epsilon = 1$ or $\epsilon = 0$. Denote D as the decision of the individual to purchase the forecast. It is given by the following:

[21] Sources of unobserved heterogeneity being ignored are non-farm income, production function heterogeneity and prior heterogeneity.

[22] First assumption ensures that marginal utility from extra consumption is lower in good state and the second ensures that was used to establish the sign when using implicit function theorem.

$$D = \mathbb{1}\{\bar{V}(\theta, s_0, \eta) - \lambda q > V(\theta, s_0, \eta)\} \tag{B.3}$$

where λ is marginal utility of money (assumed to be constant). After the purchase, the individual will solve either $V(\theta, 1, \eta)$ or $V(\theta, 0, \eta)$. The corresponding observed labor outcome L, if the forecast predicts $\epsilon = 1$, will be:

$$L = D \cdot l^*(1, \eta, \theta) + (1 - D)l^*(s_0, \eta, \theta) \tag{B.4}$$

The testable implication of the model is that $l^*(1, \eta, \theta) > l^*(s_0, \eta, \theta)$. Intuitively, the value of the forecast comes from the ability to re-optimizing labor to better match expected rainfall – lowering l if you receive a bad forecast and increasing l if you receive a good forecast – raising profits in both states.

B.2 Varying forecast skill

Denote by $\tilde{\epsilon}$ the forecast that the farmer receives. Define the forecast skill as the probability of ϵ being equal to $\tilde{\epsilon}$ conditional on the realization of ϵ i.e. the forecast skill $Pr(\tilde{\epsilon} = \epsilon|\epsilon)$.[23] Upon purchasing the forecast the farmer updates his prior and uses the posterior probability in the utility maximization problem. The relevant posterior probabilities are given by the following:

$$\Pr(\epsilon = 1|\tilde{\epsilon} = 1) = \frac{\Pr(\tilde{\epsilon} = 1|\epsilon = 1)\Pr(\epsilon = 1)}{\Pr(\tilde{\epsilon} = 1|\epsilon = 1)\Pr(\epsilon = 1) + \Pr(\tilde{\epsilon} = 1|\epsilon = 0)\Pr(\epsilon = 0)}$$

$$\Pr(\epsilon = 0|\tilde{\epsilon} = 0) = \frac{\Pr(\tilde{\epsilon} = 0|\epsilon = 0)\Pr(\epsilon = 0)}{\Pr(\tilde{\epsilon} = 0|\epsilon = 0)\Pr(\epsilon = 0) + \Pr(\tilde{\epsilon} = 0|\epsilon = 1)\Pr(\epsilon = 1)}$$

Both these functions are increasing in forecast skill.

Denote the posterior $Pr(\epsilon = \tilde{\epsilon}|\tilde{\epsilon})$ as s_1. Ex-post knowing the forecast and the forecast skill, the farmer solves the following problems:

$$\begin{aligned} \tilde{V}(\theta, s_1, \tilde{\epsilon} = 1, \eta) = \max_{c,l} \quad & s_1 u(c, \eta|\epsilon = 1) + (1 - s_1)u(c, \eta|\epsilon = 0) \\ \text{s.t.} \quad & c = y - w \cdot l + p \cdot g(l, \epsilon) \\ & y = w \cdot l \end{aligned} \tag{B.5}$$

[23] We assume that $Pr(\tilde{\epsilon} = 1|\epsilon = 1) = Pr(\tilde{\epsilon} = 0|\epsilon = 0)$

$$
\begin{aligned}
\tilde{V}(\theta, s_1, \tilde{\epsilon}=0, \eta) = \max_{c,l} \quad & (1-s_1)u(c,\eta|\epsilon=1) + s_1 u(c,\eta|\epsilon=0) \\
\text{s.t.} \quad & c = y - w \cdot l + p \cdot g(l,\epsilon) \\
& y = w \cdot l
\end{aligned} \tag{B.6}
$$

Ex-ante, since the farmer does not know the forecast at the point of purchase but knows the forecast quality, the gross value of the purchase is:

$$
\hat{V}(\theta, s_0, s_1, \eta) = s_0 \tilde{V}(\theta, s_1, \tilde{\epsilon}=1, \eta) + (1-s_0)\tilde{V}(\theta, s_1, \tilde{\epsilon}=0, \eta) \tag{B.7}
$$

where we have assumed that the individual uses his prior beliefs to assess whether the forecast will predict $\tilde{\epsilon}=1$ or $\tilde{\epsilon}=0$. The willingness to pay equation will change to the following:

$$
D = \mathbb{1}\{\hat{V}(\theta, s_0, s_1, \eta) - \lambda q > V(\theta, s_0, \eta)\} \tag{B.8}
$$

After the purchase, the individual will solve either $\tilde{V}(\theta, s_1, \tilde{\epsilon}=1, \eta)$ or $\tilde{V}(\theta, s_1, \tilde{\epsilon}=0, \eta)$. The corresponding observed labor outcome L, for a forecast of $\epsilon = 1$, will be:

$$
L = D \cdot l^*(\theta, s_1, \tilde{\epsilon}=1, \eta) + (1-D)l^*(s_0, \eta, \theta) \tag{B.9}
$$

As before, the testable implication of the model is that $l^*(\theta, s_1, \tilde{\epsilon}=1, \eta) > l^*(s_0, \eta, \theta)$ if $s_1 > s_0$.

B.3 Insurance

In this section we use the same model framework to illustrate the value an insurance product provides farmers. Suppose the farmer has access to rainfall linked insurance (i.e. they pay a premium in all states but receives a compensation only in the states where there is a late monsoon). The problem can be written as:

$$
\begin{aligned}
V(\theta, s_0, \eta, b) = \max_{c,l} \quad & s_0 u(c,\eta|\epsilon=1) + (1-s_0)u(c,\eta|\epsilon=0) \\
\text{s.t.} \quad & c = y - w \cdot l + p \cdot g(l,\epsilon) + \mathbb{1}\{\epsilon=0\} \cdot b
\end{aligned} \tag{B.10}
$$

where $\epsilon \in \{0, 1\}$ and b denotes the benefit, respectively. The decision to take-up insurance is give by:

$$D = \mathbb{1}\{V(\theta, s_0, \eta, b) - \lambda r(b) > \underbrace{V(\theta, s_0, \eta, 0)}_{=V(\theta, s_0, \eta) \text{ from (1)}}\} \tag{B.11}$$

where $r(b)$ is the premium and λ is the marginal utility of money. The value of insurance is two-fold. First, it provides a direct payout in the event of a late monsoon. Second, by relieving the budget constraint in the bad state, it enables farmers to invest more in production. Therefore, as with insurance, the model implies that $l^*(\theta, s_0, \eta, b) > l^*(\theta, s_0, \eta, 0)$.

C BDM appendix

C.1 Methodological overview

The Becker, DeGroot, and Marschak (BDM) is an incentive compatible process through which a rational participant should reveal their true maximum WTP. We implement the BDM procedure using the following steps:

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.

C.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.