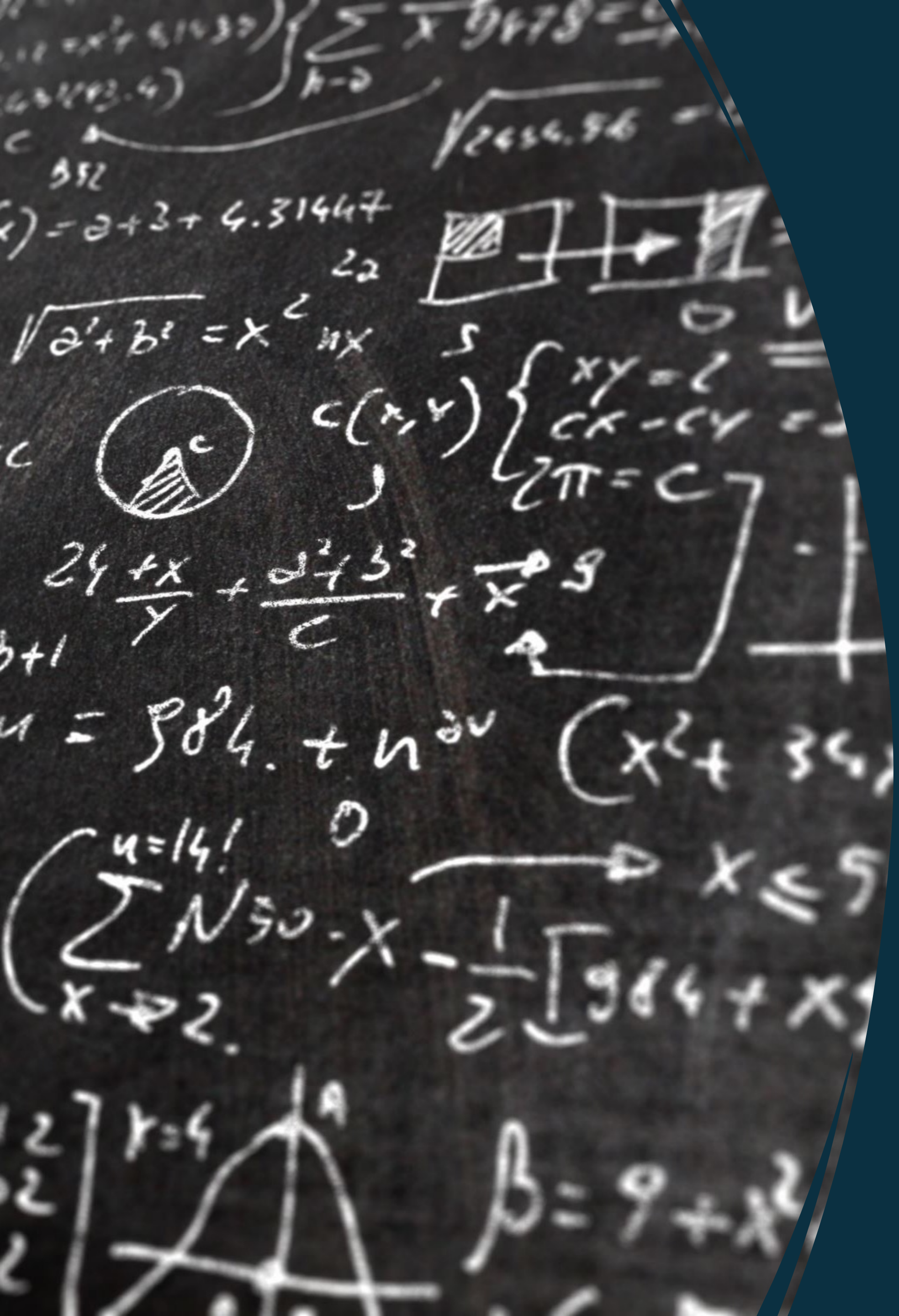

Over- and Underreaction to Information

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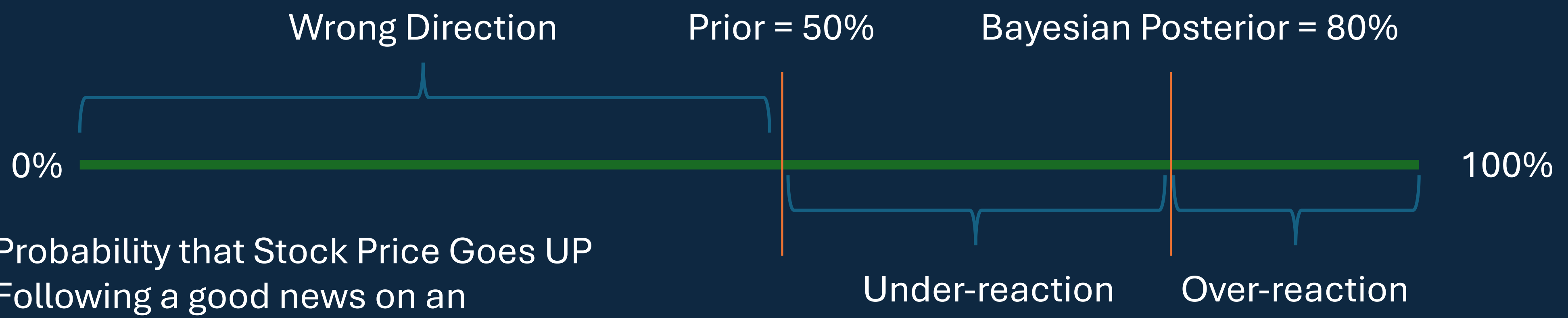
Overarching Question: How do people update their belief according to new information?

- **Traditional Assumption**: Bayes' Rule for rational updating. – Benchmark

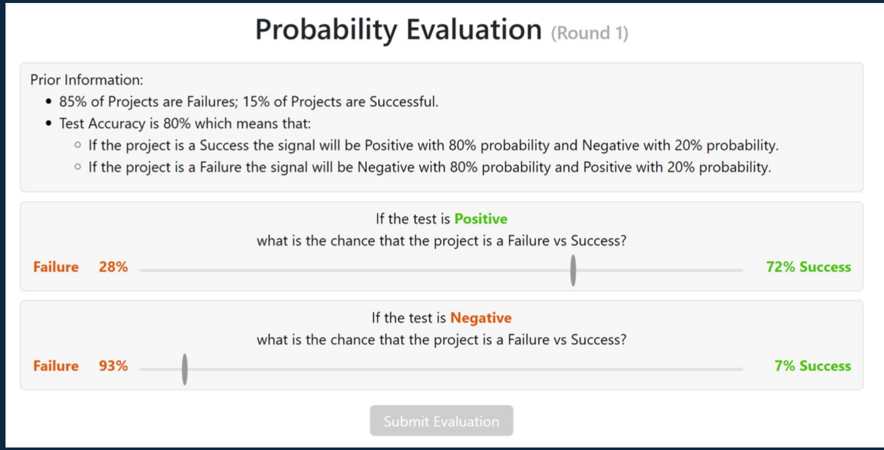
- Human Behaviour:



Probability that Stock Price Goes UP Following a good news on an unexpected increase in profit announcement

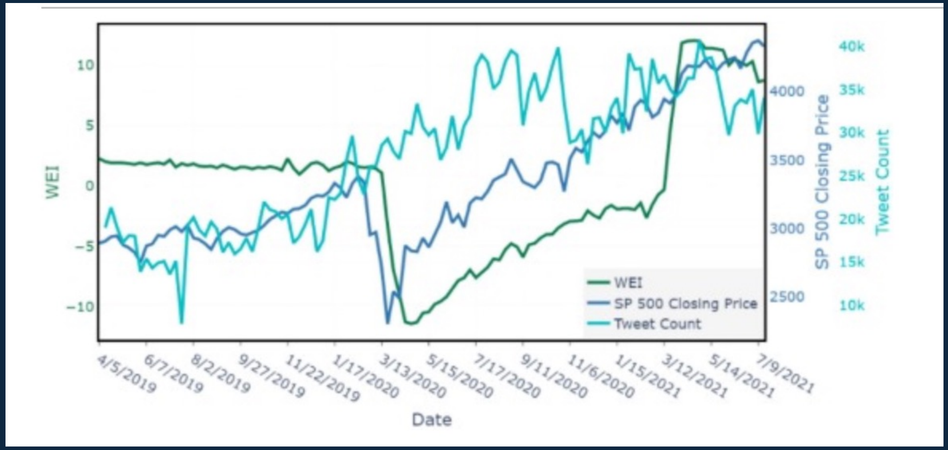
Empirical Evidence: Under-reaction in lab setting but Over-reaction in real world stock market

Lab Experiment: Under-reaction



2 latent States
2 Possible Realised Outcomes
1 Sample
Usually signal not noisy (85%-15% here)

Stock Market: Over-reaction



>2 latent States
- Company Future Earnings

2 Possible Realised Outcomes
- Stock Price Increase or Decrease

>1 Sample
Usually noisy signals (e.g. 60%-40%)

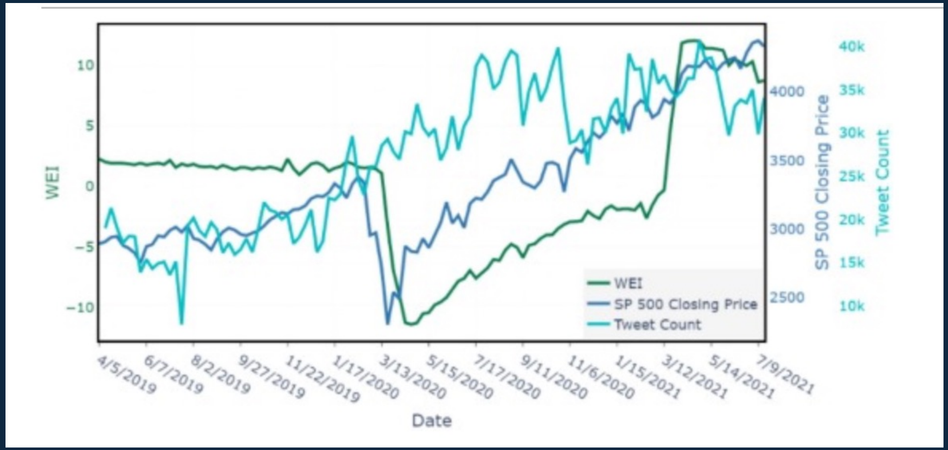
Pre-registered Hypothesis: Over-reaction happens in more complex environments and noisier signals

Manipulate

1. the number of states
2. signal diagnosticity (noisiness)

to test to test over(under)-reaction

Stock Market: Over-reaction



>2 latent States

- Company Future Earnings

2 Possible Realised Outcomes

- Stock Price Increase or Decrease

>1 Sample

Usually noisy signals (e.g. 60%-40%)

Method: Classical ‘bookbag-and-poker-chip’ design (aka urn selection problem). N=2210 participants on Prolific

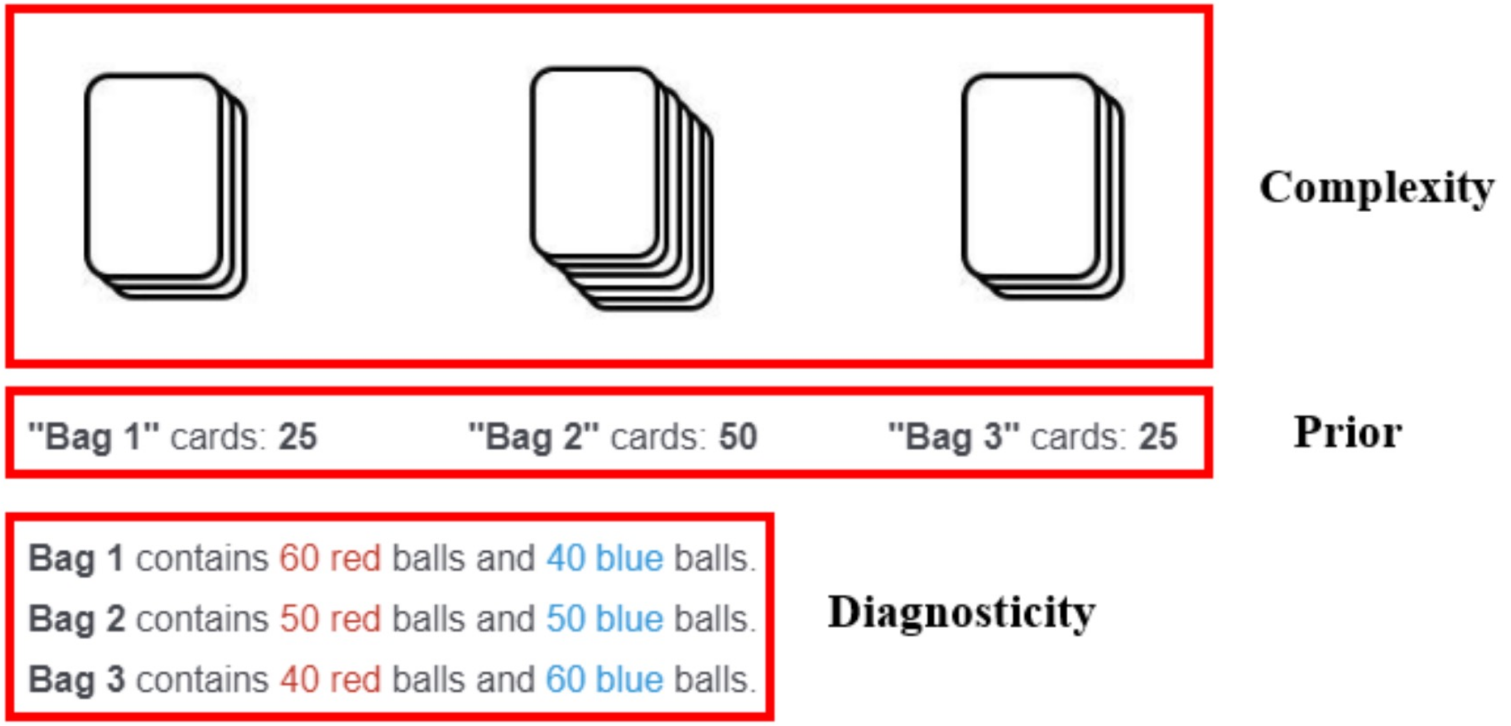


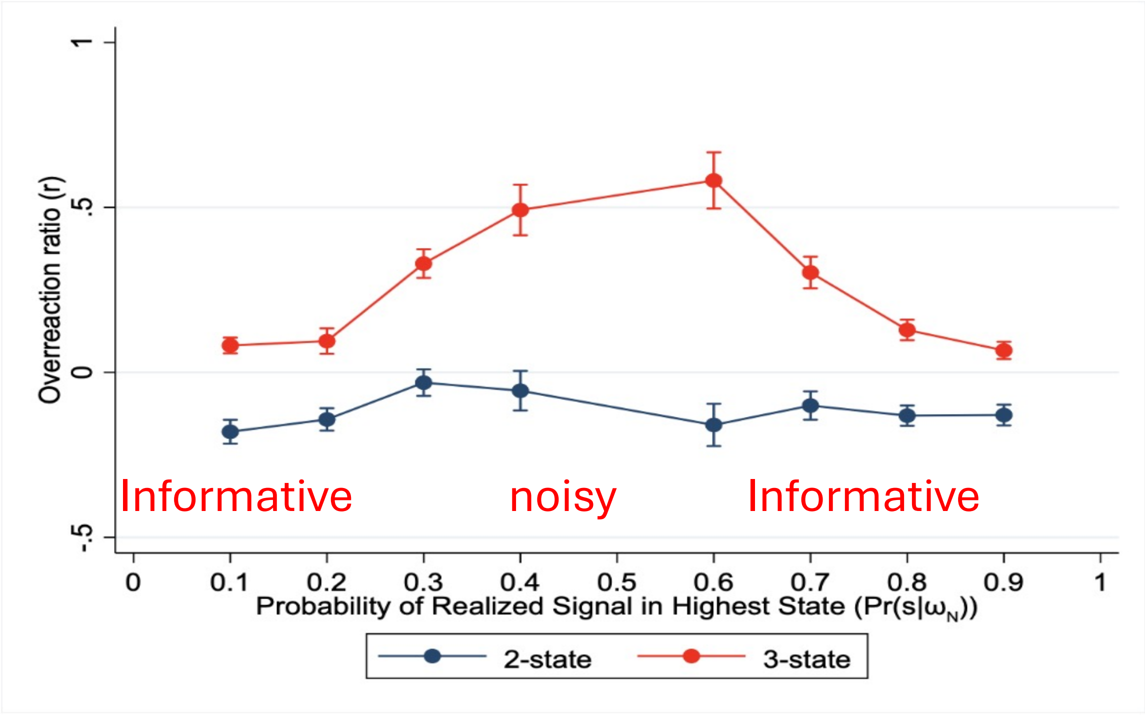
FIGURE 1. Experimental design for 3-state treatment

A bag is selected by randomly drawing a card from a card deck with a number of cards representing each bag. Then balls are extracted from the selected bag.

Task:
Calculate posterior given prior after observing signals

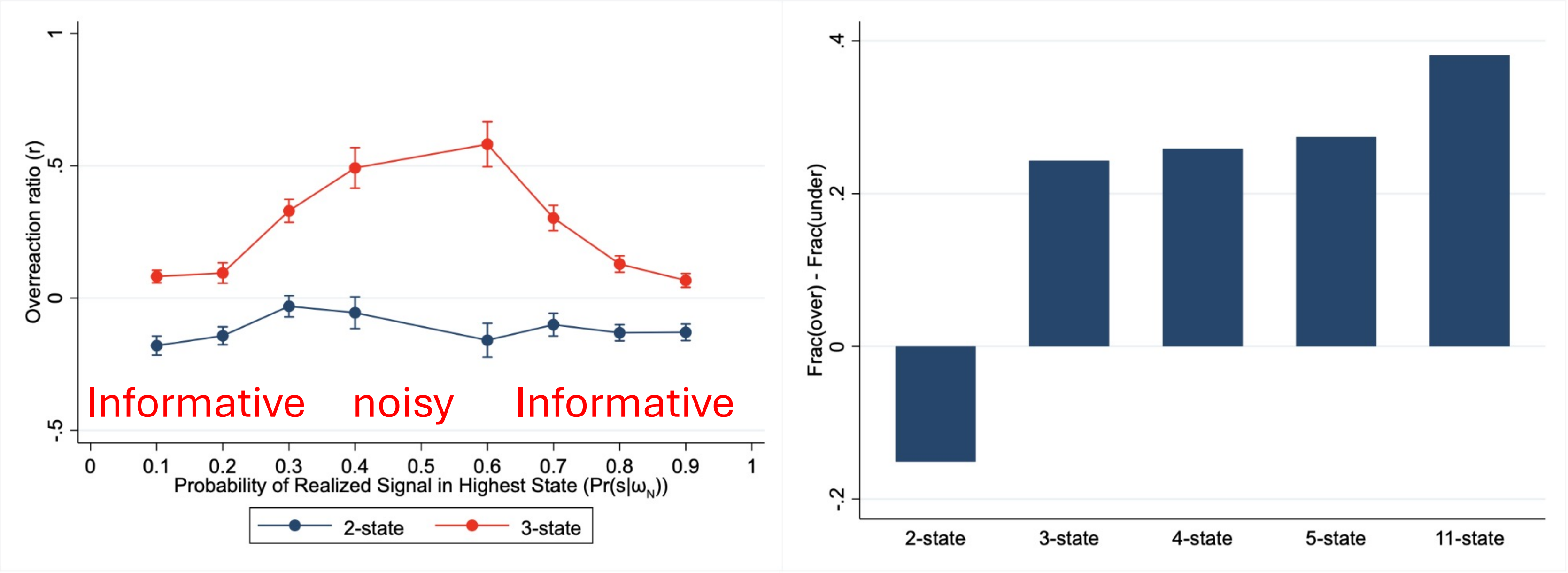
With Context:
Given number of cards (prior), a series of bags (states) with balls (signal diagnosticity), observe one ball draw (signal), calculate the probability of each bag being the selected bag (posterior).

Result 1: Significant Underreaction in 2-state treatment, Overreaction in >= 3-state treatment at all signal diagnosticity level



(A) Overreaction Ratio

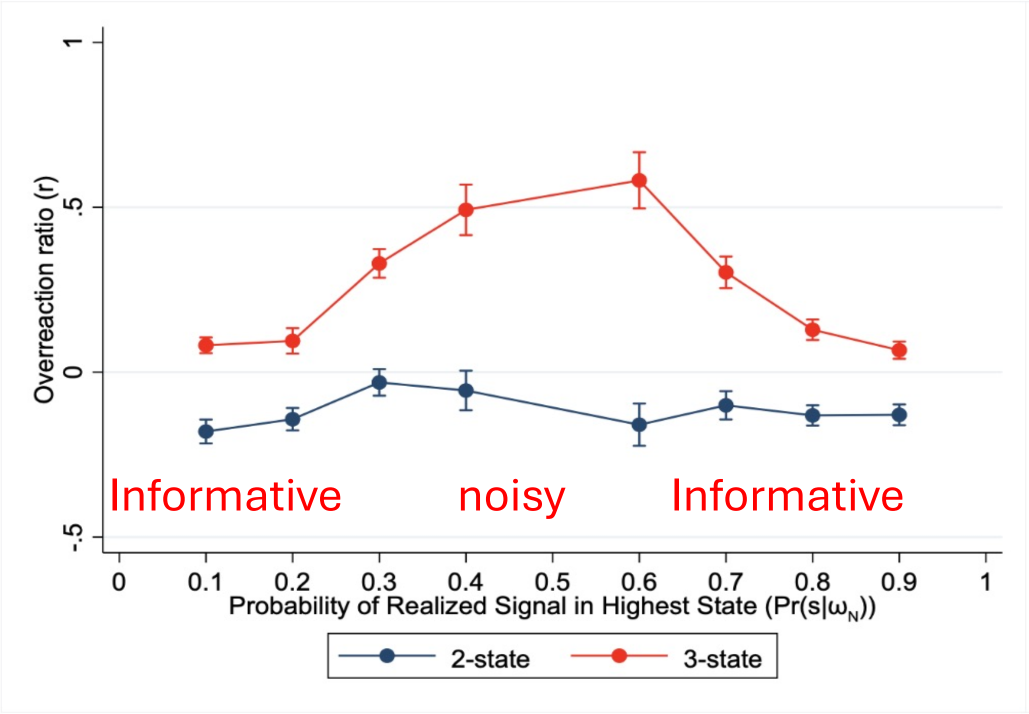
Result 2: Underreaction is more prevalence in 2-state, as state space increase, overreaction become more prevalence



(A) Overreaction Ratio (B) % Overreact - % Underreact

FIGURE 2. Complexity increases overreaction

Result 3: Overreaction decreases as signals become more precise



(A) Overreaction Ratio

TABLE 2. Overreaction decreases in signal diagnosticity

	Overreaction Ratio			
	(1) 2 States	(2) 3 States	(3) 4 States	(4) 5 States
$d = 0.7$	0.0450	-0.218***	-0.370***	-0.196**
	(0.0483)	(0.0502)	(0.0655)	(0.0863)
$d = 0.8$	-0.0268	-0.421***	-0.597***	-0.402***
	(0.0498)	(0.0496)	(0.0692)	(0.0864)
$d = 0.9$	-0.0432	-0.461***	-0.669***	-0.558***
	(0.0484)	(0.0505)	(0.0725)	(0.0878)
Constant	-0.110**	0.535***	0.703***	0.644***
	(0.0475)	(0.0554)	(0.0755)	(0.0942)
N	870	1347	2754	2629
adj. R^2	0.002	0.070	0.117	0.059

Why? This is could be due to representativeness and cognitive imprecision

- **Representativeness**: how much a particular state stands out or seems likely based on new information. If the likelihood of a state increases significantly after observing new information, that state is considered more representative.

- Mathematically, $R(w_i, s_j) = \frac{p(w_i|s_j)}{p_0(w_i)}$

More representative for white ball draw

Why? This is could be due to representativeness and cognitive imprecision Cont.

- **Representativeness**: how much a particular state stands out or seems likely based on new information. If the likelihood of a state increases significantly after observing new information, that state is considered more representative. Mathematically, $R(w_i, s_j) = \frac{p(w_i|s_j)}{p_0(w_i)}$

- **Cognitive Imprecision**: people's internal representation of information is noisy and not perfectly aligned with the true probability distribution. The higher the noise in cognition, the less precise the mental representation is.

$$\tilde{y}(s_i) \sim \frac{1}{\eta} Multi(\eta, N, p_R(s_i))$$

- $y(s_i)$ represents the **noisy internal representation** of the signal
- $p_R(s_i)$ is the actual probability distribution under Bayesian inference
- $Multi(\eta, N, p_R(s_i))$ refers to a multinomial distribution, where N represents the number of states, and $p_R(s_i)$ represents the probabilities of those states.
- η is a parameter that controls the precision of cognition—a larger η corresponds to more precise cognitive representations (less noise).

Aggregated Level: On average human Representativeness and Cognitive Imprecision are all higher than the Bayesian Benchmark

TABLE 5. Aggregate-level estimates of θ and λ

	θ	95% CI	λ	95% CI
Parameter Estimates	0.85	(0.82, 0.92)	0.70	(0.69, 0.70)

Notes: Parameter estimates that minimize the average KL divergence at the aggregate level. Includes all information environments listed in Table 9, except for the 11-state complexity; excludes wrong direction updates. The 95% confidence intervals are obtained from 300 bootstrap samples.

The representativeness parameter on average is 0.85, where Bayesian suggest 0.

The cognitive precision parameter on average is 0.7, where Bayesian suggest 1.

Individual Level: 70% of participants exhibit both the representativeness and cognitive imprecision, 16% exhibit neither

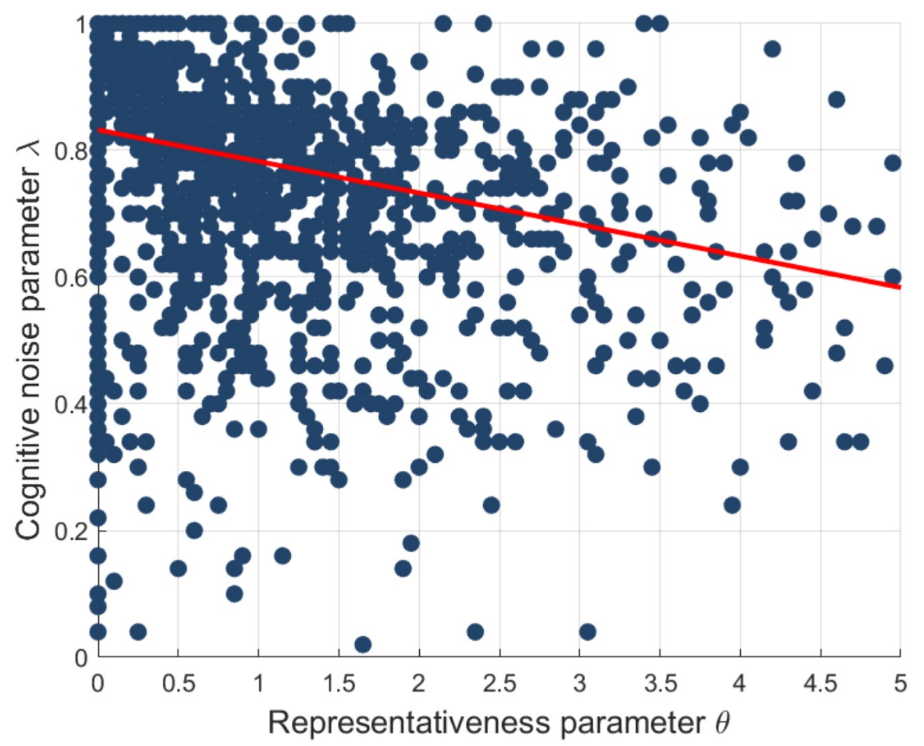


FIGURE 6. Individual level parameter estimates.

9% exhibits only cognitive imprecision

5% exhibits only representativeness

Two-Stage Model performs the best, showing representativeness and cognitive imprecision are cognitive compliments

Completeness: a model M is 0% complete if it predicts no better than Bayesian updating and 100% complete if predicts as accurately as the best prediction among the 3 identified models

Restrictiveness: a model is 0% restrictive if it fits synthetic data perfectly and 100% restrictive if it fits synthetic data no better than Bayes' rule

TABLE 8. Completeness and Restrictiveness

	Completeness		Restrictiveness	
	2 states	>2 states	2 states	>2 states
Two-Stage Model	1.00	0.92	0.73	0.91
	(0.15)	(0.05)	(0.00)	(0.00)
Cognitive-noise-only Model	1.00	0.36	0.76	0.97
	(0.06)	(0.02)	(0.00)	(0.00)
Representativeness-only Model	0.00	0.00	1.00	1.00
	(0.15)	(0.04)	(0.00)	(0.00)

Notes: Includes all information environments listed in Table 9 except for the 11-state complexity; includes wrong direction updates. Restrictiveness is estimated from 1000 simulations.