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

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Motivation

- Society today is more polarized (McCarty et al. 2008)
  Increase in Polarization Literature
- Information is more easily accessible (lower cost)

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- Democratic votes like referendums are often binary choices about complex questions - status quo vs. a new policy

Main Question:

How are such binary choices connected with the belief polarization (information selection)

Motivating example

Consider the 2016 Brexit referendum

- Surveys suggest that polarization increased after the 2016 Brexit vote (see e.g. YouGov)

Motivating Example

Setting

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

- Stay: “safe” choice [status quo]
- Leave: uncertainty about the outcome of the policy [state s]

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	Leave	**Stay**	
s	v_s	R_A	R_B
bad	0	0.45	0.55
medium	0.5	0.45	0.55
good	1	0.45	0.55

- Assume uniform prior $g_s = \frac{1}{3}$ and risk neutrality

Motivating Example

No Learning

Alice and Bob have the same beliefs over s and $EV(\text{Leave})$

- $EV(\text{Leave}) = 0.5$

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Alice and Bob make different choices

- A chooses Leave as $0.5 = EV(\text{Leave}) > EV(\text{Stay}) = 0.45$
- B chooses Stay as $0.5 = EV(\text{Leave}) < EV(\text{Stay}) = 0.55$

	Leave	**Stay**	
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Motivating Example

Learning

- Same problem as before, but now A and B can collect "some" information about the outcome
- Can ask question for a cost $\epsilon > 0$:

"Is the realized state i, or is it not?"

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"Is the realized state i, or is it not?"

- Note that we have 2 actions (L/S) and 3 states (b/m/g)
- Alice with one question can receive the following partition:

	Leave	**Stay**
s	v_s	R_A
bad	0	0.45
medium	0.5	0.45
good	1	0.45

Motivating Example

How many questions would they ask?

- If they decide to ask at least one question, then they will not ask the second.

What is the optimal question?

- For Alice it *cannot* be optimal to ask if the outcome of Leave is (b/m) or g

	Leave	**Stay**
s	v_s	R_A
bad	0	0.45
medium	0.5	0.45
good	1	0.45

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- If they decide to ask at least one question, then they will not ask the second.

What is the optimal question?

- For Alice it is *sufficient* to ask
  if the outcome of Leave is (m/g) or b

	Leave	**Stay**
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Motivating Example

How many questions would they ask?

- If they decide to ask at least one question, then they will not ask the second.

What is the optimal question?

- For Bob it is *sufficient* to ask
  if the outcome of Leave is (b/m) or g

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s	v_s	R_A	R_B
bad	0	0.45	0.55
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Motivating Example

Beliefs

- If the Leave outcome is good (bad) they agree about the action Leave (Stay)
- But they do not agree about how good (bad) the outcome is
  - Good: $EV_A(L|g) = 0.75 < EV_B(L|g) = 1$
  - Bad: $EV_A(L|b) = 0 < EV_B(L|b) = 0.25$

Motivating Example

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- But they do not agree about how good (bad) the outcome is
  - Good: $EV_A(L|g) = 0.75 < EV_B(L|g) = 1$
  - Bad: $EV_A(L|b) = 0 < EV_B(L|b) = 0.25$

- If the outcome is medium they still disagree about the action
- But they also disagree about the expected outcome of Leave
  - Alice chooses Leave: $EV_A(L|m) = 0.75$
  - Bob chooses Stay: $EV_B(L|m) = 0.25$

Motivating Example

Summary

- Alice and Bob have the same prior beliefs
- But they have different valuation of **the status quo** option
- The introduction of **endogenous information collection** created disagreement about outcome of the new policy

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- Referendum vote (e.g. Brexit), Stock/bond investment, etc.

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- Alice and Bob have the same prior beliefs
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- The introduction of **endogenous information collection** created disagreement about outcome of the new policy
- Referendum vote (e.g. Brexit), Stock/bond investment, etc.

Definition

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

Today's Presentation

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

Our Theoretical Approach and Contribution

- 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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- The framework does not include
  - Communication between agents
  - Dynamic information acquisition

Literature

Our Theoretical Results

- Polarization as **a result of inattentiveness**
- Polarization even for people with **the same prior belief**
- Polarization in **expectations** (before signal realizations)

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- Polarization even for people with **the same prior belief**
- Polarization in **expectations** (before signal realizations)

- **Status quo** importance
- Endogenous **state pooling** effect

- **Cheaper** information $\implies$ **more polarized** society

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- The results rely on many optimality assumptions
  - Many of which at odds with the evidence
- Observe beliefs polarization in the lab setting
  - A change in the status quo generates “information switch” as predicted, and creates belief polarization
- Identify the drivers (and weaknesses) of the result
  - We replicate well-known results in multiple states design (compression of WTP, preference for certainty)
  - We report new evidence of preference for “state pooling” and “extreme” information

The Model

Model

- An agent faces a discrete binary choice problem

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

- Status quo
  - known value R (e.g. GDP growth 2%)

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- Status quo
  - known value R (e.g. GDP growth 2%)
- New policy
  - value v_s, where $s \in S = \{1, \ldots, n\}$
  - states are labeled, such that $v_1 < v_2 < ... < v_n$
    e.g. consequent GDP growth $-10\% < -9\% < \cdots < 5\%$
  - Assumption: $v_1 < R < v_n$

Model

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

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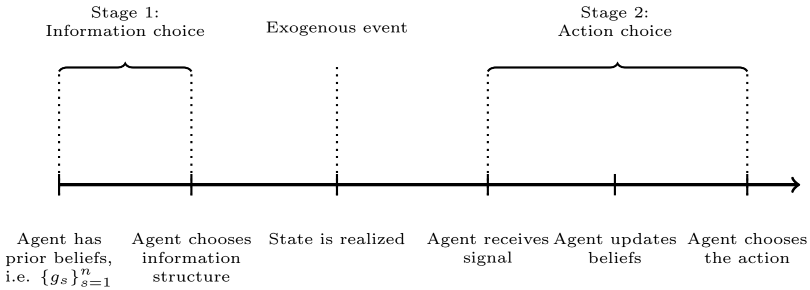
$$\max_{\text{Information strategy}} \{\mathbb{E}(U) - \text{cost of information}\}$$

Agent's Problem



Agent's problem

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

subject to

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

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

and

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

Back Solution

Main idea: Evolution of Beliefs

We are interested in updating of expectations

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

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

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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^*,

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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 $\boldsymbol{\Delta}(\mathbf{s}^*)$ about the payoff of the new policy

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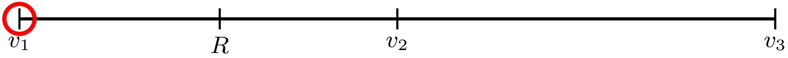
Extreme states

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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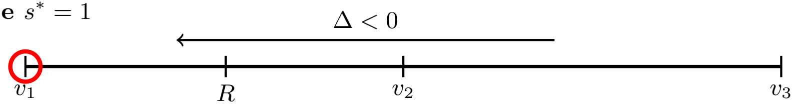

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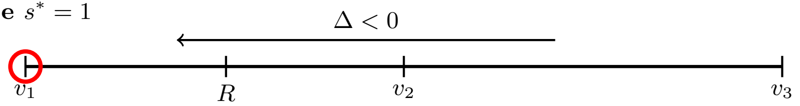
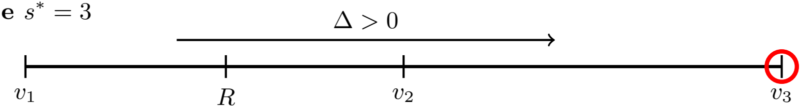
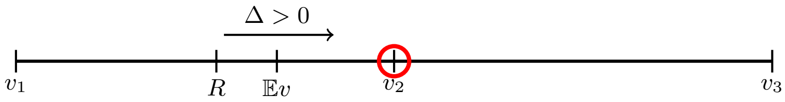


State $s^* = 3$



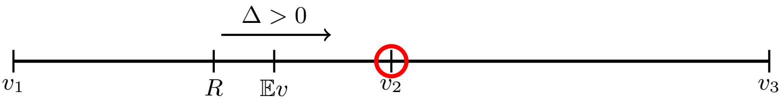
Updating away from the realized state

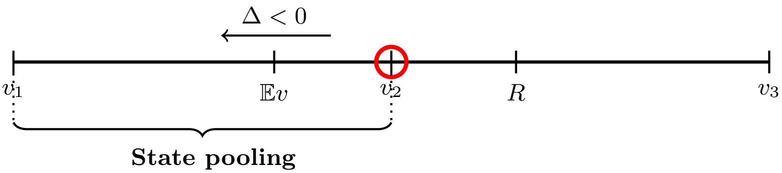
State $s^* = 2$



Updating away from the realized state

State $s^* = 2$



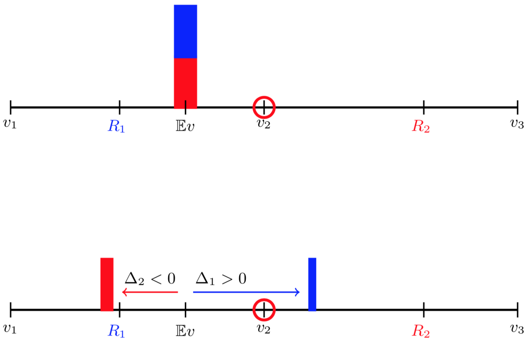


Polarization result

Definition

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

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

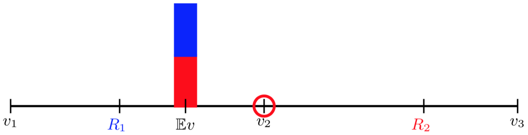


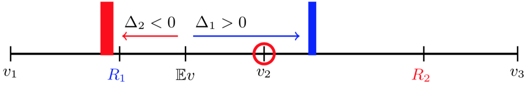
Polarization result

Definition

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

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





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

- **Do we observe belief polarization by changing R?**

Laboratory Experiment

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- Stage 1: choose or “hire” a signal structure
- Observe the signal realization
- Stage 2: select an action [risky/safe]

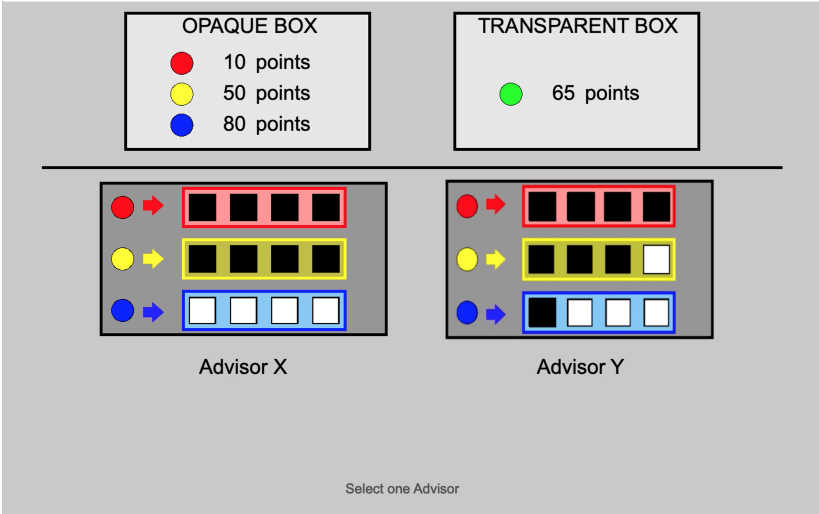
- We collect separately
  - Choices over sources of information (advisors)
  - Action (conditional on realized signals)
  - Elicited beliefs (signal probability and posterior)
  - Willingness to pay for signal structures

Laboratory Experiment

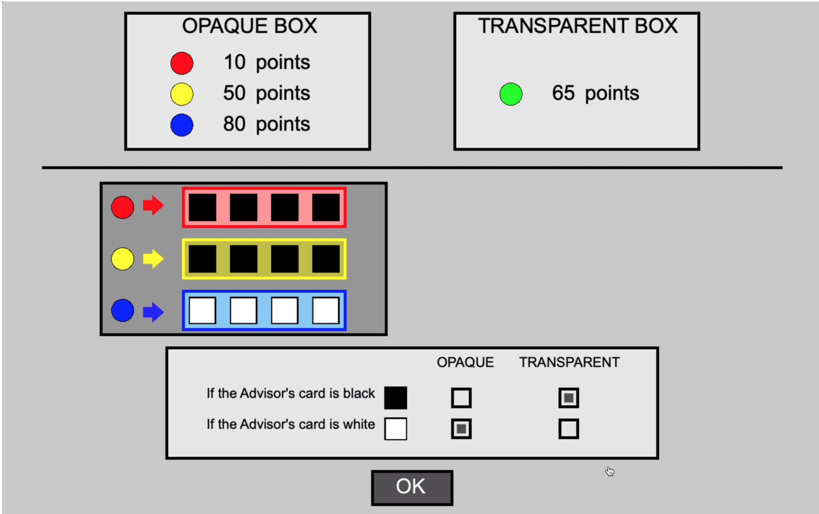
- Experiment conducted at Columbia in September 2019
- 85 participants (undergraduate and graduate students)
- Average time 80 minutes, Average payment ∼\$25
  - Show-up fee (\$10)
  - Main experiment, 4 parts (probability points, \$15 prize)
  - Risk attitude (Holt-Laury, \$0.10-\$4.00)
  - Intelligence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

Main Task

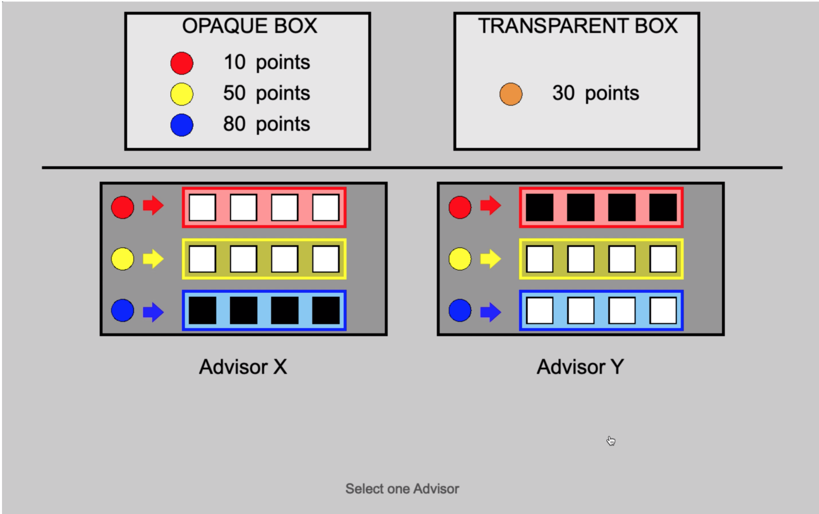
Task 2 - Hiring screen



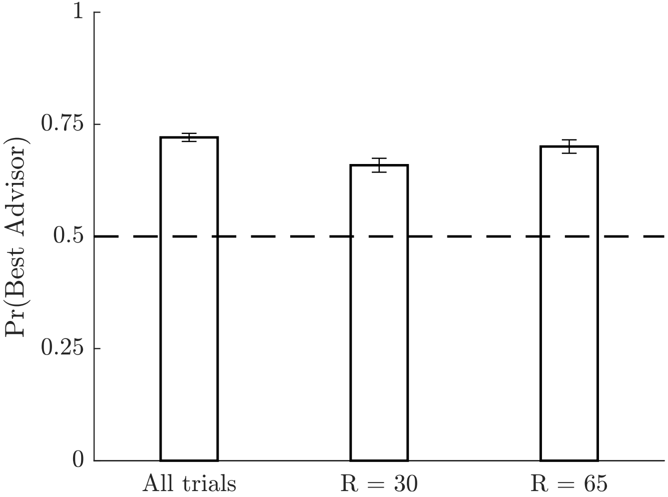
Task 2 - Choice screen



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

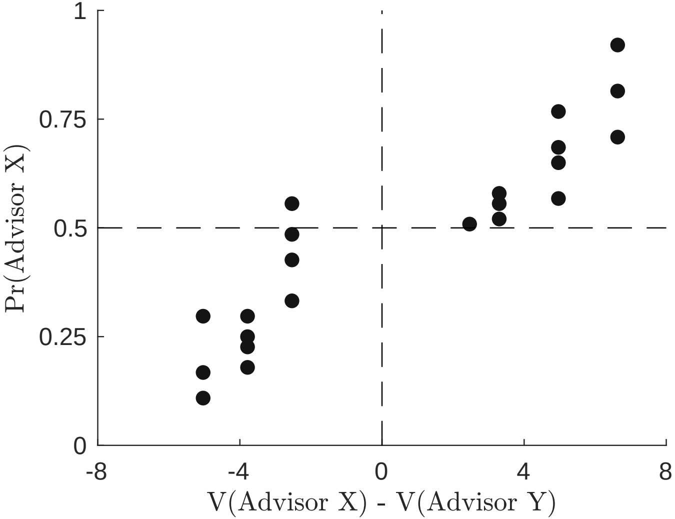


Most of participants "switch" advisor optimally



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



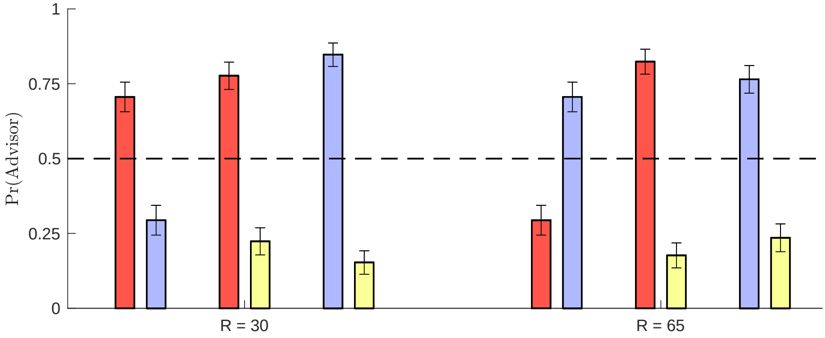
Probability of choosing Advisor X given a pair X,Y.
22/40 trials, 85 observations per trial.

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 $p > 0$.

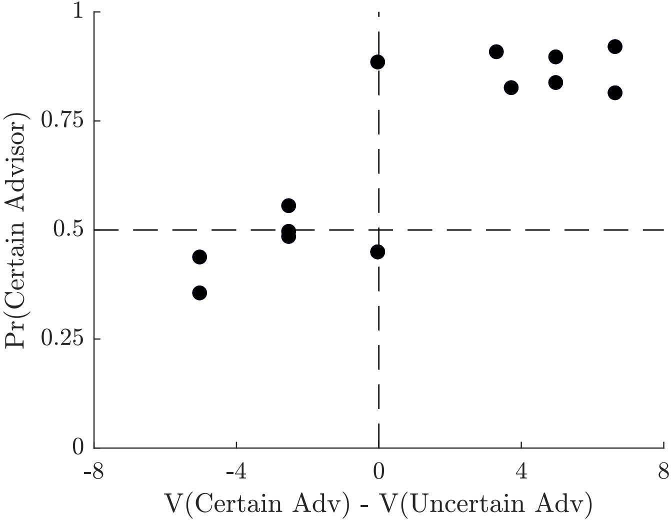
	SP	**Not SP**
C	(0, 1, 1)	(0, 1, 0)
Not C	$(0,\ \frac{3}{4}, \frac{3}{4})$	$(\frac{1}{4}, \frac{3}{4}, \frac{3}{4})$

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.

Aggregate Valuation of Advisors - Logit Regression

	(1)
v_I^{Bayes}	0.210***
	(0.0346)
Best Advisor	0.106
	(0.143)
Certainty	
State Pooling	
Certainty × SP	
Trials	All
Observations	3,400

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

Estimated value $v_X = \beta_0 + \beta_1 v_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$

Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)
v_I^{Bayes}	0.210***	0.236***
	(0.0346)	(0.0110)
Best Advisor	0.106	
	(0.143)	
Certainty		0.1876***
		(0.0708)
State Pooling		
Certainty × SP		
Trials	All	All
Observations	3,400	3,400

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Estimated value $v_X = \beta_0 + \beta_1 v_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$

Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)	(3)
v_I^{Bayes}	0.210***	0.236***	0.2108***
	(0.0346)	(0.0110)	(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 $v_X = \beta_0 + \beta_1 v_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$

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

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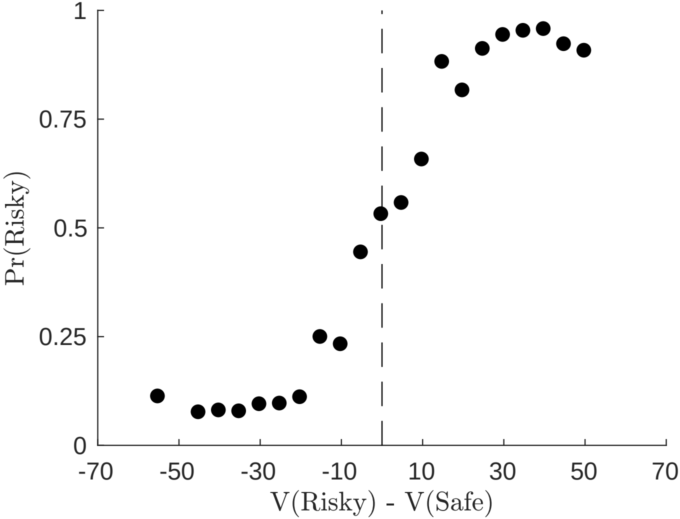
Estimated value $v_X = \beta_0 + \beta_1 v_I^{Bayes} + \beta_2 D_{\text{Best}} + \beta_3 D_{\text{Certain}} + \beta_4 D_{\text{SP}} + \beta_5 D_{\text{CxSP}}$

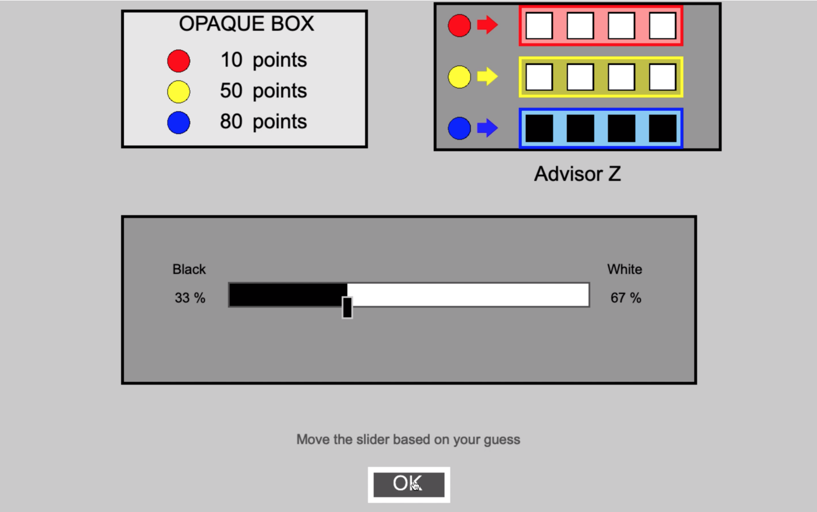
Action Selection



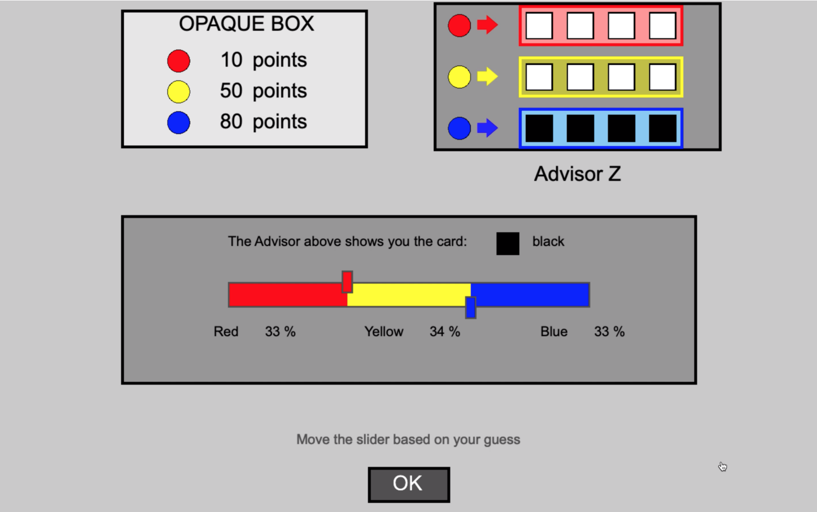
Observed probability of choosing the risky action in task 2. 6,800 observations grouped in 21 bins (different sample size).

Beliefs

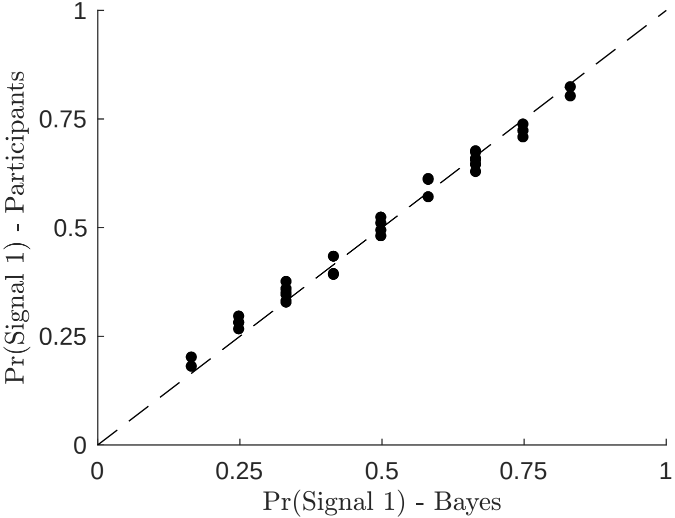
Task 3 - Belief elicitation



Task 4 - Belief elicitation

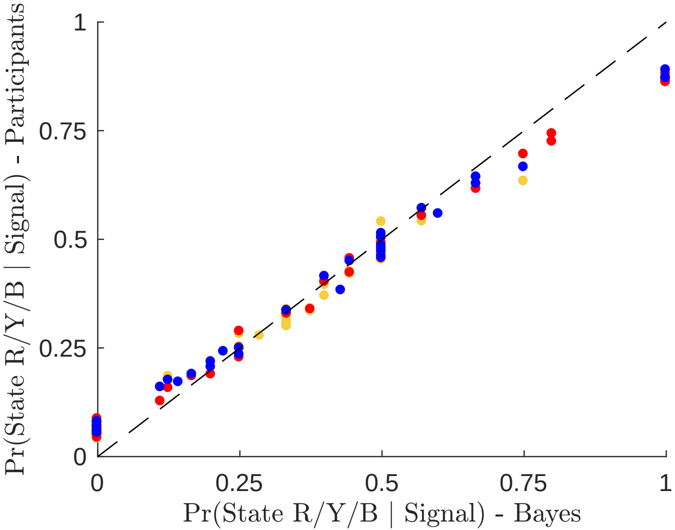


Elicited Beliefs - Card color



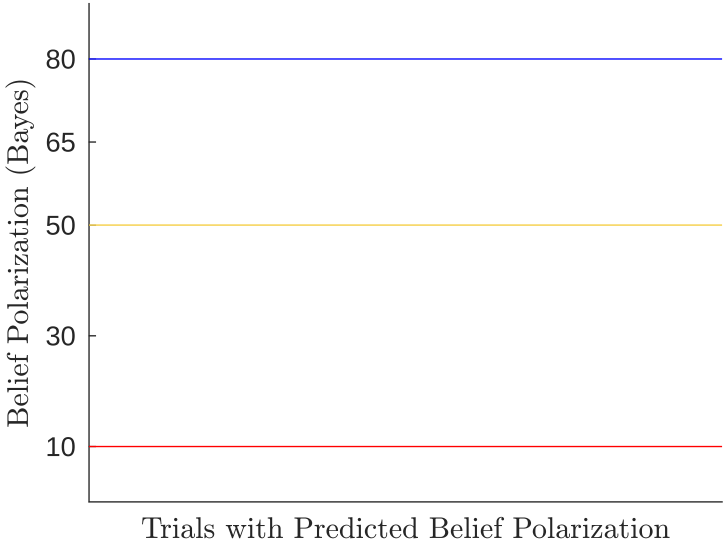
Estimated probability of receiving a signal realization in task 3: subjective and optimal estimates. 1,700 observations across 20 trials (85 obs. per point).

Elicited Beliefs - Ball color

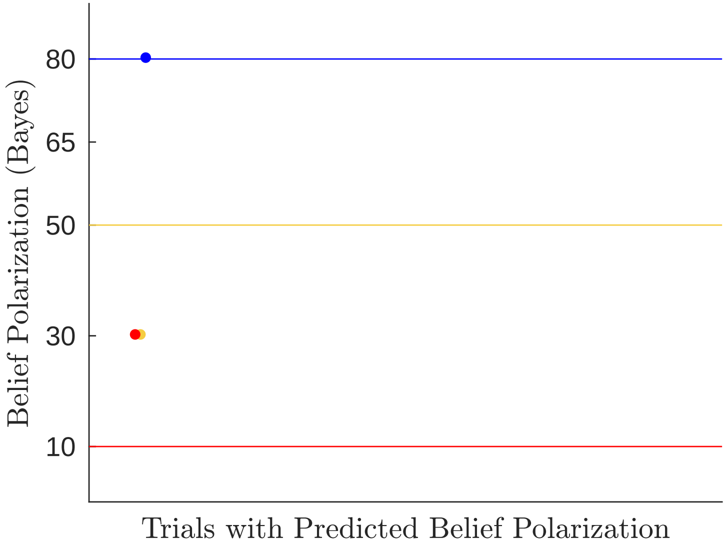


Estimated posterior probability in task 4: subjective and optimal estimates. Colors indicate the state. 20,400 observations across 40 trials (85 obs. per point).

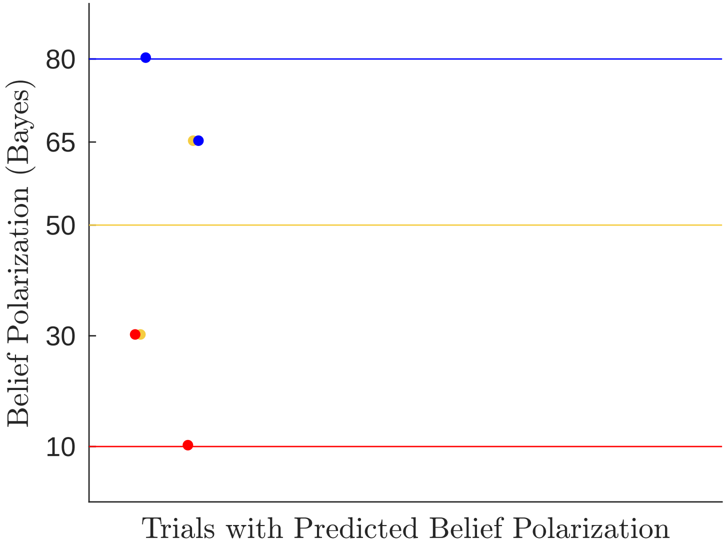
Beliefs Polarization - Predictions



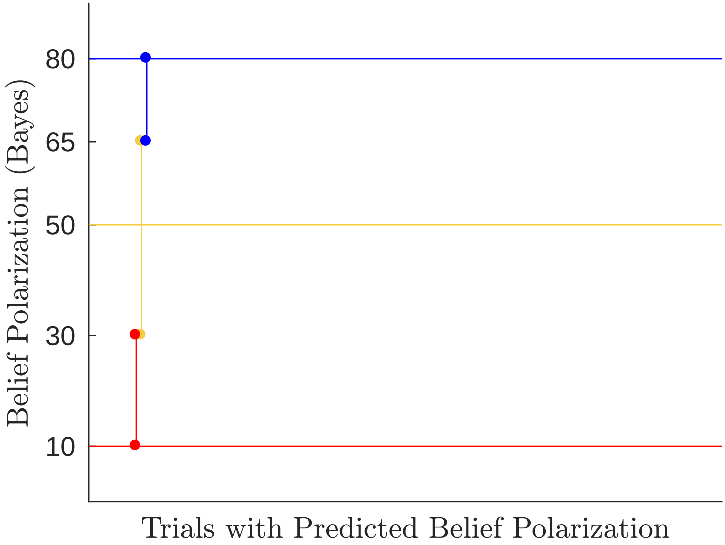
Beliefs Polarization - Predictions



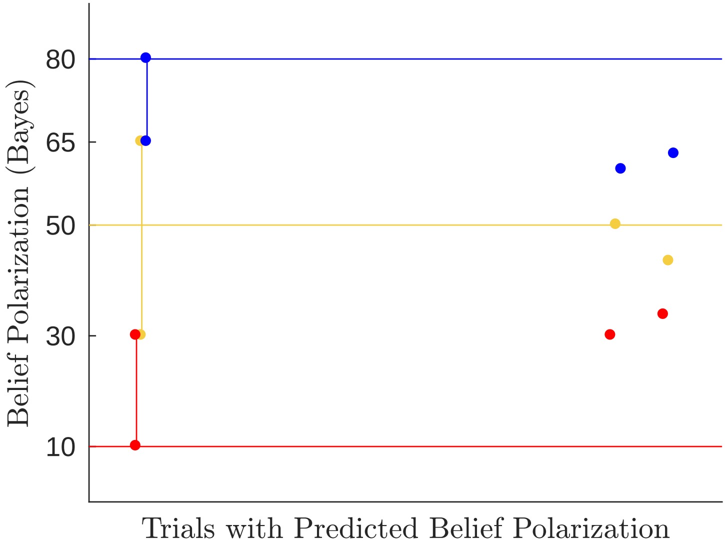
Beliefs Polarization - Predictions



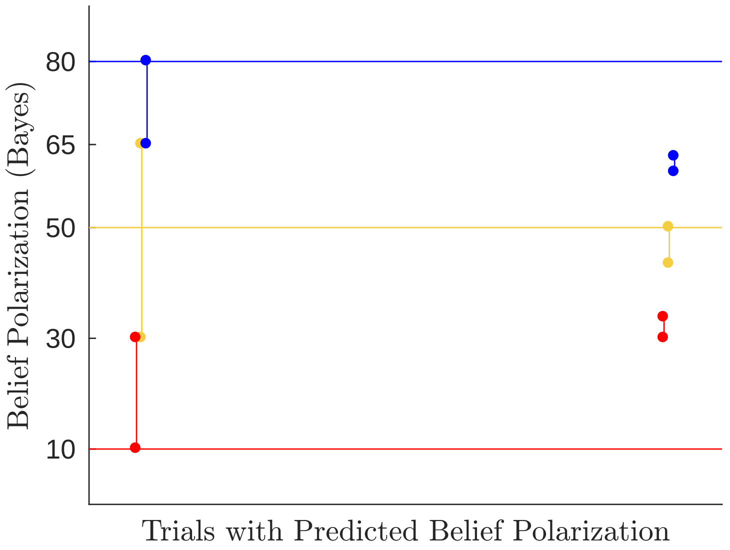
Beliefs Polarization - Predictions



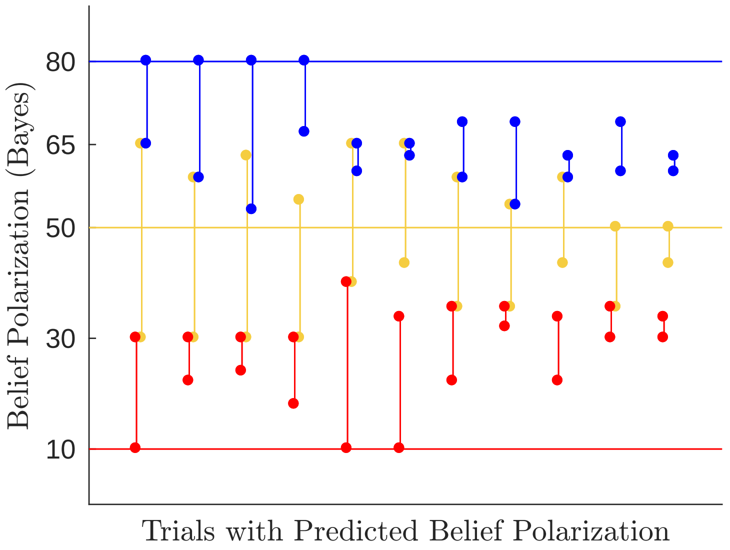
Beliefs Polarization - Predictions



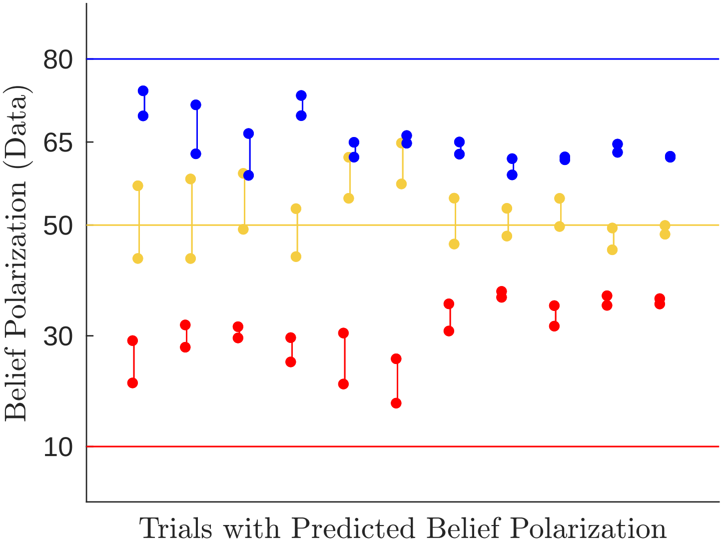
Beliefs Polarization - Predictions



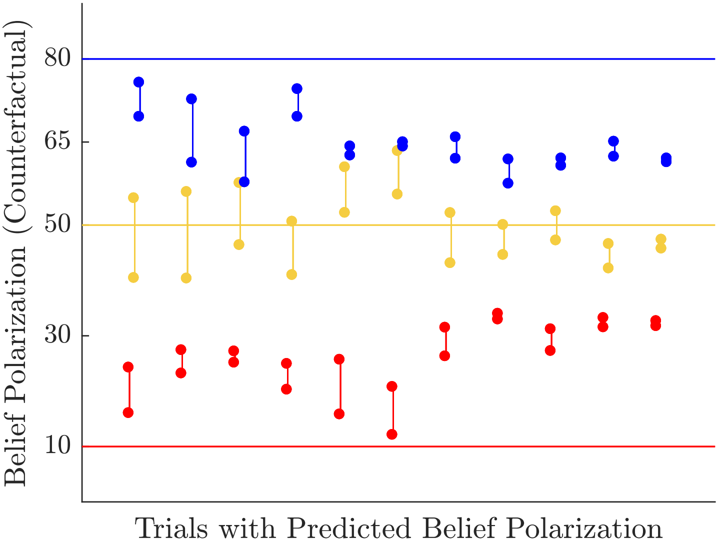
Beliefs Polarization - Predictions



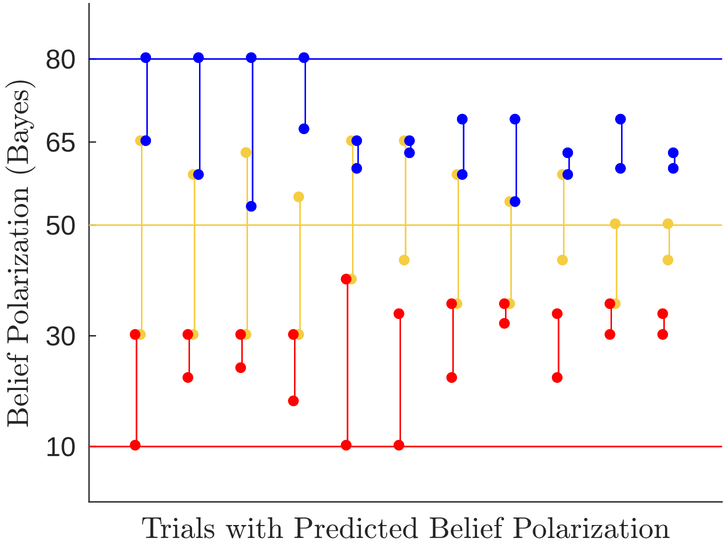
Beliefs Polarization - Data



Beliefs Polarization - Counterfactual

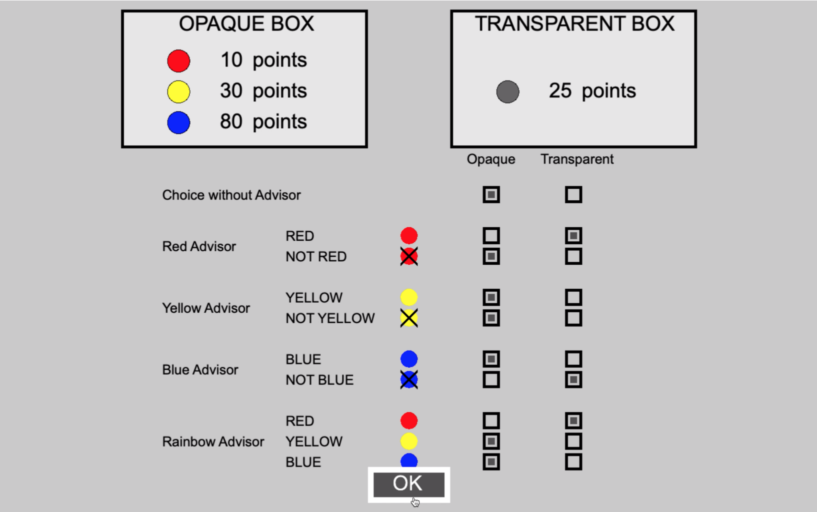


Beliefs Polarization - Predictions

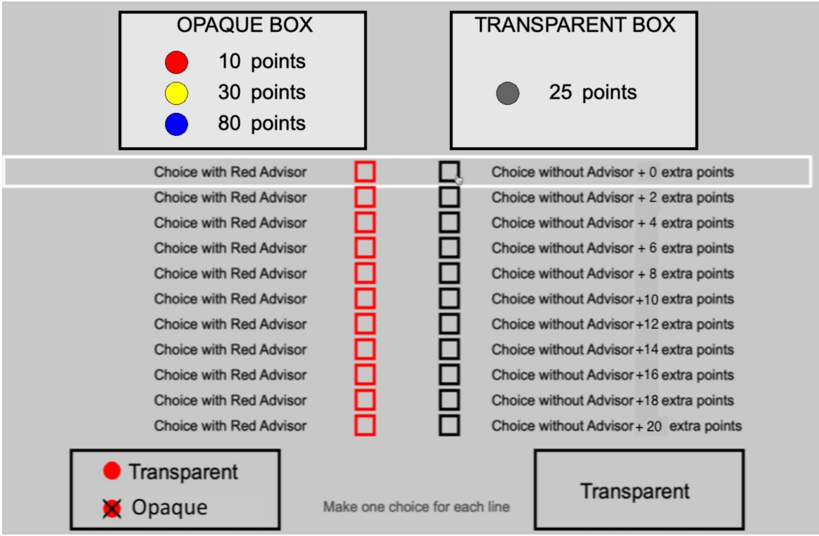


Task 1

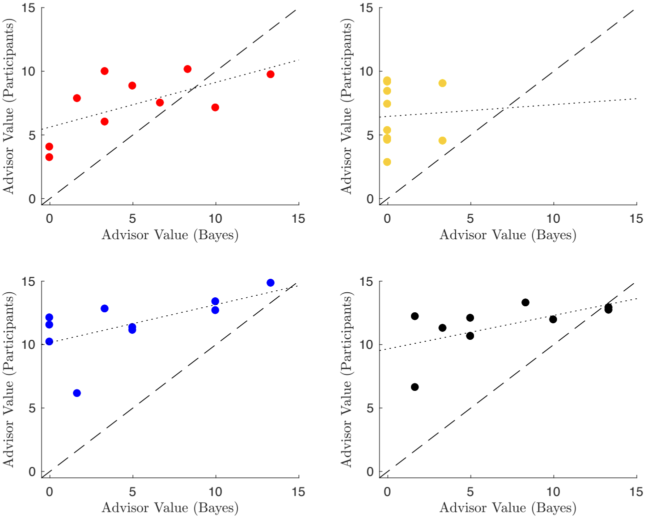
Task 1 - Choice screen



Task 1 - Hiring screen



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”.

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

Silvio Ravaioli

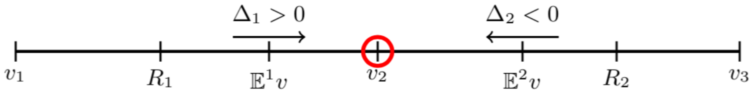
Columbia University

joint work with
Andrei Matveenko and Vladimír Novák
(University of Copenhagen) (CERGE-EI)

Micro Theory Colloquium
November 20th, 2019

Thank you for your attention

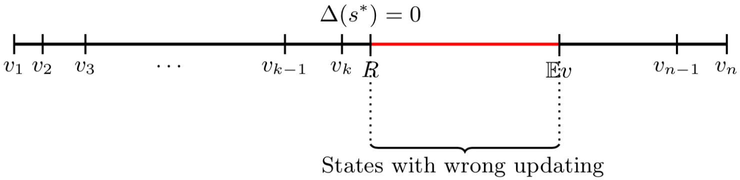
Convergence



Back

Monotonicity of $\Delta(s^*)$

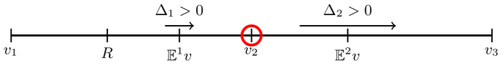
Proposition Change in mean of beliefs $\Delta(s^*)$ is an increasing function of s^*.



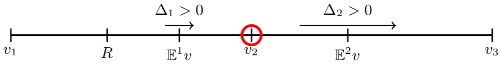
$$W = \begin{cases} \{s \mid R < v_s < \mathbb{E}v\}, & \text{if } \mathbb{E}v > R \\ \{s \mid \mathbb{E}v < v_s < R\}, & \text{otherwise} \end{cases}$$

Back

Divergence while updating in the same direction



Divergence while updating in the same direction



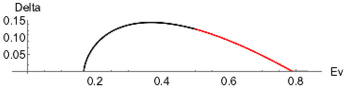


Figure: $\Delta(s^* = 2)$ as a function of $\mathbb{E}v$ for R_1 and λ_2. The red area depicts the region of wrong updating.

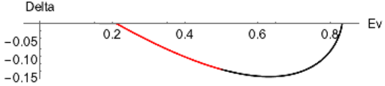


Figure: $\Delta(s^* = 2)$ as a function of $\mathbb{E}v$ for R_2 and λ_2. The red area depicts the region of wrong updating.

Comparative statics

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

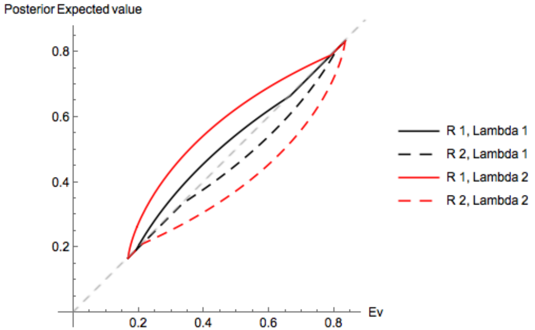


Figure: $\mathbb{E}_i[\mathbb{E}(v|i)|s^*]$ as a function of $\mathbb{E}v$ for different levels of R and λ. The solid lines are the case with R_1 and dashed with R_2. Black corresponds to cases with λ_1 and red is used for λ_2.

Back

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)

Back

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)

Back

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), Blackwell and Dubins (1962)
- Bimodality of preferences - Dixit and Weibull (2007)
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Laboratory experiments

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Related Literature: Rational Inattention | Bayes Update

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Related Literature: Rational Inattention
Bayes Update

Bayesian Updating

Realized state

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

Signal

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

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.

Back

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

$$\begin{aligned} \forall i:\ \mathcal{P}(i|s) &\geq 0 \qquad && \forall s = 1, \dots, n\ , \\ \sum_{i=1}^{2} \mathcal{P}(i|s) &= 1 \qquad && \forall s = 1, \dots, n\ , \end{aligned}$$

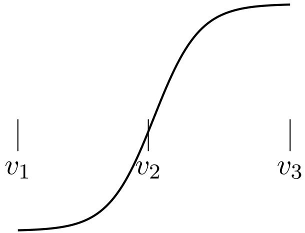
and

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

Back

Solution

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



$\mathcal{P}(i|s)$ - logit

Back

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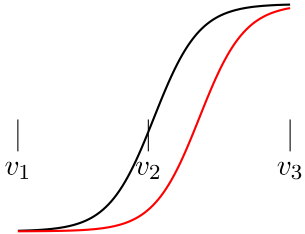

$\mathcal{P}(i|s)$ - logit

Back

Lemma 1: Solution

Conditional on the realized state of the world s^*

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

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

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

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

Back

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:

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

Theorem 1 Back

Theorem 1

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

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

Back

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, $\exists\, i : \mathcal{P}(i) = 1$.

Back

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: Parameters used in this section

Back