

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

Vladimír Novák
CERGE-EI

joint work with
Andrei Matveenko and Silvio Ravaioli
(University of Copenhagen) (Columbia University)

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Motivation

- ▶ Society today is more polarized (McCarty et al. 2006)
Increase in Polarization Literature
- ▶ Information is more easily accessible (lower cost)

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- ▶ Information is more easily accessible (lower cost)
- ▶ Democratic votes 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

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

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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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Learning

- ▶ Same problem as before, but now A and B can collect “some” information about the outcome
- ▶ Can ask question for a cost $\alpha > 0$:
“Is the realized state i , or is it not? ”

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- ▶ Can ask question for a cost $\alpha > 0$:
“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 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

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

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Motivating Example

How many questions would they ask?

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What is the optimal question?

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

	Leave	Stay	
s	v_s	R_A	R_B
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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

Beliefs

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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

Direction of updating - richer space of questions

- If the realized state is medium then for Alice

$$\mathbb{E}_i[\mathbb{E}(v|i)|s = m] = \frac{1}{2}v_m + \frac{1}{2}v_g.$$

$i \in \{\text{leaving the EU, staying in the EU}\}$

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Interestingly, if $\mathbb{E}V_L - \alpha > \mathbb{E}V_{NL} > v_m$, the following inequality holds:

$$\mathbb{E}_i[\mathbb{E}(v|i)|s = m] > \mathbb{E}V_{NL} > v_m.$$

Alice's conditional expected posterior belief about the outcome of the Leave [new policy] is higher than the prior expected belief and as the true outcome.

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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- ▶ The introduction of **endogenous information collection** created disagreement about outcome of the new policy
- ▶ Stock/bond investment, Referendum vote (e.g. Brexit), etc.

Definition

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

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

Our Theoretical Approach and Contribution

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 - ▶ Rational endogenous information acquisition
 - ▶ We do not assume exogenous biases
 - ▶ Can receive any information
 - ▶ Information is costly
- ▶ Impact of the current situation - **Status quo**
- ▶ Disciplined model - evolution of the disagreement in different environments
- ▶ **Multiple states** environment
- ▶ Impact of **increased information availability** on polarization e.g. internet, social networks

Our Theoretical Results

- ▶ Polarization as **a result of inattentiveness**
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- ▶ **Status quo** importance
- ▶ Endogenous **state pooling** effect

- ▶ **Cheaper** information \implies **more polarized** society
- ▶ **Policy lesson:**
focus on the valuation of the status quo

Our Experimental Contribution

Can we observe belief polarization
and identify its drivers in a lab experiment?

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**Can we observe belief polarization
and identify its drivers in a lab experiment?**

This question can be divided into three smaller ones:

- 1. How do agents evaluate and choose information sources?**

We replicate well-known results in multiple states design (compression of WTP wrt optimal value, preference for certainty)

- 2. Do we observe (preference for) state pooling?**

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

- 3. Do we observe belief polarization
(by changing status quo)?**

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),
Blackwell and Dubins (1962)
- ▶ 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

- ▶ The Model

- ▶ Laboratory Experiment

- ▶ Design
- ▶ Results

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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e.g. consequent GDP growth $-10\% < -9\% < \dots < 5\%$

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 - ▶ states are labeled, such that $v_1 < v_2 < \dots < v_n$
e.g. consequent GDP growth $-10\% < -9\% < \dots < 5\%$
- ▶ 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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$$\max_{\text{Information strategy}} \{\mathbb{E}(U) - \text{cost of information}\}$$

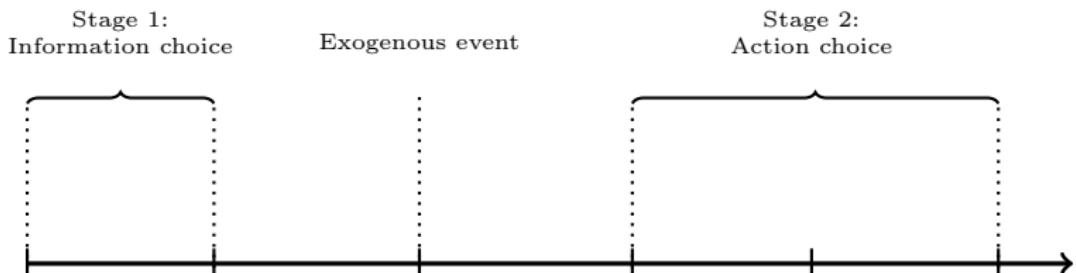
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Agent's Problem with Rational Inattention



Agent has prior beliefs,
i.e. $\{g_s\}_{s=1}^n$ Agent chooses information structure State is realized Agent receives signal Agent updates beliefs Agent chooses the action

Our work vs. previous RI models
e.g. Sims (2003), Matějka and McKay (2015):
State-dependent precision/pooling

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^* ,

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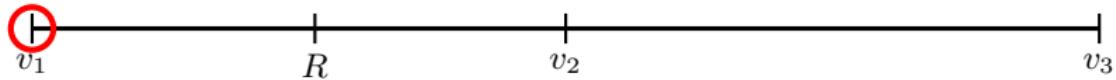
the sign of the change in the mean of beliefs $\Delta(s^*)$ about the payoff of the new policy **is the same as the sign of** $(v_{s^*} - R)$.

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 $s^* = 1$

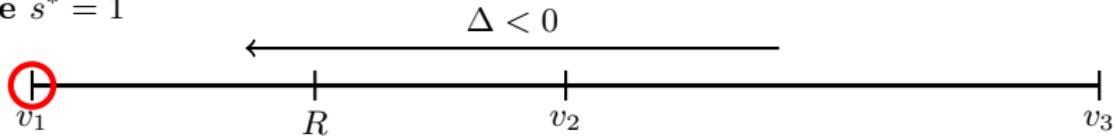


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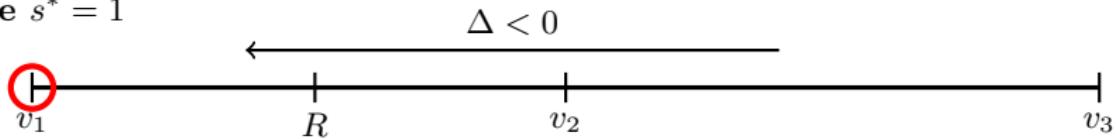


Extreme states

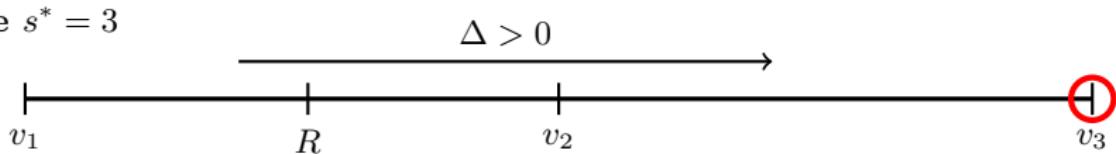
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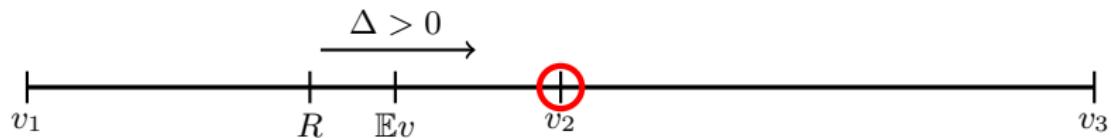


State $s^* = 3$



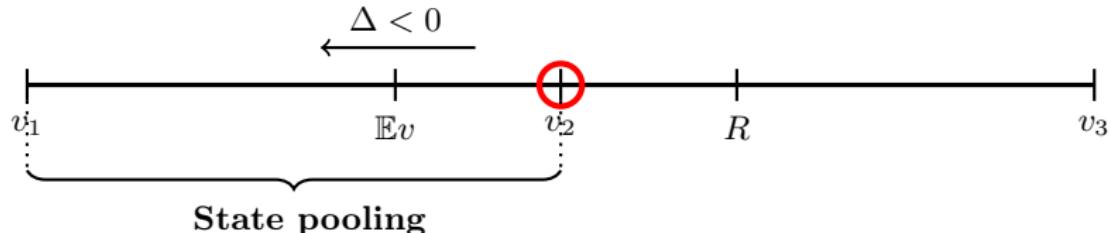
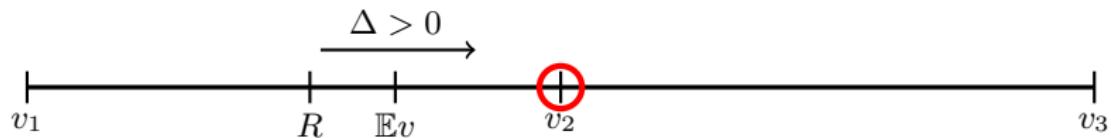
Updating away from the realized state

State $s^* = 2$



Updating away from the realized state

State $s^* = 2$

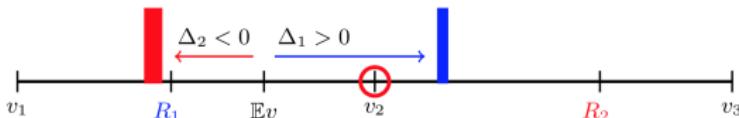
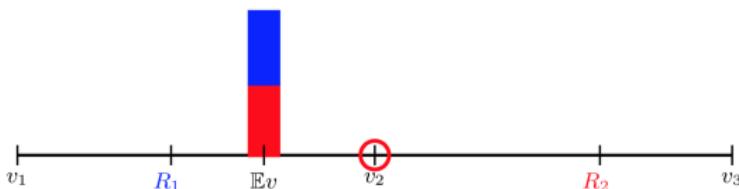


Polarization result

Proposition

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.



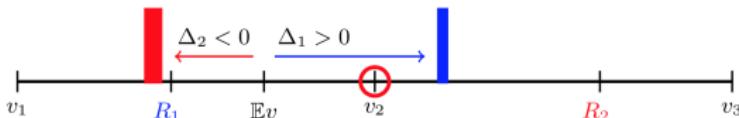
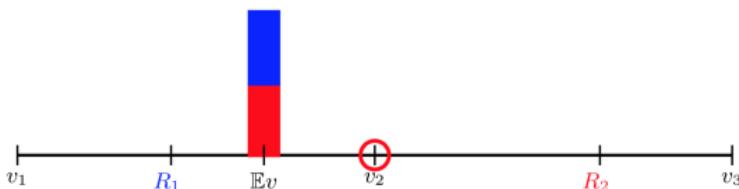
Polarization result

Definition

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

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

are satisfied.



Other Results

Convergence of beliefs Convergence

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

Divergence while updating in the same direction Divergence

Comparative statics Comparative statics

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

Laboratory Experiment

Laboratory Experiment

- ▶ How do agents evaluate and choose information sources?
- ▶ Do we observe (preference for) state pooling?
- ▶ Do we observe belief polarization (by changing Safe)?

Laboratory Experiment

- ▶ How do agents evaluate and choose information sources?
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-
- ▶ Stage 1: choose or “hire” an advisor (experiment)
 - ▶ Observe 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 August-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)

TASK 1

Task 1 - Choice screen

OPAQUE BOX		TRANSPARENT BOX	
	10 points		25 points
	30 points		
	80 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

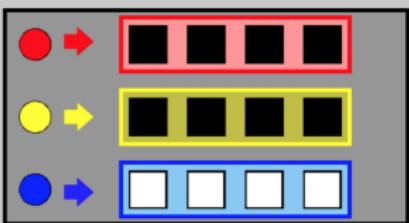
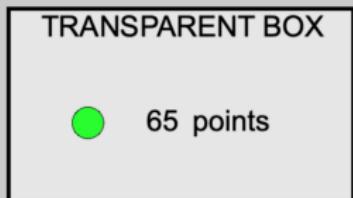
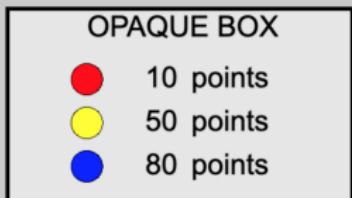
 Opaque

Make one choice for each line

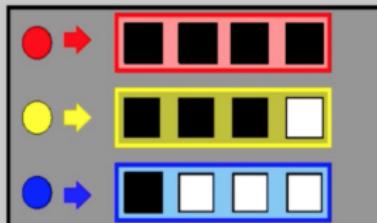
Transparent

TASK 2

Task 2 - Hiring screen



Advisor X



Advisor Y

Select one Advisor

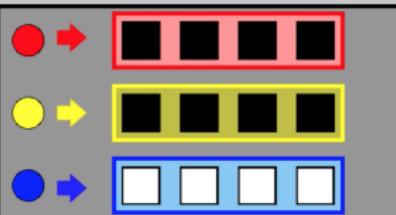
Task 2 - Choice screen

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

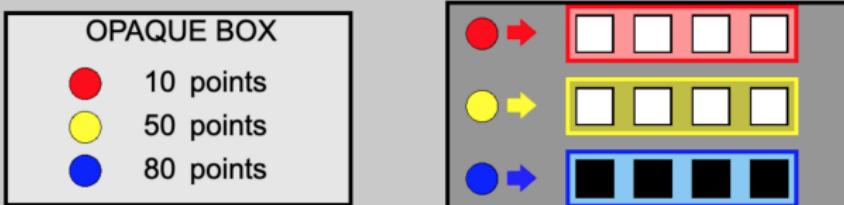


OK

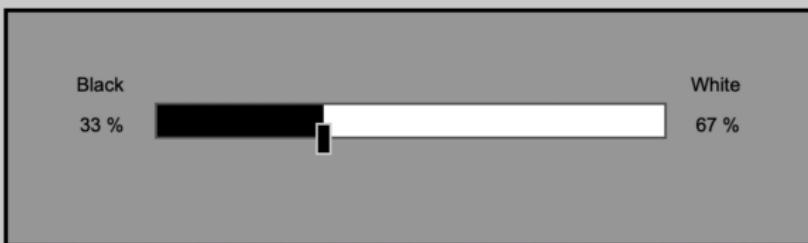


TASK 3

Task 3 - Belief elicitation



Advisor Z

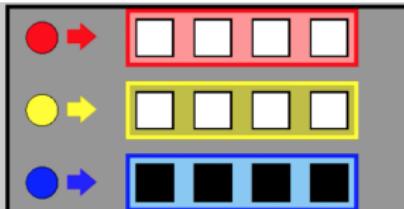
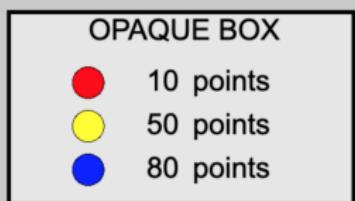


Move the slider based on your guess

OK

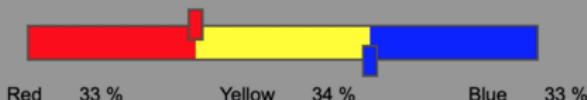
TASK 4

Task 4 - Belief elicitation



The Advisor above shows you the card:

black



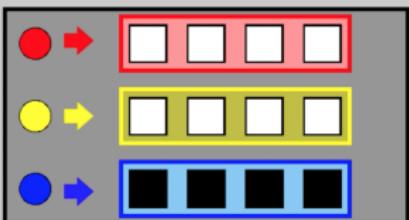
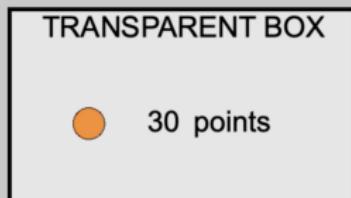
Move the slider based on your guess

OK

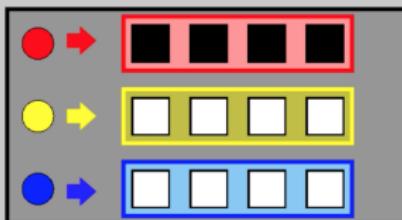


EXPERIMENTAL RESULTS

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



Advisor X

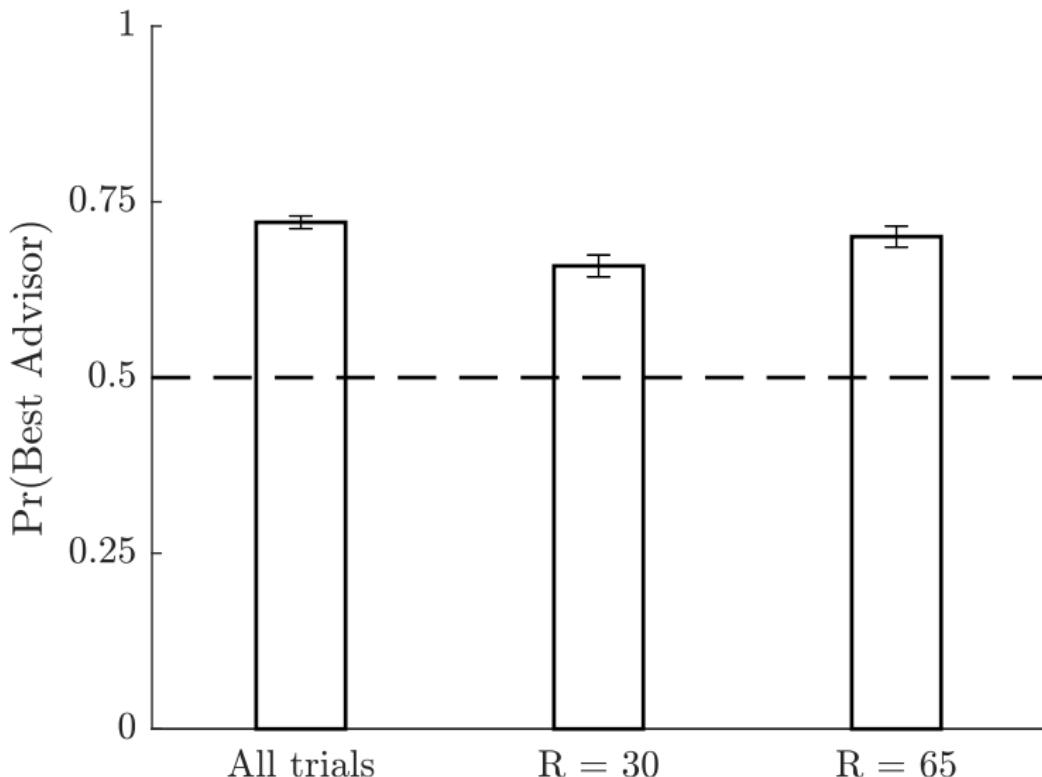


Advisor Y

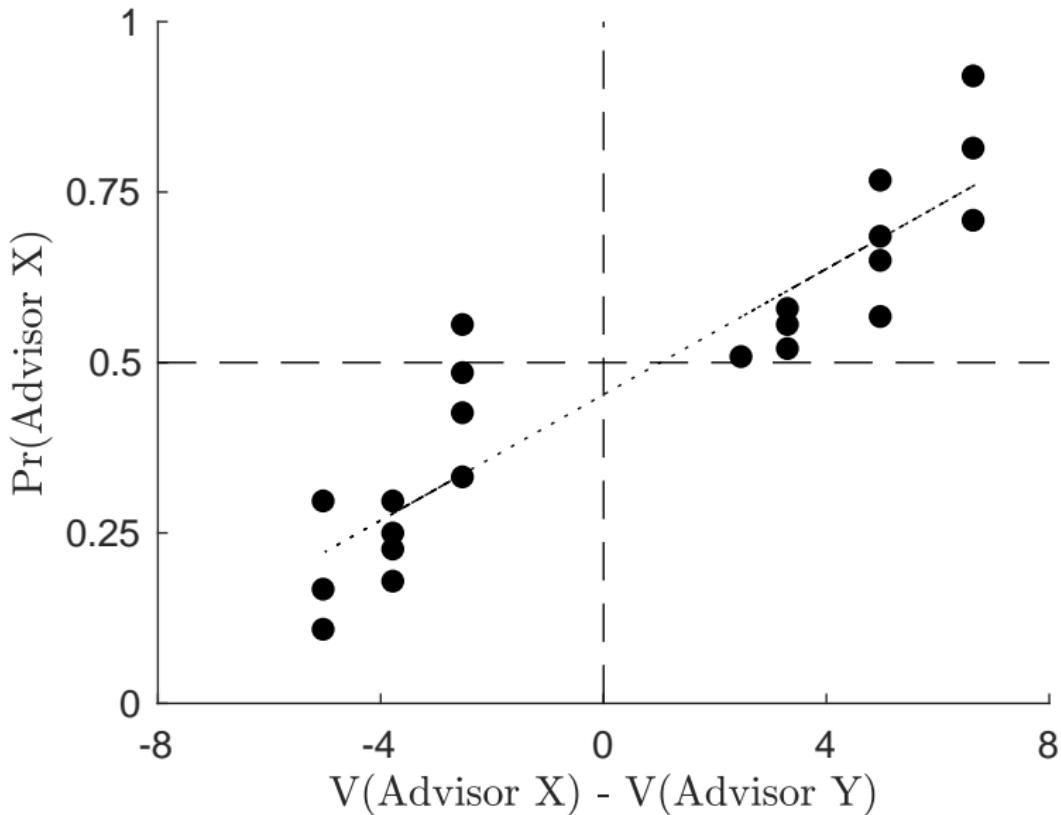


Select one Advisor

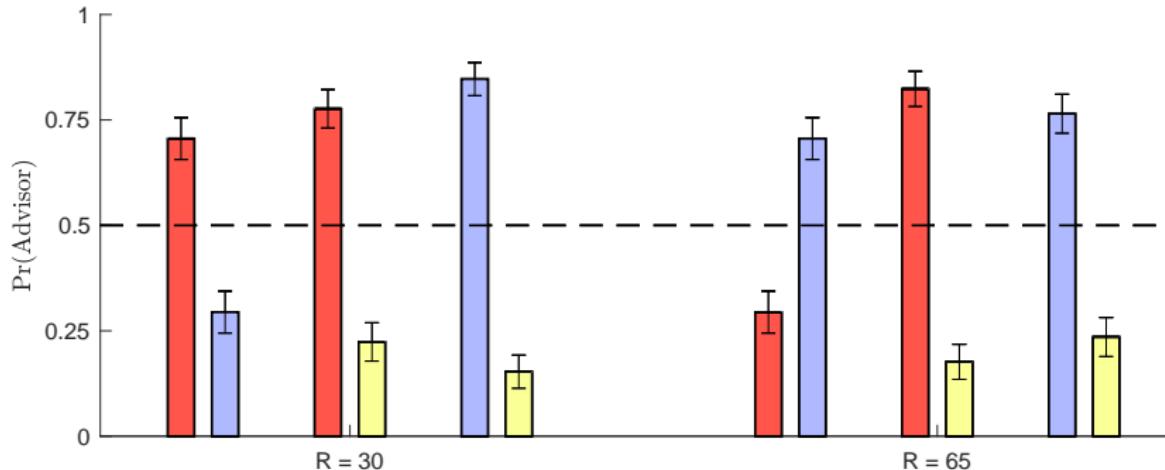
Most of participants “switch” advisor optimally



Accuracy depends on the stakes

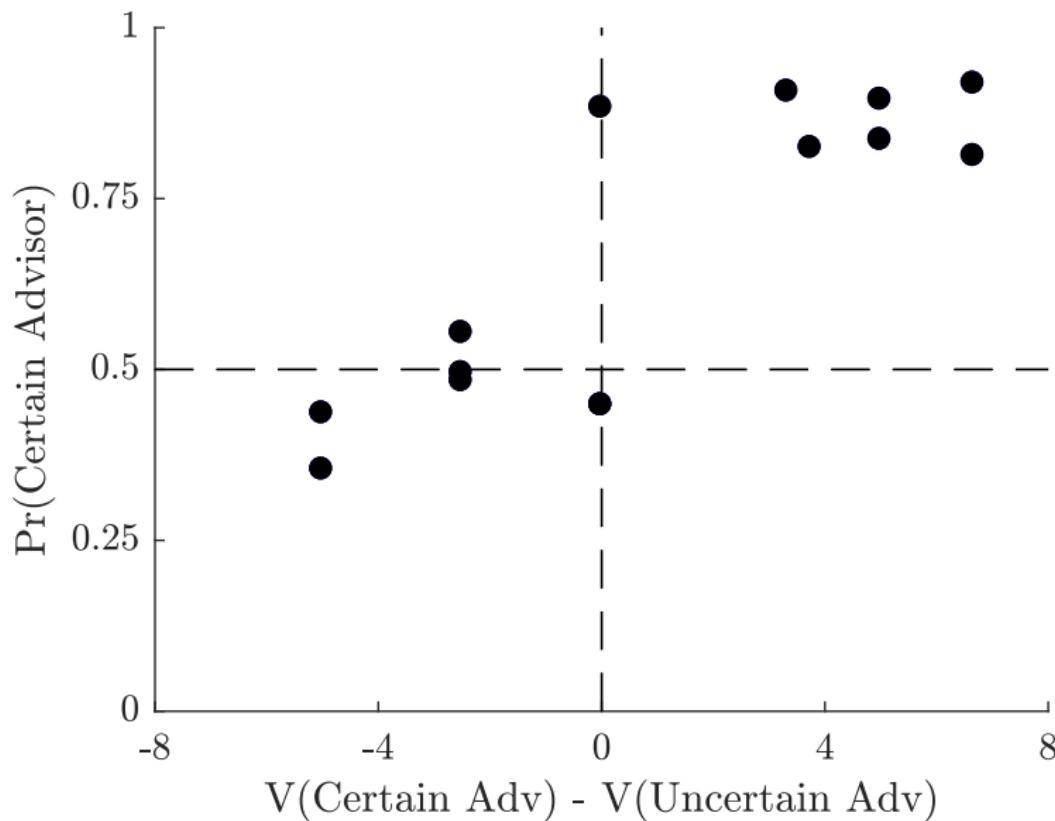


Simple Advisors: Certainty vs Certainty

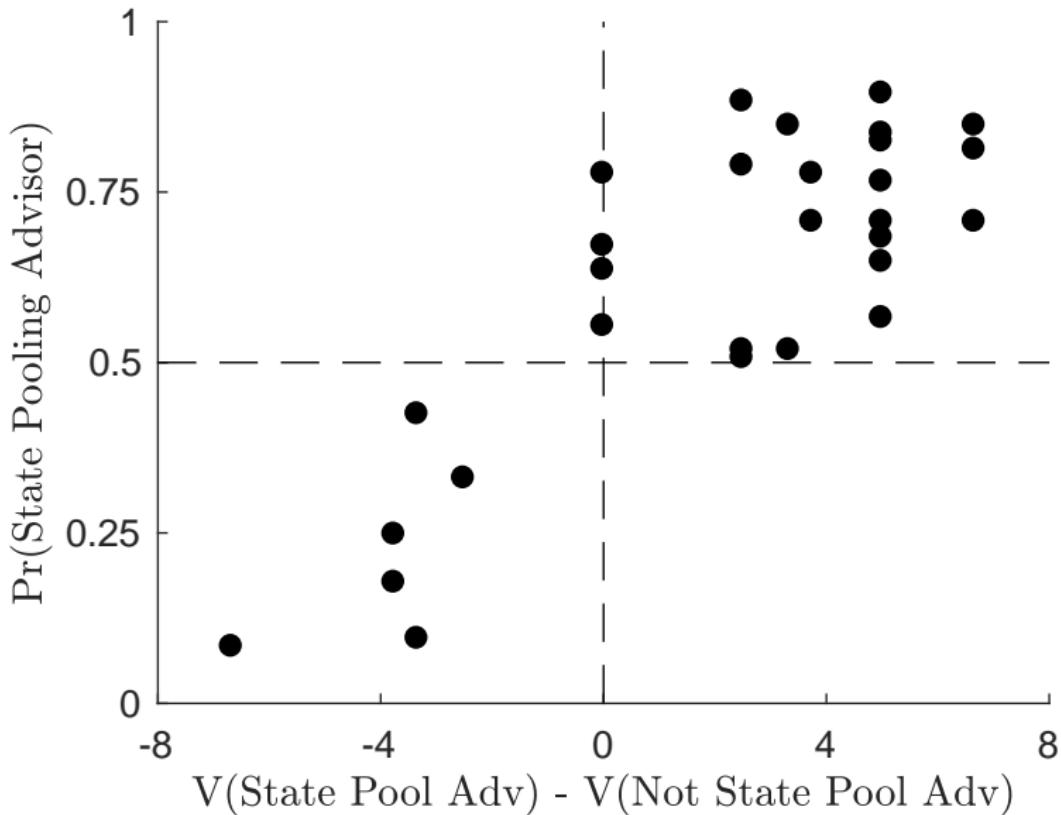


- ▶ Each advisor “pools” two states out of three
- ▶ These trials are easy to interpret
- ▶ Participants switch in the red/blue choice...
- ▶ ...but they switch only when it is valuable to do so

Certainty vs Uncertainty



State Pooling vs Not Pooling



Aggregate Valuation of Advisors - Logit Regression

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

State Pooling

Certainty \times SP

Trials	All
Observations	3,400

The significance levels concern the hypothesis that the coefficient is 0.

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

Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)
v_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

The significance levels concern the hypothesis that the coefficient is 0.

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

Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)	(3)
v_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

The significance levels concern the hypothesis that the coefficient is 0.

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

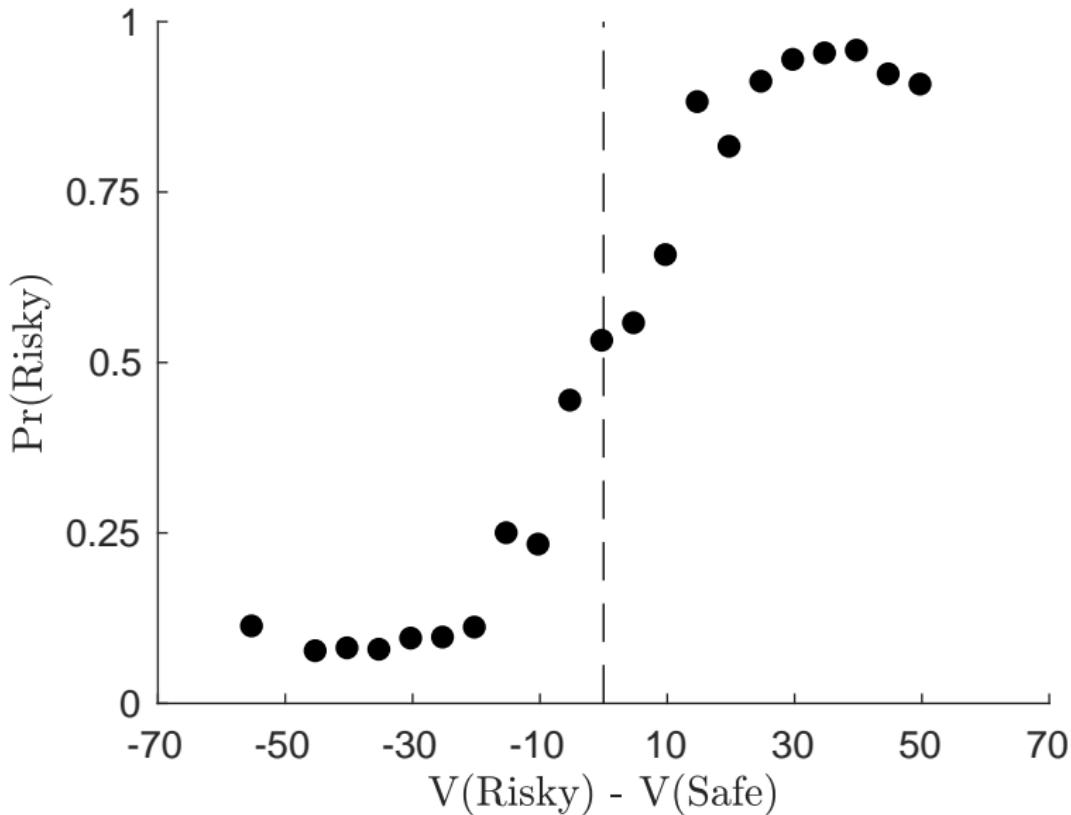
Aggregate Valuation of Advisors - Logit Regression

	(1)	(2)	(3)	(4)
v_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

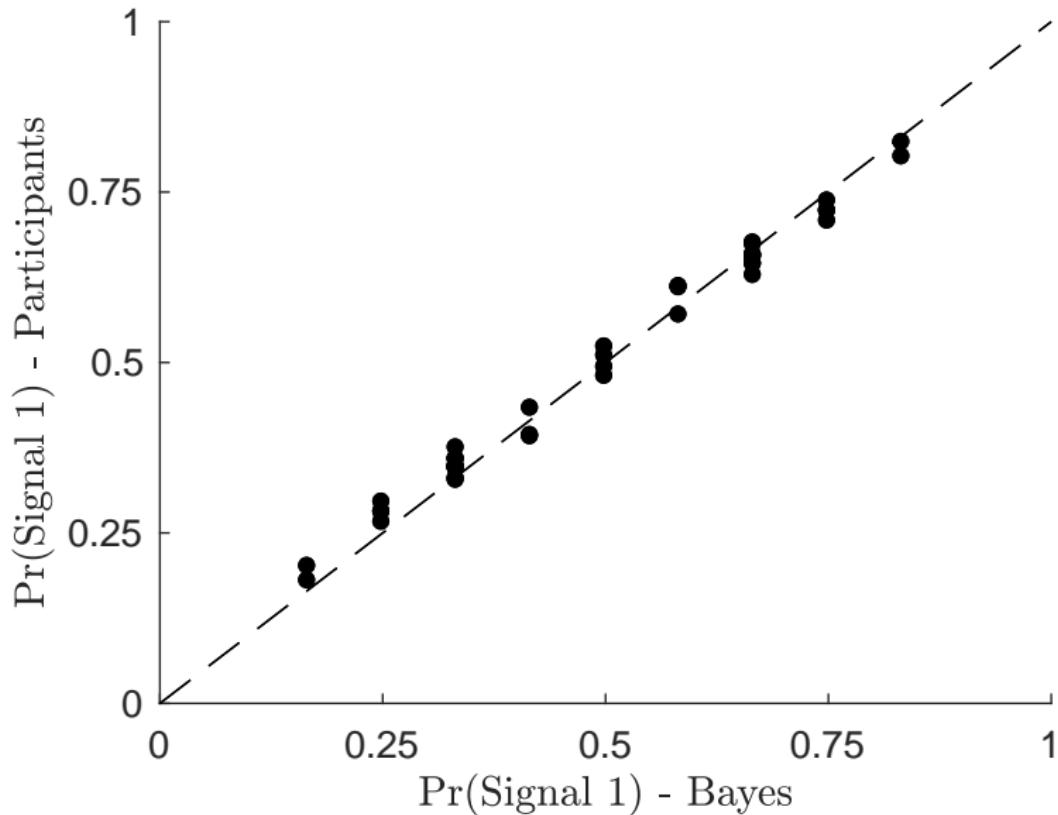
The significance levels concern the hypothesis that the coefficient is 0.

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

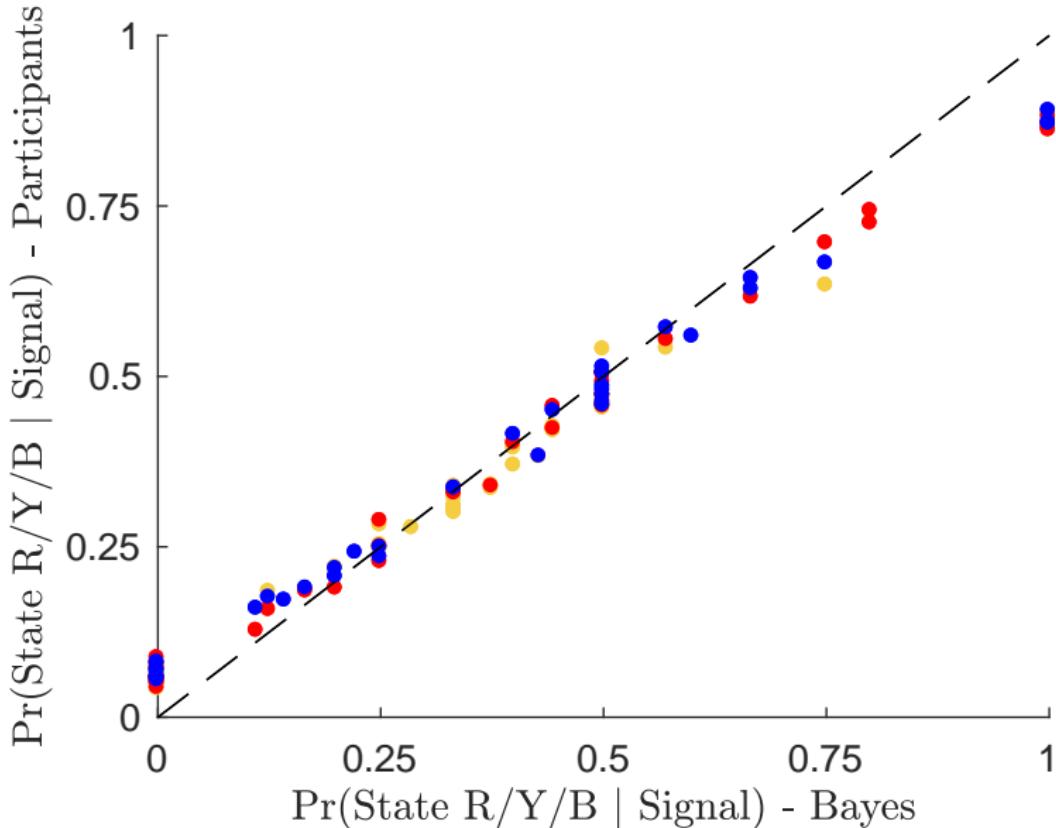
Action Selection



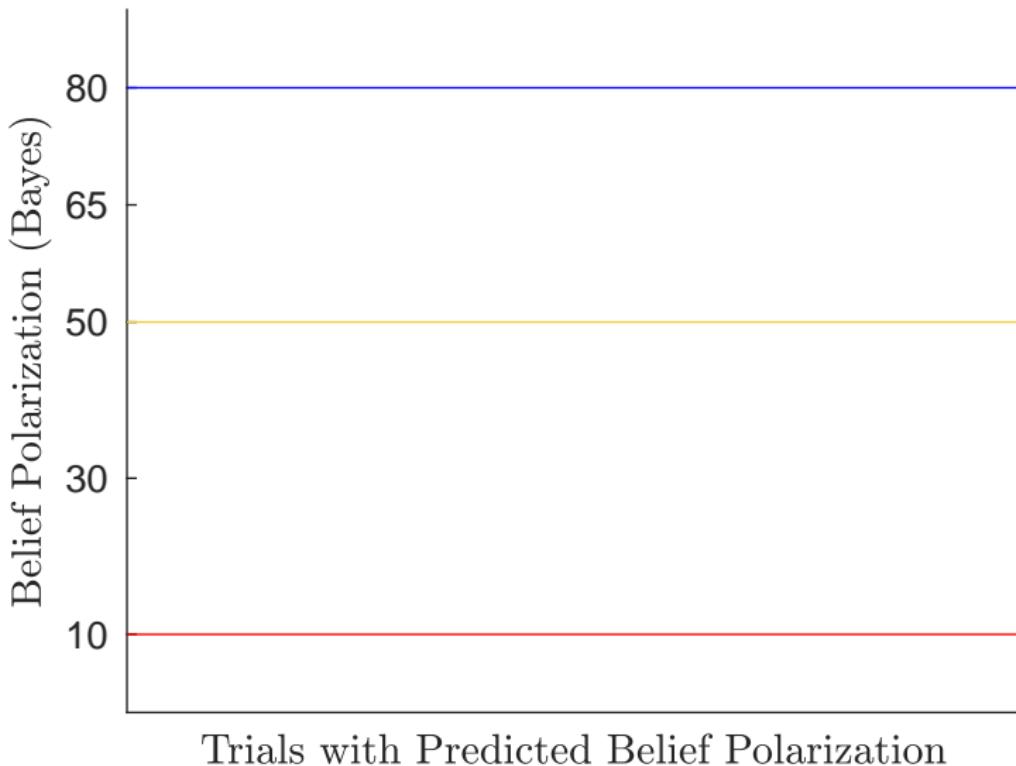
Elicited Beliefs - Card color



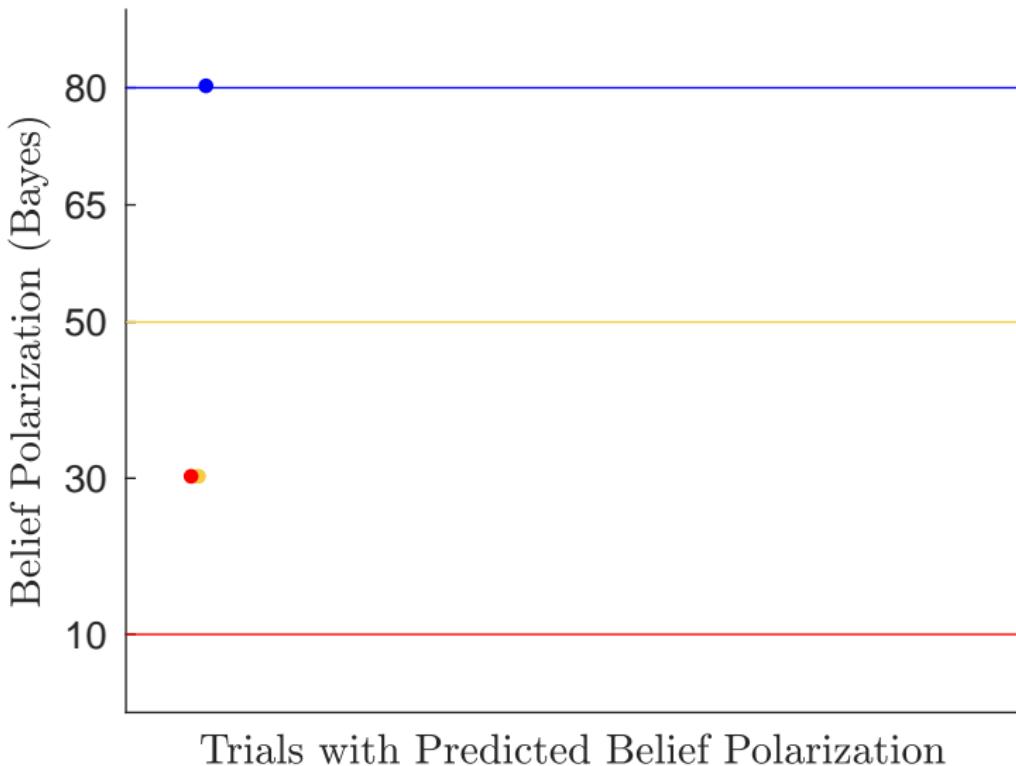
Elicited Beliefs - Ball color



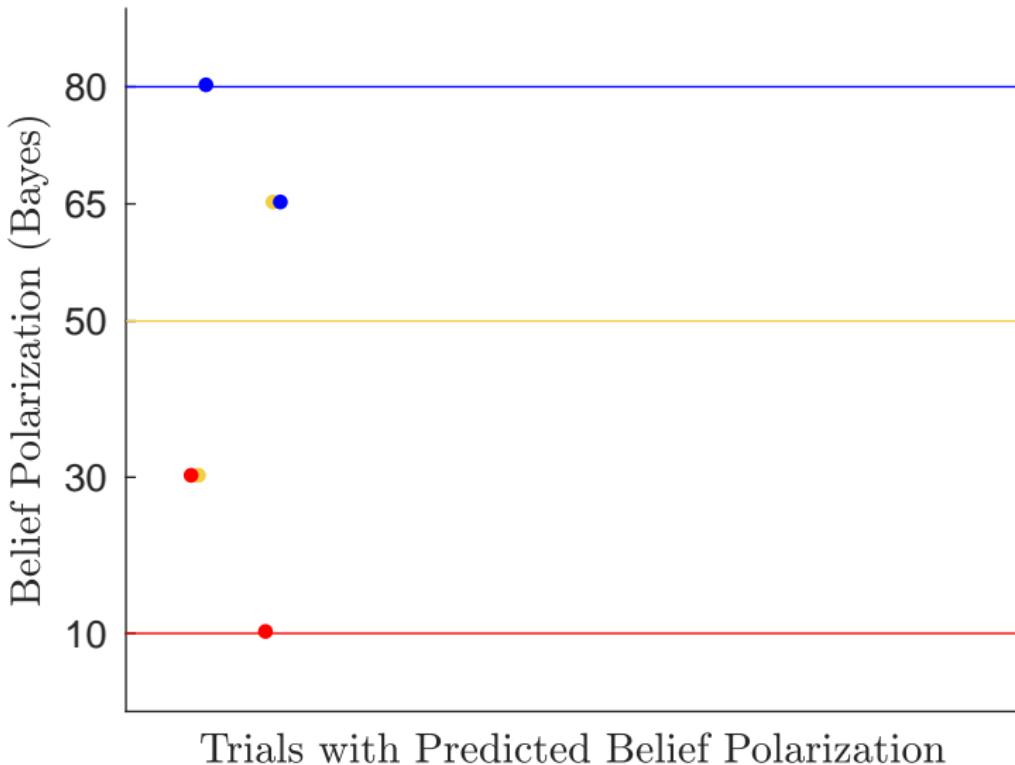
Beliefs Polarization - Predictions



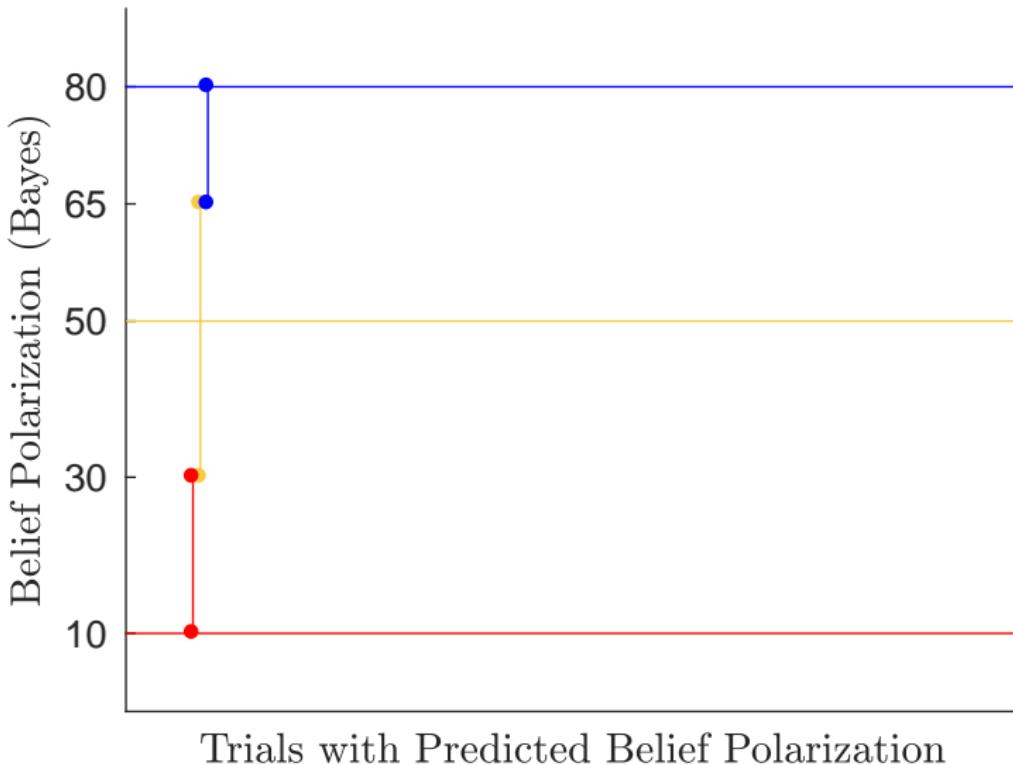
Beliefs Polarization - Predictions



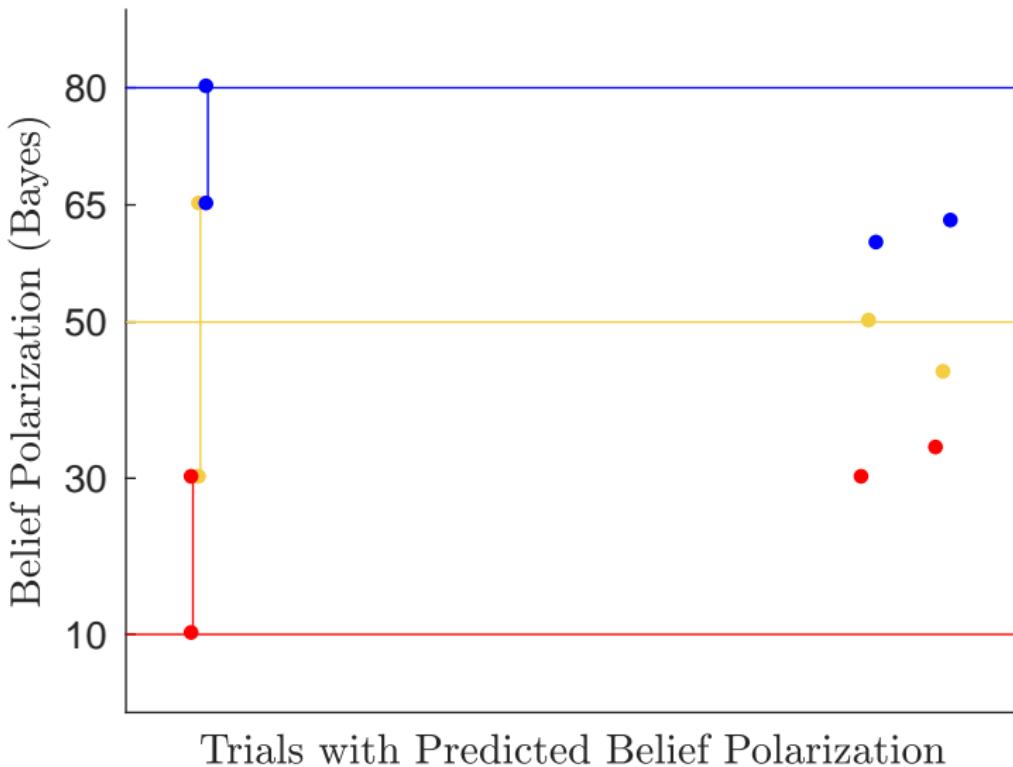
Beliefs Polarization - Predictions



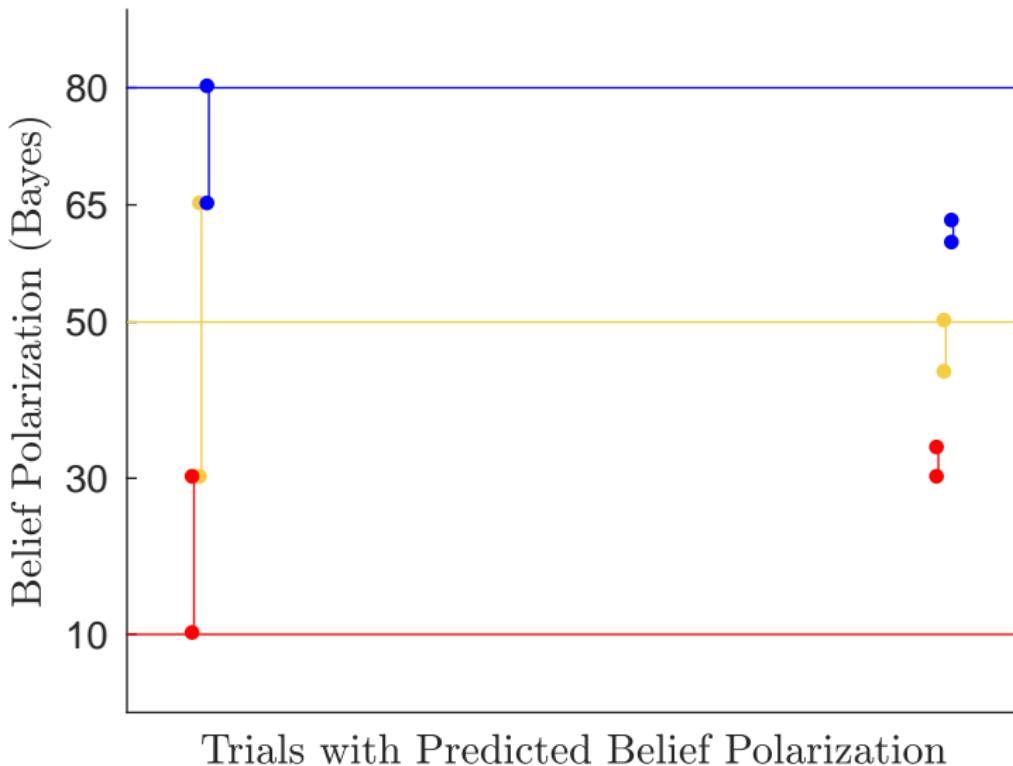
Beliefs Polarization - Predictions



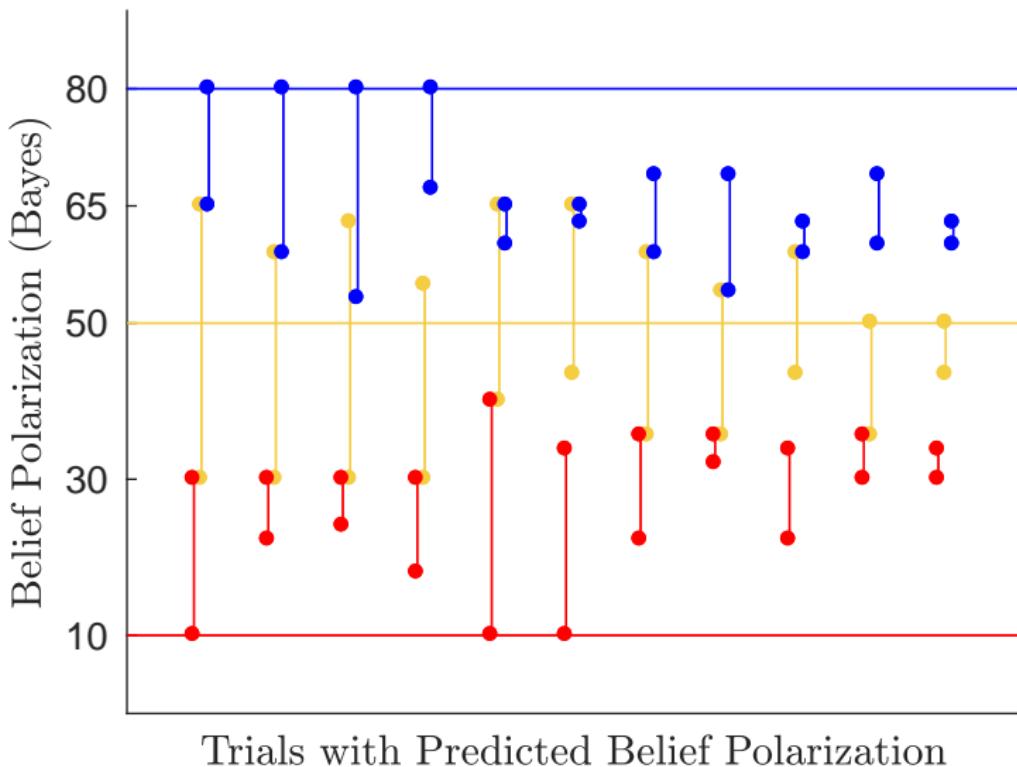
Beliefs Polarization - Predictions



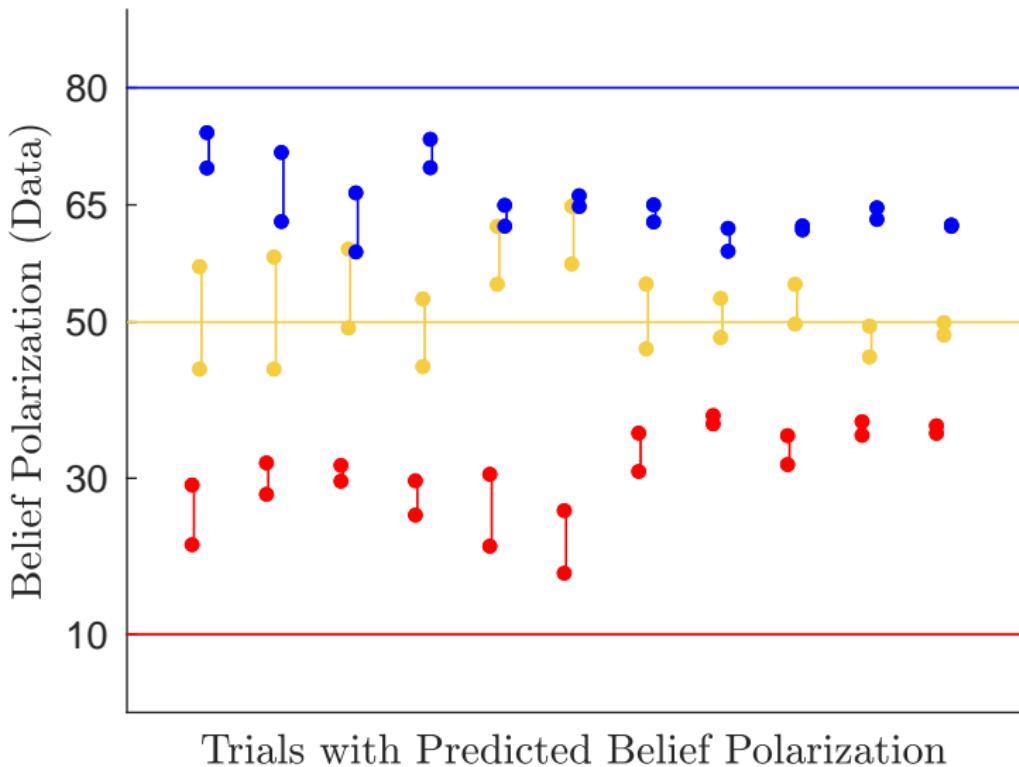
Beliefs Polarization - Predictions



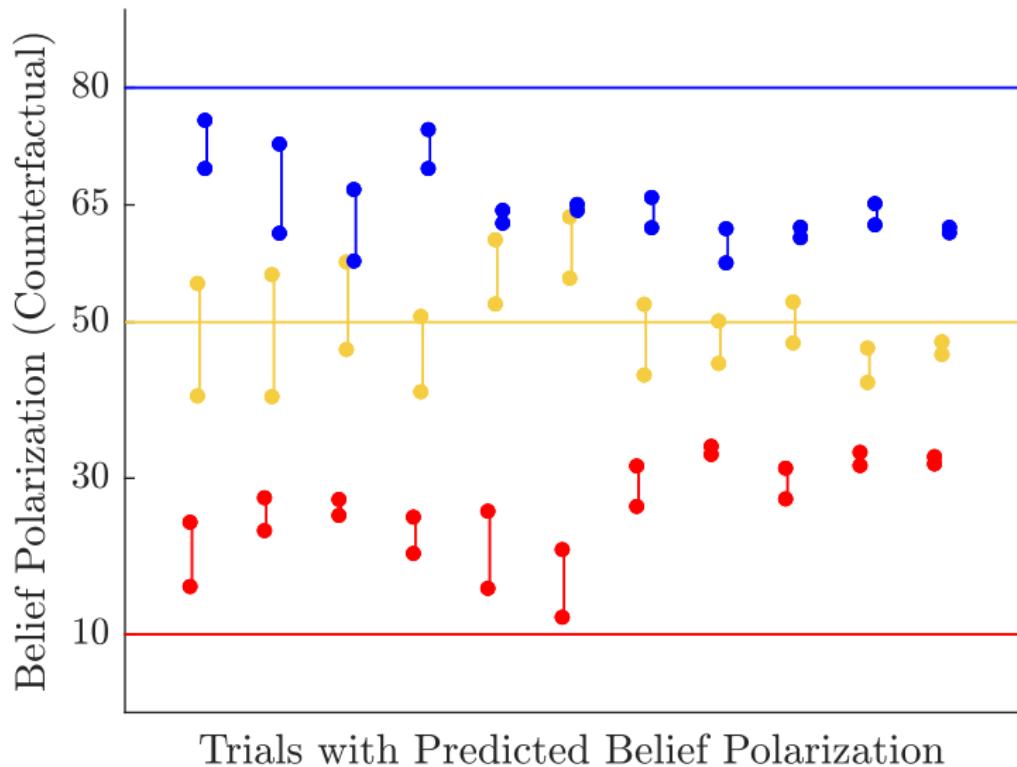
Beliefs Polarization - Predictions



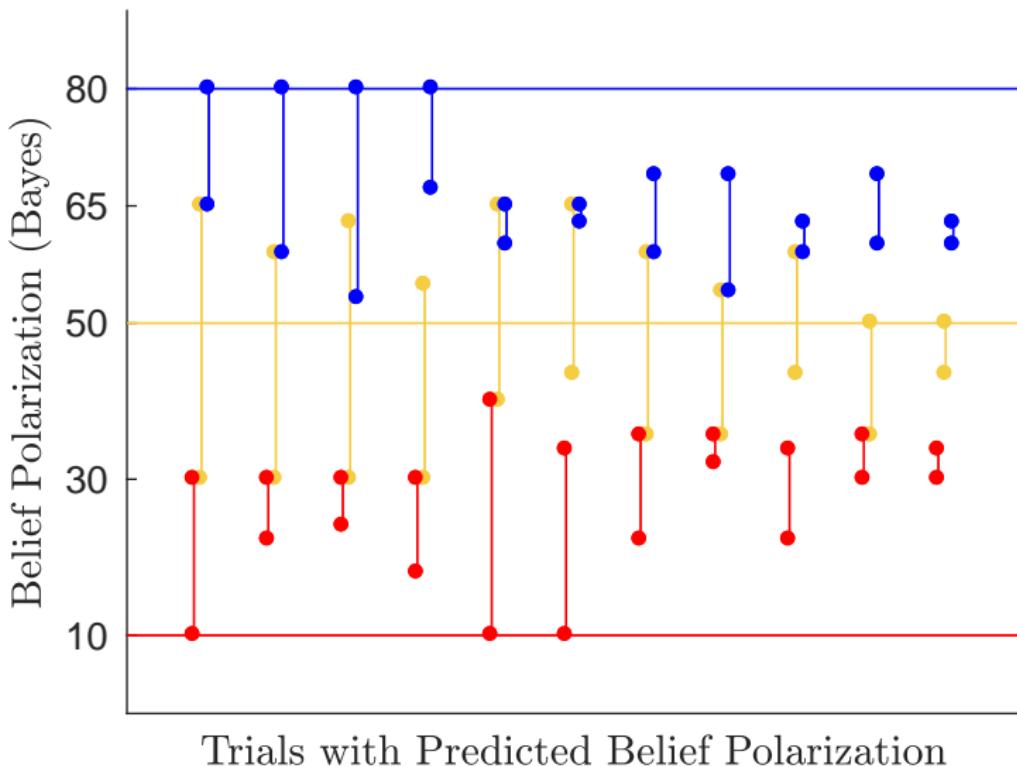
Beliefs Polarization - Data



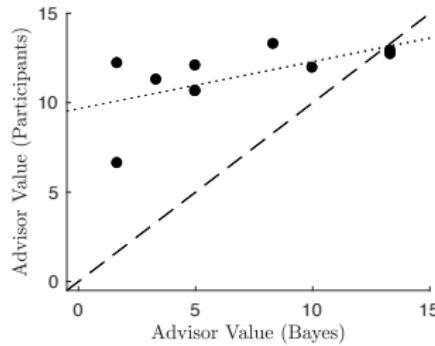
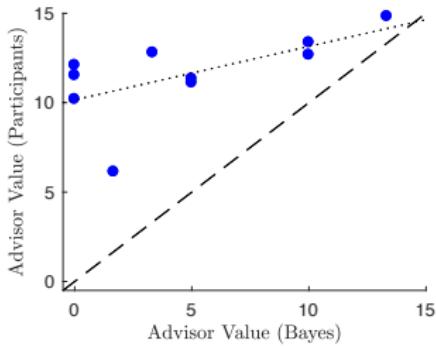
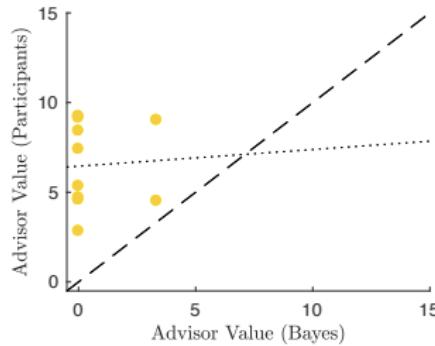
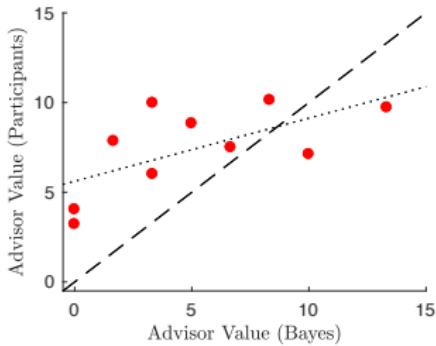
Beliefs Polarization - Counterfactual



Beliefs Polarization - Predictions



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

Conclusion

- ▶ Endogenously arising rational theory of polarization with multiple states
- ▶ Role of the status quo for information acquisition
- ▶ Endogenous state pooling effect
- ▶ Cheaper information leading to more polarized society

Lab experiment:

- ▶ A change in the safe option generates “advisor switches” as predicted...
- ▶ ... 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” and “extreme states” advisors.

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

Vladimír Novák

CERGE-EI

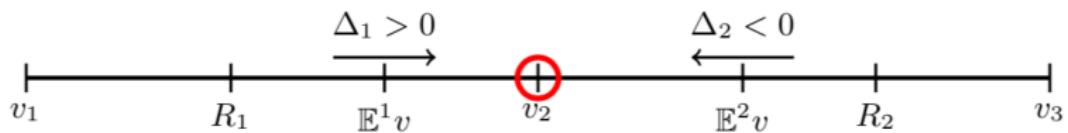
joint work with

Andrei Matveenko and Silvio Ravaioli
(University of Copenhagen) (Columbia University)

CERGE-EI Brown Bag
October 30th, 2019

Thank you for your attention

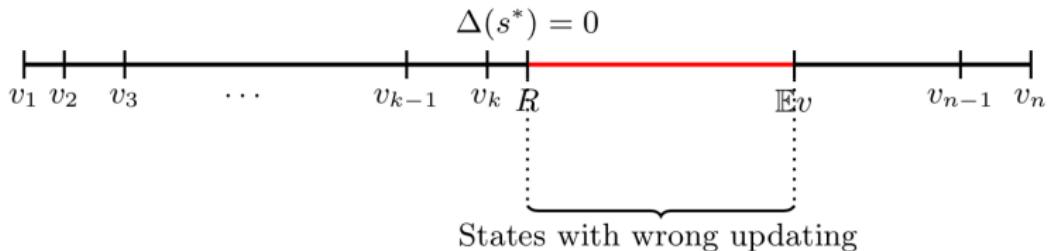
Convergence



Back

Monotonicity of $\Delta(s^*)$

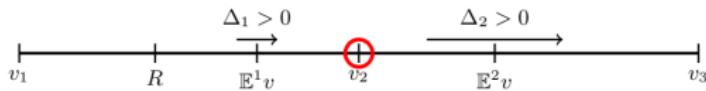
Proposition Change in mean of beliefs $\Delta(s^*)$ is an increasing function of s^* .



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

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Divergence while updating in the same direction



Divergence while updating in the same direction

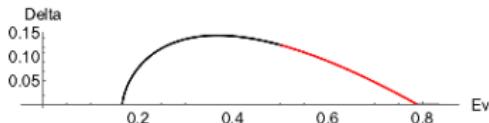
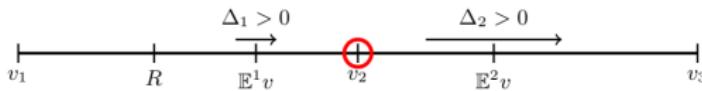


Figure: $\Delta(s^* = 2)$ as a function of $\mathbb{E}v$ for R_1 and λ_2 . The red area depicts the region of wrong updating.

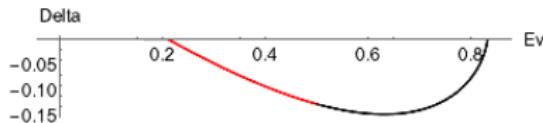


Figure: $\Delta(s^* = 2)$ as a function of $\mathbb{E}v$ for R_2 and λ_2 . The red area depicts the region of wrong updating.

Comparative statics

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

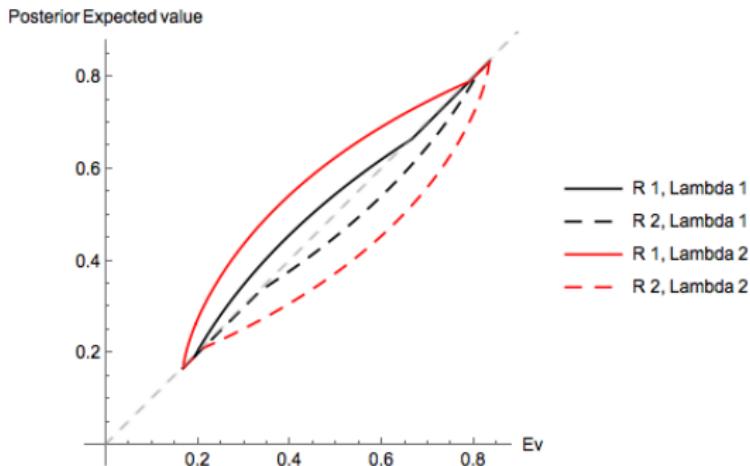


Figure: $E_i[\mathbb{E}(v|i)|s^*]$ as a function of Ev for different levels of R and λ . The solid lines are the case with R_1 and dashed with R_2 . Black corresponds to cases with λ_1 and red is used for λ_2 .

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)

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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)

Back

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

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

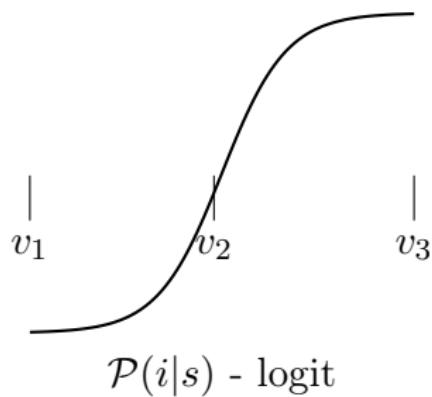
$$\sum_{i=1}^2 \mathcal{P}(i|s) = 1 \quad \forall s = 1, \dots, n ,$$

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

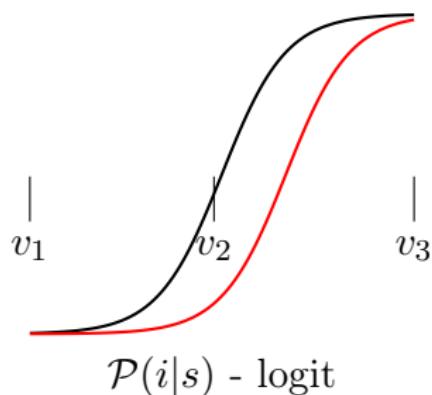
$\mathcal{P}(i|s) \forall i, s$ - characterize information strategy due to consistency of prior and posterior beliefs



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Solution

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



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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: Parameters used in this section

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