

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

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# Climate change will harm the world's farming poor

**65%** of the world's working poor depends on agricultural livelihoods (Castaneda et al 2010)

Agricultural risk is significant in poor countries:

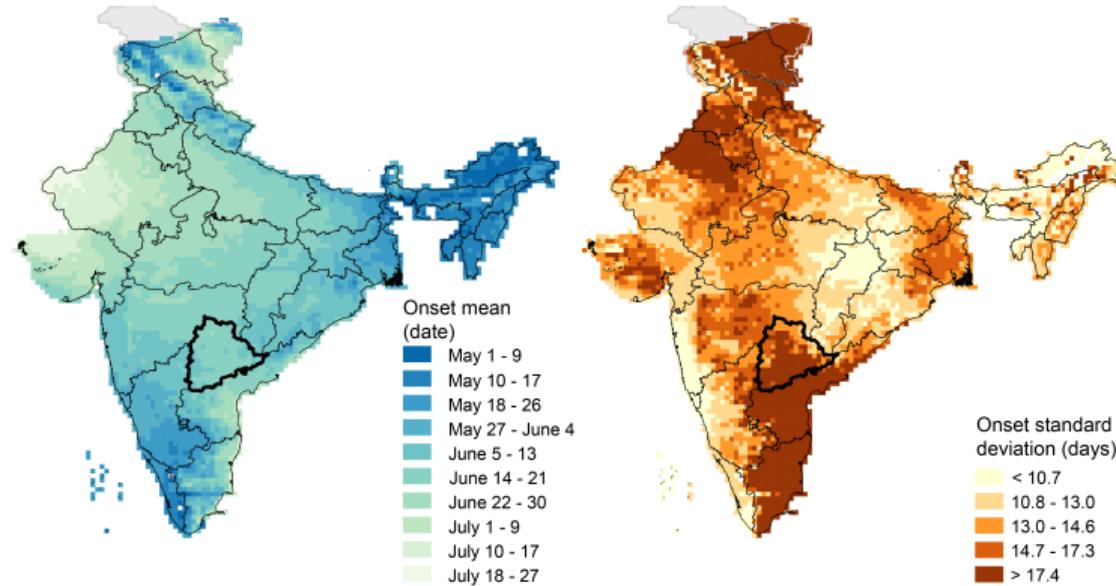
- Uninsured risk leads farmers to underinvest (Rosenzweig and Binswanger 1993)
- This in turn raises the agricultural productivity gap between rich and poor countries (Donovan (2021))

Climate change is disrupting weather patterns

- Timing of rainfall is becoming more variable



# These issues are particularly salient in Indian monsoon-fed agriculture



- 70% of rainfall: during the monsoon season; highly variable (Kumar et al 2013)
- Onset timing matters: Effect of late monsoon on yields is 3x worse for cotton than rice
- Relevant beyond India: > 33% of global pop lives in the Asian monsoon region

# Current adaptation tools can be further developed

- Existing tools for adaptation (infrastructure/seeds) can be costly
  - New seed varieties work well in lab, but are hard to spread & lock farmers into single crop
- Formal insurance markets largely do not exist, gov't insurance program has collapsed
  - Index-insurance has promising theoretical properties but has proven very hard to implement
- Informal mutual insurance arrangements are not designed for weather shock
  - Informal mutual insurance arrangements are unlikely to help when everyone affected
- Information systems designed to help farmers are still limited
  - Farmer beliefs are accurate on average, but predicting particular realization is difficult

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**Farmers' ability to effectively adapt to weather shocks (monsoon variability) is limited**

# We introduce a new tool: long-range monsoon forecasts

## Long-range monsoon forecasts:

- Provide information about the monsoon well in advance of its arrival (4-6 weeks)
- Provide information relevant to the full growing season, not just tomorrow
- Come in two types:
  - Onset timing: Says when the monsoon will arrive
  - Quantity: Says how much rain will fall

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## Forecasts are promising:

- ① Farmers have inaccurate beliefs about onset, and demand for information is high
- ② Forecasts can be delivered at low cost (e.g. via SMS)
- ③ They enable non-marginal behavioral change

**Important note:** Monsoon forecasts are **distinct from** short-range weather forecasts!

# Our forecast is a significant advance over previously-available options

## Our forecast:



POTSDAM INSTITUTE  
FOR CLIMATE IMPACT RESEARCH

- Monsoon onset forecast
- Useful over agricultural regions (Telangana)
- Correct 10 / last 10 years
- Issued  $\approx$  40 days in advance

## Existing forecast:



India Meteorological Department  
Ministry Of Earth Sciences  
Government Of India

- Monsoon onset forecast
- Useful only over Kerala (not ag region)
- Issued  $\approx$  14 days in advance
- Quantity forecast uncorrelated with actual rainfall (Rosenzweig & Udry 2019)

Science of monsoon has not changed → even as variability increases, PIK forecast is viable

We use a cluster-randomized trial to evaluate monsoon forecasts

**This paper: What are the causal impacts of long-range monsoon forecasts for farmers?**

- How do forecasts affect farmer beliefs?
- How do farmers adjust their *ex ante* inputs in response to the forecast?
- What effects does the forecast have on agricultural outcomes and welfare metrics?
- How do these impacts compare to those of index insurance?

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**Why evaluate? In theory, providing accurate information should improve welfare, but...**

- These forecasts are a new technology → adoption may be low
- Farmers must trust information for it to be useful; status quo is low-quality forecasts
- Farmers may not know how to productively use info
- Prior evidence on info & extension services is mixed (J-PAL 2023)

## 1 First experimental evidence on long-range forecasts

- Meza, Hansen, and Osgood (2008): existing RCT evidence only on SR forecasts (still true!)
- New science is making LR forecasts possible (but no info on ground impacts)
- Build on Rosenzweig & Udry (2019): forecasts could be valuable, but limited skill
- Theory + empirics demonstrating the importance of farmer priors

- ① **First experimental evidence on long-range forecasts**
- ② **Forecasts provide new mechanisms for coping with agricultural risk**
  - Forecasts enable farmers to tailor planting decision to coming growing season
  - Insurance: risk smoothing but no tailoring, v. expensive in practice (Cole and Xiong (2017))
  - Different farmers respond to forecasts vs. insurance (addressing gap in insurance lit)

We contribute to literature in development and climate change economics

- ① **First experimental evidence on long-range forecasts**
- ② **Forecasts provide new mechanisms for coping with agricultural risk**
- ③ **In situ evaluation of climate adaptation technology**
  - Lots of work on economics of mitigation (Pindyck (2013)) and costs of climate change (Carleton and Hsiang (2016))
  - New literature incorporating adaptation (Hultgren et al (2023), Carleton et al (2022))
  - We test a particular strategy with a climate-vulnerable population

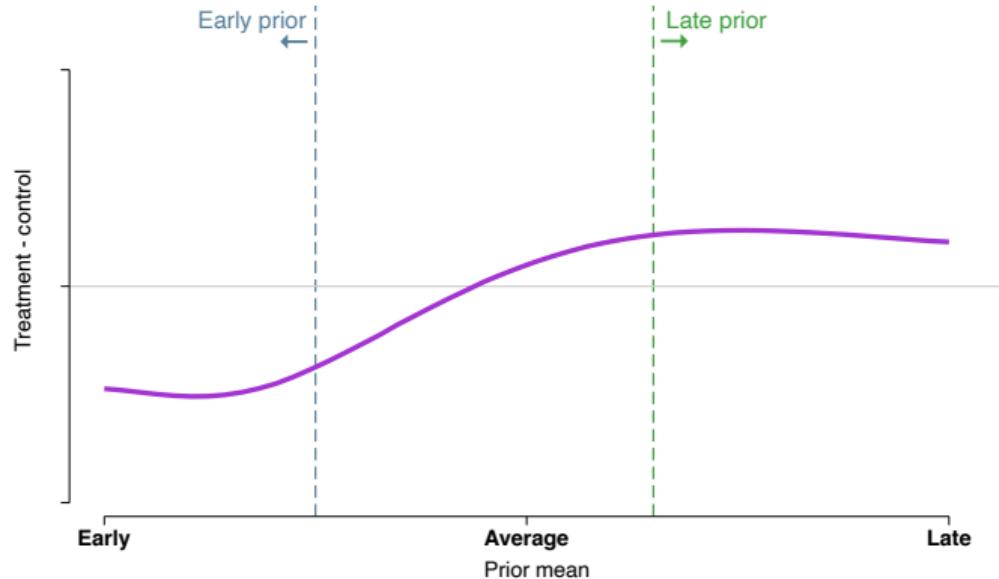
# Simple model of farming under risk to generate predictions

- Two-period model of farmers' decision-making under uncertainty
  - Period 1: Farmers decide how much to save, consume and invest
  - Period 2: Farmers consume production and savings
- Production function depends on the state of the world
  - An earlier monsoon arrival being associated with greater returns to investment
- Farmers have beliefs over the probability distribution of these states
  - They use them to weight possible future outcomes
- Farmers use the forecast to update their priors

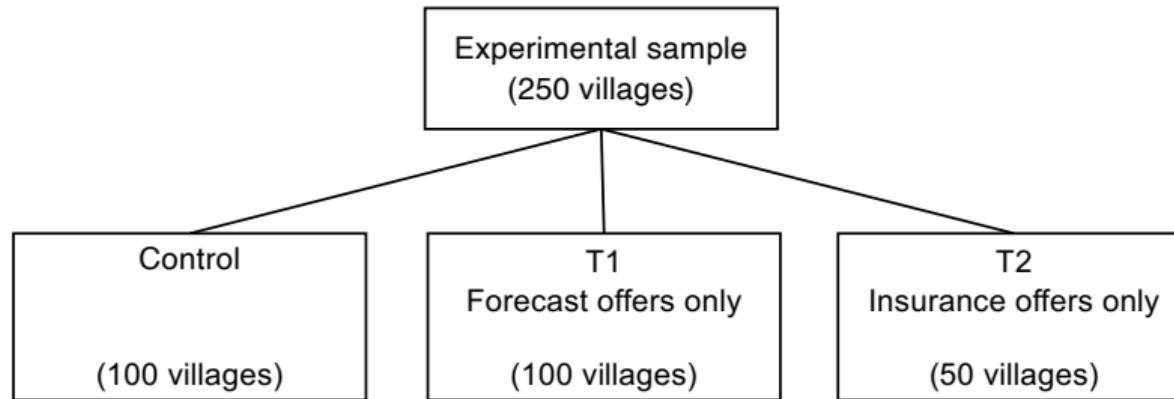
# The effect of the forecast on investments depends on farmer priors

## Forecast effects in the model:

- Causes farmer to update beliefs
- And optimize inputs to states
- Direction of adjustment depends on a farmer's prior
  - Early priors (optimistic)
    - receive bad news
    - reduce investment
  - Late priors (pessimistic)
    - receive good news
    - increase investment



# We use a cluster-randomized trial to evaluate the impacts of forecasts

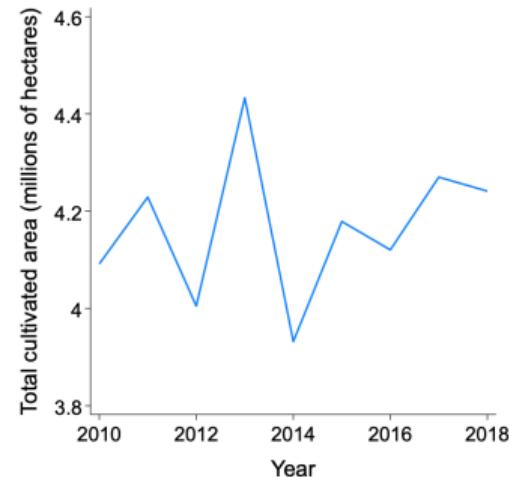
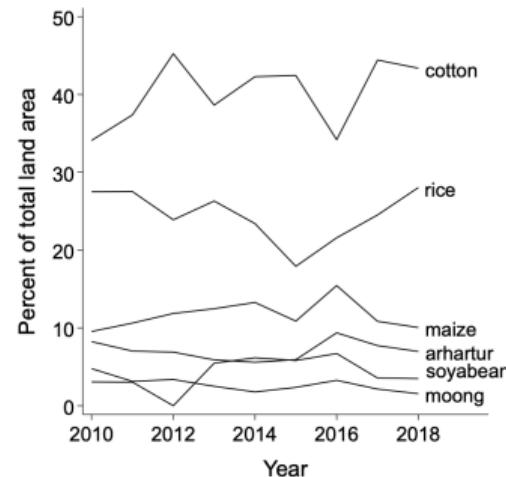


- Sample frame: Villages in Mahabubnagar and Medak districts with low levels of irrigation
- Village-level randomization stratified by district, sampled 5-10 farmers per village
- Implemented in partnership with ICRISAT
- Pre-analysis plan registered with *JDE*

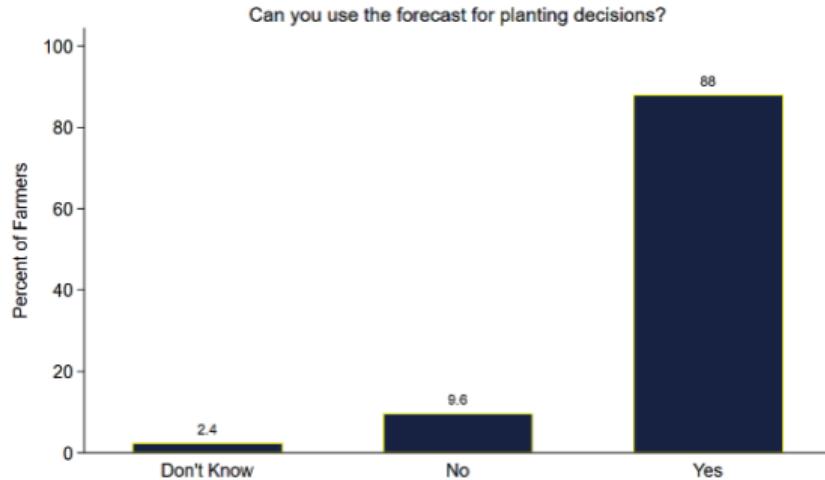
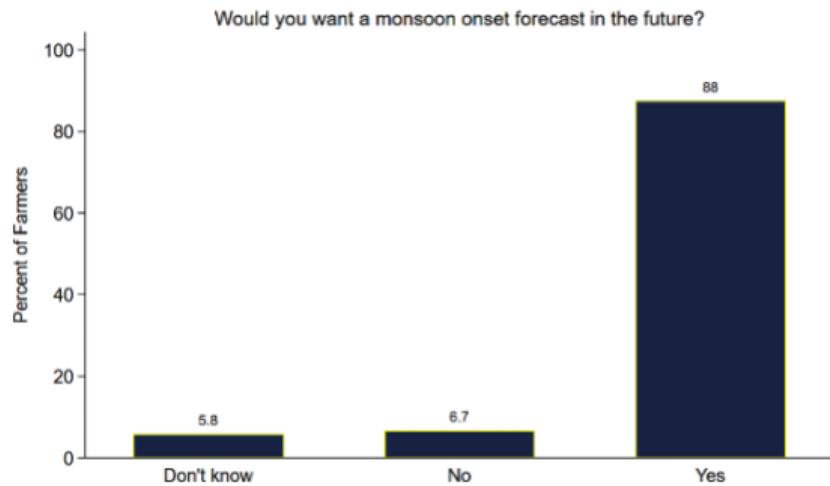
# We carry out our research in Telangana

**With variable monsoons and significant cropping, Telangana is an ideal setting**

- 35 million people. 55% of labor force in ag, while ag only provides 15% of GSVA
- Mean landholdings: 1 hectare
- Main staple crop: Paddy
- Significant cash crop production
- No existing public crop insurance



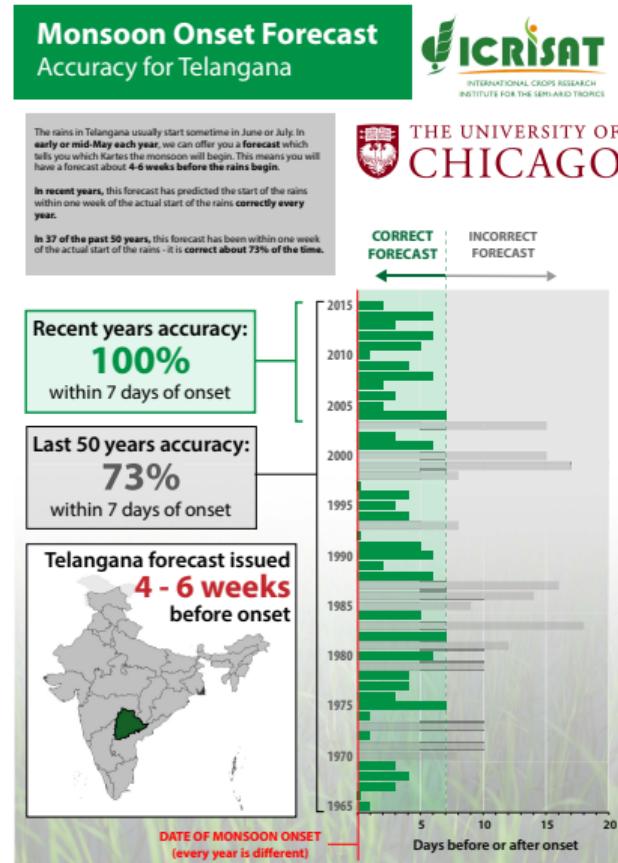
# Farmers in Telangana report that monsoon onset forecasts would be useful



# The actual forecast provides information about this year's monsoon

## Forecast script:

This year's forecast says the monsoon is likely to start over Telangana between June 11th and June 19th, in Mrigashira kartes. This is likely to be followed by a dry spell from June 20th to June 29th, in the first half of Aarudra kartes. The continuous monsoon rainfall is expected after June 29th, in the second half of Aarudra kartes.



# Our insurance is a conditional cash transfer based on monsoon onset time

Modeled on Mobarak and Rosenzweig (2014):

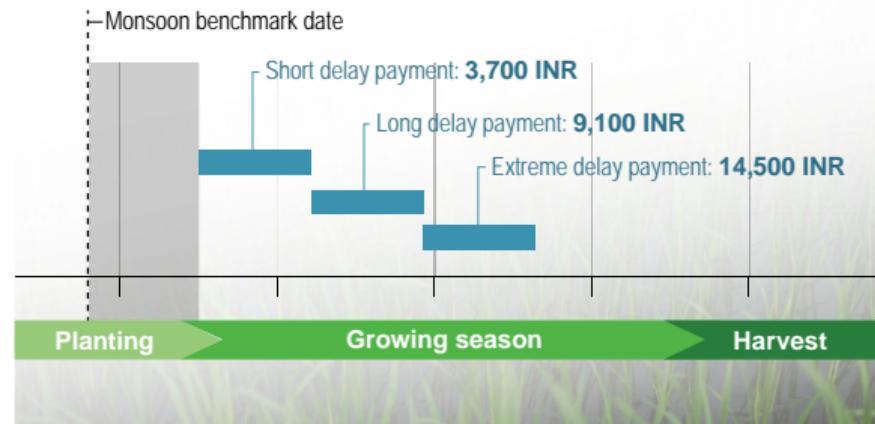
- Village-specific “on time” date
- If the monsoon is:
  - 15-20 days late: small payout
  - 20-30 days late: medium payout
  - 30+ days late: large payout
- Max payout: approx 20% of average revenue
- Measured with local rain gauges
- Farmers receive an SMS informing them of payout status

## Monsoon Onset Payment Payout in case of late rains

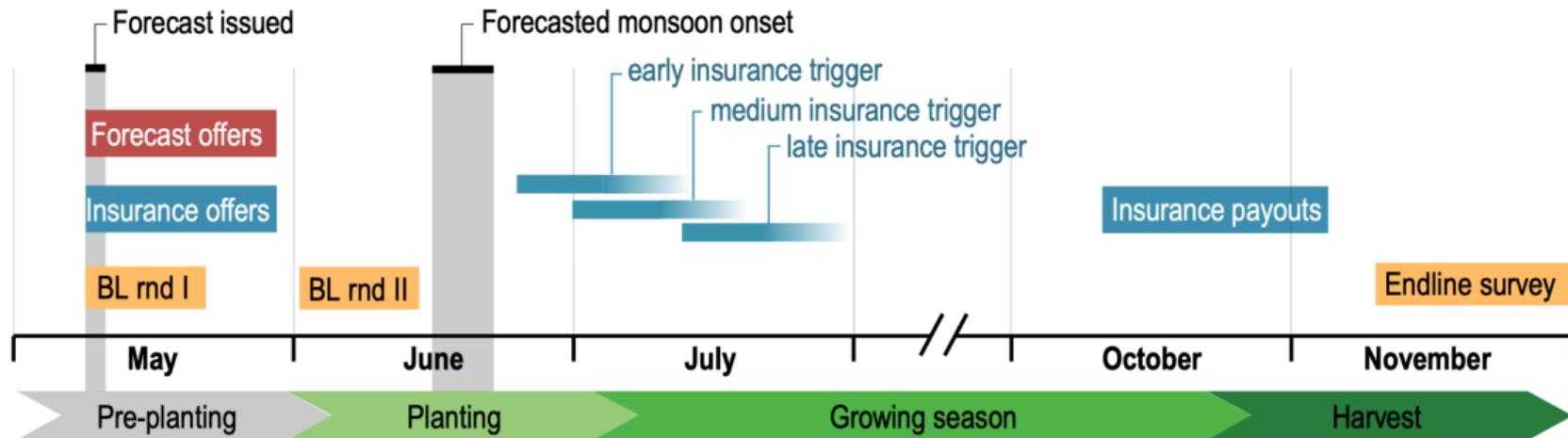
The payout is based on the timing of the start of the rains, measured by a local weather station.

If the rains start before a benchmark date, there will be no payout.

If they are late, payouts will be made according to how late they are. Larger payouts will be made for longer delays.



# Our experiment took place in Kharif 2022



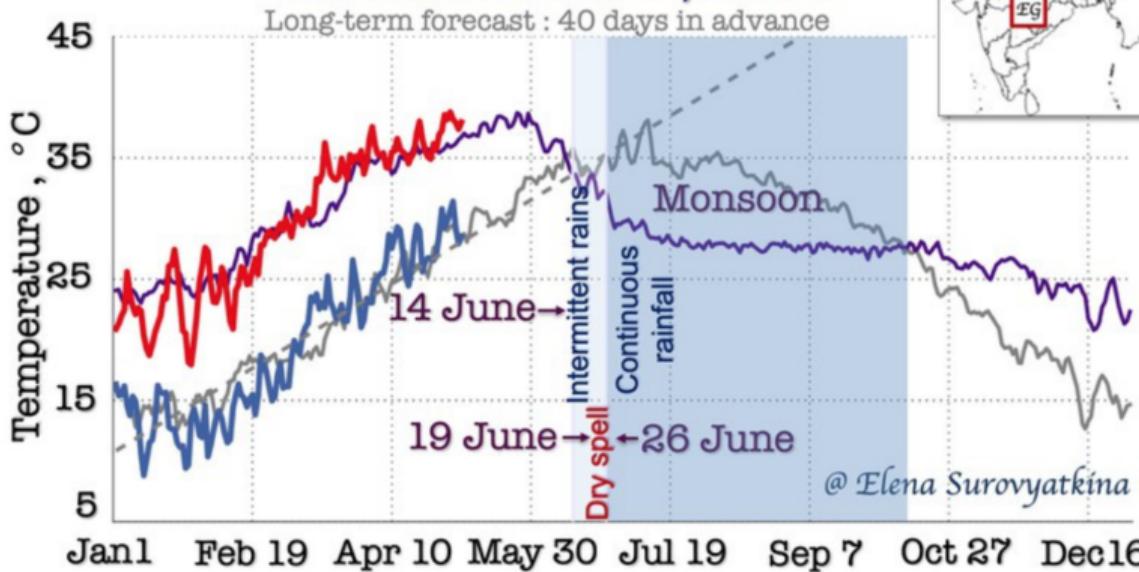
## Key survey details:

- **Baseline I:** Elicits priors before forecast was presented
- **Baseline II:** Elicits posteriors after forecast was presented
- **Endline:** Collects growing season details (crops, inputs, yield, profit, etc)

# The 2022 forecast was accurate

8 May 2022

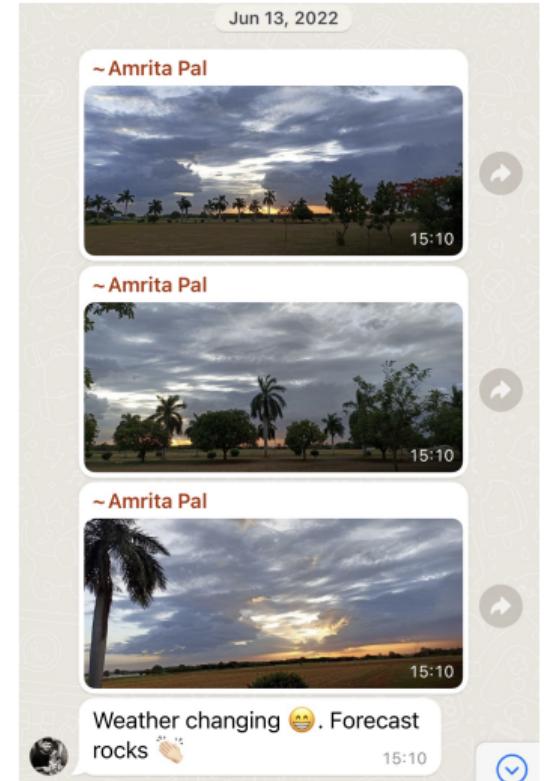
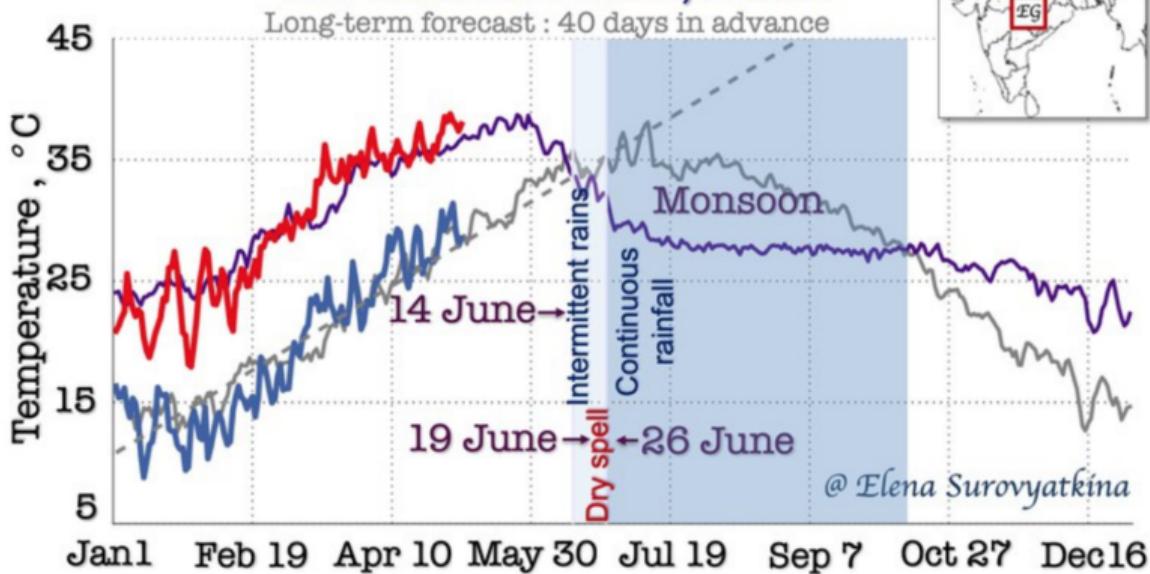
## PIK - Monsoon Onset Forecast for Central India, 2022



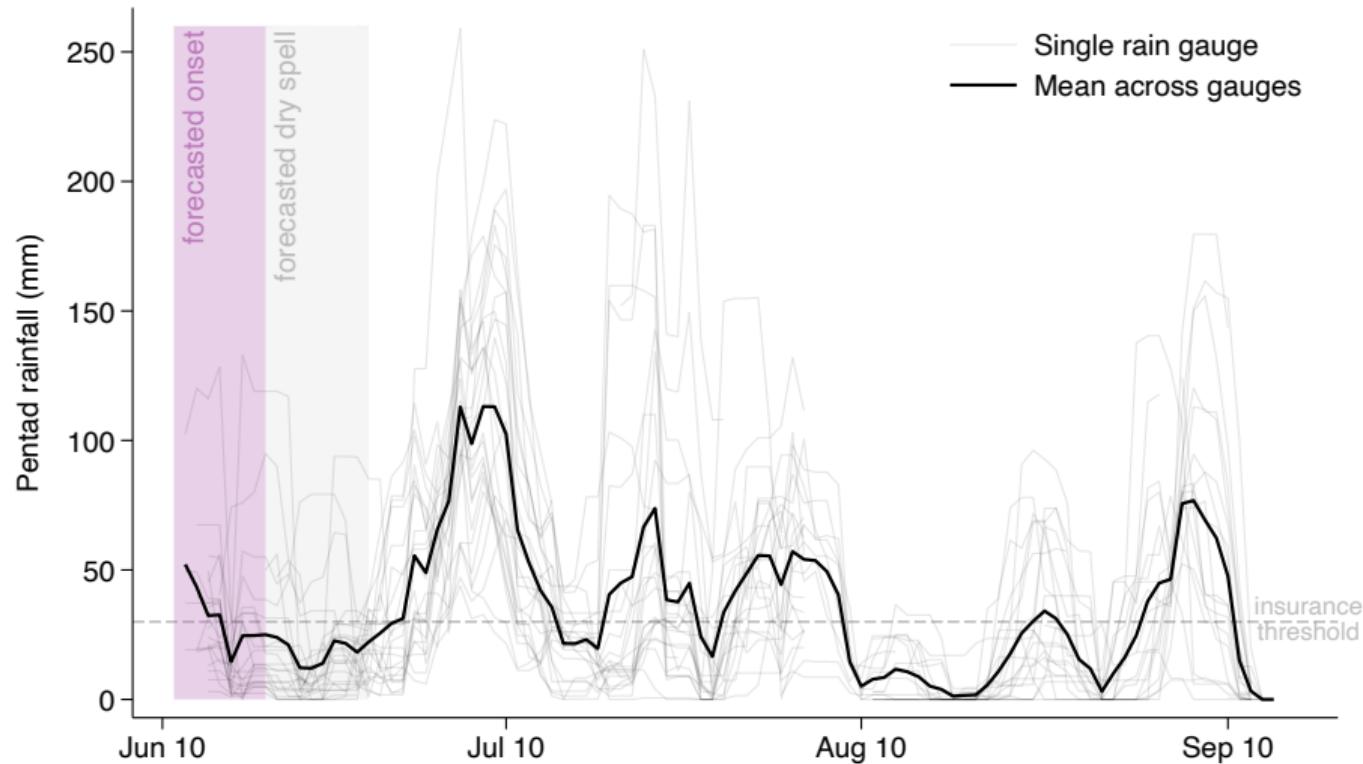
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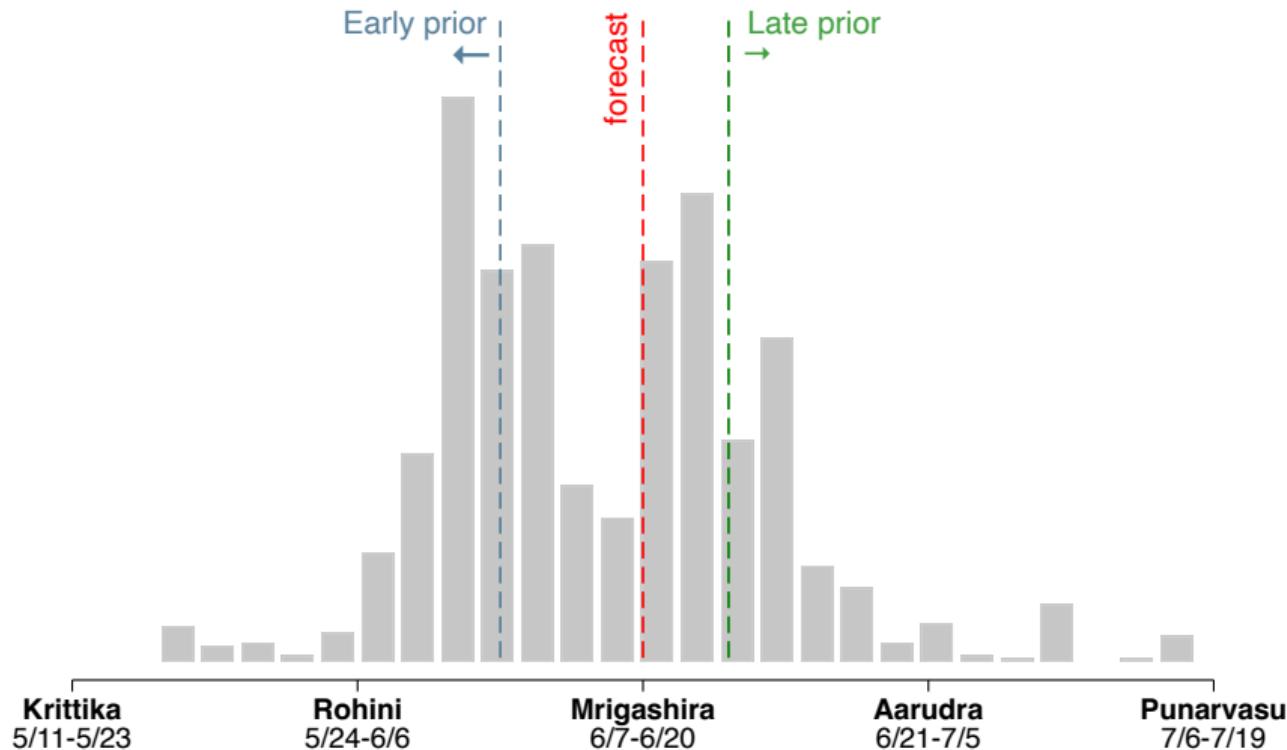
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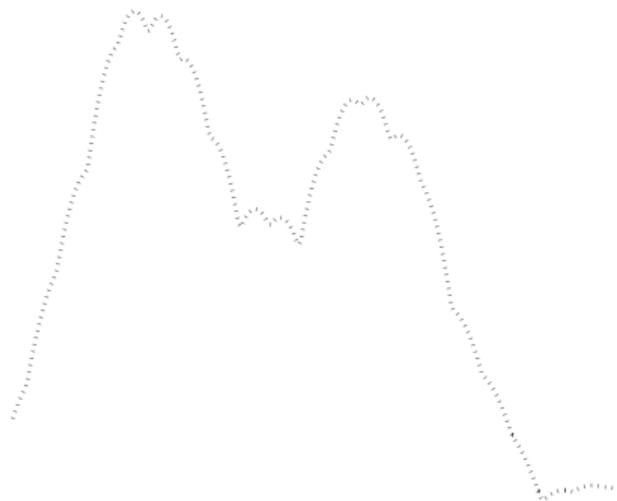
# The 2022 forecast was accurate



# Farmers' priors are centered on the onset date



# The forecast shifts farmers' posterior beliefs toward the forecast



**Rohini**  
5/24-6/6

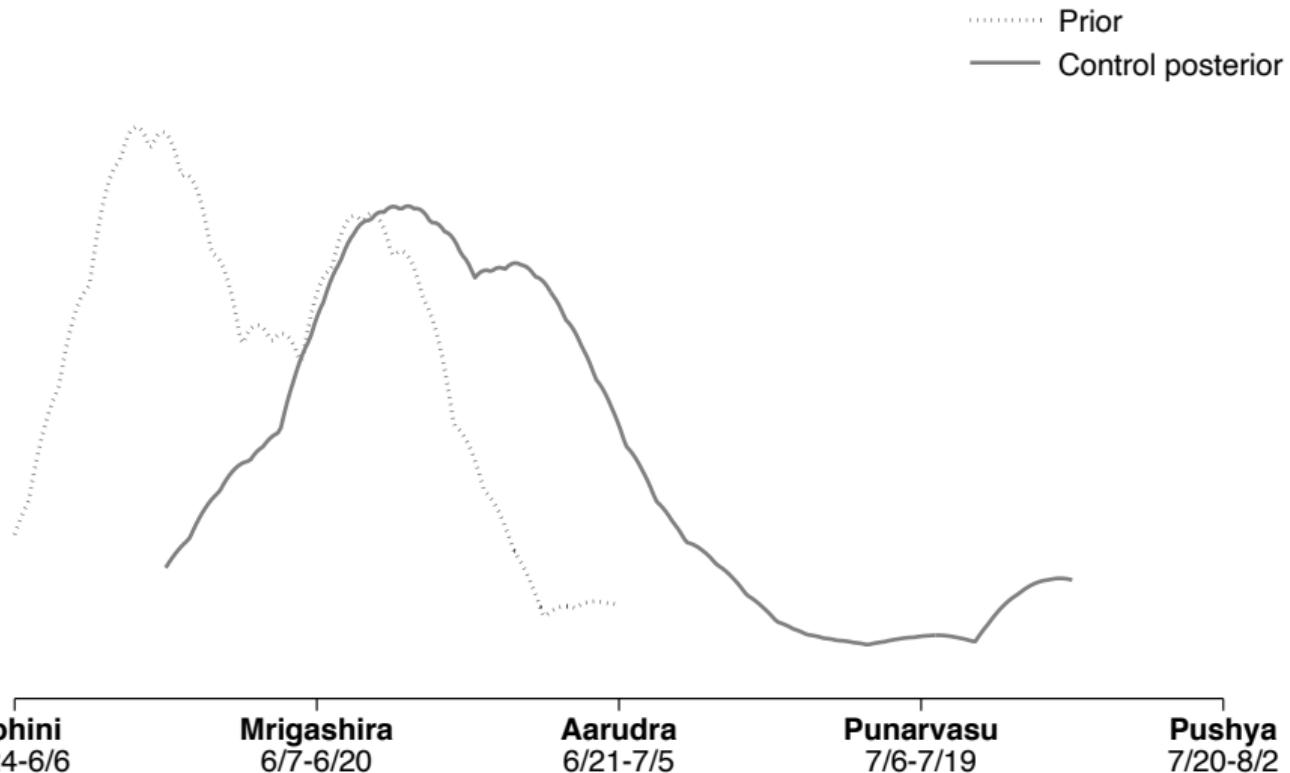
**Mrigashira**  
6/7-6/20

**Aarudra**  
6/21-7/5

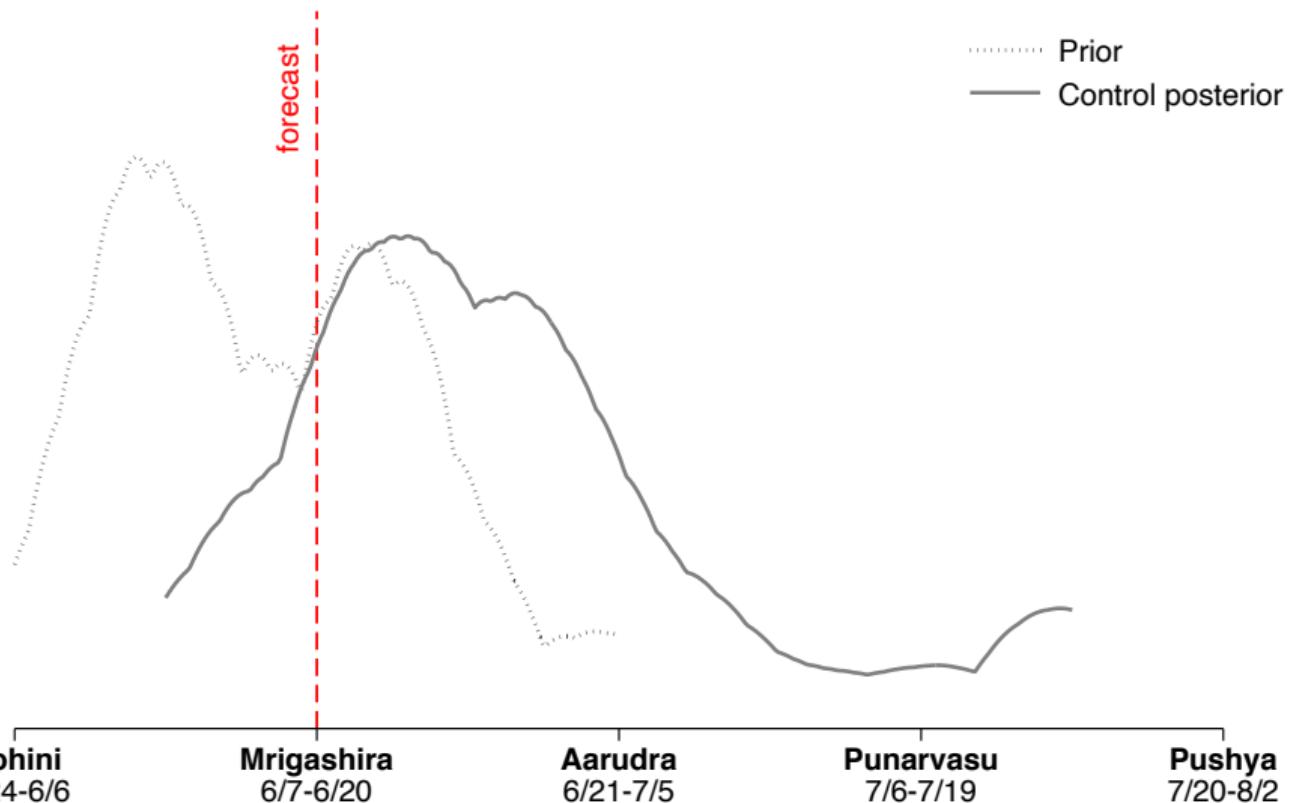
**Punarvasu**  
7/6-7/19

**Pushya**  
7/20-8/2

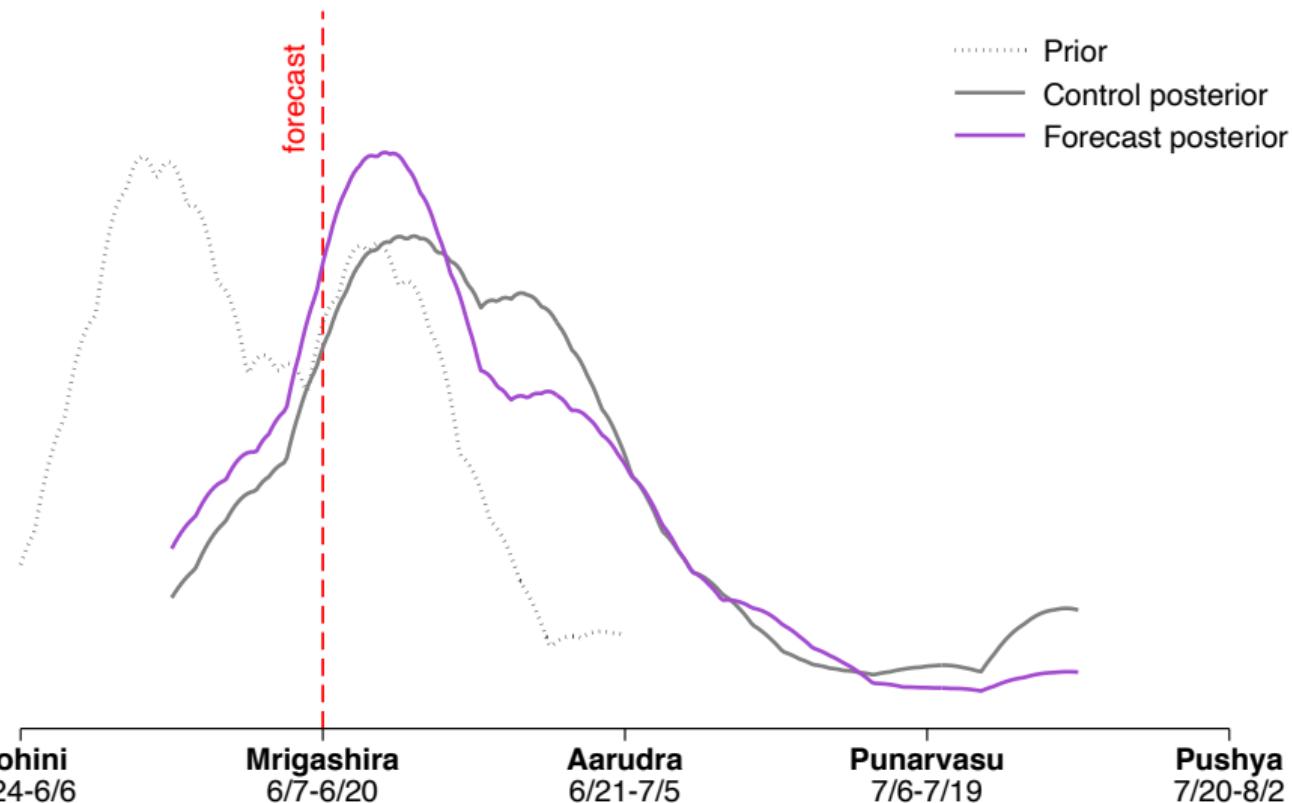
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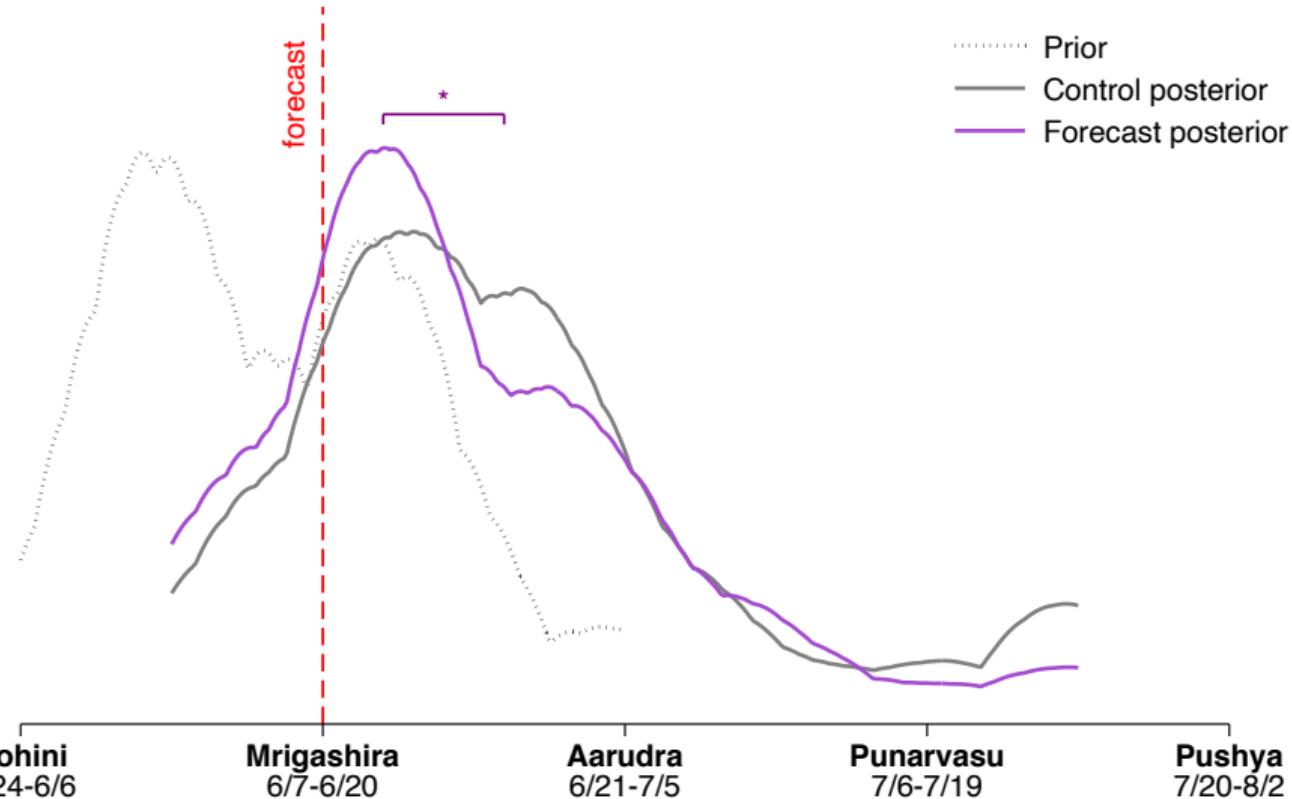


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# The forecast shifts farmers' posterior beliefs toward the forecast

▶ Reg



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5/24-6/6

**Mrigashira**  
6/7-6/20

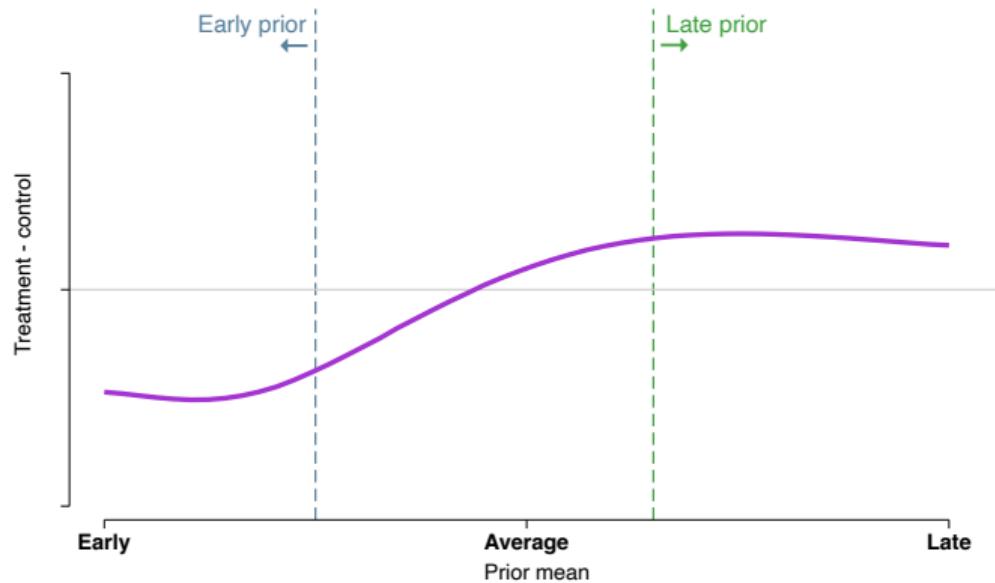
**Aarudra**  
6/21-7/5

**Punarvasu**  
7/6-7/19

**Pushya**  
7/20-8/2

# Recall theoretical prediction: expect heterogeneity by beliefs

- Early priors → **bad news**
- Average priors → **neutral news**
- Late priors → **good news**



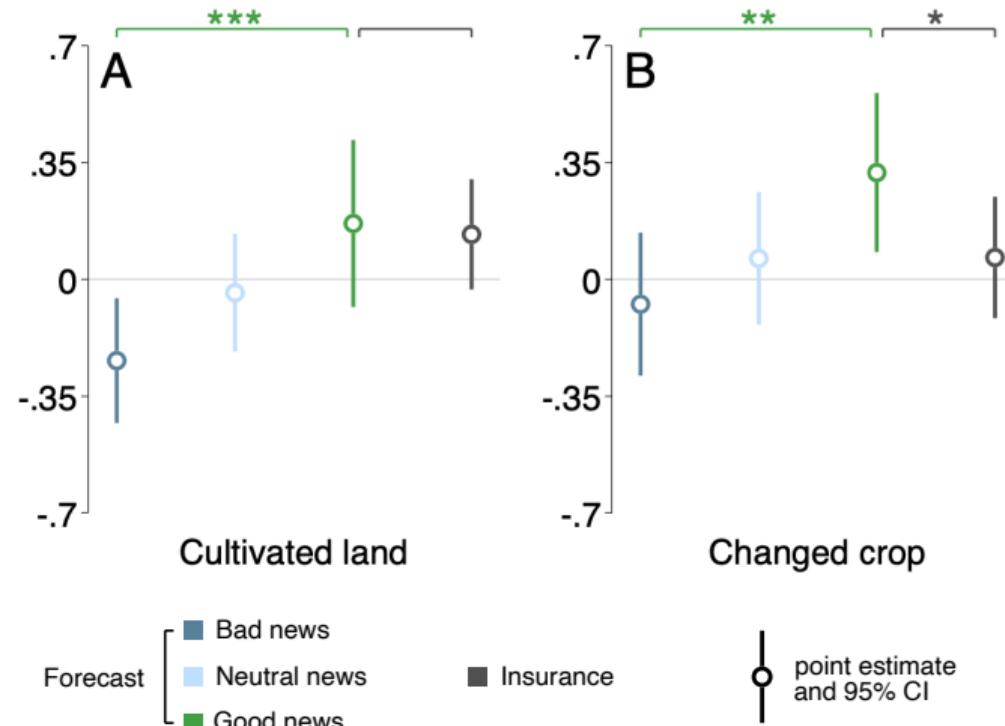
# Theory informs estimation: examine by prior tercile (early, average, late)

Main specification:

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

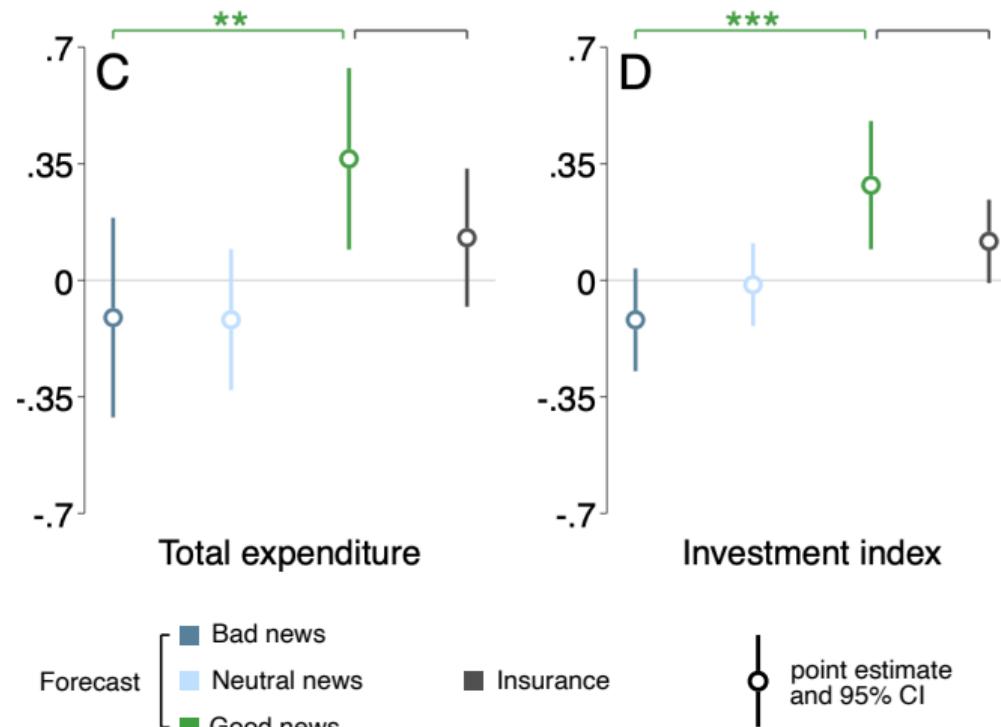
- We compare forecast farmers in each prior tercile to control farmers *with similar priors*
- Estimate average effect of insurance
- LASSO controls and strata fixed effects
- SE's clustered by village

# The forecast substantially changes land use and cropping



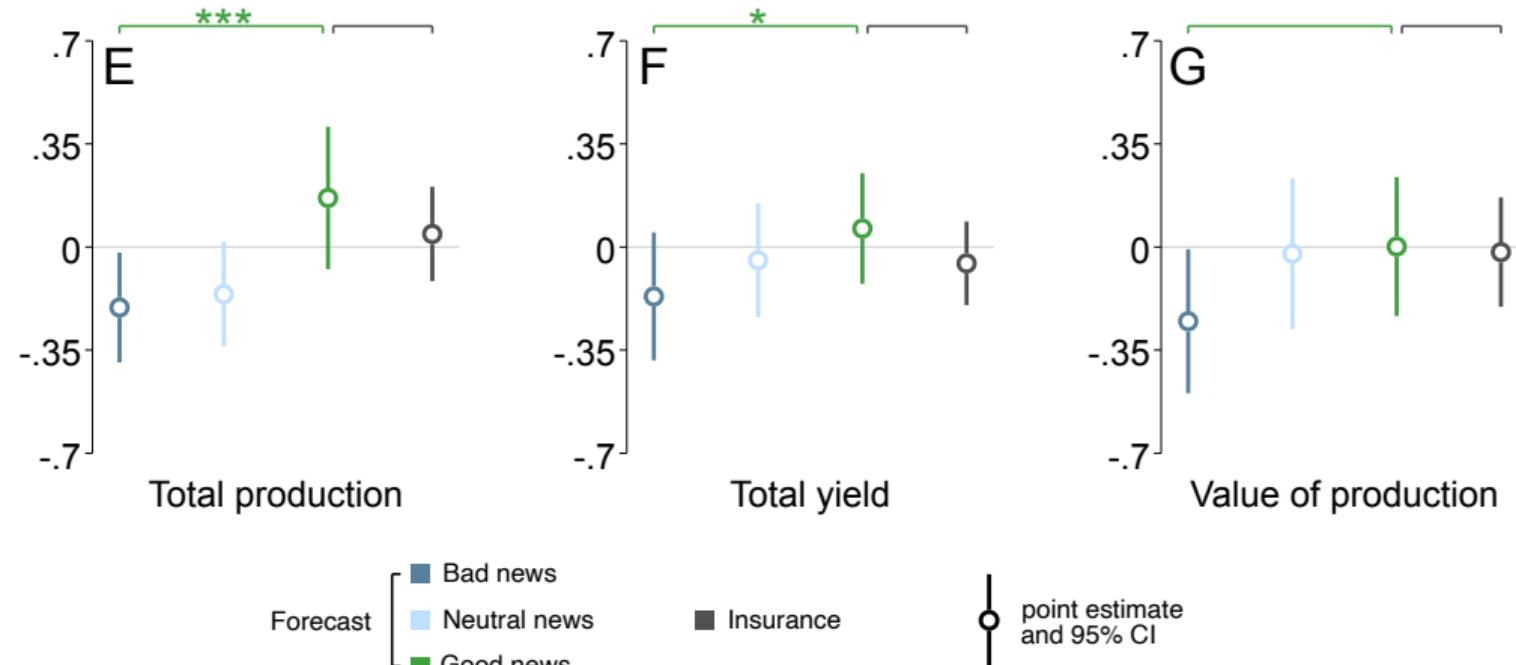
**Crop change driven by new cash crops for good-news farmers**

# Farmers change investments in response to the forecast



**Good-news farmers: 34% increase in total input expenditure**

## Bad-news farmers produce less ag value, good-news null results



**Bad-news farmers: production & value decline consistent with investment reduction**  
**Good-news farmers: production increase, but no change in value**

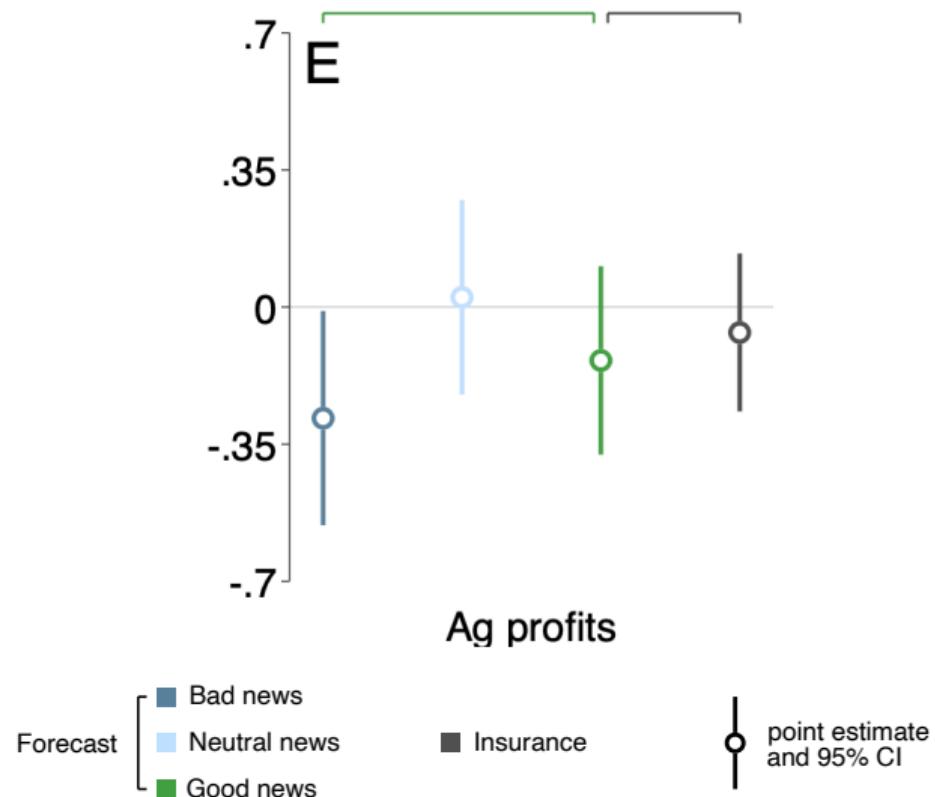
# Changes in investments & cropping outcomes → changes in ag profits

Ag profit effects by type of news:

**Bad:** Invest ↓, profits ↓

**Neutral:** No Δ

**Good:** Invest ↑, profits **no** Δ?



# Lack of agricultural profit impacts for good news farmers is a puzzle

We are evaluating a series of possible explanations:

- **The forecast was inaccurate?** Ruled out: rain gauges align with forecasted onset
- **Farmers did not change beliefs?** Ruled out: farmer beliefs move towards forecast
- **No resulting behavior change?** Ruled out: substantial changes in investment
- **GE effects?** Ruled out: intervention small; no impact on prices
- **Issues with price data?** Survey relatively early, sales endogenously poor? (TBD)
- **Onset is not binding constraint?** Was 2022 a long but bad (e.g., hot) season? (TBD)
- **Farmers don't know how to use forecast?** Were investments low-return?
- **Others?** We welcome feedback on what else to examine!

To better understand ag profit effects, we turn to machine learning

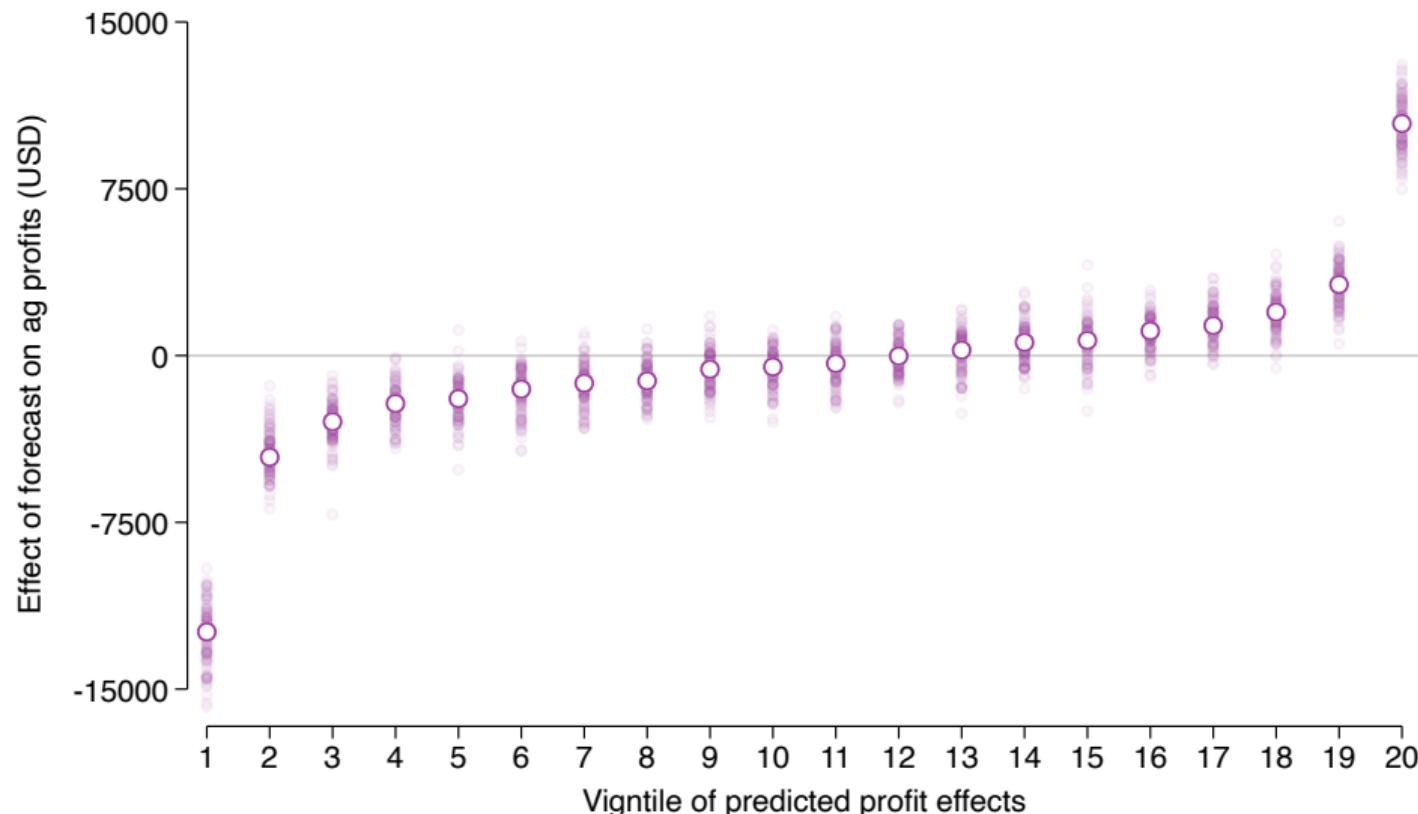
**We want to know:**

- Can we predict heterogeneity in agricultural profit treatment effects?
- Who are the farmers with high predicted treatment effects?
- What do these farmers' *ex ante* investments look like?
- Does this line up with other evidence?

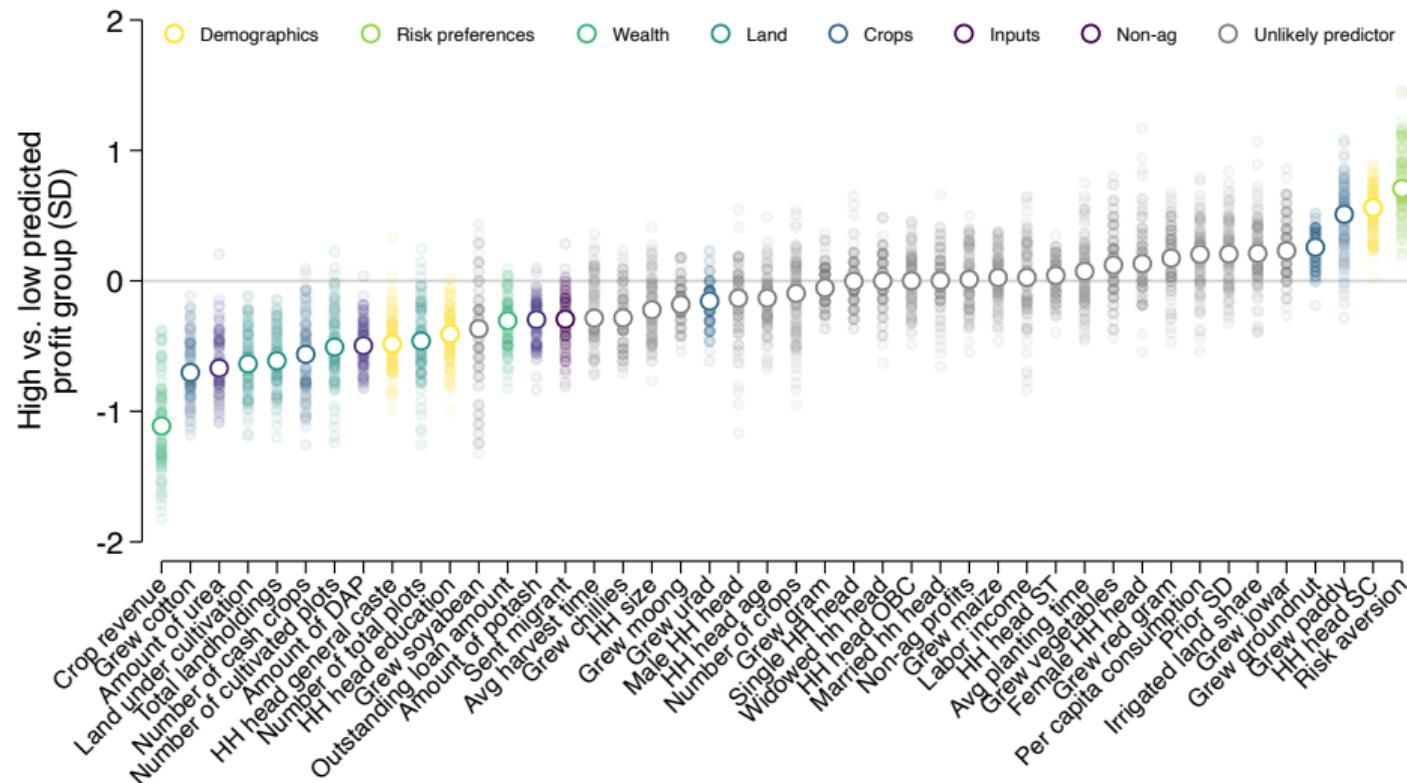
**Chernozhukov, Demirer, Duflo, and Fernández-Val (2023):**

- Generic ML approach to predict TE heterogeneity
- We implement via random forest, creating 100 distinct runs

# Predicted treatment effects indeed predict realized treatment effects



# If anything, higher (predicted) profit effects among least well-off



## Farmers with high predicted TEs farm more land but do less cash cropping

A. Land use	(1) Land Ha.	(2) Cash Crop	(3) Changed Crop	(4) Added Crop	(5) Sub Crop
Forecast	-0.197*** (0.107)	0.061*** (0.015)	0.006 (0.008)	-0.009*** (0.008)	-0.027*** (0.006)
Forecast × CATE	0.028*** (0.006)	-0.004*** (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)
CATE (00 USD)	-0.047*** (0.007)	-0.002 (0.001)	0.001 (0.001)	0.001* (0.001)	0.000 (0.001)
Control mean	2.51	0.51	0.57	0.36	0.39
Observations	955	955	955	955	955

**Magnitude:** 25th → 75th percentile in predicted profit TE → an 0.58 ha larger TE on land cultivation and a reduction of 8.4 pp on cash cropping TE

## Farmers with high predicted TEs spend less on inputs

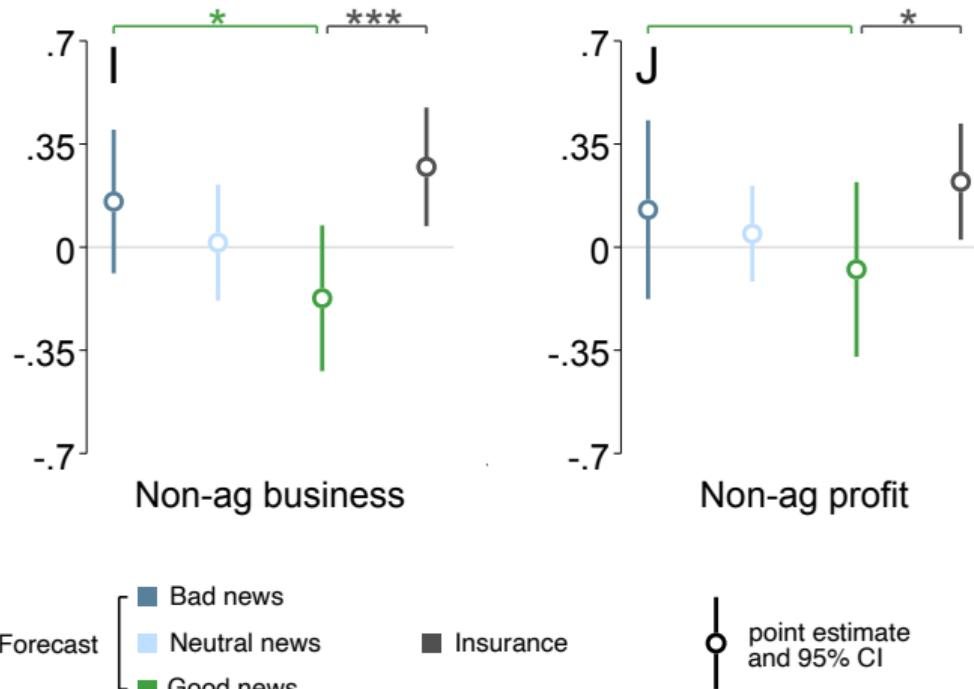
B. Input use	(1) Fert	(2) Seed	(3) Irri	(4) Labor	(5) Total
Forecast	-38.46*** (16.58)	-160.70*** (59.72)	9.41*** (2.51)	43.89*** (15.96)	-161.81*** (76.73)
Forecast × CATE	-4.20*** (1.87)	-18.81*** (4.39)	-0.45 (0.33)	1.66 (2.20)	-22.36*** (7.50)
CATE (00 USD)	-1.94 (1.61)	8.74*** (3.40)	0.20 (0.21)	-9.51*** (1.82)	-5.76 (6.44)
Control mean	492.51	434.41	54.05	761.96	1948.48
Observations	955	955	955	955	955
CATE runs (00 USD)	Mean -4.68	Median -2.79	SD 19.31	P25 -14.14	P75 6.75

**Magnitude:** 25th → 75th pctile in predicted profit TE → a \$460 lower total expenditure TE

# Control farmers also see returns to land, not spending

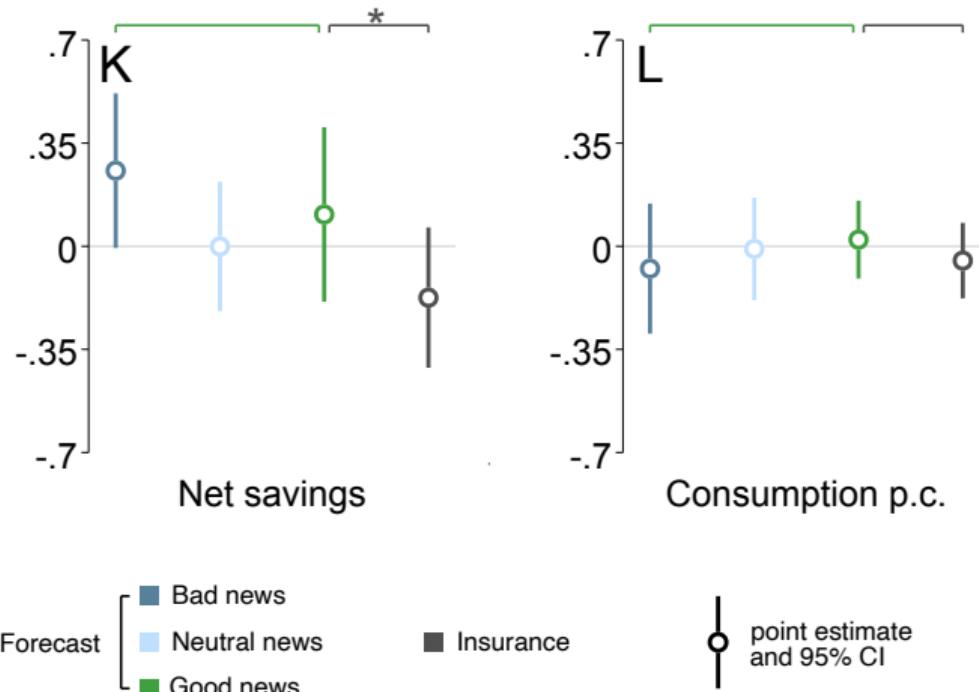
	X	LASSO
Ag land (ha)	838.24*** (128.16)	614.20*** (136.85)
Cash crop (1/0)	28.93 (461.56)	-244.19 (446.94)
Total expend. (USD)	-0.67*** (0.16)	
Fert. expend. (USD)		-0.03 (0.72)
Seed expend. (USD)		-1.30*** (0.18)
Irri. expend. (USD)		-1.29*** (0.17)
Labor expend. (USD)	0.27 (0.61)	0.22 (0.63)
Other expend. (USD)	-0.52 (0.66)	-0.42 (0.69)
Controls	X	LASSO

## Suggestive evidence that **bad-news** farmers do more off-farm work



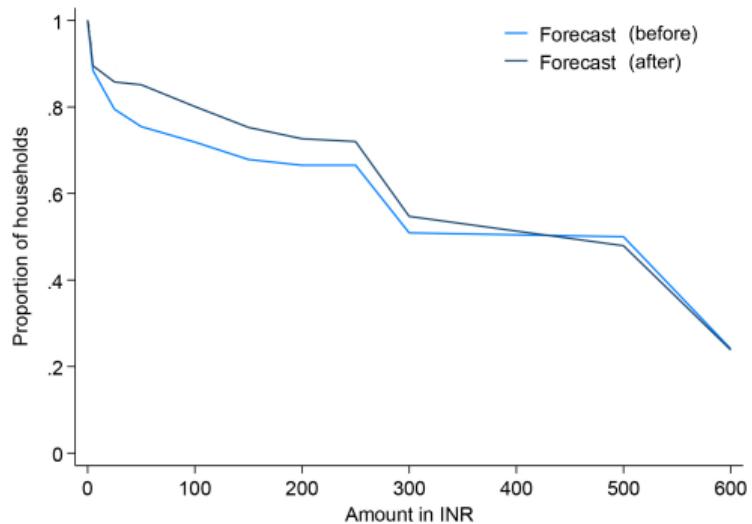
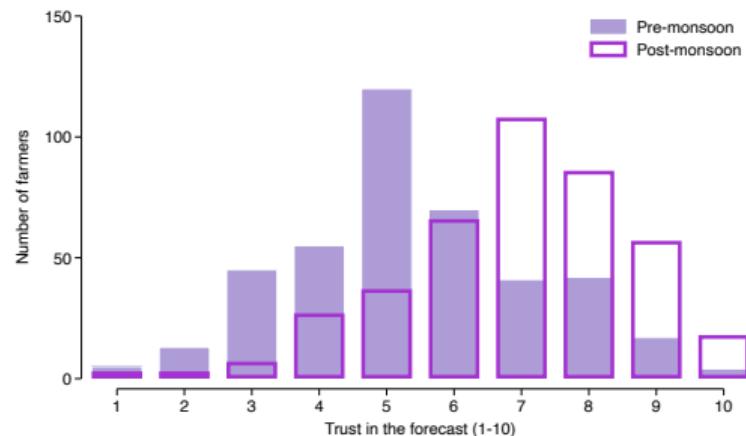
**Bad-news farmers substitute out of agriculture**

## Suggestive evidence that forecast farmers are weakly better off



**Bad-news farmers increase net savings by \$560; 50% reduction in debt**

# How do farmers perceive the forecast after the fact?

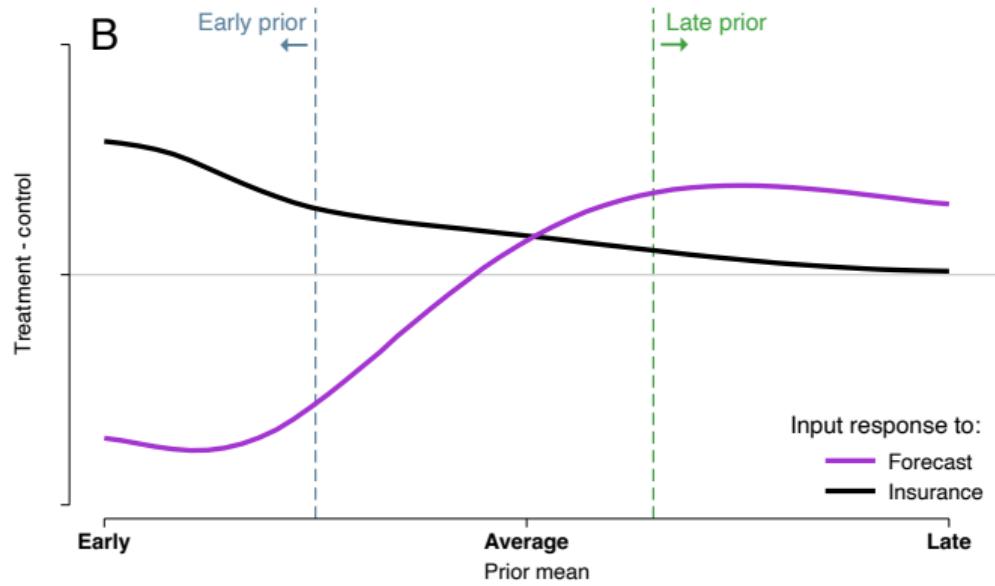


**Trust in the forecast increases, WTP does not decline (vs people who have not gotten forecast before)**

# Theory predicts different responses to the forecast vs. insurance

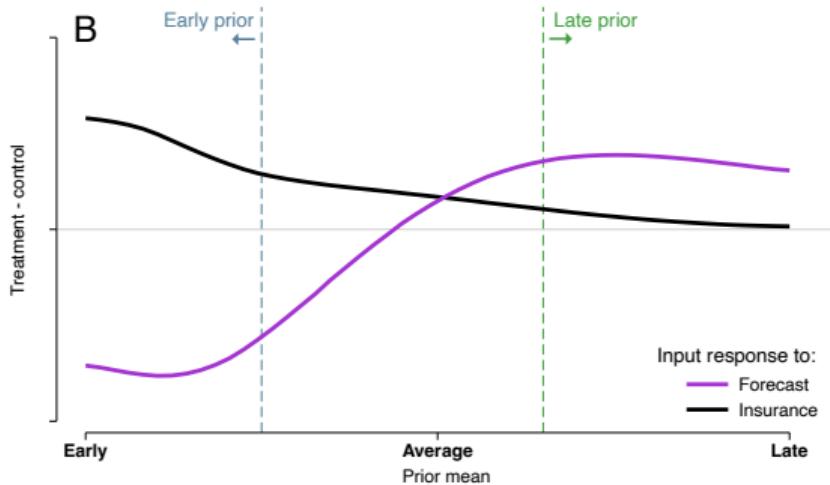
## Insurance effects in the model:

- Induces all farmers to (weakly) increase investment
- Does not allow farmers to optimize to specific state
- “Optimistic” farmers respond, “pessimistic” farmers do not

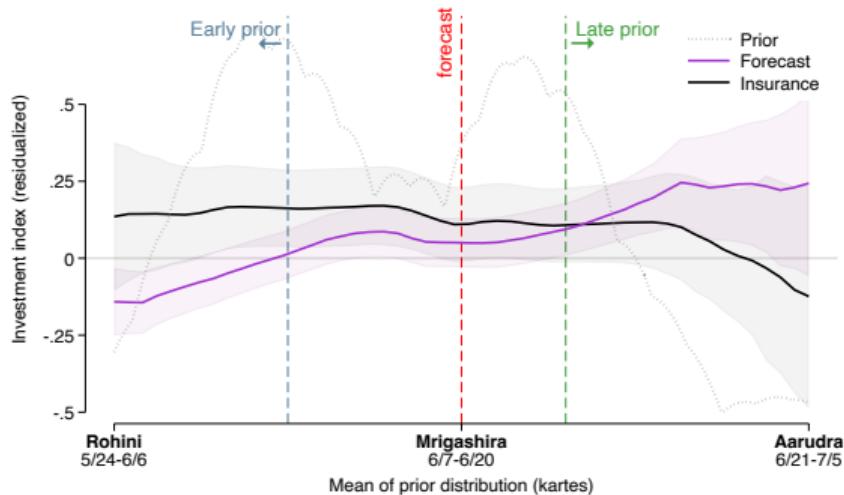
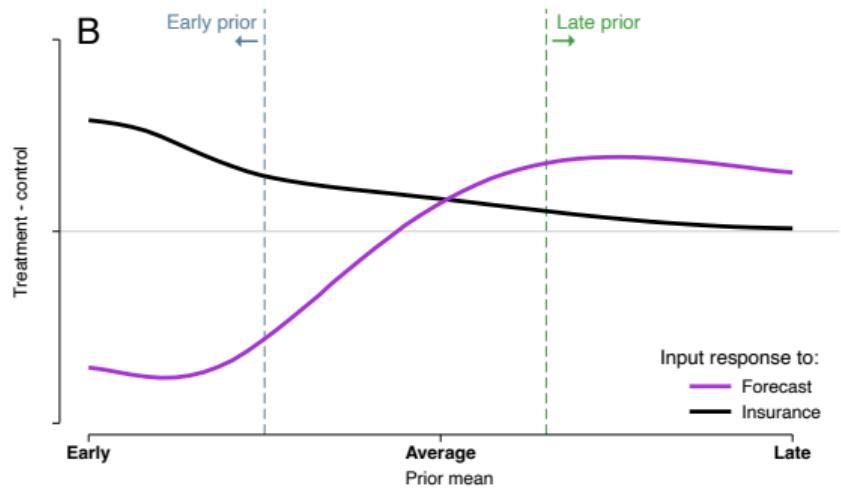


⇒ Clear contrast in responses to insurance vs. forecasts by prior beliefs

# We take these predictions to the data...



..and find evidence in support of them



# We evaluate forecasts' potential as climate adaptation

We use simple theory and an RCT to study a new and an old approach to coping with risk.

---

## Forecasts:

- Shift farmers' beliefs about monsoon onset towards the forecast
- Heterogeneity by priors: good news invest more, bad news less, and change crops
- Profit heterogeneity suggests helps poor most; weak positive welfare effects

## Insurance:

- Insurance causes farmers to expand operations
- Increases in expenditures, no change to cash cropping
- Heterogeneity by priors: optimistic do more, pessimistic do nothing

## In progress:

- Unpack profit effect puzzle further
- Scale: Indian MoA&FW disseminating SMS-based forecasts

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Thank you!

Comments? Questions?

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