

The Status Quo and Beliefs Polarization of Inattentive Agents: Theory and Experiment

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joint work with
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European University Institute
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Motivation

- ▶ Society today is more polarized (McCarty et al. 2006)

Increase in Polarization Literature

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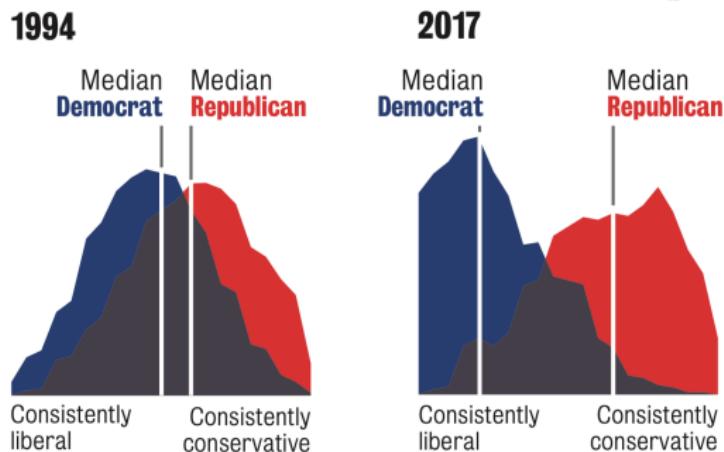


Figure 1: Pew Research Center (2017)

Polarization:

- ▶ Beliefs are further apart
- ▶ Beliefs move in the opposite directions

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We present both **theoretically and experimentally**
an **endogenously arising mechanism**
how the nature of such binary choices leads to **beliefs**
polarization, in expectations.

Motivating Example

Setting

Alice and Bob face a choice: vote to Leave or Stay in the EU

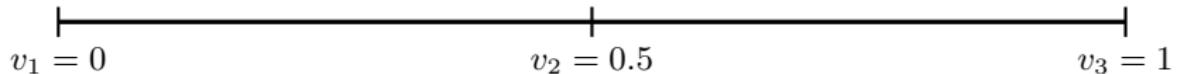
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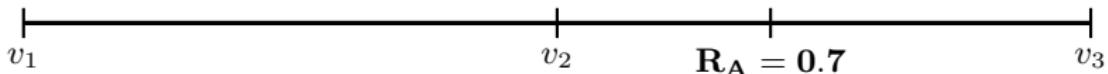


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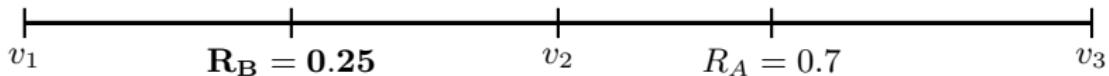


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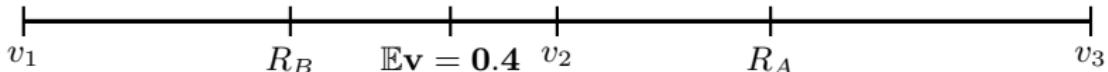


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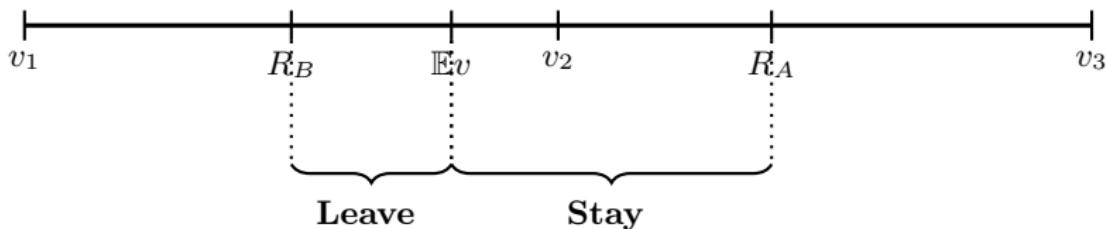


- ▶ Assume common prior $g_s^A = g_s^B \forall s$ and risk neutrality

Motivating Example

No Learning

- ▶ Alice and Bob have the same beliefs over s and $\mathbb{E}v(\text{Leave})$
- ▶ Alice and Bob make different choices
 - ▶ Alice chooses Stay as $\mathbb{E}v(\text{Leave}) < R_A$
 - ▶ Bob chooses Leave as $\mathbb{E}v(\text{Leave}) > R_B$



Motivating Example

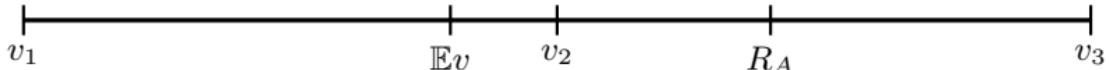
Learning

- ▶ Can ask questions for a cost $\alpha > 0$:
“ Is the realized state i , or is it not? ”

Motivating Example

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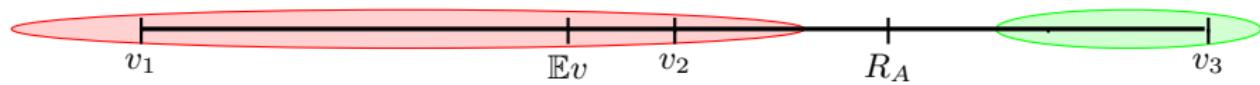
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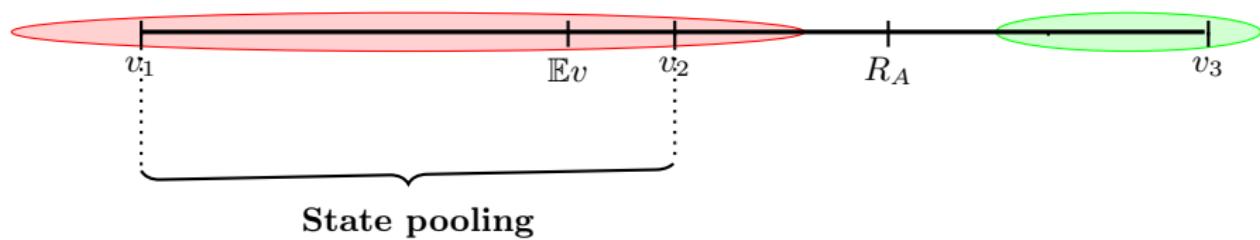
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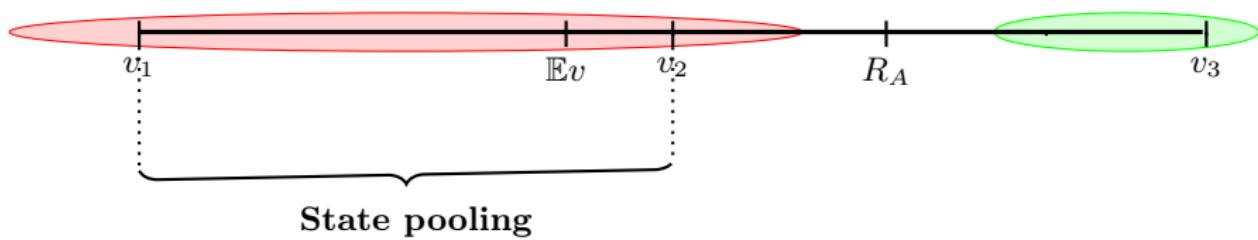
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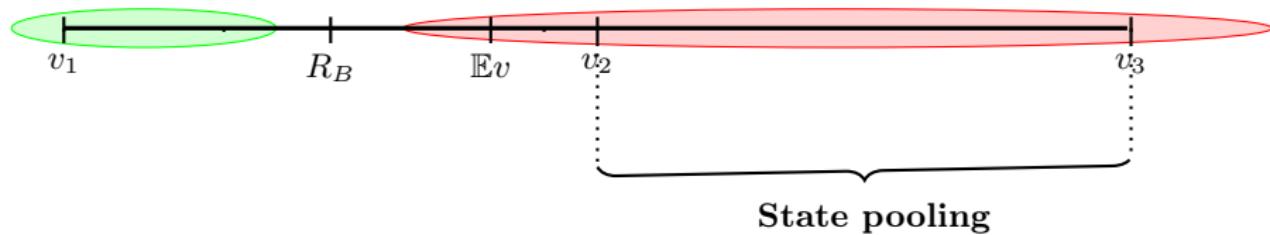
Definition

- ▶ **State pooling:** agents avoid redundant information and “pool together” states associated with the same action

Motivating Example

Learning

- ▶ Can ask questions for a cost $\alpha > 0$:
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- ▶ For **Bob**



Disciplined model of the preference for the positive and negative information.

Motivating Example

Evolution of the beliefs

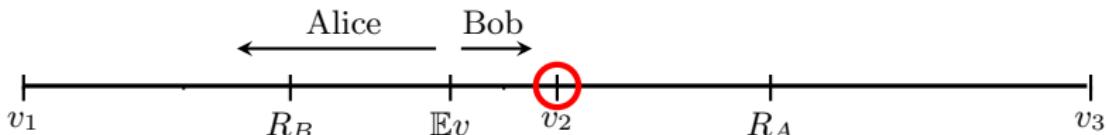
If the realized outcome is medium ($s^* = 2$)

Motivating Example

Evolution of the beliefs

If the realized outcome is medium ($s^* = 2$)

- ▶ Alice and Bob become **polarized**
disagree more and update in opposite directions



Preview of results - Theory

Set up

- ▶ Agent's are modelled to be **rationally inattentive**
 - ▶ Rational endogenous information acquisition
 - ▶ We do not assume exogenous biases
 - ▶ Can receive any information
 - ▶ Information is costly

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Results

- ▶ Polarization **in expectation** as a result of **inattentiveness**
- ▶ Endogenously arising **state pooling effect** and a crucial role of the **status quo**
- ▶ Under some conditions **cheaper** information leads to **more polarized** society

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Objective

- ▶ To test if our theoretical results are a good description of the actual behavior

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YES, we report new evidence of preference for “state pooling” and “extreme” information

- ▶ Does it lead to polarization?

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YES, we report new evidence of preference for “state pooling” and “extreme” information

- ▶ Does it lead to polarization?

YES, a change in the safe option generates “information switch” as predicted, and creates belief polarization

Previous literature

Polarization - exogenous biases

- ▶ Rabin and Schrag (1999) - signal misreading,
Klayman and Ha (1987) - positive test strategy,
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Persistent polarization

- ▶ Bayesian agents would converge over time - Savage (1954),
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- ▶ Bimodality of preferences - Dixit and Weibull (2007)
- ▶ Inattentiveness - Nimark and Sundaresan (2019)

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Laboratory experiments

- ▶ Masatlioglu, Orhun and Raymond (2017) - preference for skewed information
- ▶ Charness, Oprea and Yuksel (2018) - choices between biased info
- ▶ Ambuehl and Li (2018) - demand for information

Today's Presentation

- ▶ Model
 - ▶ Setup
 - ▶ Evolution of beliefs
 - ▶ Beliefs polarization
- ▶ Experiment
 - ▶ Response to status quo
 - ▶ Beliefs polarization
 - ▶ Non-instrumental preferences

The Model

Model

- ▶ An agent faces a discrete binary choice problem

$$i \in \{1, 2\} = \{\underbrace{\text{new policy}}_{\text{leaving EU}}, \underbrace{\text{status quo}}_{\text{staying in EU}}\}$$

- ▶ New policy
 - ▶ value v_s , where $s \in S = \{1, \dots, n\}$
 - ▶ states are labeled, such that $v_1 < v_2 < \dots < v_n$

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- ▶ Status quo
 - ▶ known value R (e.g. GDP growth 2%)
 - ▶ Assumption: $v_1 < R < v_n$

Model

- ▶ Prior beliefs about realized state $\mathbf{g} = [g_1 \ g_2 \ \dots \ g_n]$
- ▶ Agent is rationally inattentive (Sims, 2003, 2006)
 - ▶ Can acquire information about the state
 - ▶ Information acquisition is costly (\propto uncertainty reduction)

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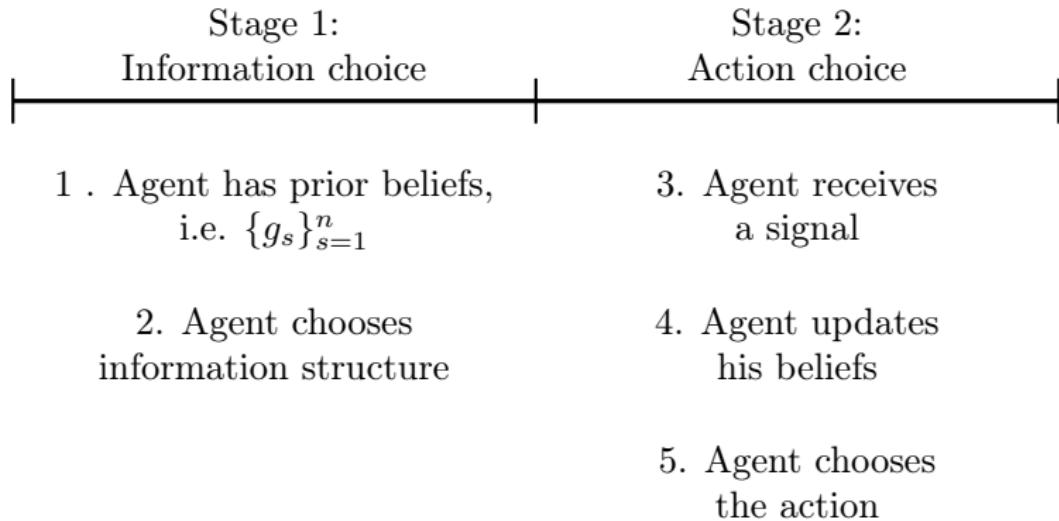
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Agent's Problem with Rational Inattention



Agent's problem

$$\max_{\{\mathcal{P}(i|s) | i=1,2; s \in S\}} \left\{ \sum_{s=1}^n (v_s \mathcal{P}(i=1|s) + R \mathcal{P}(i=2|s)) g_s - \lambda \kappa \right\},$$

subject to

$$\forall i : \mathcal{P}(i|s) \geq 0 \quad \forall s \in S,$$

$$\sum_{i=1}^2 \mathcal{P}(i|s) = 1 \quad \forall s \in S,$$

and

$$\kappa = \underbrace{- \sum_{i=1}^2 \mathcal{P}(i) \log \mathcal{P}(i)}_{\text{prior uncertainty}} - \sum_{s=1}^n \left(\underbrace{- \left(\sum_{i=1}^2 \mathcal{P}(i|s) \log \mathcal{P}(i|s) \right) g_s}_{\text{posterior uncertainty in state } s} \right).$$

Main idea: Evolution of Beliefs

We are interested in updating of expectations

$$\Delta(s^*) = \underbrace{\mathbb{E}_i[\mathbb{E}(v|i)|s^*]}_{\text{Posterior expected mean}} - \underbrace{\mathbb{E}_g[v]}_{\text{Prior mean}}$$

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where

$$\mathbb{E}_i[\mathbb{E}(v|i)|s^*] = \sum_{i=1}^2 \left(\sum_{s=1}^n v_s \mathcal{P}(s|i) \right) \mathcal{P}(i|s^*),$$

where option $i \in \{1, 2\} = \{\text{new policy, status quo}\}$

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Proposition 1

Given that the agent is in a learning area ($0 < \mathcal{P}(i = 1) < 1$) and that the realized state of the world is s^* ,

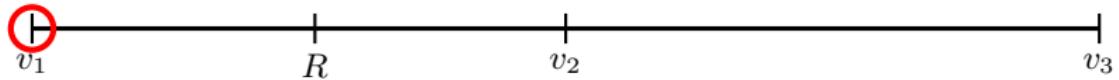
the sign of the change in the mean of beliefs $\Delta(s^*)$ about the payoff of the new policy **is the same as the sign of** $(v_{s^*} - R)$.

Extreme states

Updating towards the realized state

$$\underbrace{\text{sign } \Delta(s^*)}_{\text{change in mean of beliefs}} = \underbrace{\text{sign } (v_{s^*} - R)}_{\text{true payoff} - \text{status quo}}$$

State $s^* = 1$

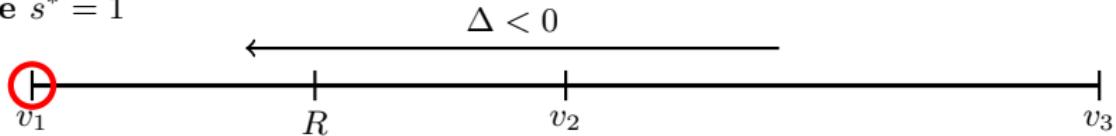


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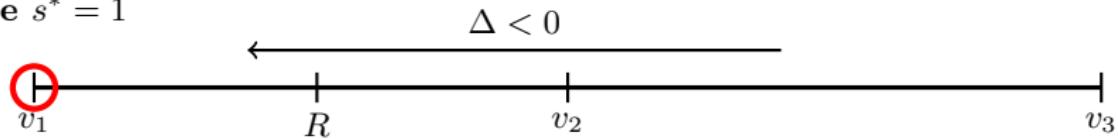


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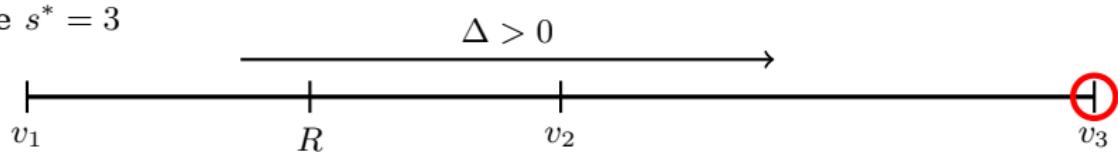
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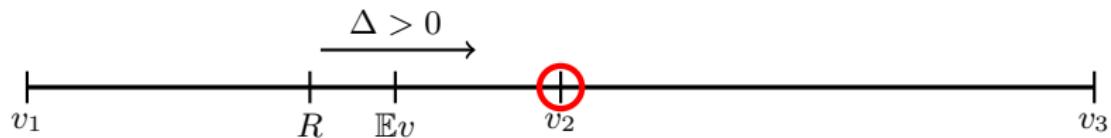


State $s^* = 3$



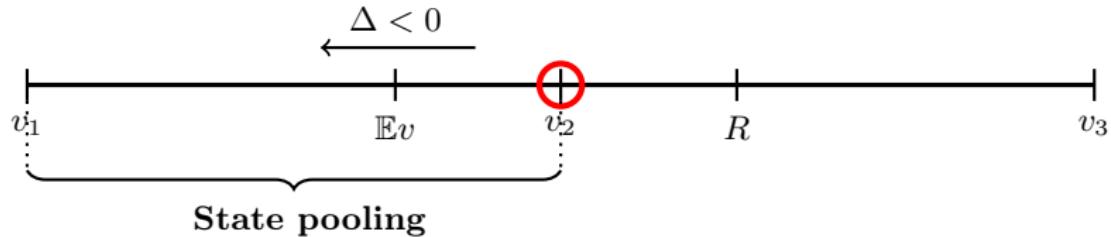
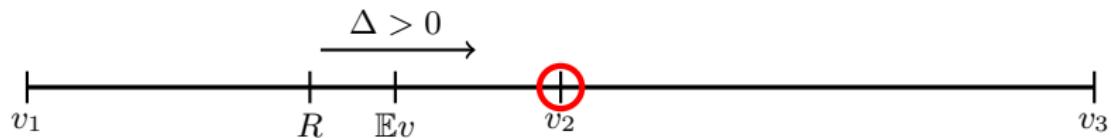
Updating away from the realized state

State $s^* = 2$

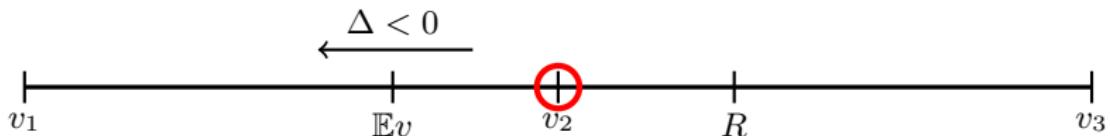


Updating away from the realized state

State $s^* = 2$



Updating away from the realized state



Theorem 1

If and only if, in a state $s^* \in S$ holds that

$$(v_{s^*} - R)(\mathbb{E}v - v_{s^*}) > 0,$$

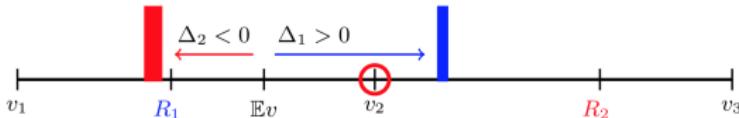
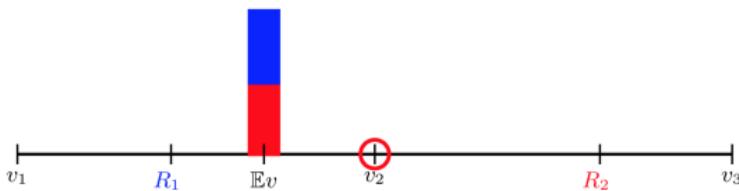
then, the agent is updating in **the opposite direction** from the realized value v_{s^*} .

Polarization result

Definition

Agents $j = 1, 2$ are **polarized**, i.e. exists such $(R_j, \mathbb{E}_g^j[v])$ that

- ▶ Posterior expected beliefs are further away than the prior
 - ▶ Agents update in opposite directions
- are satisfied.



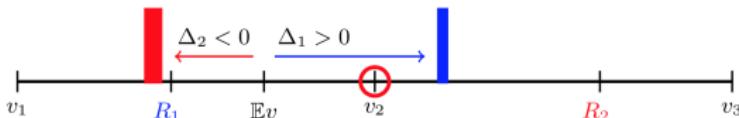
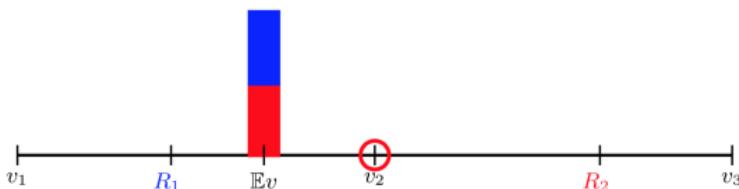
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- ▶ $|\mathbb{E}_i^1[\mathbb{E}(v|i)|s^*] - \mathbb{E}_i^2[\mathbb{E}(v|i)|s^*]| > |\mathbb{E}^1 v - \mathbb{E}^2 v|.$
- ▶ $\Delta_1(s^*) \cdot \Delta_2(s^*) < 0.$

are satisfied.



Other Results

Convergence of beliefs Convergence

- ▶ Conditions for beliefs convergence

Monotonicity of $\Delta(s^*)$ Monotonicity

- ▶ Mean beliefs change $\Delta(s^*)$ is increasing in s^*

Divergence while updating in the same direction Divergence

- ▶ Agents with the same status quo but different beliefs

Comparative statics Comparative statics

- ▶ **Cheaper** information might lead to **higher** polarization

Laboratory Experiment

Laboratory Experiment and Theory

Objective

- ▶ To test if our theoretical results are a good description of the actual behavior

Laboratory Experiment and Theory

Objective

- ▶ To test if our theoretical results are a good description of the actual behavior
- ▶ Do we observe predicted information acquisition (state pooling)?
- ▶ Do we observe belief polarization by changing R?

Laboratory Experiment

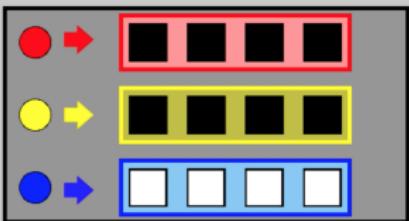
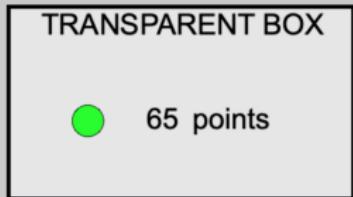
- ▶ Stage 1: choose or “hire” a signal structure
- ▶ Observe the signal realization
- ▶ Stage 2: select an action [risky/safe]
- ▶ We collect separately
 - ▶ Choices over sources of information (advisors)
 - ▶ Action (conditional on realized signals)
 - ▶ Elicited beliefs (signal probability and posterior)
 - ▶ Willingness to pay for signal structures

Laboratory Experiment

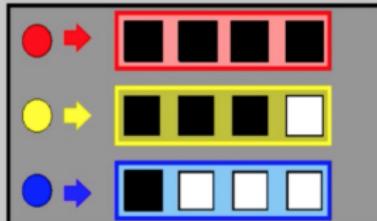
- ▶ Experiment conducted at Columbia in September 2019
- ▶ 85 participants (undergraduate and graduate students)
- ▶ Average time 80 minutes, Average payment ~\$25
 - ▶ Show-up fee (\$10)
 - ▶ Main experiment, 4 parts (probability points, \$15 prize)
 - ▶ Risk attitude (Holt-Laury, \$0.10-\$4.00)
 - ▶ Intelligence (Raven's Progressive Matrices, 5 x \$0.50)
 - ▶ Unrewarded questionnaire (strategy, LOT-R, demographics)

MAIN TASK

Task 2 - Hiring screen



Advisor X



Advisor Y

Select one Advisor

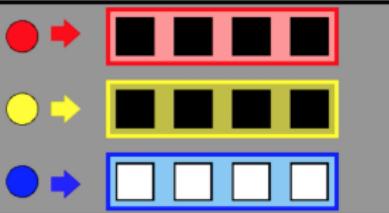
Task 2 - Choice screen

OPAQUE BOX

-  10 points
-  50 points
-  80 points

TRANSPARENT BOX

 65 points



OPAQUE

TRANSPARENT

If the Advisor's card is black

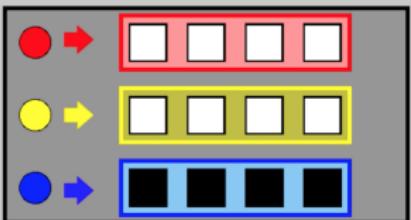
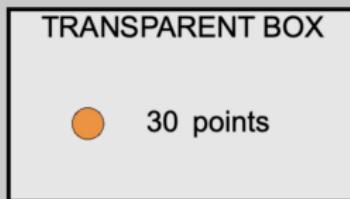
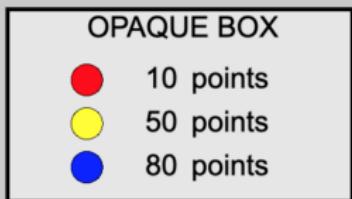


If the Advisor's card is white

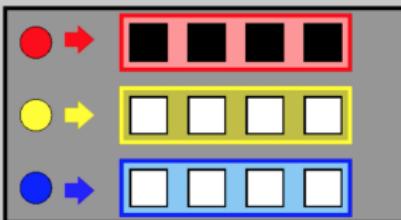


OK

Task 2 - How did we design the pairs of advisor?



Advisor X

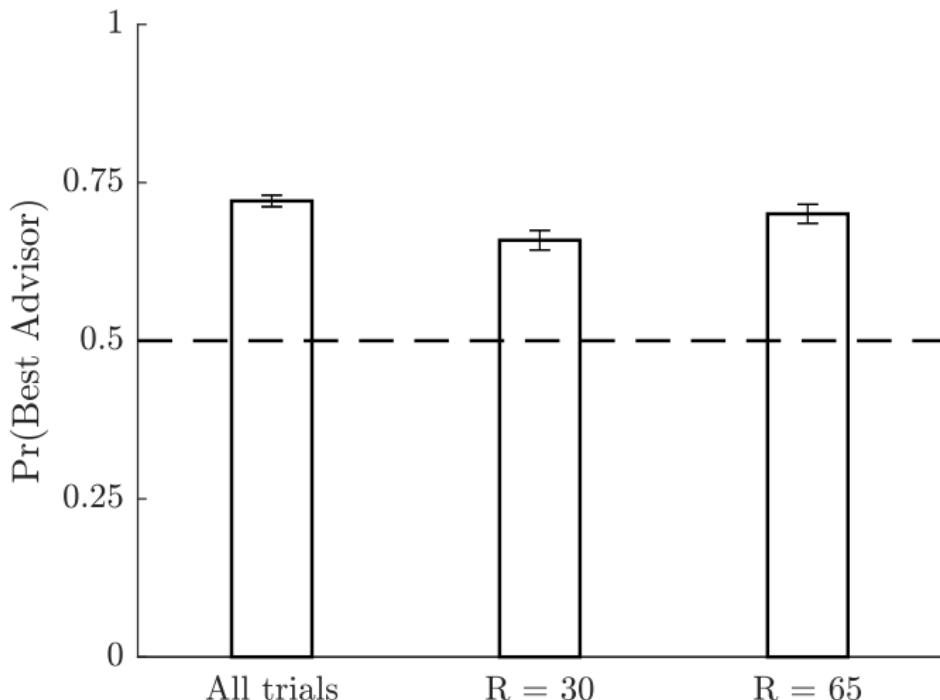


Advisor Y



Select one Advisor

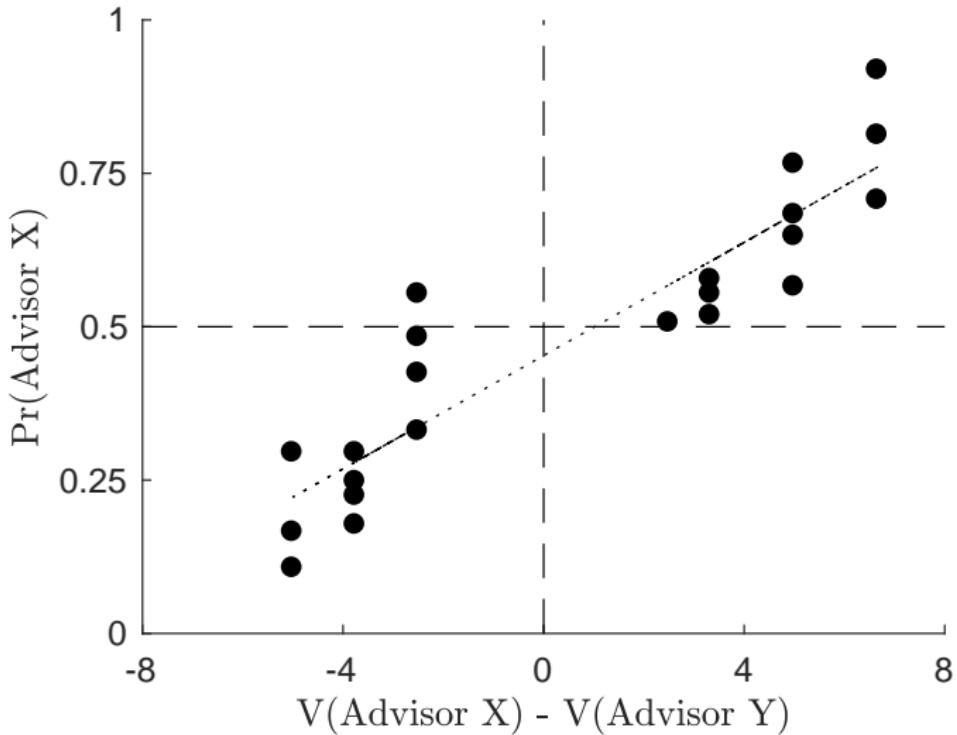
Most of participants “switch” advisor optimally



Probability of correct answers for all participants.

(Bar 1) 29/40 trials, 2.465 obs. (Bars 2,3) 11/40 trials, 935 obs.

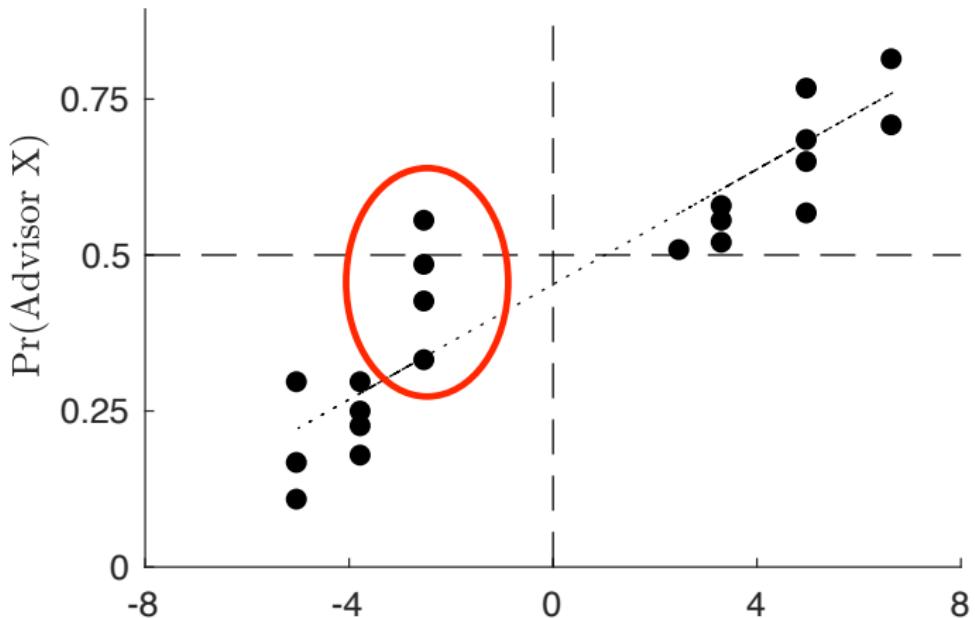
Accuracy depends on the stakes



Probability of choosing Advisor X given a pair X,Y.

22/40 trials, 85 observations per trial. [Jump to Beliefs](#)

Accuracy depends on the stakes



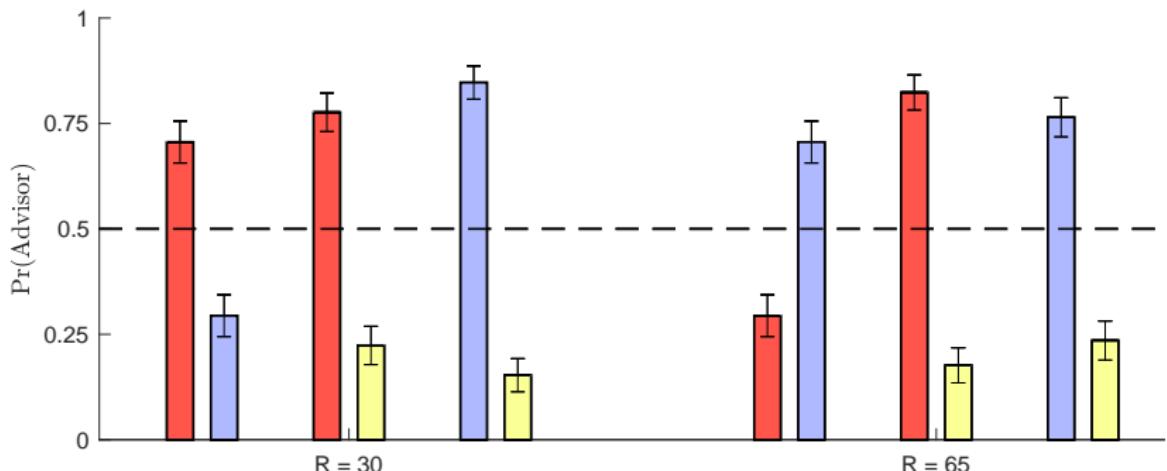
Probability of choosing Advisor X given a pair X, Y .
22/40 trials, 85 observations per trial.

Certainty and State Pooling Advisors

- ▶ An advisor with information structure I provides **certainty** when there exists a state s such that *every signal* generates a degenerate posterior about the state being s .
- ▶ An advisor with information structure I provides **state pooling** when there exists a *signal* that generates the posterior $[p, 1 - p, 0]$ or $[0, 1 - p, p]$, with $p > 0$.

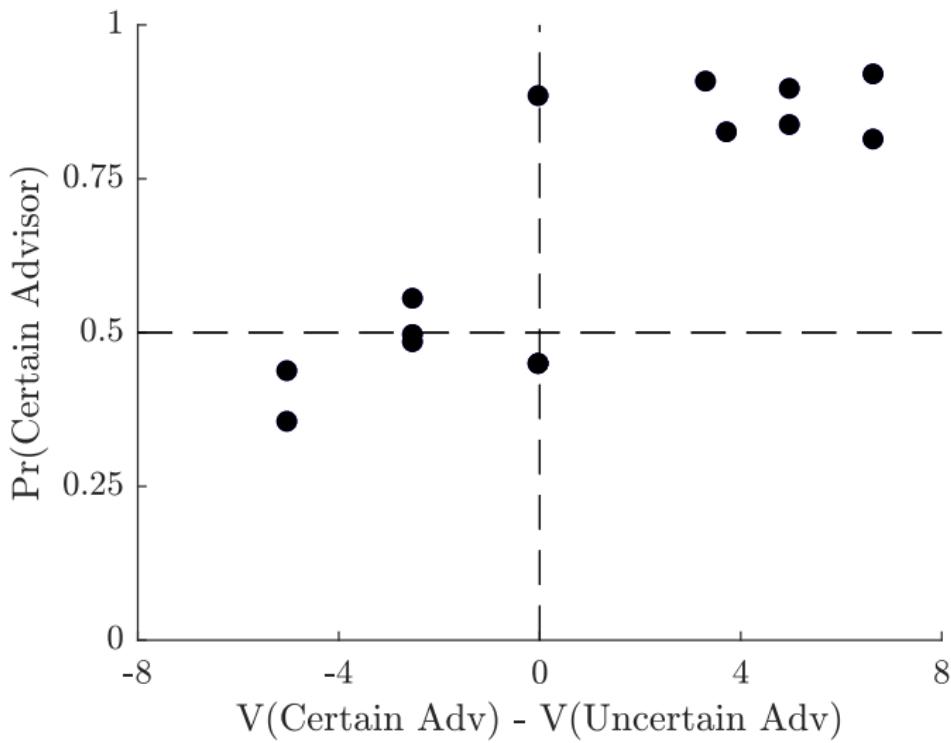
		SP	Not SP
		(0, 1, 1)	(0, 1, 0)
		(0, $\frac{3}{4}$, $\frac{3}{4}$)	($\frac{1}{4}$, $\frac{3}{4}$, $\frac{3}{4}$)
C	SP	(0, 1, 1)	(0, 1, 0)
	Not SP	(0, $\frac{3}{4}$, $\frac{3}{4}$)	($\frac{1}{4}$, $\frac{3}{4}$, $\frac{3}{4}$)

Simple Advisors: Certainty vs Certainty



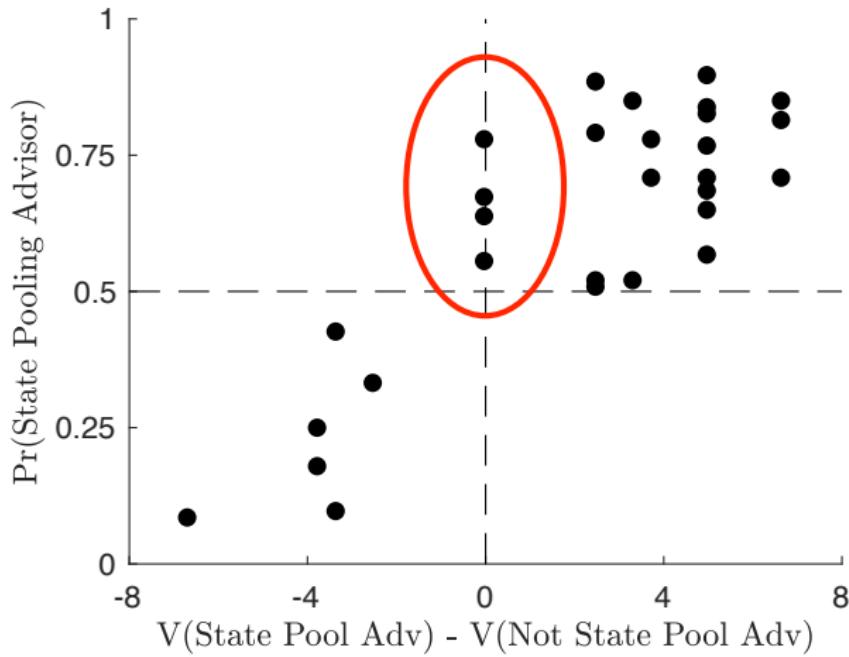
Comparison of advisors providing certainty about one state. The color of the bar shows which state they are revealing with certainty. 85 observations per trial.

Certainty vs Uncertainty



Probability of choosing the certain advisor, in the trials that have a certain and an uncertain advisor (14/40 trials). 85 observations per trial.

State Pooling vs Not Pooling



Probability of choosing the state pooling advisor, in the trials that have a SP and a not SP advisor (16/40 trials). 85 observations per trial.

Aggregate Valuation of Advisors - Logit Regression

	(1)
w_I^{Bayes}	0.210*** (0.0346)
Best Advisor	0.106 (0.143)
Certainty	

State Pooling

Certainty \times SP

Trials	All
Observations	3,400

Notation: *** p<0.01, ** p<0.05, * p<0.1

Estimated value $v_X = \beta_0 + \beta_1 w_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$
where $w_I^{Bayes} = Pr(\sigma = 1) \cdot (EV[V_1|\sigma = 1] - EV[V_0|\sigma = 1])$

Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)
w_I^{Bayes}	0.210*** (0.0346)	0.236*** (0.0110)
Best Advisor	0.106 (0.143)	
Certainty		0.1876*** (0.0708)
State Pooling		

Certainty \times SP

Trials	All	All
Observations	3,400	3,400

Notation: *** p<0.01, ** p<0.05, * p<0.1

Estimated value $v_X = \beta_0 + \beta_1 w_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$
 where $w_I^{Bayes} = Pr(\sigma = 1) \cdot (EV[V_1|\sigma = 1] - EV[V_0|\sigma = 1])$

Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)	(3)
w_I^{Bayes}	0.210*** (0.0346)	0.236*** (0.0110)	0.2108*** (0.0113)
Best Advisor	0.106 (0.143)		
Certainty		0.1876*** (0.0708)	
State Pooling			0.742*** (0.0757)
Certainty \times SP			0.488*** (0.0825)
Trials	All	All	All
Observations	3,400	3,400	3,400

Notation: *** p<0.01, ** p<0.05, * p<0.1

Estimated value $v_X = \beta_0 + \beta_1 w_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$
 where $w_I^{Bayes} = Pr(\sigma = 1) \cdot (EV[V_1|\sigma = 1] - EV[V_0|\sigma = 1])$

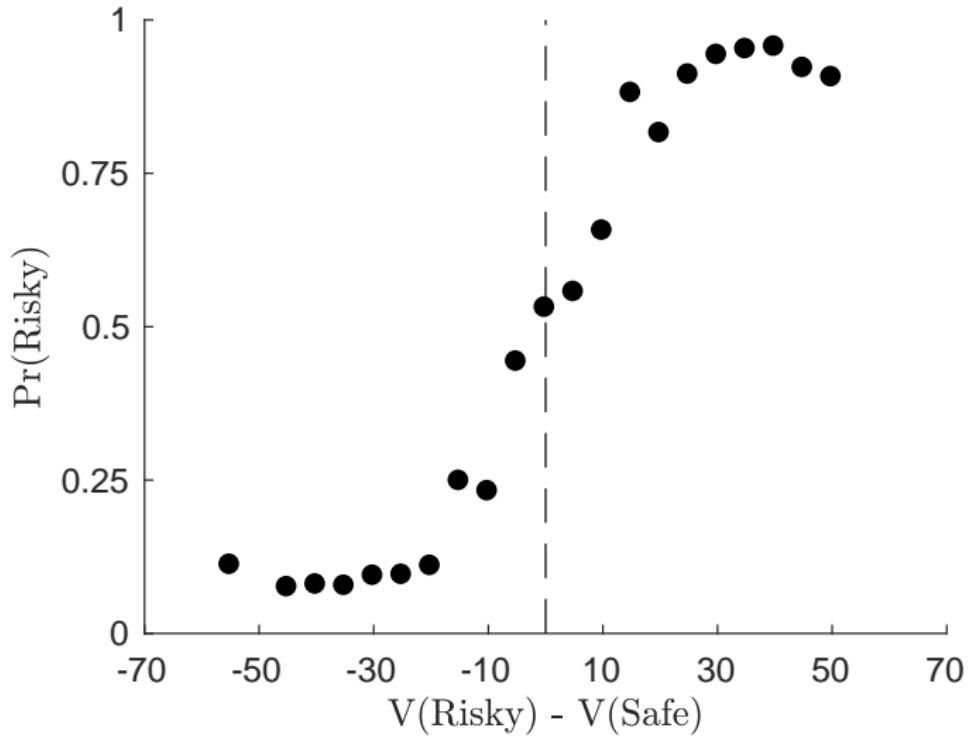
Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)	(3)	(4)
w_I^{Bayes}	0.210*** (0.0346)	0.236*** (0.0110)	0.2108*** (0.0113)	0.253*** (0.0358)
Best Advisor	0.106 (0.143)			-0.186 (0.149)
Certainty		0.1876*** (0.0708)		0.596*** (0.154)
State Pooling			0.742*** (0.0757)	1.041*** (0.111)
Certainty \times SP			0.488*** (0.0825)	-0.0601 (0.164)
Trials	All	All	All	All
Observations	3,400	3,400	3,400	3,400

Notation: *** p<0.01, ** p<0.05, * p<0.1

Estimated value $v_X = \beta_0 + \beta_1 w_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$
 where $w_I^{Bayes} = Pr(\sigma = 1) \cdot (EV[V_1|\sigma = 1] - EV[V_0|\sigma = 1])$

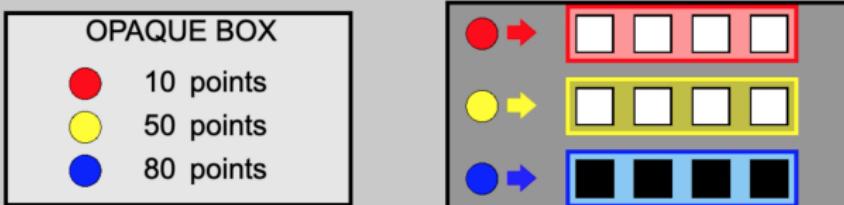
Action Selection



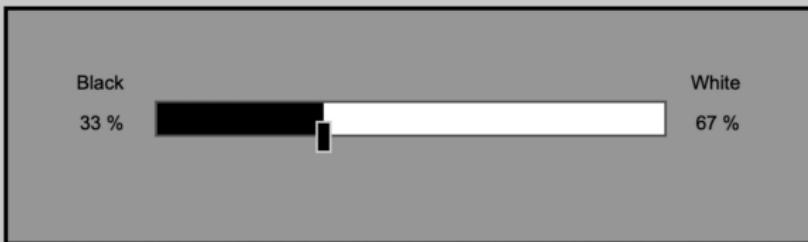
Observed probability of choosing the risky action in task 2. 6,800 observations grouped in 21 bins (different sample size).

BELIEFS

Task 3 - Belief elicitation



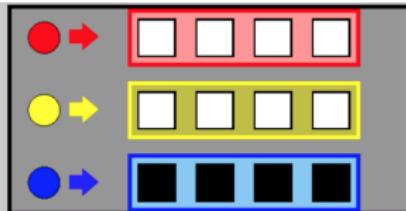
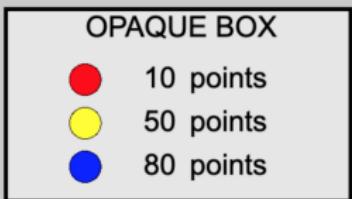
Advisor Z



Move the slider based on your guess

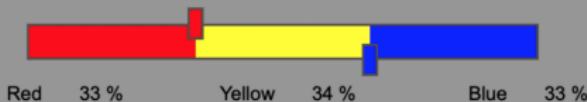
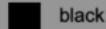
OK

Task 4 - Belief elicitation



Advisor Z

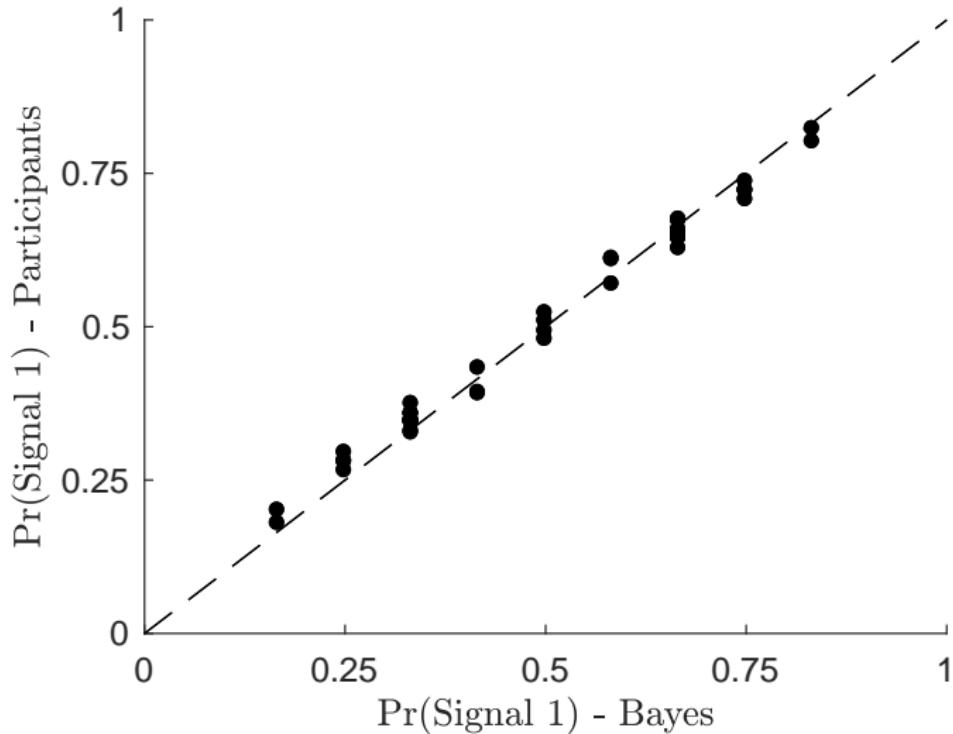
The Advisor above shows you the card:



Move the slider based on your guess

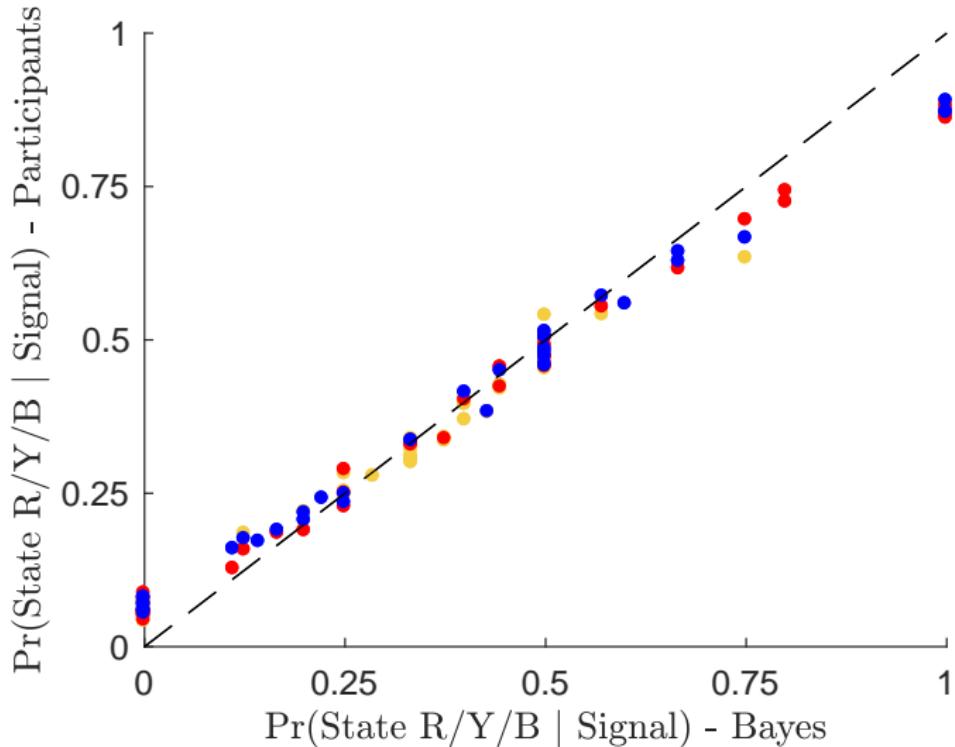
OK

Elicited Beliefs - Card color



Estimated probability of receiving a signal realization in task 3: subjective and optimal estimates. 1,700 observations across 20 trials (85 obs. per point).

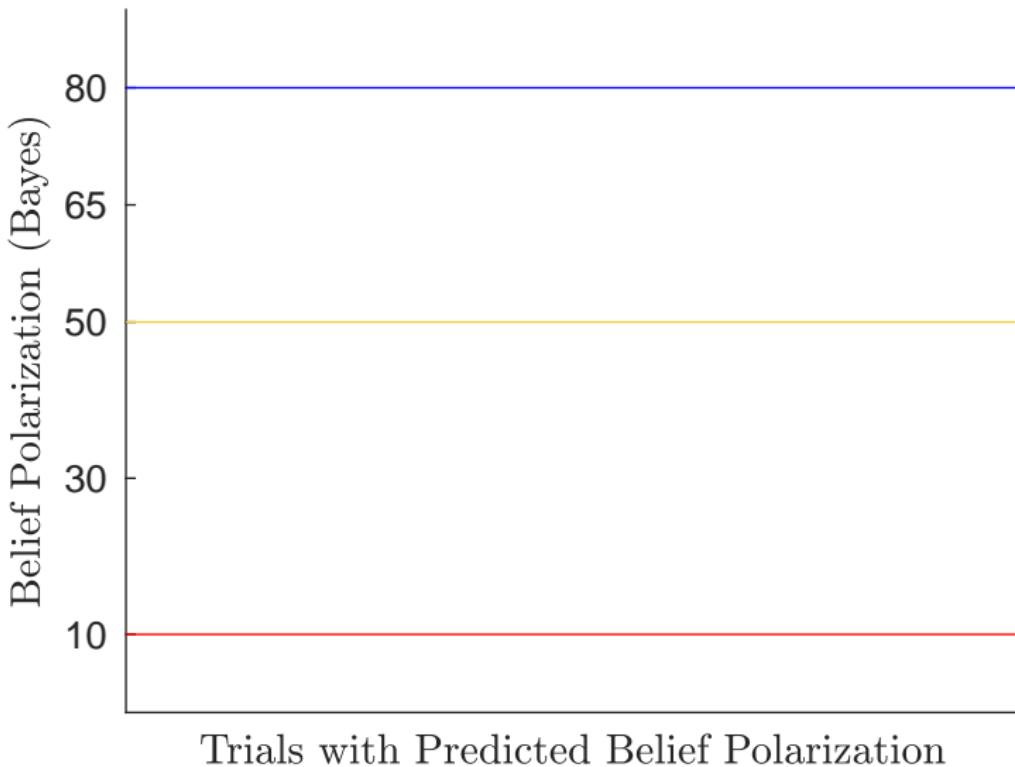
Elicited Beliefs - Ball color



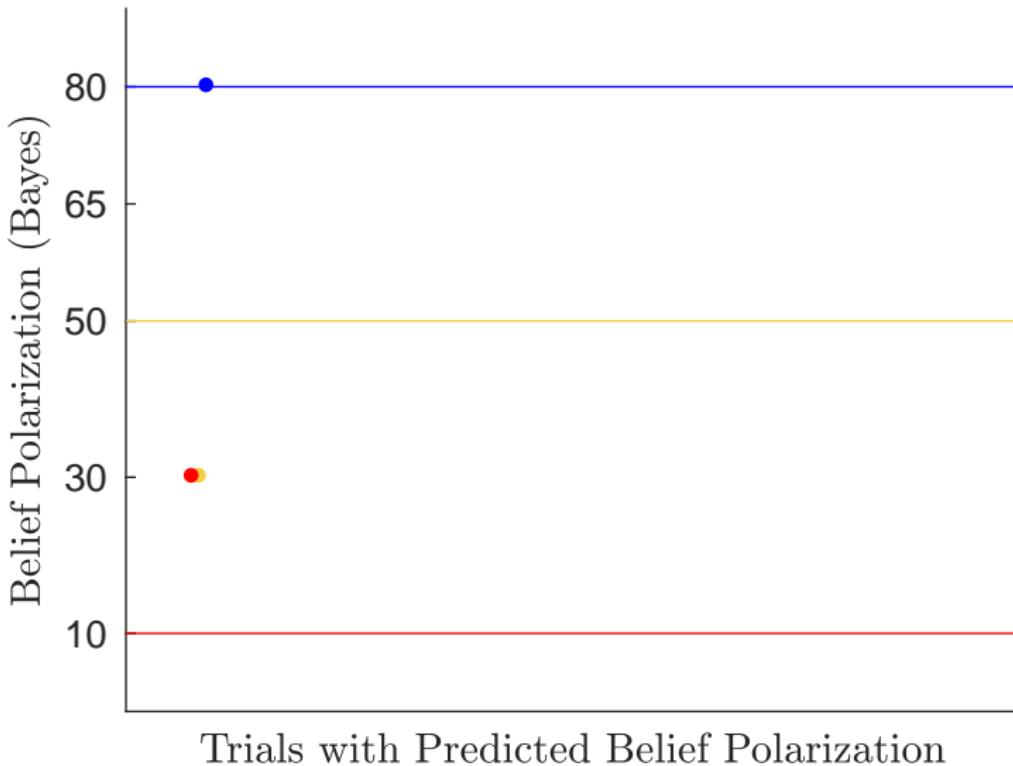
Estimated posterior probability in task 4: subjective and optimal estimates.

Colors indicate the state. 20,400 observations across 40 trials (85 obs. per point).

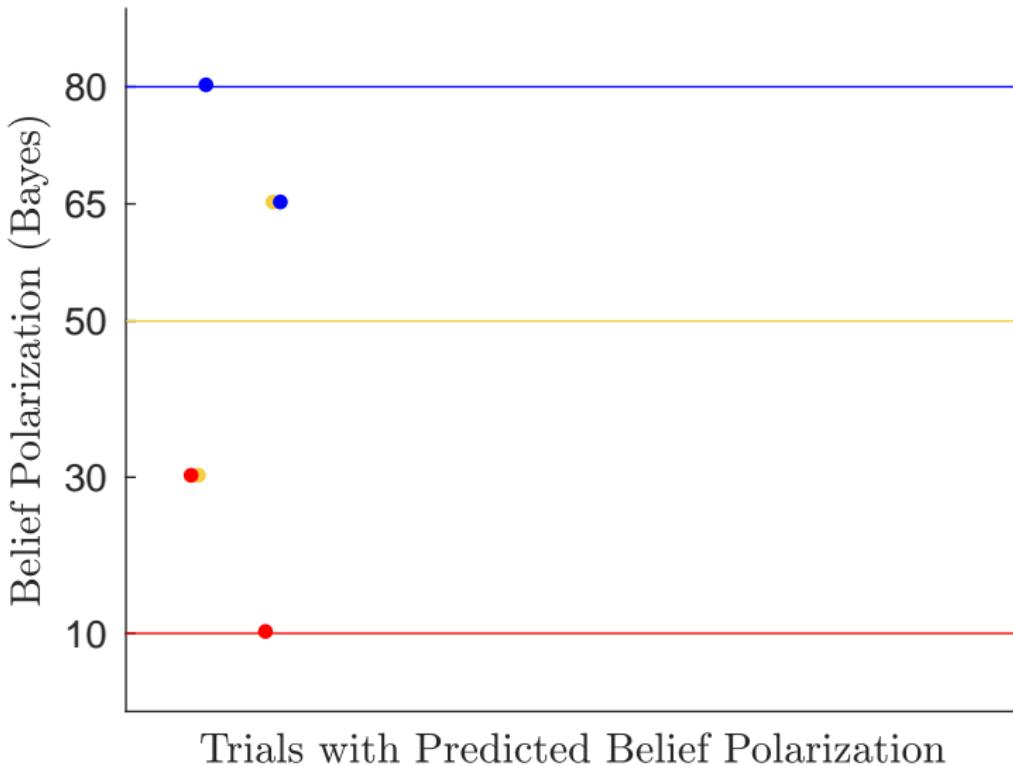
Beliefs Polarization - Predictions



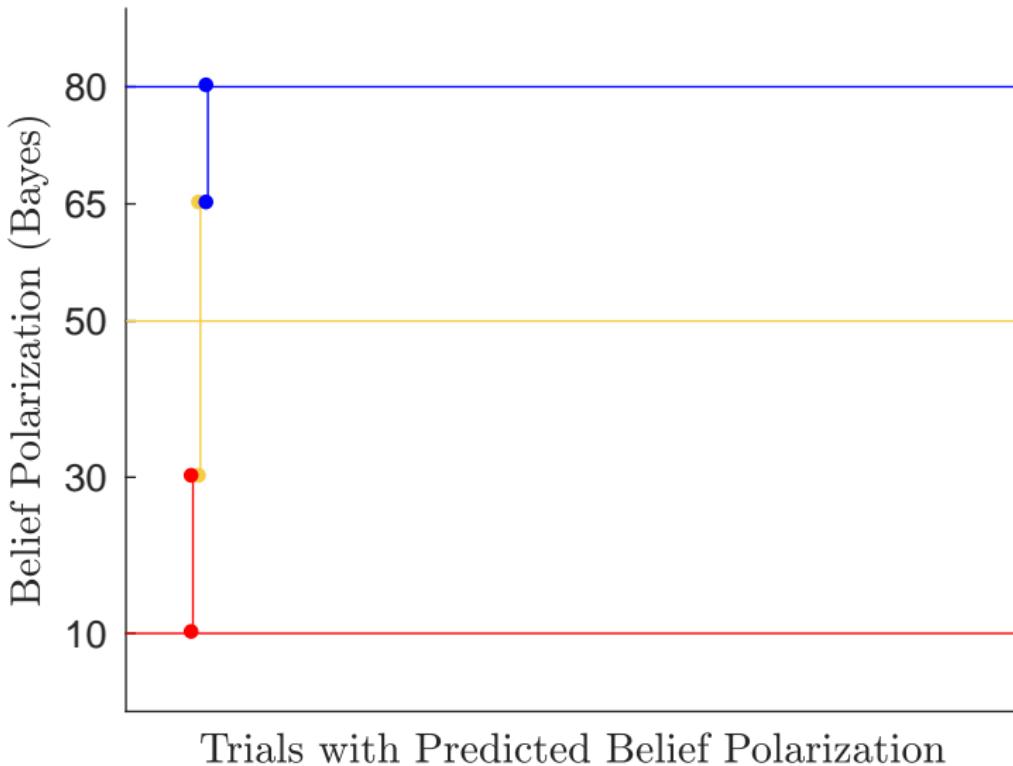
Beliefs Polarization - Predictions



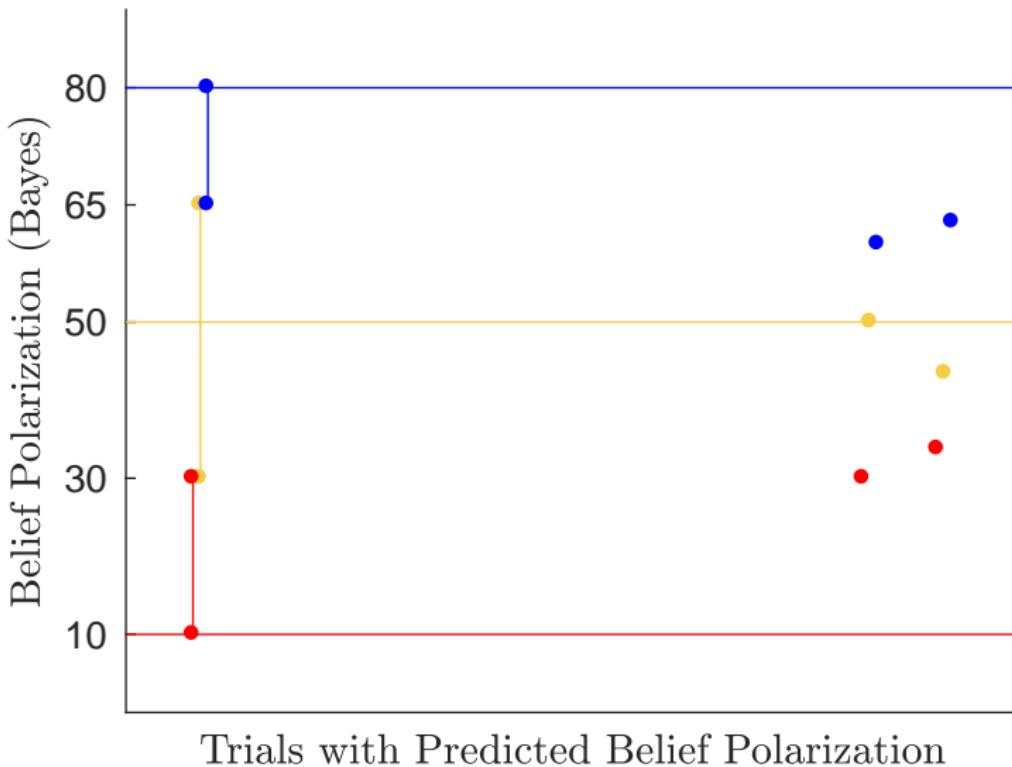
Beliefs Polarization - Predictions



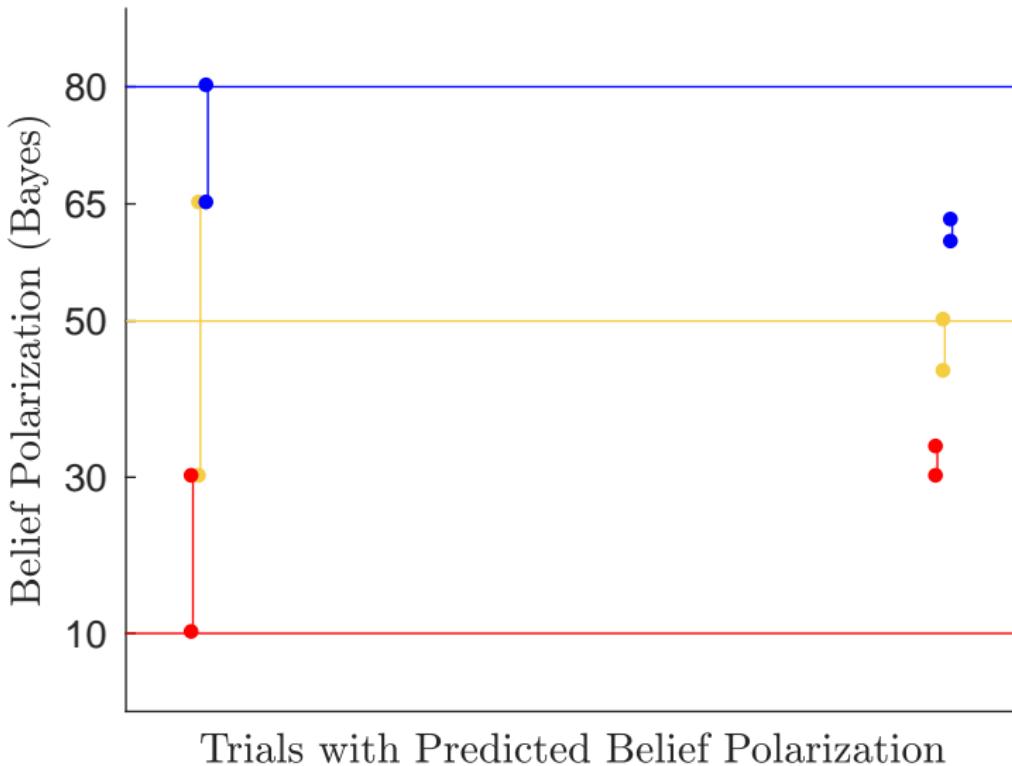
Beliefs Polarization - Predictions



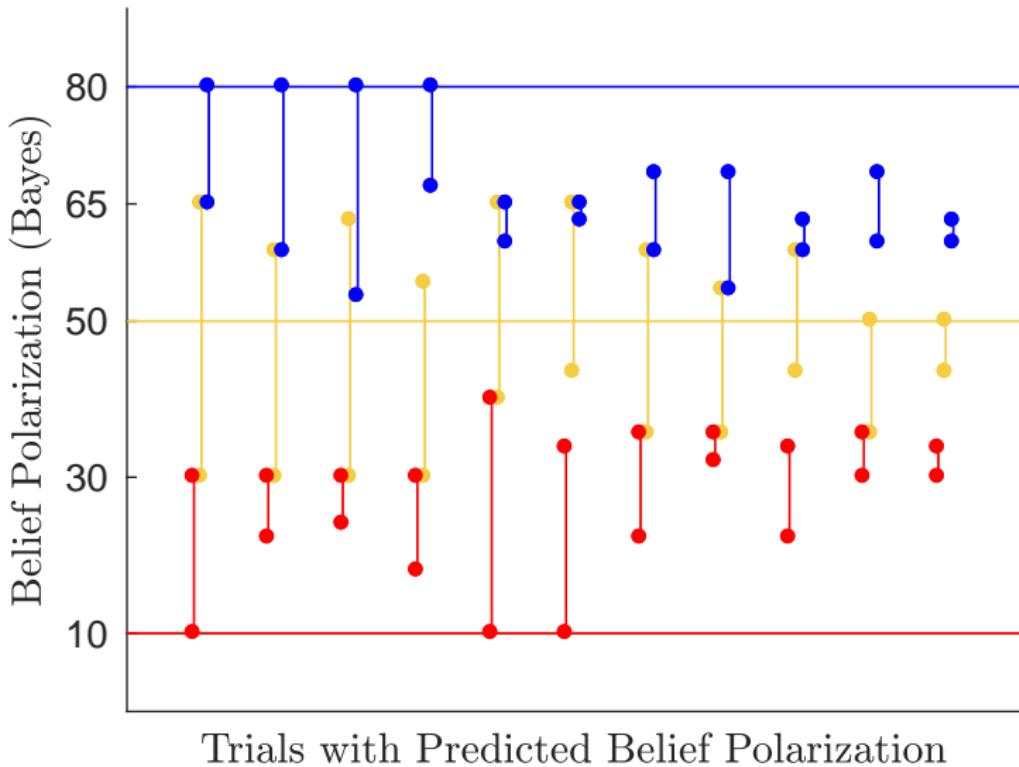
Beliefs Polarization - Predictions



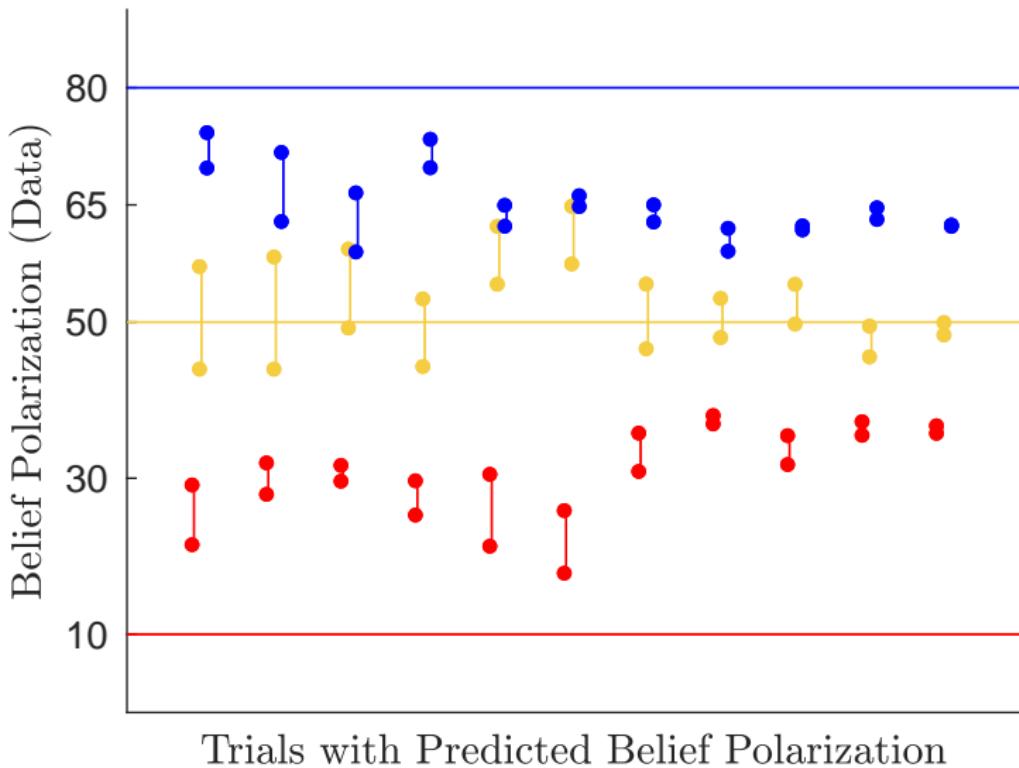
Beliefs Polarization - Predictions



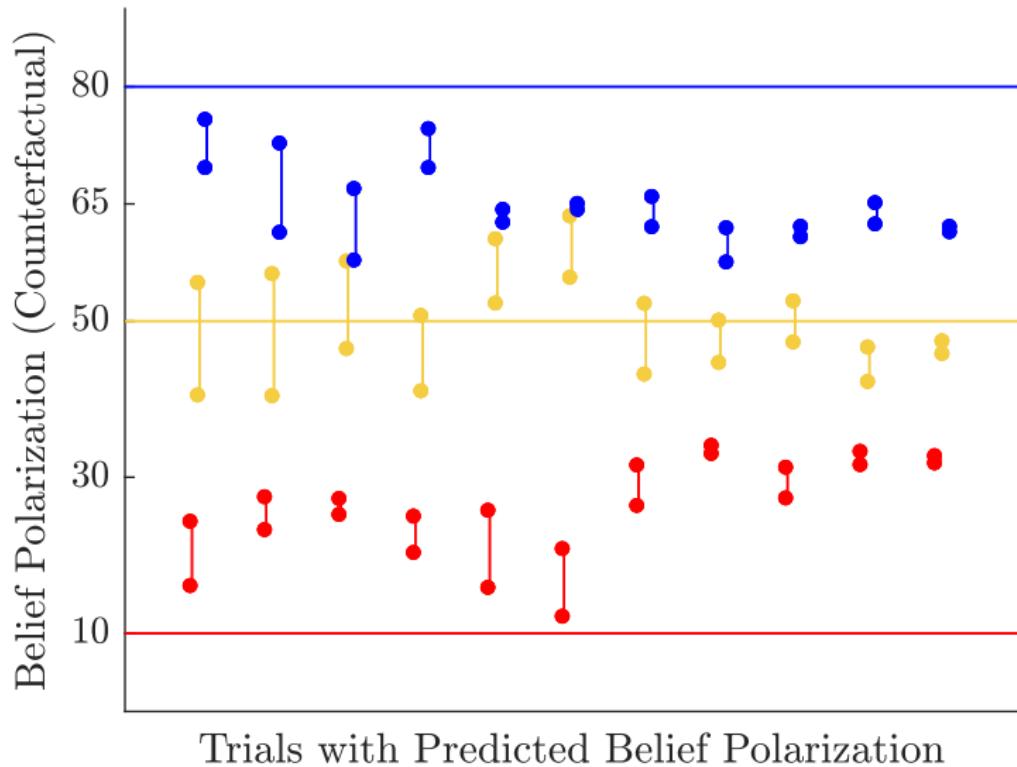
Beliefs Polarization - Predictions



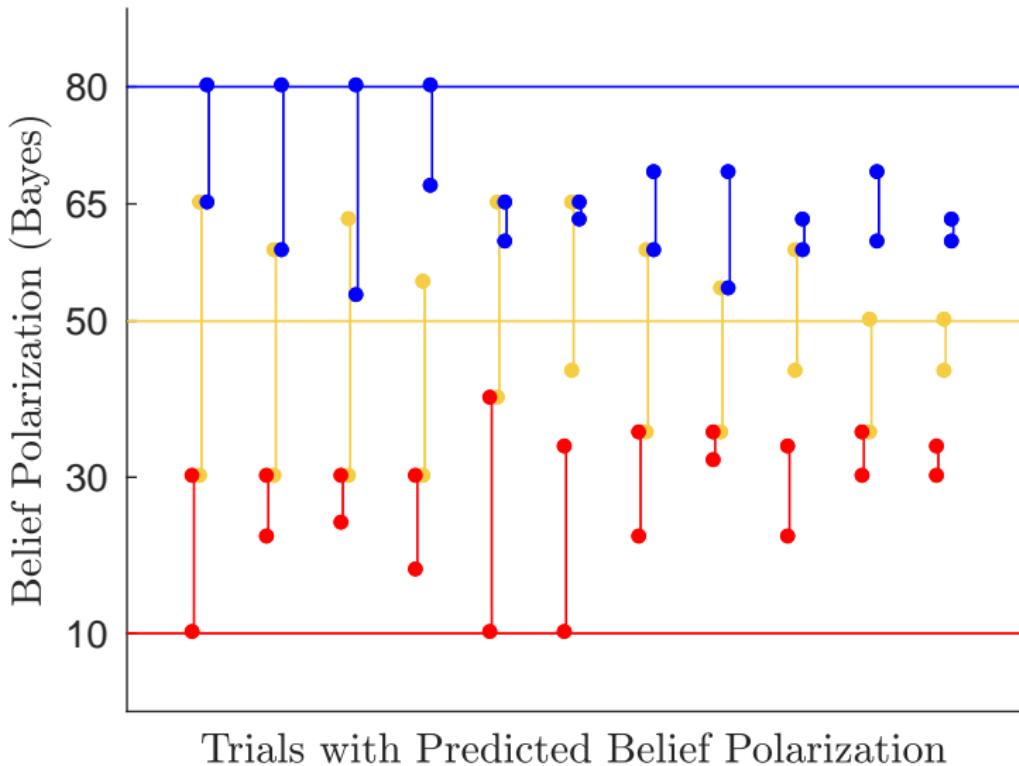
Beliefs Polarization - Data



Beliefs Polarization - Counterfactual



Beliefs Polarization - Predictions



TASK 1

Task 1 - Choice screen

OPAQUE BOX	
	10 points
	30 points
	80 points
TRANSPARENT BOX	
25 points	
	Opaque
	Transparent

Choice without Advisor

Red Advisor RED
NOT RED

Yellow Advisor YELLOW
NOT YELLOW

Blue Advisor BLUE
NOT BLUE

Rainbow Advisor RED
YELLOW
BLUE

OK

Task 1 - Hiring screen

OPAQUE BOX

-  10 points
-  30 points
-  80 points

TRANSPARENT BOX

-  25 points

Choice with Red Advisor

Choice without Advisor + 0 extra points

Choice without Advisor + 2 extra points

Choice without Advisor + 4 extra points

Choice without Advisor + 6 extra points

Choice without Advisor + 8 extra points

Choice without Advisor + 10 extra points

Choice without Advisor + 12 extra points

Choice without Advisor + 14 extra points

Choice without Advisor + 16 extra points

Choice without Advisor + 18 extra points

Choice without Advisor + 20 extra points

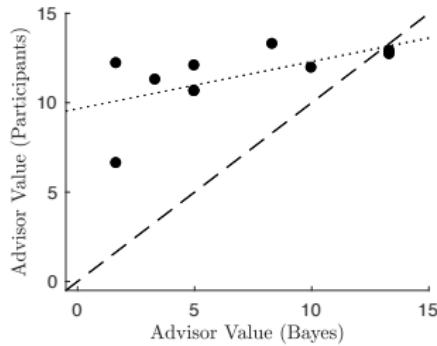
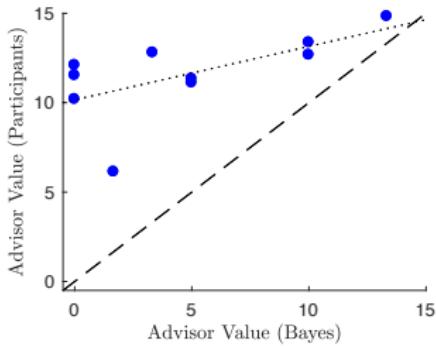
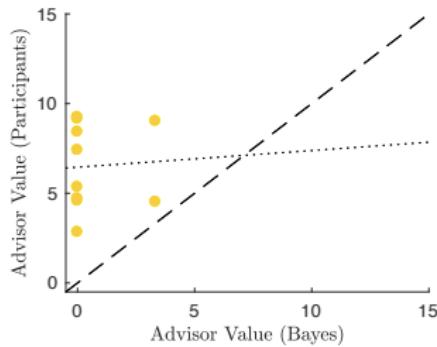
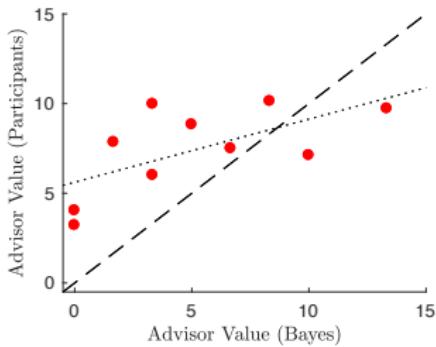
 Transparent

 Opaque

Make one choice for each line

Transparent

Compression in the WTP for Advisors in Task 1



Questionnaire - Strategies

State Pooling

- ▶ If low ball in transparent box, pick advisor most likely to reveal blue or yellow, vice versa
- ▶ I chose based on whichever advisor's information could tell me more about the single ball I either really did or did not want to pick

Other strategies

- ▶ CERTAINTY - I would choose the advisor which had the same color of cards for each color ball
- ▶ BLUE - To make sure if it is blue
- ▶ RED - I chose the advisor of the ball I didn't want to get on the opaque box, and if that was the color that was on the box, I went with the transparent box
- ▶ TALKATIVE - Probability

Conclusions

Model:

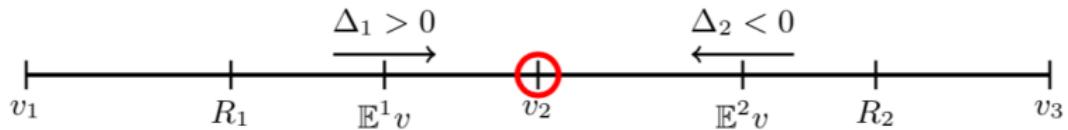
- ▶ **Rational and endogenous** polarization with multiple states
- ▶ Role of **the status quo** for information acquisition
- ▶ Endogenous **state pooling effect**
- ▶ **Cheaper** information leading to **more** polarization

Lab experiment:

- ▶ A change in the safe option generates “advisor switches”
- ▶ and creates (mitigated) belief polarization.
- ▶ We replicate well-known results (compression, preference for certainty) in a new setup with 3 states
- ▶ and we report novel evidence: preference for “state pooling”.

Thank you for your attention

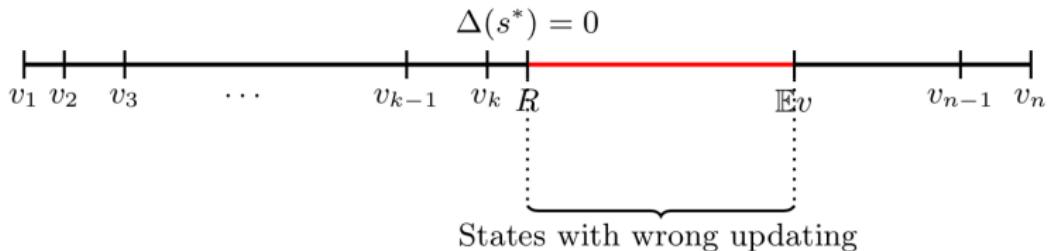
Convergence



[Back](#)

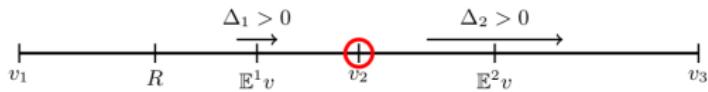
Monotonicity of $\Delta(s^*)$

Proposition Change in mean of beliefs $\Delta(s^*)$ is an increasing function of s^* .



$$W = \begin{cases} \{s \mid R < v_s < \mathbb{E}v\}, & \text{if } \mathbb{E}v > R \\ \{s \mid \mathbb{E}v < v_s < R\}, & \text{otherwise} \end{cases}$$

Divergence while updating in the same direction



Divergence while updating in the same direction

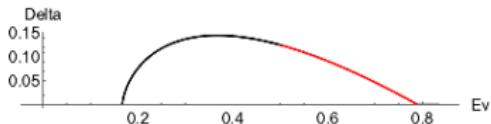
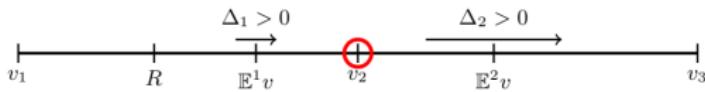


Figure 2: $\Delta(s^* = 2)$ as a function of $\mathbb{E}v$ for R_1 and λ_2 . The red area depicts the region of wrong updating.

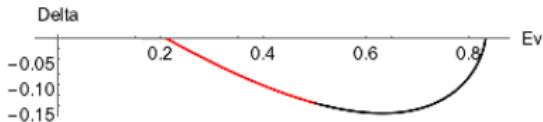


Figure 3: $\Delta(s^* = 2)$ as a function of $\mathbb{E}v$ for R_2 and λ_2 . The red area depicts the region of wrong updating.

Comparative statics

Cheaper information ($\lambda_2 < \lambda_1$) might lead to higher polarization

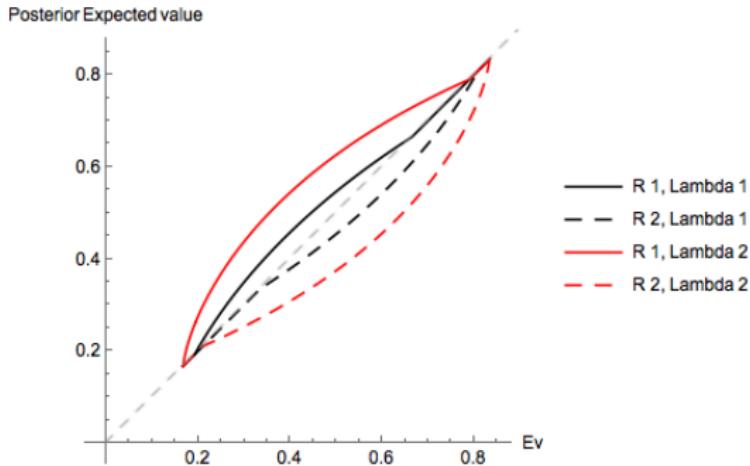


Figure 4: $E_i[\mathbb{E}(v|i)|s^*]$ as a function of $\mathbb{E}v$ for different levels of R and λ . The solid lines are the case with R_1 and dashed with R_2 . Black corresponds to cases with λ_1 and red is used for λ_2 .

Increase in polarization

- ▶ Political polarization (e.g., Boxwell, Gentzkow and Shapiro, 2017)
- ▶ Disagreement about objective truths
(e.g., McCright and Dunlap, 2011)
- ▶ Polarization as a backlash to events: globalization, etc.
(e.g., Pástor and Veronesi, 2018)

Back

Related literature:

- 1. Persistent disagreement of the Bayesian agents with exogenous info.**
 - ▶ Blackwell and Dubins (1962), Gerber and Green (1999); Dixit and Weibull (2007), and many other
- 2. Persistent disagreement with endogenous info.**
 - ▶ Su (2015); Nimark and Sundaresan (2019)
- 3. Reference based preferences**
 - ▶ Koszegi and Rabin (2006, 2007); Bordalo, Gennaioli and Shleifer (2012); Genicot and Ray (2017)
- 4. Empirical literature**
 - ▶ Charness, Oprea and Yuksel (2018); Ambuehl and Li (2018); Masatlioglu, Orhun and Raymond (2017)

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Related literature Rational Inattention

► Discrete choice

- ▶ Matejka and McKay (2015); Steiner, Stewart, Matejka (2017)

► Macroeconomics

▶ Linear-Quadratic

- ▶ Sims (1998,2003,2006); Mackowiak and Wiederholt (2009,2011, 2015); Afrouzi (2017)
- ▶ Sims(2006), Woodford(2009,2015), Matejka(2010), Matejka and Sims(2010)

▶ RI Kalman filter

- ▶ Mackowiak, Matejka and Wiederholt (2018)

► Political economics

- ▶ Matejka and Tabellini (2017)

► Finance

- ▶ Van Nieuwerburgh, Veldkamp(2008); Mondria(2009); Peng (2005); Kacperczyk, Van Nieuwerburgh and Veldkamp (2016)

Bayesian Updating

Realized state

$$X \sim \mathcal{N}(\mu_0, \sigma_X^2)$$

Signal

$$S = X + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$$

where ϵ and X are independent.

Conditional on realization of X posterior mean $\bar{\mu}$ is a weighted average of μ_0 and X

That is, the direction of updating on average is **towards** the realized state.

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Agent's problem

$$\max_{\mathcal{P}=\{\mathcal{P}(i|s)|i=1,2; s=1,\dots,n\}} \left\{ \sum_{i=1}^2 \sum_{s=1}^n v_s \mathcal{P}(i|s) g_s - \lambda \kappa \right\},$$

subject to

$$\forall i : \mathcal{P}(i|s) \geq 0 \quad \forall s = 1, \dots, n ,$$

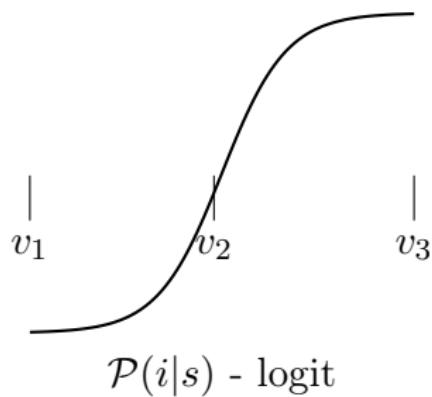
$$\sum_{i=1}^2 \mathcal{P}(i|s) = 1 \quad \forall s = 1, \dots, n ,$$

and

$$\kappa = \underbrace{- \sum_{i=1}^2 \mathcal{P}(i) \log \mathcal{P}(i)}_{\text{prior uncertainty}} - \underbrace{\left(- \sum_{s=1}^n \left(\sum_{i=1}^2 \mathcal{P}(i|s) \log \mathcal{P}(i|s) \right) g_s \right)}_{\text{posterior uncertainty}}.$$

Solution

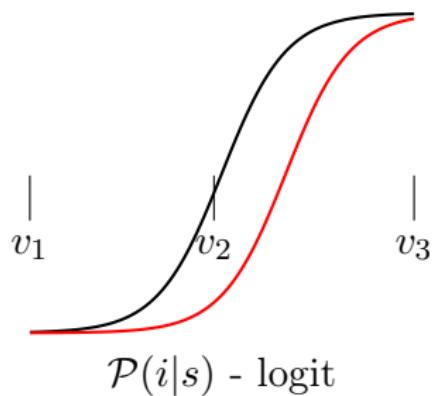
$\mathcal{P}(i|s) \forall i, s$ - characterize information strategy due to consistency of prior and posterior beliefs



Back

Solution

$\mathcal{P}(i|s) \forall i, s$ - characterize information strategy due to consistency of prior and posterior beliefs



Back

Lemma 1: Solution

Conditional on the realized state of the world s^*

$$\mathcal{P}(\text{new policy } | s^*) = \mathcal{P}(i = 1 | s^*) = \frac{\mathcal{P}(i = 1) e^{\frac{v_{s^*}}{\lambda}}}{\mathcal{P}(i = 1) e^{\frac{v_{s^*}}{\lambda}} + (1 - \mathcal{P}(i = 1)) e^{\frac{R}{\lambda}}} \quad \text{a.s.,}$$

$$\mathcal{P}(\text{status quo } | s^*) = \mathcal{P}(i = 2 | s^*) = \frac{(1 - \mathcal{P}(i = 1)) e^{\frac{R}{\lambda}}}{\mathcal{P}(i = 1) e^{\frac{v_{s^*}}{\lambda}} + (1 - \mathcal{P}(i = 1)) e^{\frac{R}{\lambda}}} \quad \text{a.s.,}$$

$\mathcal{P}(i = 1)$ - unconditional probability of choosing a new unknown policy

$\lambda = 0$ chooses the option with the highest value with probability one

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Description of Evolution of Beliefs

- Agent's prior expected value of the new policy is:

$$\mathbb{E}v = \sum_{s=1}^n v_s g_s$$

we **fix the state** of the nature: it is s^*

- Observer sees agent's updated expected belief:

$$\begin{aligned}\mathbb{E}_i[\mathbb{E}(v|i)|s^*] &= \mathcal{P}(\text{status quo}|s^*)\mathbb{E}(v|\text{status quo}) + \\ &\quad + \mathcal{P}(\text{new policy}|s^*))\mathbb{E}(v|\text{new policy}),\end{aligned}$$

Theorem 1

The expected posterior value of the new policy given s^* ,
for $i \in \{\text{new policy, status quo}\} = \{1, 2\}$ is:

$$\mathbb{E}_i[\mathbb{E}(v|i)|s^*] = \sum_{s=1}^n v_s g_s \frac{\mathcal{P}(i = 1|s^*)e^{\frac{v_s}{\lambda}} + (1 - \mathcal{P}(i = 1|s^*))e^{\frac{R}{\lambda}}}{\mathcal{P}(i = 1)e^{\frac{v_s}{\lambda}} + (1 - \mathcal{P}(i = 1))e^{\frac{R}{\lambda}}}.$$

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Description of Evolution of Beliefs

Corollary $\Delta(s^*) = 0$ holds if at least one of the following conditions is satisfied:

- (a) $v_{s^*} = R$
- (b) the agent is not acquiring any information, $\exists i : \mathcal{P}(i) = 1$.

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Parameters

v_1	v_2	v_3	g_1	g_2	g_3	R_1	R_2	λ_1	λ_2	λ_3	λ_4
0	$\frac{1}{2}$	1	$g \in (0, \frac{2}{3})$	$\frac{1}{3}$	$\frac{2}{3} - g$	$\frac{3}{8}$	$\frac{5}{8}$	$\frac{1}{8}$	$\frac{1}{4}$	$\frac{3}{8}$	1

Table 1: Parameters used in this section

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