How Do People Choose Between Biased Information Sources?

Evidence from a Laboratory Experiment

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Motivation

- We frequently make decisions on where to get information.
  - News, websites, product reviews, medical advice, research, think tanks, market forecasters.
- Information sources are often biased.
  - They *select*, *discuss*, and *present* facts differently, and do so in ways that systematically favor one side or the other.
- Concerns of bias increase as there are more information sources.
  - There is a worry that people self-select into different *information bubbles*.

Common claim: People suffer from confirmation bias.

Motivation

Confirmation-seeking behavior:

- Forms
  - *Selective search* - Consume info. sources that generate confirmatory signals.
  - *Selective interpretation* - Put more weight on confirmatory signals.
- Explanations
  - *Motivated reasoning* - Information has non-instrumental value.
  - *Reputation* - Trust info. sources that align with prior more.

What we do

We study (in a lab experiment), how agents learn from biased information sources.

Our goal is to study:

- How agents *choose* between biased information sources.
- How agents *interpret* signals from biased information sources.

What we do

We study (in a lab experiment), how agents learn from biased information sources.

Features of the experimental design:

- Abstract setting, no attachment to prior.

  Removing motivated reasoning.

- Bias of the information sources are transparent.

  Removing quality concerns.

Literature Review

Non-bayesian interpretation of information:

Eil and Rao (2011), Charness and Levin (2005), Charness et al. (2007), Jin et al. (2016), Enke and Zimmermann (2017), Enke (2017), Frechette et al. (2017), Eliaz and Schotter (2010), Moebius et al. (2013), Golman and Loewenstein (2015), Ambuehl and Li (2018)

Timing/concentration of information:

Zimmermann (2014), Falk and Zimmermann (2014), Holder (2016), Masatlioglu et al. (2016), Nielsen (2018)

Psychology experiments on evidence seeking:

Klayman Ha (1987) Skov Sherman (1986), Slowiaczek et al. (1992), Baron et al. (1988)

Emergence of bias and motivated reasoning:

Brocas et al. (2011), Mullainathan and Shleifer (2005), Rabin and Schrag (1999), Benabou (2015), Che and Mierendorff (2017)

Theoretical Framework

Setup

- Unobserved state of the world $\theta \in \Theta := \{L, R\}$.
- An information structure σ is a mapping from Θ to S.
- Let $s \in S := \{l, n, r\}$.
- Prior p_0 is the probability that $\theta = R$.
- Agent tries to match the state: $a \in \Theta$.

Forms of Bias

Bias by commission:

- bias through false reports.
- non-verifiable information as in cheap talk games.

Bias by omission:

- bias through strategic omission of information.
- verifiable information as in disclosure games.

Bias by commission

σ_A

	l	r
$\theta = L$	1	0
$\theta = R$	$1-\lambda$	λ

σ_B

	l	r
$\theta = L$	λ	$1-\lambda$
$\theta = R$	0	1

Remark 1: σ_B is biased to the right of σ_A.

Bias by commission

σ_A

	l	r
$\theta = L$	1	0
$\theta = R$	$1-\lambda$	λ

σ_B

	l	r
$\theta = L$	λ	$1-\lambda$
$\theta = R$	0	1

Remark 1: σ_B is biased to the right of σ_A.

Defining Relative Bias

Gentzkow et al. (2015)

σ' is biased to the right of σ if

(i) σ and σ' are consistent, and

(ii) distribution of posteriors shift to the right ($FOSD$) when σ is replaced by σ' without the agent's awareness.

Bias by commission

σ_A

	l	r
$\theta = L$	1	0
$\theta = R$	$1-\lambda$	λ

σ_B

	l	r
$\theta = L$	λ	$1-\lambda$
$\theta = R$	0	1

Remark 2: Optimal information structure is the one that is biased in the *same* direction as one's prior.

Bias by commission

σ_A

	l	r
$\theta = L$	1	0
$\theta = R$	$1 - \lambda$	λ

σ_B

	l	r
$\theta = L$	λ	$1 - \lambda$
$\theta = R$	0	1

Remark 2: Optimal information structure is the one that is biased in the *same* direction as one's prior.

Bias by omission

σ_A

	l	n	r
$\theta = L$	λ_h	$1 - \lambda_h$	0
$\theta = R$	0	$1 - \lambda_l$	λ_l

σ_B

	l	n	r
$\theta = L$	λ_l	$1 - \lambda_l$	0
$\theta = R$	0	$1 - \lambda_h$	λ_h

where $\lambda_h > \lambda_l$.

Remark 3: σ_B is biased to the right of σ_A.

Bias by omission

σ_A

	l	n	r
$\theta = L$	λ_h	$1 - \lambda_h$	0
$\theta = R$	0	$1 - \lambda_l$	λ_l

σ_B

	l	n	r
$\theta = L$	λ_l	$1 - \lambda_l$	0
$\theta = R$	0	$1 - \lambda_h$	λ_h

where $\lambda_h > \lambda_l$.

Remark 4: Optimal information structure is the one that is biased in the *opposite* direction as one's prior.

Bias by omission

σ_A

	l	n	r
$\theta = L$	λ_h	$1 - \lambda_h$	0
$\theta = R$	0	$1 - \lambda_l$	λ_l

σ_B

	l	n	r
$\theta = L$	λ_l	$1 - \lambda_l$	0
$\theta = R$	0	$1 - \lambda_h$	λ_h

where $\lambda_h > \lambda_l$. (Assume $p_0 > 0.5$.)

Remark 4: Optimal information structure is the one that is biased in the *opposite* direction as one's prior.

Bias by omission

σ_A

	l	n	r
$\theta = L$	λ_h	$1 - \lambda_h$	0
$\theta = R$	0	$1 - \lambda_l$	λ_l

σ_B

	l	n	r
$\theta = L$	λ_l	$1 - \lambda_l$	0
$\theta = R$	0	$1 - \lambda_h$	λ_h

where $\lambda_h > \lambda_l$. (Assume $p_0 > 0.5$.)

Remark 4: Optimal information structure is the one that is biased in the *opposite* direction as one's prior.

Bias by omission

σ_A

	l	n	r
$\theta = L$	λ_h	$1 - \lambda_h$	0
$\theta = R$	0	$1 - \lambda_l$	λ_l

σ_B

	l	n	r
$\theta = L$	λ_l	$1 - \lambda_l$	0
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where $\lambda_h > \lambda_l$. (Assume $p_0 > 0.5$.)

Remark 4: Optimal information structure is the one that is biased in the *opposite* direction as one's prior.

Bias by omission

σ_A

	l	n	r
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$\theta = R$	0	$1 - \lambda_l$	λ_l

σ_B

	l	n	r
$\theta = L$	λ_l	$1 - \lambda_l$	0
$\theta = R$	0	$1 - \lambda_h$	λ_h

where $\lambda_h > \lambda_l$. (Assume $p_0 > 0.5$.)

Remark 4: Optimal information structure is the one that is biased in the *opposite* direction as one's prior.

Summary

When information structures are symmetrically biased,

and the bias-type is commission:

- optimal to choose information structure biased **towards** prior.

and the bias-type is omission:

- optimal to choose information structure biased **against** prior.

Potential Types

Optimal:

- *Chooses the optimal information structure.*

Confirmation-seeking:

- *Chooses information structure biased* ***towards*** *prior.*

Contradiction-seeking:

- *Chooses information structure biased* ***against*** *prior.*

Certainty-seeking:

- *Chooses information structure to maximize* ***fully-revealing*** *signals.*

Experimental Design

Design

Endogenous (END) Information Structure Block:

- 14 rounds of information problems.

Exogenous (EX) Information Structure Block:

- 12 rounds of exogenously assigned information structures.

Survey

- Advice on how to choose between information sources.
- Questions on cognitive ability, media habits, political attitudes.

Design

In each round of END block, subjects are asked to guess the color of a ball drawn from a known urn.

1. Advisor Choice:
   - Two (computerized) advisors presented.
   - Subjects choose an advisor to receive a signal from.
   - Bias in the available information structures vary:
     Commission, *Omission* + *Blackwell*
     $\lambda = \lambda_h = 1 - \lambda_l = 0.7$, $p_0 \in \{\frac{14}{20}, \frac{15}{20}, \frac{16}{20}\}$ (varying direction).

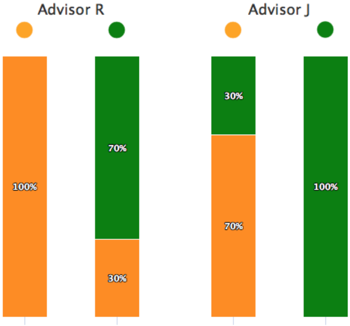
2. Beliefs and Guesses:
   - Conditional on the advisor choice, using the strategy method, subjects make a guess and state beliefs on state.

In each round of EX block, the advisor choice stage is removed.

Screenshot: Commission

There are 14 orange balls and 6 green balls in a basket

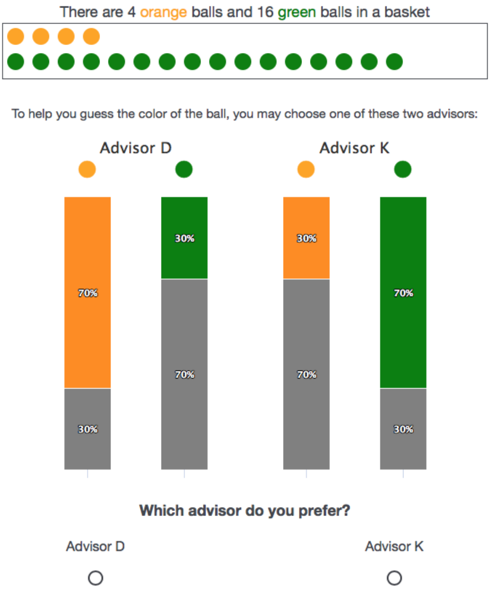
To help you guess the color of the ball, you may choose one of these two advisors:



Which advisor do you prefer?

Advisor R ○ Advisor J ○

Screenshot: Omission



Screenshot: Guess and Belief Elicitation

If the advisor said orange:

- What is the likelihood that the ball is orange vs. green?

50% Orange 50% Green

- Which color would you guess the ball is?

Orange Green

If the advisor said green:

- What is the likelihood that the ball is orange vs. green?

50% Orange 50% Green

- Which color would you guess the ball is?

Orange Green

Design

Incentives:

- \$7 for show up + filling out the survey.
- \$0, or \$10 for guessing the state correctly on randomly selected round.
- \$0, or \$1 for answers to belief questions on randomly selected round. (BSR)
- (Repeated for EX treatment in sessions 10-18.)
- \$1 if advice is selected as the most useful one.
- Up to \$2.5 on cognitive ability questions.

Overview

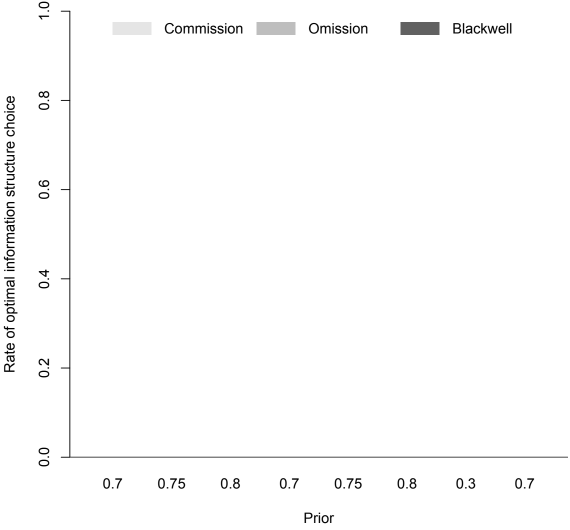
- Data from 344 subjects in 18 sessions at UCSB.
- Sessions computerized using *Qualtrics*
- Questions presented in semi-random order.
- Earnings varied between $7.50 to $31.75.

Results

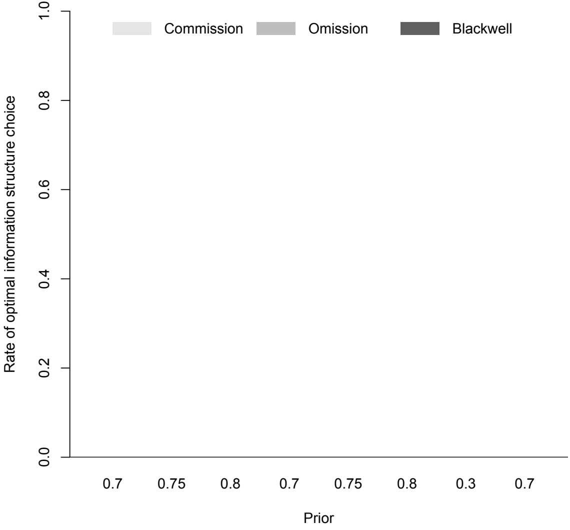
Organization of results

1. Choices over information structures
2. Connection to guesses
3. Connection to beliefs
4. Advice data
5. Connection to cognitive ability

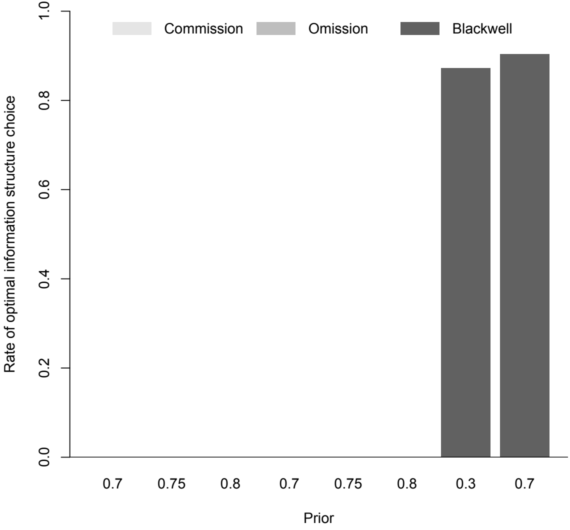
Choices over information structures



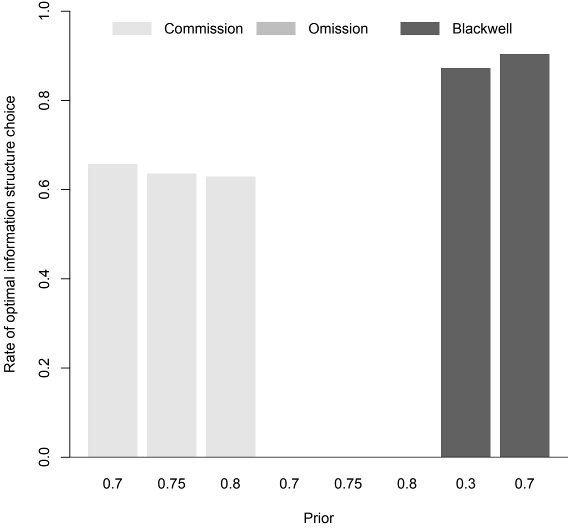
Choices over information structures



Subjects are not confused...



...but make a lot of mistakes



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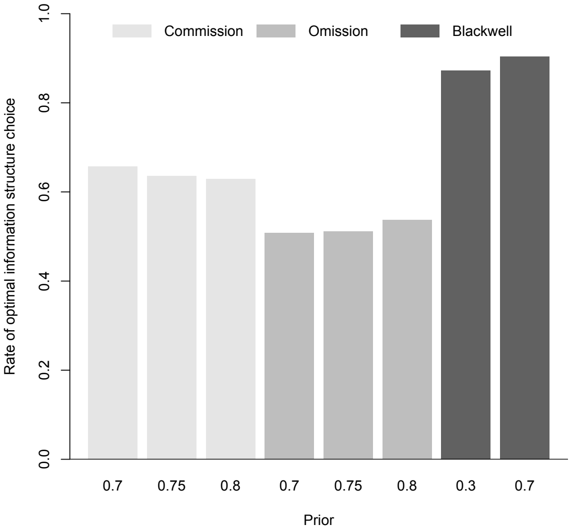
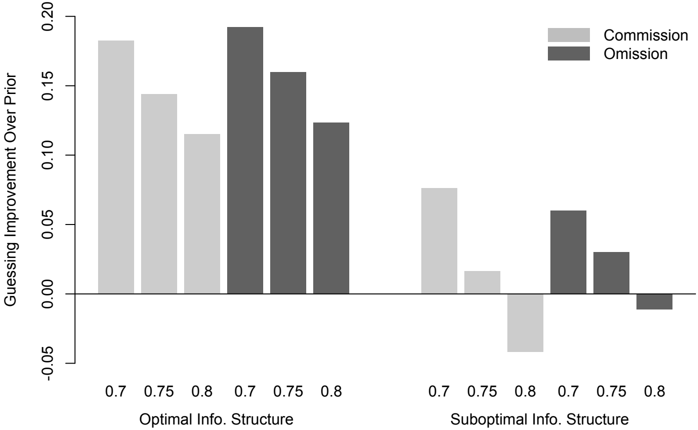


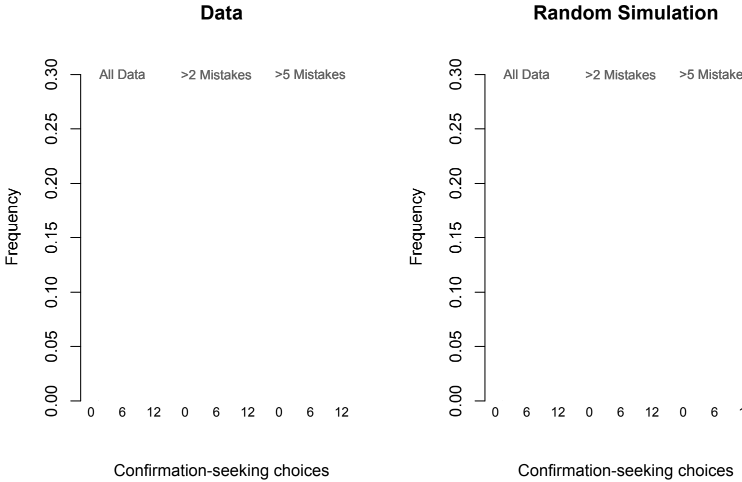
Mistakes are costly



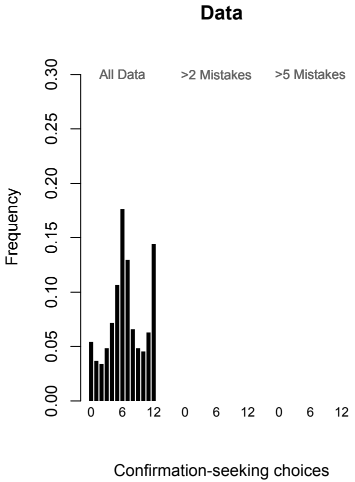
Result 1:

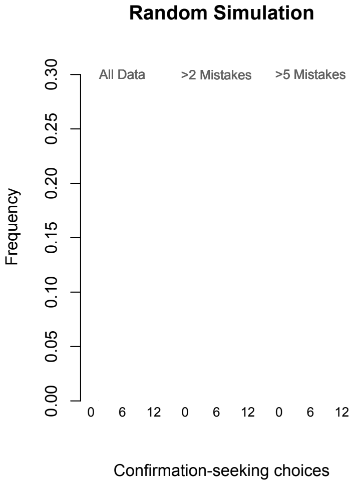
Subjects frequently choose sub-optimal information structures, leading to failures in learning.

Behavior is not random

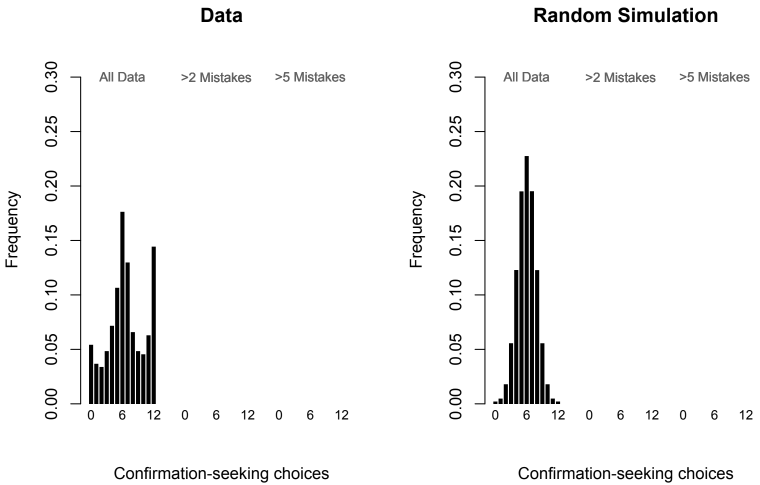


Behavior is not random

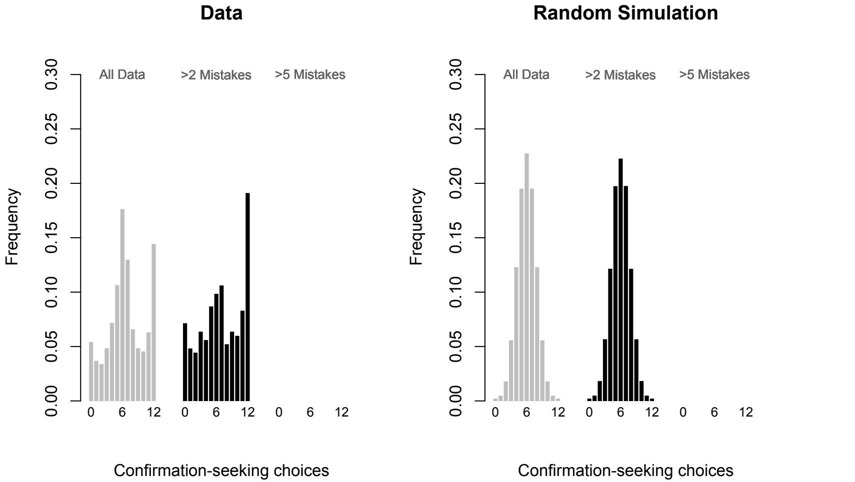




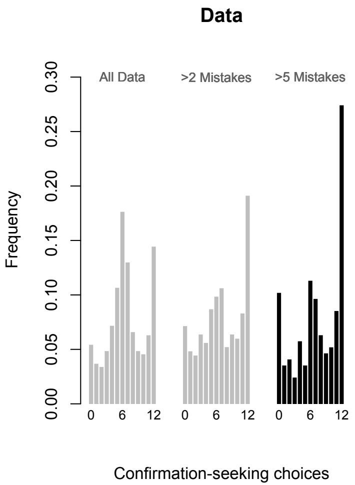
Behavior is not random

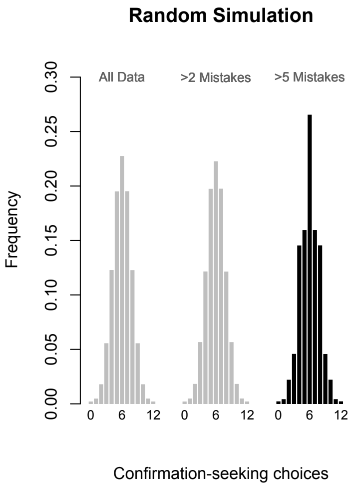


Mistakes are skewed towards confirmation-seeking



Mistakes are skewed towards confirmation-seeking

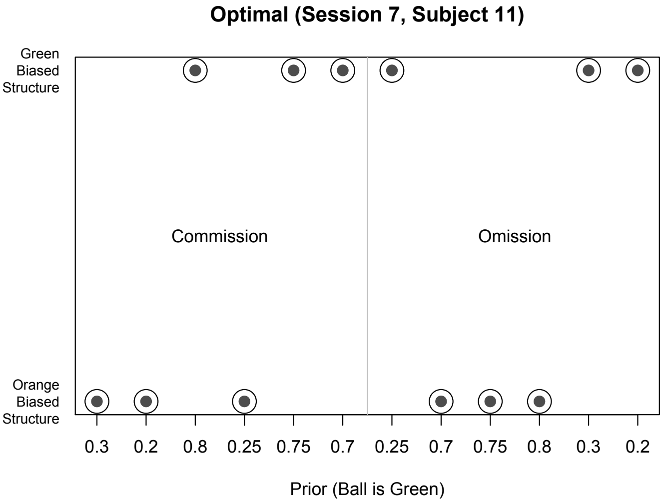




Result 2:

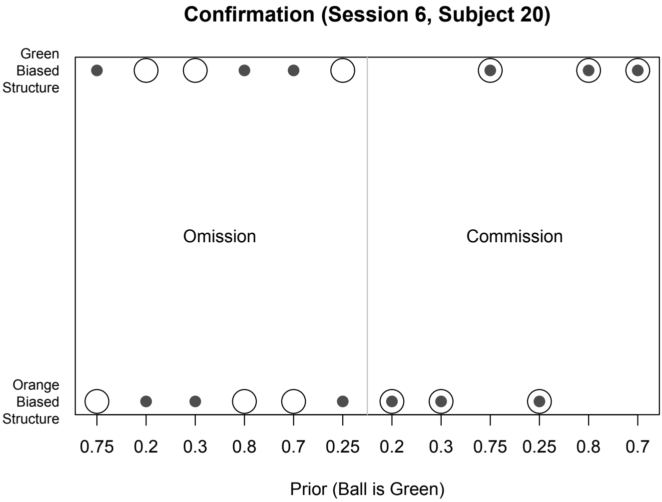
Mistakes in choices over information structures are not random, but tend to be skewed towards pure confirmation-seeking or (to a much lesser extent) pure contradiction-seeking behavior.

Optimal



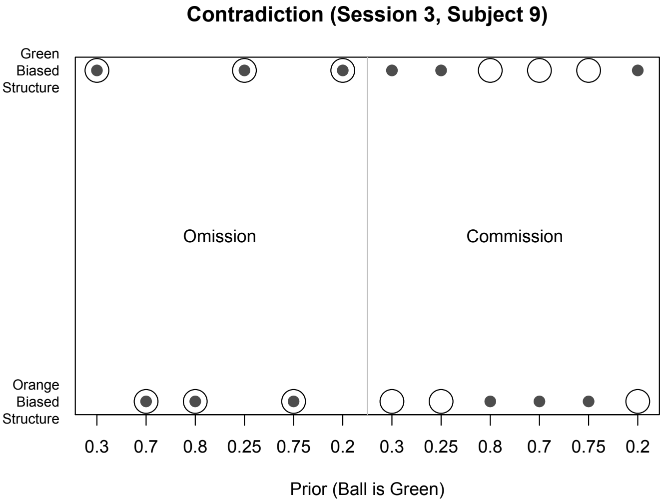
Hollow dots show optimal choices; solid dots show the subject's actual choices.

Confirmation



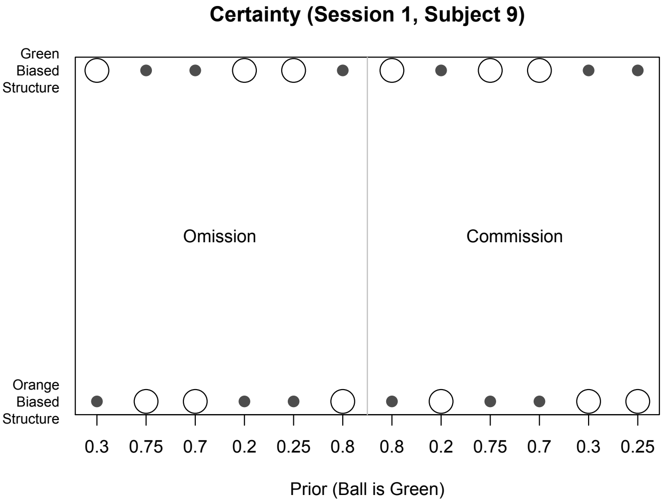
Hollow dots show optimal choices; solid dots show the subject's actual choices.

Contradiction



Hollow dots show optimal choices; solid dots show the subject's actual choices.

Certainty



Hollow dots show optimal choices; solid dots show the subject's actual choices.

Type Distribution

Type share among classified subjects (%)	Classification method Perfect
Optimal	28
Confirmation	47
Contradiction	17
Certainty	9
Share classified in data	31

Type Distribution

Type share among classified subjects (%)	Classification method		
	Perfect	$\leq$ 1 error	$\leq$ 2 error
Optimal	28	33	35
Confirmation	47	39	35
Contradiction	17	17	17
Certainty	9	11	13
Share classified in data	31	52	70

How likely is it to observe these patterns?

- Apply classification method to a large random sample.
  - Simulate 10^7 random subjects to generate benchmark type distribution.
- Estimate a mixture model.
  - $(\omega_O, \omega_{Cf}, \omega_{Ct}, \omega_{Ce})$ denotes the share of types.
  - κ denotes implementation noise.
  - All other choices are assumed to be random.
  - Estimate parameters on 344×12 decisions.

Type Distribution

Type share among classified subjects (%)	Classification method		
	Perfect	≤ 1 error	≤ 2 error
Optimal	28	33	35
Confirmation	47	39	35
Contradiction	17	17	17
Certainty	9	11	13
Share classified in data	31	52	70
Share classified in random sample	0.1	1.2	7.7

Type Distribution

Type share among classified subjects (%)	Classification method			
	Perfect	≤ 1 error	≤ 2 error	Mixture model
Optimal	28	33	35	37
Confirmation	47	39	35	34
Contradiction	17	17	17	17
Certainty	9	11	13	12
Share classified in data	31	52	70	81
Share classified in random sample	0.1	1.2	7.7	-

Type Distribution

Type share among classified subjects (%)	Perfect	≤ 1 error	≤ 2 error	Mixture model
	Classification method			
Optimal	28	33	35	37
Confirmation	47	39	35	34
Contradiction	17	17	17	17
Certainty	9	11	13	12
Share classified in data	31	52	70	81
Share classified in random sample	0.1	1.2	7.7	-

Estimated $\kappa \approx 0.10$ implies in expectation ≈ 1.2 mistakes which is slightly higher than 0.8 observed in the data among typed subjects.

Result 3:

Subjects are as likely to exhibit confirmation-seeking behavior as they are to exhibit optimal behavior, and these two decision rules jointly describe the majority of our subjects.

Subjects are half as likely to exhibit contradiction-seeking and even more rarely certainty-seeking behavior.

Learning

Measure improvement in guessing accuracy (p_c) over prior (p_0) relative to optimal behavior (p_c^{Opt}):

$$\frac{p_c - p_0}{p_c^{Opt} - p_0}$$

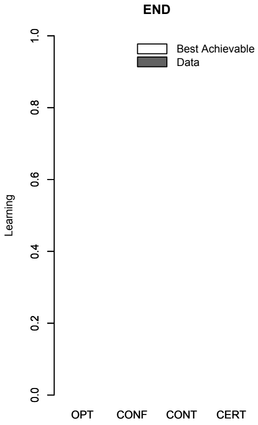
Benchmarks:

No learning: Guess according to prior: $= 0$

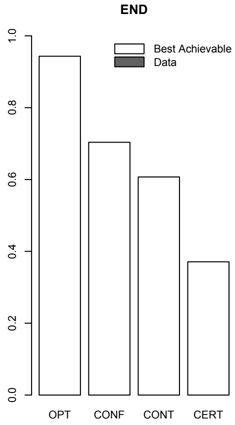
Optimal: Bayesian guess given signals from optimal information structure: $= 1$

Best Achievable: Bayesian guess conditional on information structure (maybe suboptimal): ≤ 1

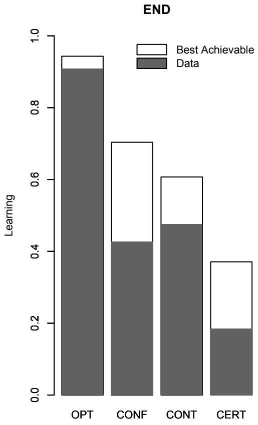
Focusing on the END block...



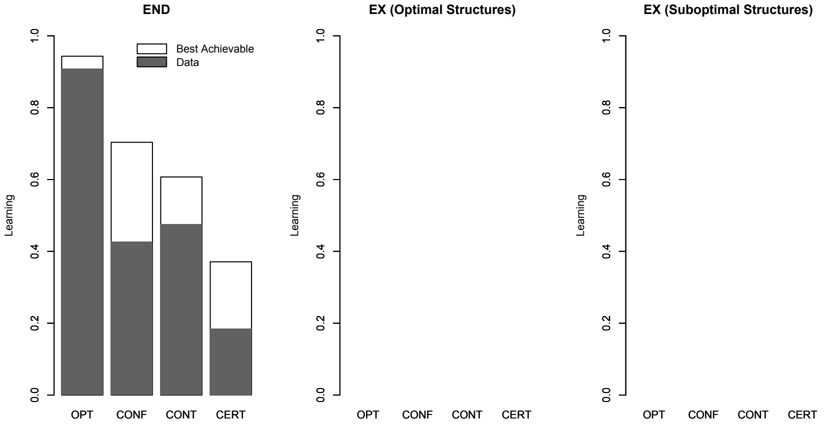
...Best Achievable differs substantially



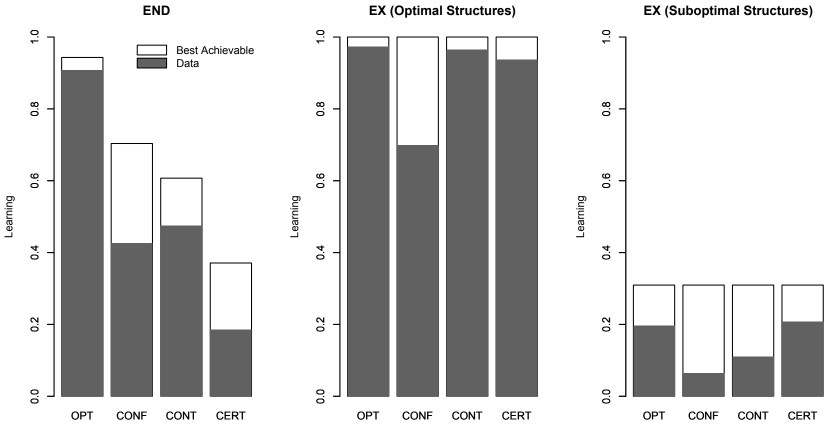
... but doesn't capture all the variation in learning



Focusing on the EX block...



... all types learn more when assigned the optimal information structure



Result 4:

All types learn significantly more from optimal than sub-optimal information structures.

Confirmation-seeking types learn less from both optimal and sub-optimal information structures than other types of subjects.

Accuracy of beliefs vary by type

Belief error is defined as $\sum_s \pi_s |p_s - p_s^{Bay}|$.

- p_s^{Bay} is the Bayesian posterior, p_s is the stated posterior of the subject conditional on signal s and π_s is the probability of receiving signal s.

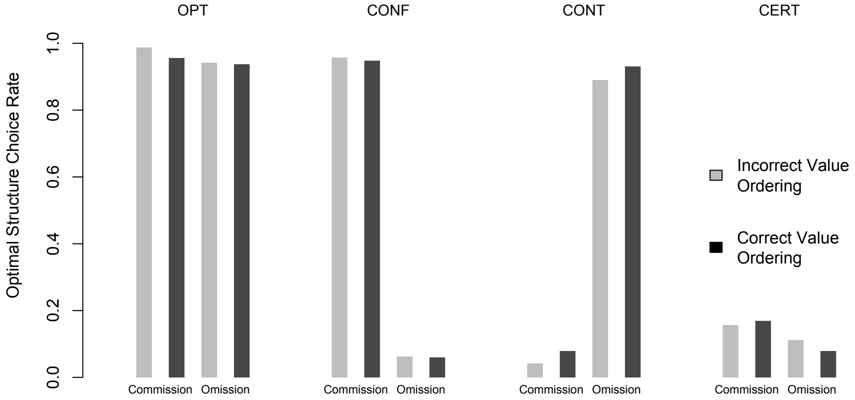
Can accuracy of beliefs explain choices over information structures?

Expected value of each information structure σ implied by the beliefs of subject i in the EX block:

$$V_i(\sigma) = \sum_s \pi_s \max\{p_s, 1 - p_s\}$$

Are i's choices over information structures consistent with ranking of V_i?

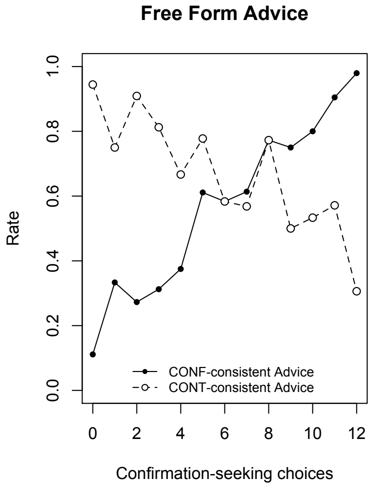
Beliefs cannot explain choices over information structures.



Result 5:

Although Optimal types form particularly accurate beliefs and Confirmation types particularly inaccurate beliefs, variation in divergence from Bayesian beliefs does little to explain patterns in choices over information structures.

Free-form advice suggest self-awareness of the decision rules used



Examples to Free-Form Advice

Confirmation-seeking:
“Look at the balls in the basket and see which one is highest, then look at which advisor leans more towards that color.”

“Select that advisor that has the highest accuracy for the color with the most balls of that color in the basket. My reasoning is that there is a higher chance of answering correctly if the advisor is most accurate in advise for the color with the highest probability to be selected.”

Contradiction-seeking:
“Choose the advisor who will MOST LIKELY (high percentage) give you the right answer for the color that has the LEAST amount of balls in the basket... you want to create a situation where if the unlikely color is chosen, the advisor will tell you so - for the color with the most balls, it already has a high chance of being chosen so luck is on your side with that color.”

Certainty-seeking:
“You want to select the advisor who is going to provide you with a CERTAIN answer most often.”

Examples to Free-Form Advice

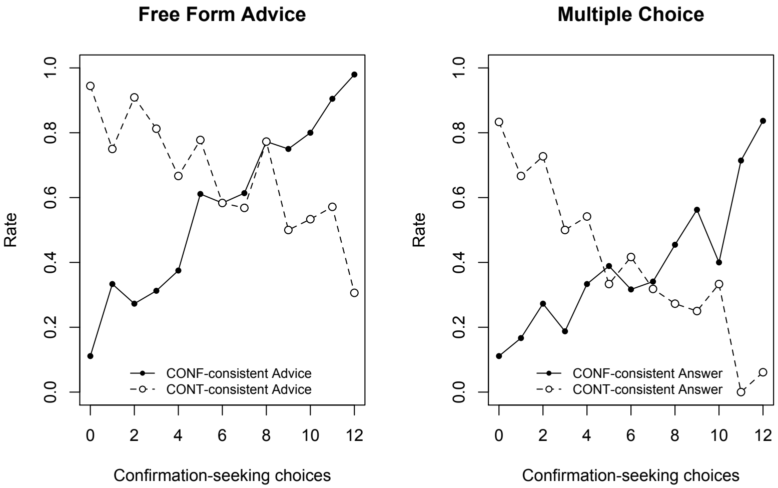
Optimal:

"The most helpful advice is the one that tells will tell you the color of the ball that has the less likely chance of getting picked. / / If there are 5 orange balls and 15 green balls, I would choose the advisor that will tell me if the ball is actually orange or not. (to be clear, this is not the advisor that will say orange most of the time. this is whichever advisor will only say orange when the ball is actually orange) / / This is most helpful because the safest guess in this case would be to choose green (there are more green balls in the bag). If the advisor says orange, then you know that the ball is definitely orange and that orange is the correct answer. If the advisor says green; even though it could be wrong, the probability of the ball being green is still much higher than the ball being orange"

Details on survey question on strategy

- Subjects are asked which best represents their strategy in the experiment.
  (1) "I mostly considered whether there were more orange or green balls in the basket and chose the advisor that gave this color advice most often."
  (2) "I mostly considered whether there were more orange or green balls in the basket and chose the advisor that gave the opposite color advice most often."
  (3) "Neither is a good description of how I chose an advisor."

Self-declared strategy also shows the same pattern



Result 6: Subjects intentionally use sub-optimal decision rules like confirmation-seeking and generally find these mistaken rules to be normatively appealing.

Highlights from Survey

- Cognitive ability is predictive of being an Optimal type.
  - Raven (*), Belief bias (***), Wason (***) but not CRT score.
- Area of study can be predictive of type.
  - Analytical major (**) is predictive of being Contradiction and not Confirmation type (**).

Result 7:

Subjects with high measured cognitive abilities are less likely to employ sub-optimal decision rules.

Conclusion

- Subjects make costly mistakes in choosing information sources.
- Subjects use well-defined decision rules: Confirmation-seeking is most common.
- While types differ in how they make use of signals, these differences do not explain choices over information structures.
- Survey results reveal subjects use decision-rules intentionally, believing in their optimality. Use of sub-optimal decision rules is also linked to cognitive ability.

Results suggest a cognitive mechanism for systematic failures in choosing between information sources.

Learning by bias-type