Learning, Adaptation, and Climate Uncertainty

Evidence from Indian Agriculture

Kala (WP 2019)

EEE READING GROUP

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December 3, 2020

Known knowns, known unknowns & unknown unknowns

- Climate change will lead to changes in the distribution of weather – some known, others unknown
- Weather-dependent decisions must be based on *incomplete* information, let alone *imperfect* information
- Unlearnable uncertainty may be an important factor that determines climate-sensitive decisions: when to plant, when to invest, when to migrate
- Part of adaptation is knowing what you don't know; should you maximize expected returns or minimize worst-case losses?
- Failure to account for decisions that are robust to this uncertainty may misstate the extent of adaptation

Today: learning about weather uncertainty in Indian agriculture

How do farmers form predictions about a weather-dependent decision (planting time) based on rainfall signals?

- Profitability of agricultural decisions depends on predictions about the weather: timing of planting is key
- Develops a robust learning model where farmers believe rainfall signals are drawn from <u>a set of distributions</u>
- Finds support for idea that farmers respond to greater uncertainty by modifying their predictions to be robust to this uncertainty

Modeling learning

Robust learning model that allows for the fact that farmers may not know the true stochastic process governing the weather.

- Observed rainfall signals are drawn from an unknown member of a set of unspecified stochastic processes
- Farmer uses past signals to decide when to plant
- As a result, farmers make decisions that are robust to **model misspecification**

Compare against two Bayesian normal learning models (where optimal planting time is time-varying or time-invariant)

- Parameter of interest being learned (optimal planting time) and signals drawn from *known* distributions

Model

$$\pi_t(\widehat{\eta}_t, G_t) = a_t - b \int (\widehat{\eta}_t - \eta_t)^2 \, dG_t(\eta_t).$$

- $\hat{\eta}$ = planting time chosen by farmer, expressed in terms of the amount of cumulative rainfall in monsoon thus
- η = optimal planting time, normally distributed (mean μ_t) random walk
- a_t = other household decisions that influence agricultural profits
- y_t = $\mu_t + \delta_t + \varepsilon_t$ = signal received by farmer

Distribution for Bayesian updating

Let F_t denote the distribution obtained from Bayesian updating. A non-robust farmer assumes $F_t = G_t$. By contrast, a **robust** farmer accounts for the fact that G_t may differ from that obtained by F_t from Bayesian updating.

Robust farmer assumes a distribution that minimizes cumulative expected profits and chooses planting date to maximize worst-case expected profits.

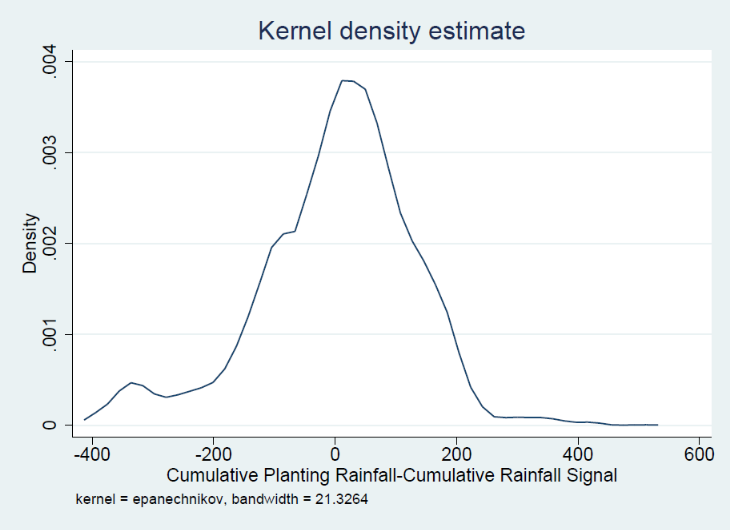
$$\hat{G}_t(\widehat{\eta}_t) = \underset{G_t}{\operatorname{argmin}} \left\{ \underbrace{\pi_t(\widehat{\eta}_t, G_t) + \sum_{t'=1}^{T-1} \pi_t(\widehat{\eta}_{t'}, G_t)}_{\text{Cumulative Profits}} + \underbrace{\frac{1}{\theta} KL(G_t, F_t)}_{\text{Nature's Penalty}} \right\},$$

Optimization

Farmers update beliefs based on past signals which are weighted differently according to their learning model.

$$\widehat{\eta}_{t+1} = (1 - K_t)\,\widehat{\eta}_t + K_t y_t,$$

Figure 2. Kernel Density of Planting Time Relative to Onset Signal



	(1)	(2)	(3)	(4)
	Cumulative Planting Rainfall			
Profit-Maximizing Cumulative Rainfall Last Year (Contemporaneous Rainfall Signal)	0.134	0.226	0.0714	0.0884
	(0.0136)	(0.0157)	(0.0167)	(0.0226)
Fixed Effects	None	Year	Village, Year	Household, Year
Observations	2,551	2,551	2,551	2,551
Mean of Dependent Variable	123.84	123.84	123.84	123.84

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors are clustered at the household level. Profit-maximizing cumulative rainfall last year was the cumulative rainfall for the 5-day period planting in which maximized mean profits in the village last year. The sample includes the first day the household is observed to plant in a given year.

Figure 3. Relative Weights on Information: Varying Signal Variance

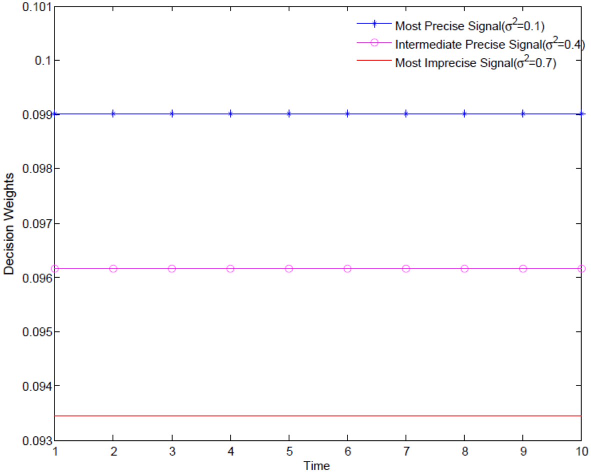


FIGURE 4. Relative Weights on Information: Varying State Variance

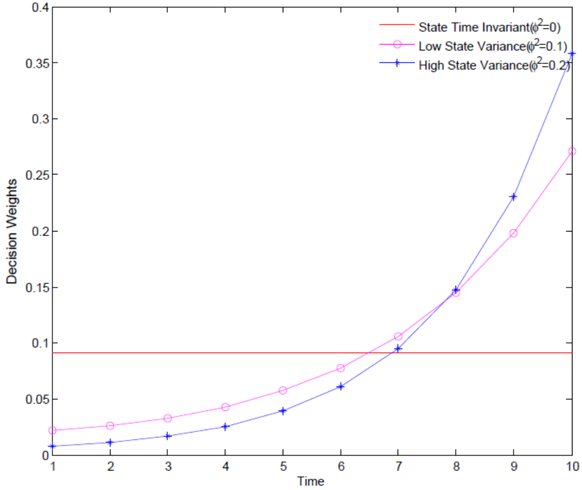
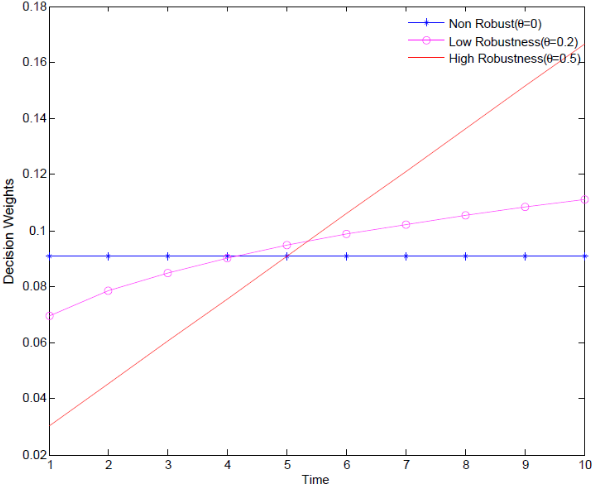
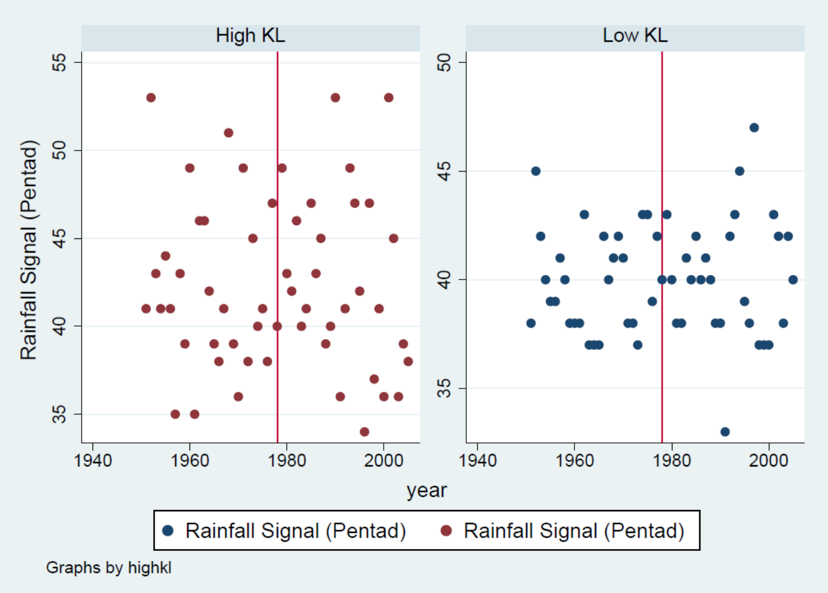
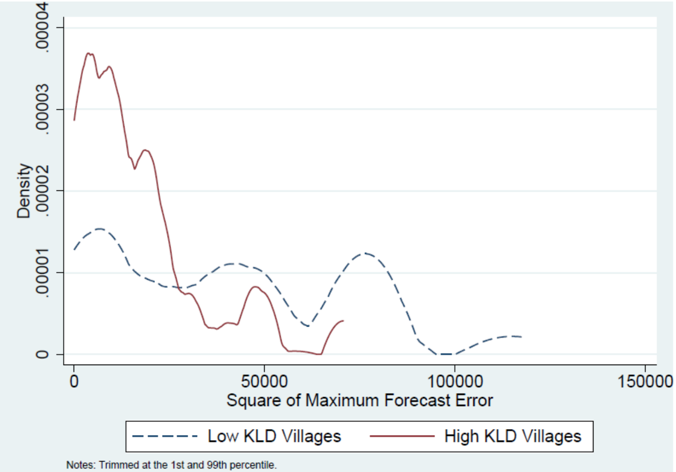


FIGURE 5. Relative Weights on Information:Varying Robustness




High KL
Low KL
Rainfall Signal (Pentad)
55
50
45
40
35
1940
1960
1980
2000
year
Rainfall Signal (Pentad)
Rainfall Signal (Pentad)
Graphs by highkl


Density
0
.00001
.00002
.00003
.00004
0
50000
100000
150000
Square of Maximum Forecast Error
Low KLD Villages
High KLD Villages
Notes: Trimmed at the 1st and 99th percentile.