Audi Alteram Partem: An Experiment on Selective Exposure to Information*

Giovanni Montanari
New York University

Salvatore Nunnari
Bocconi University

November 24, 2022

Abstract

We report the results of an experiment on selective exposure to information. A decision maker interested in learning about an uncertain state of the world can acquire information from one of two sources which have opposite biases: when informed on the state, they report it truthfully; when uninformed, they report their favorite state. A Bayesian decision maker is better off seeking confirmatory information unless the source biased against the prior is sufficiently more reliable. In line with the theory, subjects are more likely to seek confirmatory information when sources are symmetrically reliable. On the other hand, when sources are asymmetrically reliable, subjects are more likely to consult the more reliable source even when prior beliefs are strongly unbalanced and this source is less informative. Our experiment suggests that base rate neglect and simple heuristics (e.g., listen to the most reliable source) are important drivers of the endogenous acquisition of information.

Keywords: Information Acquisition, Biased Information Sources, Selective Exposure, Echo Chambers, Confirmation Bias, Base Rate Neglect, Laboratory Experiment

JEL Codes: C91, D81, D83, D91

*We are grateful to Gary Charness and audiences at New York University and the 2020 Global Online Meeting of the Economic Science Association for helpful comments. Nunnari gratefully acknowledges financial support from the European Research Council through ERC Grant 852526 (POPULIZATION).

1 Introduction

Social scientists have collected ample evidence that people selectively search for and attend to a subset of the available information, ignoring additional evidence. In particular, existing research in sociology, psychology, political science and economics strongly suggests that people tend to look for information that is consistent with their world view (Sears and Freedman 1967, Frey 1986, Gunther 1992, Klayman 1995, Nickerson 1998, Iyengar and Hahn 2009). In the words of Berelson and Steiner (1968), "People tend to see and hear communications that are favorable or congenial to their predispositions; they are more likely to see and hear congenial communications than neutral or hostile ones" (pp. 529–530).

This pattern of selective exposure to information contrasts with the general wisdom that the other side in a debate should always be heard — a principle that dates back to Ancient Greece[1] and that lies at the heart of the contemporary legal tradition (*audi alteram partem* or *listen to the other side*). Moreover, this behavior has raised concern, both among social scientists and in the public opinion: as the availability of media choices has been growing, selective exposure to like-minded sources has contributed to a deep partisan divide in news consumption (Lawrence et al. 2010, Gentzkow and Shapiro 2011, n.d., Del Vicario et al. 2016, Quattrociocchi et al. 2016, Peterson et al. 2021). This segregation into "echo chambers" has been associated with the observed intensification of partisan sentiment as well as with the recent populist insurgencies in the Western world (Mann and Ornstein 2012, Bakshy et al. 2015, Flaxman et al. 2016).

Why do we observe this behavior? Recent theoretical work in microeconomics suggests that individuals might have systematic preferences for information consonant with their beliefs (Mullainathan and Shleifer 2005) or that, being uncertain about an information source reliability, they interpret disconfirming evidence as less credible than confirming evidence and turn their attention towards the source they deem as more informative (Gentzkow and Shapiro 2006). Notably, even when individuals have no uncertainty about sources reliability

[1] Consider Aeschylus, "The Eumenides" 431, 435

and regard all media outlets as equally credible, selective exposure to like-minded sources can be a rational choice for an individual who has limited time or attention and can only access or process a subset of the available evidence.

In this paper, we investigate this last mechanism with an online laboratory experiment. In particular, we ask the following research questions: How should an attention constrained but otherwise rational agent optimally acquire information from multiple potential sources with different biases? What is the ability of this normative model to predict the observed demand for (dis)confirmatory information?

We introduce a simple model of optimal choice between two different information sources and test experimentally whether our theory can account for the observed patterns of information selection. In our model, decision makers have the possibility to acquire a *signal* from one of two *information sources* in order to reduce their uncertainty about a payoff relevant state of the world. Importantly, decision makers know the conditional distributions of signals for each information source, ruling out any uncertainty about the *reliability* of information sources. We also provide decision makers with an exogenous prior belief on the true state of the world and focus on an abstract decision environment which allow us to minimize the confounding effects of *desirability bias* or *motivated beliefs*.[2] Once decision makers observe the signal from the information source of choice, they guess the state of the world they deem more likely and receive a positive payoff only for a correct guess. We manipulate experimentally the probability distributions of signals delivered by each information source (in order to control their *relative reliability*) and the prior belief over the state of the world. As a consequence of our manipulations, it is optimal to follow confirmatory information sources in some treatments but not in others. We verify optimal information acquisition in both environments and test for a confirmatory pattern on top and above what can be explained

[2]Desirability bias arises when an agent's actions reflect not only a probabilistic belief over possible realizations of the state of the world, but also a desire or preference with respect to such states (Tappin et al. 2017). As Epley and Gilovich (2016) put it, motivated beliefs capture the way "people generally reason their way to conclusions they favor, with their preferences influencing the way evidence is gathered, arguments are processed, and memories of past experience are recalled. Each of these processes can be affected in subtle ways by people's motivations, leading to biased beliefs that feel objective".

by rational behavior.

Some predictions of our theory align with observed behavior, while others are not supported by the data. When the two information sources are equally reliable, information acquisition displays a *confirmatory pattern*, as the source supportive of the prior belief is the most consulted one. This is in line with theoretical predictions. On the other hand, when we manipulate the relative reliability of information sources and make the source less supportive of the prior belief more informative, participants display a *dis-confirmatory pattern* of information acquisition, regardless of the strength of the prior. This contrasts with the predictions of the model, suggesting decision makers pay undue attention to the reliability of information sources and under-weigh the importance of the ex-ante uncertainty surrounding the phenomenon to learn about.

In order to shed light on the motives underlying information acquisition, we investigate how subjects use the advice received by the information source of choice. We find that, as predicted, subjects are deferential to confirmatory advice. On the other hand, subjects follow contradictory advice sub-optimally: they are excessively skeptic of contradictory advice by the source biased towards the prior and excessively trusting of contradictory advice by the source biased against the prior. Moreover, subjects are insufficiently responsive to information misaligned with a source bias (which, in fact, perfectly reveals the state of the world) and excessively responsive to information aligned with a source bias. This suggests that biases in information processing and simple heuristics — e.g., listen to the more reliable source — are important drivers of the endogenous acquisition of information.

This paper contributes to three strands of literatures. First, our paper contributes to a literature in experimental psychology on how people gather evidence to test hypotheses (Skov and Sherman 1986, Klayman and Ha 1987, Baron et al. 1988, Slowiaczek et al. 1992).[3]

[3]Testing an hypothesis means checking whether a statement of the form "p implies q" is true. Logically, one can test the same hypothesis by checking whether a statement of the form "*not* q implies *not* p" is true. This means that, in this context, it is difficult to define what it means for information to be confirmatory or contradictory. Our experiment in not designed to test the ability to construct a logical test but rather the endogenous acquisition of an informative signal.

Second, our paper is related to a literature in experimental economics studying learning from new information and documenting deviations from Bayesian inference (Tversky and Kahneman 1971, Grether 1980, Viscusi and O'Connor 1984, Hoffrage et al. 2000, Charness and Levin 2005, Dohmen et al. 2009). Third and more directly, our paper contributes to a recent literature in experimental economics on the choice over sources of information sources with instrumental value (Ambuehl and Li 2018, Duffy et al. 2019, 2021).[4] The most closely related work is Charness et al. (2021). Similarly to some of our treatments (namely, E6 and E8), they consider experimental conditions (labeled *bias by commission*), where decision-makers choose between two information sources which are biased towards opposite states and might send an incorrect signal with the same probability (that is, they are symmetrically reliable). Contrary to their setting, we investigate experimental treatments where the two available information sources are biased towards opposite states and might send an incorrect signal with different probabilities (that is, they are asymmetrically reliable).[5]

The remainder of the paper proceeds as follows. In Section 2, we introduce a simple model of choice between information sources and present the testable hypotheses. Section 3 details our experimental design. We describe the experimental results in Section 4. Section 5 concludes and discusses directions for future research.

2 Task and Theoretical Predictions

Assume that there is a binary state of the world, $\theta = \{B, R\}$, and consider a decision maker (DM) who is uncertain about θ and has to make a guess, $a = \{B, R\}$. The DM earns a

[4]Less related to this paper, Zimmermann (2014), Falk and Zimmermann (2022), Masatlioglu et al. (2017), Nielsen (2020) investigate the choice over sources of information sources in settings where information has no instrumental value.

[5]Charness et al. (2021) also consider experimental treatments where the two information sources are asymmetrically reliable but biased towards the same state and, thus, there is no trade-off between reliability and direction of the bias (in fact, the two experts can easily be ranked by Blackwell ordering); and experimental treatments where the two information sources are biased towards opposite states and might fail to send a signal (labeled *bias by omission*). In further contrast with Charness et al. (2021), we use a between-subject rather than within-subject design and run the study online with a sample including both students and non-students rather than in the laboratory with students. See Section 3 for additional details.

(a) **Blue** Information Sources

	$s = b$	$s = r$
$\theta = B$	1	0
$\theta = R$	λ_B	$1 - \lambda_B$

(b) **Red** Information Source

	$s = b$	$s = r$
$\theta = B$	$1 - \lambda_R$	λ_R
$\theta = R$	0	1

Table 1: Conditional Distribution of Signals by Information Sources

reward (normalized to 1) only if this guess matches the state of the world.

We denote with π the DM's prior belief that $\theta = B$. Since our goal is to investigate the DM's propensity to acquire information which is consonant or dissonant with prior beliefs, we focus on unbalanced priors and, without loss of generality, we assume $\pi \in (1/2, 1)$. Before making a guess, the DM acquires a piece of information from one of two *information sources*, **Blue** and **Red**. Each information source stochastically maps the state of the world to a *signal* $s = \{b, r\}$, as described in Table 1. The DM knows the conditional distribution of signals from each source, ruling out any uncertainty over the sources' reliability.

In each panel of Table 1, each cell displays the probability of observing a signal (column) in a specific state of the world (row). We can interpret λ_σ as a measure of *bias* (or as an inverse measure of *reliability*) of source $\sigma = \{B, R\}$: **Blue** is biased towards B and λ_B represents the probability that it signals the state is B when it is, in fact, R; **Red** is biased towards R and λ_R represents the probability that it signals the state is R when it is, in fact, B. We assume that both sources are somewhat informative but also somewhat biased — that is, $\lambda_B, \lambda_R \in (0, 1)$. In line with Gentzkow and Shapiro (2006), this simple framework can capture different real-world scenarios: the information source may be uninformed about the state and report a default signal; it may strategically slant its report when the information it holds is against its favorite state; or its intended signal may inadvertently be distorted.

2.1 Optimal Guess for Given Information Source

We characterize the DM's optimal choice of information source and how it varies with prior beliefs and the sources' reliability by backward induction. First, we investigate the optimal guess for a given signal received by a given source. Second, we investigate what information source the DM prefers to consult, given the distribution of signals induced by each information source and how the DM will use these signals. In what follows, the notation $a^{\star}(s, \sigma)$ denotes the optimal guess after observing signal s from information source σ. Posterior beliefs are denoted by $Pr(\theta|s, \sigma)$. All proofs are in the Appendix.

Proposition 1 (Optimal Guess if Signal from Blue Source) *The DM always follows the signal received from source **Blue**, that is,* $a^{\star}(b, \textbf{\textit{Blue}}) = B$ *and* $a^{\star}(r, \textbf{\textit{Blue}}) = R$.

Proposition 2 (Optimal Guess if Signal from Red Source) *The DM always follows a confirmatory signal received from source **Red**, that is,* $a^{\star}(b, \textbf{\textit{Red}}) = B$. *The DM follows a contradictory signal received from source **Red** if and only if the source is sufficiently reliable, that is,* $a^{\star}(r, \textbf{\textit{Red}}) = R$ *if* $\lambda_R < \frac{1-\pi}{\pi}$ *and* $a^{\star}(r, \textbf{\textit{Red}}) = B$ *otherwise.*

Remember that the DM's prior belief favors B. When she observes a signal confirming her prior from either source, the DM's posterior belief that $\theta = B$ is strictly greater than her prior. Thus, in this case, the DM sticks with her prior belief and guesses accordingly. Receiving a signal which disagrees with the source bias — that is, receiving signal b (r) from the **Red** (**Blue**) source — is fully revealing: the DM learns the state with certainty, independently of her prior beliefs and the source reliability. Finally, when she observes signal r from **Red**, the DM's posterior belief that $\theta = B$ is strictly smaller than her prior. In this case, the optimal guess depends on the model parameters: if **Red** is sufficiently reliable (i.e., λ_R is sufficiently small), it is optimal to follow its signal. Otherwise, the DM is better off ignoring the signal altogether and sticking with the guess induced by her prior belief. The relative size of λ_R must be gauged against the prior belief: the larger the prior in favor of B, the higher the reliability of **Red** required by the DM to follow an r signal from this source.

2.2 Optimal Choice of Information Source

First, consider the expected utility from consulting the source biased in favor of the prior, that is, **Blue**. Since the DM follows any signal received from **Blue**, acquiring information from this source always improves the confidence the DM has in her guess with respect to a decision made without collecting any additional information.[6]

Second, consider the expected utility from consulting the source biased against the prior, that is, **Red**. As discussed above, when this source is sufficiently biased — that is, when $\lambda_R \geq \frac{1-\pi}{\pi}$ — the DM guesses B regardless of the signal. In this case, acquiring information from this source does not change, at least from an ex-ante perspective, the confidence the DM has in her guess with respect to a decision made without collecting any additional information. When, instead, this source if sufficiently reliable — that is, when $\lambda_R < \frac{1-\pi}{\pi}$ — the DM follows any signal received from **Red** and, similarly to **Blue**, acquiring information from this source always improves the confidence the DM has in her guess.[7]

Since consulting the source biased in favor of the prior is always informative while consulting the source biased against the prior is informative only if $\lambda_R < \frac{1-\pi}{\pi}$, the DM is better off consulting **Blue** when $\lambda_R \geq \frac{1-\pi}{\pi}$. When $\lambda_R < \frac{1-\pi}{\pi}$, both sources are informative and the choice involves a trade off. Intuitively, the DM chooses the source with the smallest probability of misleading signals. If the DM has a perfectly balanced prior, choosing **Red** over **Blue** reduces to $\lambda_R < \lambda_B$. When the prior is unbalanced, the DM has an incentive to choose the information source which is biased towards the prior. She prefers to observe a signal from **Red** only when this information source is sufficiently more reliable than the other. Proposition 3 summarizes this discussion and characterizes this threshold:

Proposition 3 (Optimal Information Source) *The DM acquires information from **Red** if $\lambda_R < \frac{1-\pi}{\pi}\lambda_B$ and acquires information from **Blue** otherwise.*

[6] As formally shown in Lemma 1 in the Appendix, the DM's expected utility from **Blue** is increasing in π (that is, the likelihood that the source bias is aligned with the state) and decreasing in λ_B.

[7] As formally shown in Lemma 2 in the Appendix, the DM's expected utility from**Red** is decreasing in π (that is, the likelihood that the source bias is aligned with the state) and decreasing in λ_R.

2.3 Summary of Testable Hypotheses

Below, we summarize the testable hypotheses that we set out to investigate empirically.

On Information Acquisition

H1 *When information sources are equally reliable, it is optimal to seek confirming information, that is, to acquire information from the source biased towards the prior.*

H2 *When the source biased against the prior is more reliable, it is optimal to acquire information from the more reliable source (even if biased against the prior) if the prior is mildly unbalanced and optimal to acquire information from the source biased towards the prior (even if less reliable) if the prior is strongly unbalanced.*

On Information Processing

H3 *It is always optimal to follow information from the source biased towards the prior.*

H4 *It is always optimal to follow confirming information from the source biased against the prior. Contradictory information from the source biased against the prior should be followed if the prior is mildly unbalanced and ignored if the prior is strongly unbalanced.*

3 Experimental Design

The experiment was conducted online on Prolific, a crowdsourcing platform for academic research. Subjects were recruited from the Prolific database of participants and screened by their characteristics: only American citizens currently residing in the U.S. whose first language was English were eligible for participation. A total of 201 subjects took part in the experiment, and no subject was able to sit for the experiment twice. While not representative of the American population, our sample is more representative than traditional samples composed of undergraduate students at elite universities.[8] The use of web-based experiments is relatively novel in experimental economics. While this methodology requires additional precautions in the design and in the instructions in order to ensure continuous attention[9], research suggests test results are in line with those obtained in more controlled environments such as laboratories (Krantz and Dalal 2000, Snowberg and Yariv 2021). Instructions and sample screens are reported in Appendix C.[10]

Setup. The task builds on the classic urn paradigm, which has been extensively used in the experimental literature since Anderson and Holt (1997). Subjects are asked to guess the color of a ball randomly drawn from an urn containing only blue and red balls, for a total of 10 balls. One of our experimental manipulations is participants' prior belief about the state which we control by varying the number of blue and red balls in the urn.

We model the information sources as imperfectly informed "experts". Before making their guess, participants have to consult either the *Blue Expert* or the *Red Expert*, randomly extracted from two population of experts (the Red population and the Blue population). In each population, a certain fraction of experts is informed about the true color of the extracted ball and issues a truthful report revealing such color. The complementary fraction of experts is uninformed about the color of the extracted ball and always issues the same report. In particular, a random *Blue Expert* is informed with probability $(1-\lambda_B)$ and, when uninformed, always reports the color of the ball is blue. Analogously, a random *Red Expert* is informed with probability $(1-\lambda_R)$ and, when uninformed, always reports the color of the ball is *red*. Both experts can be consulted for free, but participants are forced to choose only one of them.

[8] In our sample, age ranged between 19 and 75 years old, with an average age of 33.4 ($N = 192$ out of 201 participants); 51% of participants were women ($N = 198$); 28.4% of participants were students ($N = 197$); 56.3% of participants were full time workers ($N = 192$); 77% of participants had at least some college education ($N = 196$); 75.8% of participants were caucasian; the median personal income was in the $40k-$50k bracket ($N = 169$); the median household income was in the $65k-$75k bracket ($N = 157$); 50.8% of participants were Democrat (with 19.8% being a Republican and 29.5% being an Independent, $N = 193$). These statistics are based on self-declarations collected by Prolific.

[9] The rest of this Section details how we achieved this.

[10] The user interface was programmed with oTree (Chen et al. 2016).

Choosing the expert prompts participants to the following screen, where we use the *strategy method* and elicit a subject's guess about the color of the ball conditional on the expert's signal. On the same screen, we elicit a subject's confidence in each of these two conditional guesses, on a scale between 0 and 100.[11] Once these choices have been recorded, participants proceed to the final screen where they see the expert's signal, their relevant choice given the signal, the color of the extracted ball, and their payoff.

Instructions are displayed in the first screens of the experiment and followed by three multiple-choice questions to verify that participants understand the details of the experiment. After answering each of these questions, subjects see a commented feedback page with the correct answers and a further explanation of the reasoning leading to the correct answer.[12] In addition to answering a comprehension quiz, participants are required to spend a minimum amount of time on each page of the instructions and cannot continue to the following page until a specified amount of time (ranging from 30 to 60 seconds depending on the page) has elapsed.

Rounds. The discussion above describes one round of the experiment. The experiment consists in a sequence of 5 rounds. In each round, the computer draws the true state of the world and the messages sent by the two experts from the same distributions and independently from any past action or outcome. Playing multiple rounds, subjects familiarize with the structure of the experiment and have room for learning. We opted for a limited number of rounds for two reasons. First, we wanted participants to pay due attention to the instructions. Increasing the number of rounds may lead participants to skim quickly through the instructions in order to have more time to formulate each subsequent (remunerated)

[11] As detailed in the Instructions available in Appendix C, we elicit confidence with the following question: "On a scale from 0 to 100, how confident are you about this guess? For example, 0 means that you think it is just as likely that you are right or wrong and 100 means you are sure your guess is correct."

[12] 47% of participants (94 out 201) answered all three comprehension questions correctly; 87% (175 out of 201) answered at least two questions correctly; and 99% (199 out of 201) answered at least one question correctly. Below, we discuss robustness of experimental results to restricting the analyses only to subjects who answered correctly all comprehension questions. Table 6 in Appendix B reports observed behavior in the subsamples determined by the number of questions answered correctly in the comprehension quiz.

choice. Second, given the online implementation of the experiment, we wanted to avoid boredom: keeping the number of rounds at a minimum favors attention.

Choices. In each round, we elicit five choices from each participant: the expert to consult, the guess about the color of the ball for each possible signal received from the expert they choose, and their degree of confidence in each of these two guesses. The strategy method allows us to record information also for unlikely events. Moreover, we use confidence statements to construct a measure of observed posterior beliefs, which we exploit to test for systematic biases in distinct treatments.[13] In the instructions, we stress the importance of revealing truthful confidence assessments but do not incentivize these statements. We made this design choice for three reasons. First, given the experiment was administered online, we deemed as particularly important to keep the tasks simple and the total duration short (below 20 minutes). Explaining carefully a Binarized Scoring Rule and guaranteeing a full understanding of the underlying incentives would have required some additional time, possibly more than the duration of the main task, increasing attrition and reducing the quality of decisions throughout the whole experiment. Second, complex elicitation procedures as the Binarized Scoring Rule have recently been shown to systematically bias truthful reporting (Danz, Vesterlund and Wilson, 2022). Finally, rewarding the accuracy of posterior beliefs could potentially interfere with the fundamental incentive to choose the most informative expert, as it gives a motive to choose informational sources which are more likely to induce degenerate posterior beliefs.

Payoffs. On top of earning a fixed amount of $1 for taking part in the experiment, subjects are remunerated for guessing the color of the ball. In particular, they earn $1 if their guess matches the color of the drawn ball, $0 otherwise. At the beginning of the experiment participants are instructed they will play multiple rounds, but that only a randomly chosen

[13] We mapped a confidence of 0 — that is, "I think it is just as likely that I am right or wrong" — to a posterior belief of 0.5 (i.e., indifference between guessing blue and guessing red) and a confidence of 100 — that is, "I think I am sure my guess is correct" — to a posterior of 1 (i.e. almost certainty in the choice). Intermediate levels of confidence were mapped proportionally to intermediate posteriors between 0.5 and 1.

round will be selected to determine the bonus payment.

Treatments. We employ a between-subjects design, where we manipulate the prior belief that the ball drawn from the jar is blue, π, and the relative reliability of the two experts, (λ_R, λ_B). We consider both a mildly and a strongly unbalanced prior, respectively $\pi = 0.6$ and $\pi = 0.8$. Regarding the sources' bias, we consider the case where Blue and Red Experts are equally reliable, $(\lambda_R, \lambda_B) = (0.5, 0.5)$, and the case where the Red Expert is more reliable, i.e. $(\lambda_R, \lambda_B) = (0.3, 0.7)$. The combination of these two manipulations lead to four experimental treatments:

- **E6**: equal reliability, prior mildly favors ball being blue;
- **E8**: equal reliability, prior strongly favors ball being blue;
- **S6**: skewed reliability (Red is more reliable), prior mildly favors ball being blue;
- **S8**: skewed reliability (Red is more reliable), prior strongly favors ball being blue.

These four treatments have been designed to test the key predictions of the model, as summarized in Section 2. Only when the Red Expert is more reliable and when the prior is mildly unbalanced — that is, in treatment S6 — it is optimal to consult the contrarian expert. In all other treatments, it is optimal to consult the supportive expert. We can restate the predictions from Section 2.3 in terms of our treatments:

H1 Subjects acquire information from the Blue Expert in both E6 and E8.

H2 Subjects acquire information from the Red Expert in S6, from the Blue Expert in S8.

H3 Subjects always follow signals by the Blue Expert.

H4 Subjects always follow Blue signals by the Red Expert. Subjects follow Red signals by the Red Expert in E6 and S6 but ignore them in E8 and S8.

4 Experimental Results

4.1 Information Acquisition

Table 2 and Figure 2 show the percentage of decisions where subjects consulted the Blue Expert — that is, the expert biased in favor of the prior — disaggregated by treatment. When information sources are equally reliable, this happens in 66.3% of decisions with mildly unbalanced priors (treatment E6) and in 70.2% of decisions with strongly unbalanced priors (treatment E8). These proportions are statistically different from 50%, according to one-sample tests of proportions (p-values < 0.001). This behavior is in line with hypothesis H1, as the Blue Expert is always the more informative in these environments. When the information source biased against the prior (i.e., the Red Expert) is more reliable, the Blue Expert is chosen in 24% of decisions with mildly unbalanced priors (treatment S6) and in 24.3% of decisions with strongly unbalanced priors (treatment S8). These proportions are statistically different from 50%, according to one-sample tests of proportions (p-values < 0.001).

When comparing outcomes across treatments in the remainder of the paper, we use random-effects logistic regressions which takes into account the panel nature of the data (that is, the fact that the same individual contributes more than one observation to the dataset). Keeping the sources' relative reliability constant (equal or skewed) and manipulating the prior belief about the state from a mildly unbalanced one (0.6) to a strongly unbalanced one (0.8) does not affect the propensity to consult the Blue Expert (the p-value of E6 vs E8 is 0.595; the p-value for S6 vs S8 is 0.763). On the other hand, keeping the prior belief about the state constant (0.6 or 0.8) and manipulating the relative reliability of the sources from equal to being skewed in favor of Red strongly decreases the chance of consulting the Blue Expert: the difference between E6 and S6 (-42.4%) and the difference between E8 and S8 (-45.8%) are both statistically significant at the 1% level (p-values < 0.0001).[14]

[14] These results are robust to restricting the analysis to the subsample of subjects who make no mistakes in the comprehension quiz or to the subsample of experienced subjects (i.e., rounds 4 and 5 only).

Panel A: Treatment E8 (Equal Reliability, Strongly Unbalanced Prior)

	N	Observed	Theory
% Chooses Blue Expert	265	70.1	100
% Follows Advice if B Says b	186	98.9	100
% Follows Advice if B Says r	186	85.5	100
% Follows Advice if R Says b	79	98.7	100
% Follows Advice if R Says r	79	46.8	0

Panel B: Treatment S8 (Skewed Reliability, Strongly Unbalanced Prior)

	N	Observed	Theory
% Chooses Blue Expert	235	24.3	100
% Follows Advice if B Says b	57	98.3	100
% Follows Advice if B Says r	57	80.7	100
% Follows Advice if R Says b	178	96.6	100
% Follows Advice if R Says r	178	68.0	0

Panel C: Treatment E6 (Equal Reliability, Midly Unbalanced Prior)

	N	Observed	Theory
% Chooses Blue Expert	255	66.4	100
% Follows Advice if B Says b	169	97.6	100
% Follows Advice if B Says r	169	85.8	100
% Follows Advice if R Says b	86	91.9	100
% Follows Advice if R Says r	86	51.2	100

Panel D: Treatment S6 (Skewed Reliability, Mildly Unbalanced Prior)

	N	Observed	Theory
% Chooses Blue Expert	250	24.0	0
% Follows Advice if B Says b	60	91.7	100
% Follows Advice if B Says r	60	68.3	100
% Follows Advice if R Says b	190	98.4	100
% Follows Advice if R Says r	190	78.4	100

Table 2: Information Acquisition and Processing by Treatment: Theory vs. Observed

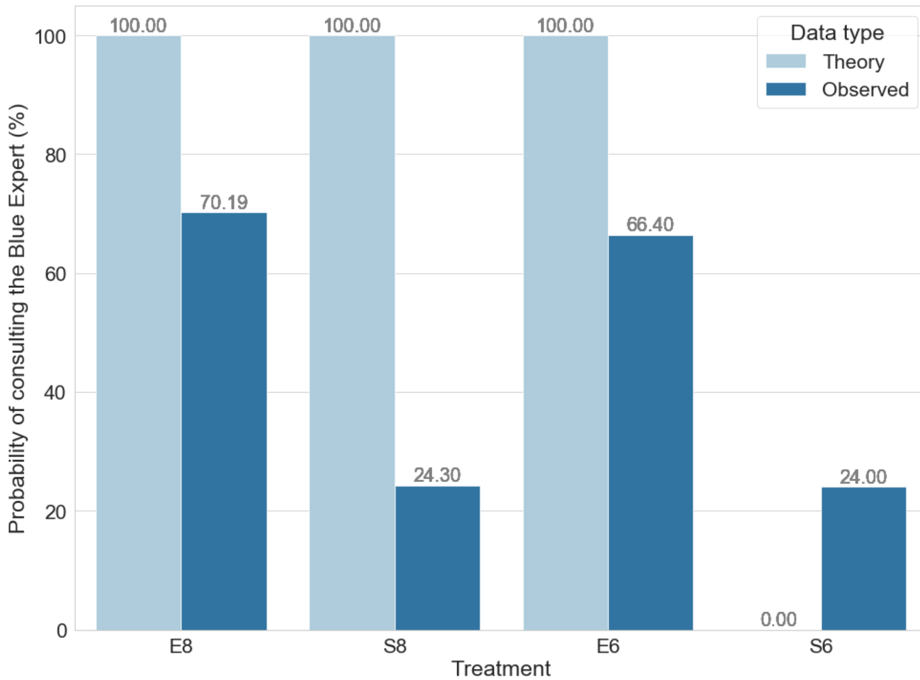


Figure 1: Information Acquisition by Treatment: Theory vs. Observed

This higlights that relative reliability trumps the importance of the prior in subjects' considerations. This behavior is in contrast with hypothesis H2, since the Red Expert is more informative only when the prior belief is mildly unbalanced. Findings 1 and 2 below summarize this discussion.

Finding 1. *When information sources are equally reliable, subjects are more likely to acquire information from the source biased towards the prior, which is the more informative.*

Finding 2. *When the source biased against the prior is more reliable, subjects are more likely to acquire information from the more reliable source, regardless of the prior and whether this source is the more informative or not.*

Even when subjects are more likely to choose the optimal source of information (in treatments E6, E8 and S6), they are prone to mistakes: when information sources are equally reliable, they listen too often to the expert biased against the prior (33.6% of decisions in E6 and 28.8% of decisions in E8); when the Red Expert is more reliable and the uncertainty on the state is sufficiently strong, they listen too often to the expert biased in favor of the prior (24% of decisions in S6). Mistakes are, of course, even more frequent when subjects are more likely to consult the less informative expert (in treatment S8, when this happens in 75.5% of decisions).

Importantly, these mistake rates come at a cost in terms of accuracy in guessing the state. To show this, Table 3 reports the average guessing accuracy improvement over the prior — that is, the change in the probability of correctly guessing the state relative to simply following the prior — disaggregated by treatment. We compare the observed guessing accuracy improvement with two benchmarks: the guessing accuracy improvement by hypothetical subjects who choose the same information source as actual subjects but process the information as Bayesian learners; and the guessing accuracy improvement by hypothetical subjects who choose the optimal information source and process the information as Bayesian learners.[15]

The results show that subjects improve guessing accuracy less than they could in all treatments. Indeed, when experts have asymmetric reliability and the prior is strongly unbalanced, subjects actually make worse guesses than they would simply following their priors. In part, this is due to subjects making sub-optimal use of the information provided by experts (regardless of whether the chosen information source was optimal or not): the improvement in average accuracy that could be obtained without changing information source but adopting Bayesian inference ranges between 2.8% (in treatment E6) to 12.4% (in treatment S6). At the same time, choosing a suboptimal information source also has a cost in terms of guessing accuracy, especially in treatments S8 and E6.

Finding 3. *In all treatments, subjects frequently acquire information from the less informative source and this leads to sub-optimal learning.*

[15] Note that, for comparability with the other columns, the accuracy improvements in the last column of Table 3 are the *empirical* ones, which (as for the other columns) are computed for the finite number of observations in our experimental dataset (using as true state of the world the color of the ball drawn by the computer in those observations). The *theoretical* accuracy improvements over the prior when choosing the optimal source and updating beliefs as a Bayesian learner (which coincide with the empirical ones only in the limit as the sample size grows larger) are +10% for E8, +6% for S8, +20% for E6 and +22% for S6.

Treatment	N	Observed Source & Observed Guess	Observed Source & Optimal Guess	Optimal Source & Optimal Guess
E8	265	+1.1	+7.2	+8.7
S8	235	-3.4	+1.7	+7.7
E6	255	+6.6	+9.4	+16.8
S6	250	+14.8	+27.2	+28.4

Table 3: Guessing Accuracy Improvement over Prior by Treatment

4.2 Information Processing

To shed light on subjects' choice of information source and understand why they are prone to mistakes, we analyze the use subjects make of the information they obtain from experts. Table 2 and Figure 3 shows the percentage of decisions which follow the advice from the chosen information source, disaggregated by treatment, information source and advice.[16] We define confirmatory advice as a signal which aligns with the prior belief. Pooling together all treatments, subjects follow confirmatory advice from the Blue Expert 97.5% of the time and confirmatory advice from the Red Expert 96.8% of the time. This is in line with our theoretical model: since both information sources are somehow informative, confirmatory advice increases the confidence in the state being the blue one, regardless of the information source it comes from.

Finding 4. *Subjects follow confirmatory advice optimally.*

On the other hand, subjects suffer from biases in interpreting contradictory advice. A Bayesian learner always follows contradictory advice from the Blue Expert, regardless of the prior and the source reliability (indeed, this message perfectly reveals the state). Pooling together all treatments, subjects follow a red message by the Blue Expert 82.8% of the time. Moreover, a Bayesian learner follows contradictory advice from the Red Expert only when messages from this expert are sufficiently informative. Given our experimental parameters, this is the case only with mildly unbalanced priors. In the experiment, subjects follow a red

[16]We must note that interpreting these results is complicated, at least in part, by self selection, as subjects choose their information source.

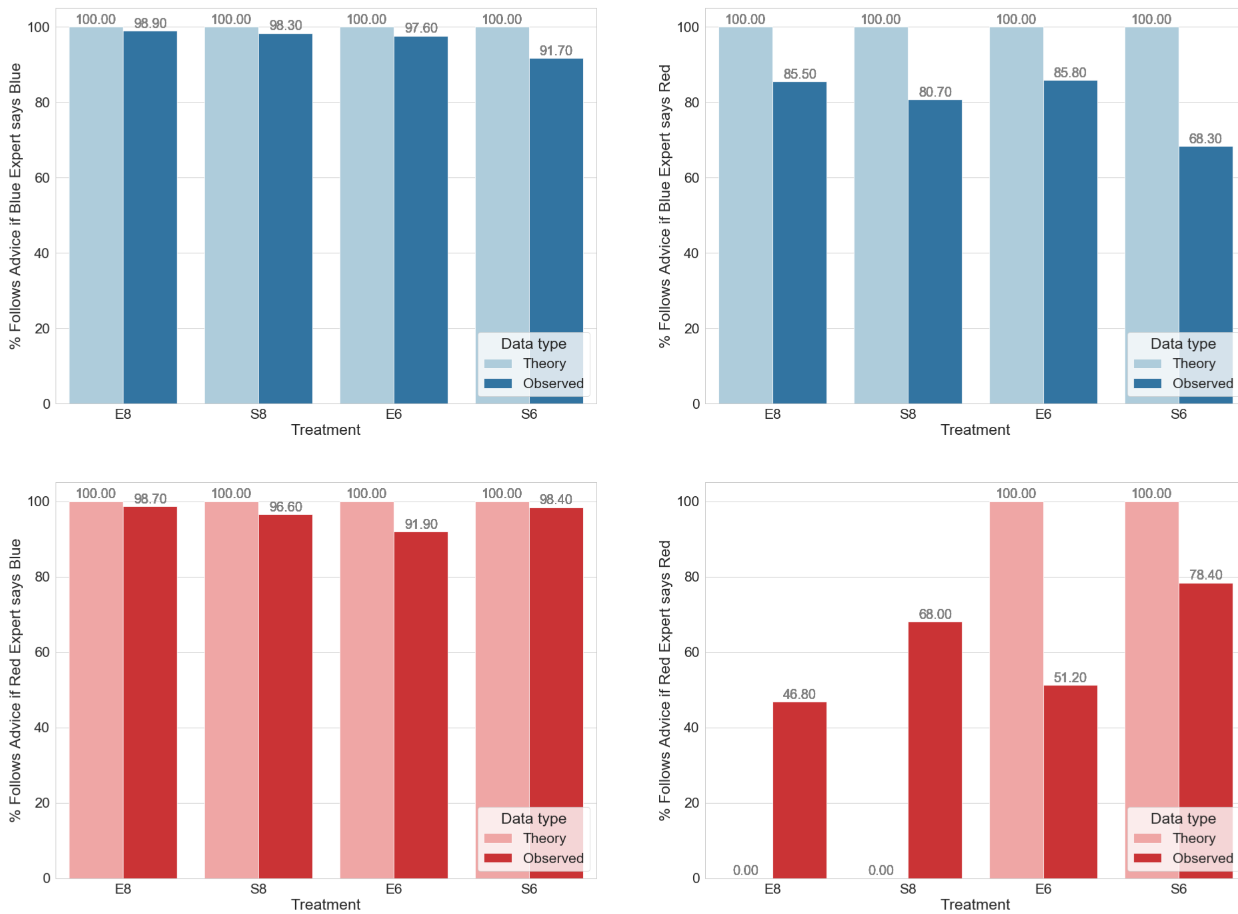


Figure 2: % Following Advice by Treatment and Information Set: Theory vs. Observed

message by the Red Expert 69.9% of the time when the prior is mildly unbalanced (treatments E6 and S6), and 61.5% of the time when the prior is strongly unbalanced (treatments E8 and S8). The difference between the two pairs of treatments is not statistically significant (p-value = 0.378).[17] Keeping the prior belief constant, subjects are more likely to follow contradictory advice by the Red Expert when this information source is more reliable: this happens 51.1% of the time in treatment E6 against 78.4% of the time in treatment S6 (p-value = 0.019); and 46.8% of the time in treatment E8 against 68% of the time in treatment S8 (p-value = 0.327).[18] Theoretically, even if increasing the Red Expert's reliability does

[17]The difference remains statistically indistinguishable from zero when restricting the analysis to subjects who make no mistakes in the comprehension quiz or to the experienced subjects (i.e., rounds 4 and 5 only).

[18]The difference between S6 and E6 continues to be statistically significant when restricting the analysis to subjects who make no mistakes in the comprehension quiz or to experienced subjects. The difference between S8 and E8 becomes statistically significant when restricting the analysis to these two subsamples.

increase the sensitivity of posterior beliefs to its advice, contradictory advice by the Red Expert should affect the optimal guess only when the initial belief is not too strong (and for both levels of reliability).

Finding 5. *Subjects follow contradictory advice sub-optimally: they are excessively skeptic of contradictory advice by the expert biased towards the prior and excessively trusting of contradictory advice by the expert biased against the prior.*

To understand why subjects' decision-making after receiving a contradictory signal is different from the Bayesian benchmark, we map the (non-incentivized) confidence levels in the guess to posterior beliefs on the state of the world and analyze them. We follow Charness et al. (2021) and define *responsiveness to information* as follows:

$$\alpha_s = \frac{p_s - p_0}{p_s^{Bay} - p_0}$$

where p_s is the observed posterior belief, p_0 is the prior belief and p^{Bay} is the posterior belief held by a Bayesian learner with the same information. Note that $\alpha_s = 1$ corresponds to Bayesian updating, $\alpha_s < 1$ corresponds to under-responsiveness and $\alpha_s > 1$ corresponds to over-responsiveness. We calculate α_s for each decision and show the average by treatment and information set in Table 4.

Table 4 shows that subjects' posterior beliefs are statistically indistinguishable from those of Bayesian learners when advice is in line with the source bias and the prior is more favorable to this bias: average responsiveness is not statistically different from 1 when the prior is strongly unbalanced and the Blue Expert suggests blue; and when the prior is mildly unbalanced and the Red Expert suggests red. At the same time, subjects are too trusting of advice in line with an expert's bias when the prior is less favorable to this bias: subjects are excessively responsive to a blue message by the Blue Expert when the prior is mildly unbalanced (average responsiveness being 1.5 in E6 and 2.5 in S6); and excessively responsive to a red message by the Red Expert when the prior is strongly unbalanced (average

Panel A: Treatment E8 (Equal Reliability, Strongly Unbalanced Prior)

	N	Observed	Theory	p-value
Mean Responsiveness if B Says b	186	0.8	1	0.252
Mean Responsiveness if B Says r	186	0.8	1	0.000
Mean Responsiveness if R Says b	79	0.7	1	0.006
Mean Responsiveness if R Says r	79	2.2	1	0.011

Panel B: Treatment S8 (Skewed Reliability, Strongly Unbalanced Prior)

	N	Observed	Theory	p-value
Mean Responsiveness if B Says b	57	1.3	1	0.408
Mean Responsiveness if B Says r	57	0.7	1	0.012
Mean Responsiveness if R Says b	178	0.6	1	0.000
Mean Responsiveness if R Says r	178	1.7	1	0.000

Panel C: Treatment E6 (Equal Reliability, Midly Unbalanced Prior)

Equal Reliability, Prior = 0.6 (E6)	N	Observed	Theory	p-value
Mean Responsiveness if B Says b	169	1.5	1	0.001
Mean Responsiveness if B Says r	169	0.8	1	0.001
Mean Responsiveness if R Says b	86	0.8	1	0.006
Mean Responsiveness if R Says r	86	0.8	1	0.409

Panel D: Treatment S6 (Skewed Reliability, Mildly Unbalanced Prior)

	N	Observed	Theory	p-value
Mean Responsiveness if B Says b	60	2.5	1	0.002
Mean Responsiveness if B Says r	60	0.5	1	0.001
Mean Responsiveness if R Says b	190	0.9	1	0.001
Mean Responsiveness if R Says r	190	1.0	1	0.712

Table 4: Belief Updating (from Confidence Statements) by Treatment. Notes: the unit of observation is a decision made by a subject in a round; p-values for comparison with theory are based on one-sample t-tests with standard errors clustered at the subject level.

responsiveness being 2.2 in E8 and 1.7 in S8). Moreover, subjects are always too skeptic of advice in conflict with an expert's bias (which, in fact, perfectly reveals the state of the world): the average responsiveness in these cases ranges from 0.5 (in treatment S6 when the Blue Experts says red) to 0.9 (in treatment S6 when the Red Expert says blue) and is statistically different from 1 for all treatments and information sets. Finding 6 summarizes this discussion.

Finding 6. *Subjects are insufficiently responsive to information misaligned with a source bias and excessively responsive to information aligned with a source bias.*

5 Conclusions

This paper formalized a model of selective exposure based on Bayesian updating, and tested its predictions through an online experiment. We ask two research questions: when is it rational to seek (dis)confirmatory information? Do experimental subjects behave according to rationality or do we need to impose additional structures? We modeled the problem of selective exposure to information as a choice between experts with different reliability. Overall, our experiment suggests that explaining selective exposure to information sources with Bayesian inference has some limitations: in line with Bayesian learning, we do observe confirmatory patterns in the selection of information source when experts are equally reliable; at the same time, these trends switch to dis-confirmatory attitudes as soon as the expert biased against the prior becomes more informative, with no role for the strength of prior beliefs. We see many possible directions for future research: while we study the simplest possible setup to investigate selective exposure to information sources, it would be interesting to investigate more complex environments where decision-makers have the opportunity to collect multiple pieces of information from experts, or must pay a (possibly heterogeneous) price to receive messages from an information source.

References

Ambuehl, Sandro and Shengwu Li, "Belief Updating and the Demand for Information," *Games and Economic Behavior*, 2018, *109*, 21–39.

Anderson, Lisa R and Charles A Holt, "Information Cascades in the Laboratory," *American Economic Review*, 1997, *87* (5), 847–862.

Bakshy, Eytan, Solomon Messing, and Lada A Adamic, "Exposure to ideologically diverse news and opinion on Facebook," *Science*, 2015, *348* (6239), 1130–1132.

Baron, Jonathan, Jane Beattie, and John C Hershey, "Heuristics and Biases in Diagnostic Reasoning II: Congruence, Information, and Certainty," *Organizational Behavior and Human Decision Processes*, 1988, *42* (1), 88–110.

Berelson, Bernard and Gary A Steiner, *Human Behavior: An Inventory of Scientific Findings*, Springer, 1968.

Charness, Gary and Dan Levin, "When Optimal Choices Feel Wrong: A Laboratory Study of Bayesian Updating, Complexity, and Affect," *American Economic Review*, 2005, *95* (4), 1300–1309.

_ , Ryan Oprea, and Sevgi Yuksel, "How Do People Choose Between Biased Information Sources? Evidence from a Laboratory Experiment," *Journal of the European Economic Association*, 2021, *19* (3), 1656–1691.

Chen, Daniel L, Martin Schonger, and Chris Wickens, "oTree: An Open-Source Platform for Laboratory, Online, and Field Experiments," *Journal of Behavioral and Experimental Finance*, 2016, *9*, 88–97.

Danz, David, Lise Vesterlund, and Alistair J Wilson, "Belief Elicitation and Behavioral Incentive Compatibility," *American Economic Review*, 2022, *112* (9), 2851–83.

Dohmen, Thomas J, Armin Falk, David Huffman, Felix Marklein, and Uwe Sunde, "The Non-Use of Bayes Rule: Representative Evidence on Bounded Rationality," *Unpublished Manuscript*, 2009.

Duffy, John, Ed Hopkins, and Tatiana Kornienko, "Lone Wolf or Herd Animal? Information Choice and Learning from Others," *European Economic Review*, 2021, *134*, 103690.

_ , _ , _ , and Mingye Ma, "Information Choice in a Social Learning Experiment," *Games and Economic Behavior*, 2019, *118*, 295–315.

Epley, Nicholas and Thomas Gilovich, "The Mechanics of Motivated Reasoning," *The Journal of Economic Perspectives*, 2016, *30* (3), 133–140.

Falk, Armin and Florian Zimmermann, "Information Demand: Experimental Evidence on Preferences for Information," *Unpublished Manuscript*, 2022.

Flaxman, Seth, Sharad Goel, and Justin M Rao, "Filter Bubbles, Echo Chambers, and Online News Consumption," *Public Opinion Quarterly*, 2016, *80* (S1), 298–320.

Frey, Dieter, "Recent Research on Selective Exposure to Information," *Advances in Experimental Social Psychology*, 1986, *19*, 41–80.

Gentzkow, Matthew and Jesse M Shapiro, "Media Bias and Reputation," *Journal of Political Economy*, 2006, *114* (2), 280–316.

_ and _ , "Ideological Segregation Online and Offline," *Quarterly Journal of Economics*, 2011, *126* (4), 1799–1839.

Grether, David M, "Bayes Rule as a Descriptive Model: The Representativeness Heuristic," *Quarterly Journal of Economics*, 1980, *95* (3), 537–557.

Gunther, Albert C, "Biased press or biased public? Attitudes toward media coverage of social groups," *Public Opinion Quarterly*, 1992, *56* (2), 147–167.

Hoffrage, Ulrich, Samuel Lindsey, Ralph Hertwig, and Gerd Gigerenzer, "Communicating Statistical Information," *Science*, 2000, *290* (5500), 2261–2262.

Iyengar, Shanto and Kyu S Hahn, "Red Media, Blue Media: Evidence of Ideological Selectivity in Media Use," *Journal of Communication*, 2009, *59* (1), 19–39.

Klayman, Joshua, "Varieties of Confirmation Bias," *Psychology of Learning and Motivation*, 1995, *32*, 385–418.

_ **and Young-Won Ha**, "Confirmation, Disconfirmation, and Information in Hypothesis Testing.," *Psychological Review*, 1987, *94* (2), 211.

Krantz, John H and Reeshad Dalal, "Validity of Web-Based Psychological Research," in "Psychological Experiments on the Internet," Elsevier, 2000, pp. 35–60.

Lawrence, Eric, John Sides, and Henry Farrell, "Self-Segregation or Deliberation? Blog Readership, Participation, and Polarization in American Politics," *Perspectives on Politics*, 2010, *8* (1), 141–157.

Mann, Thomas E. and Norman J. Ornstein, *It's Even Worse Than It Looks: How the American Constitutional System Collided with the New Politics of Extremism*, Basic Books, New York, NY, 2012.

Masatlioglu, Yusufcan, A Yesim Orhun, and Collin Raymond, "Intrinsic Information Preferences and Skewness," *Unpublished Manuscript*, 2017.

Mullainathan, Sendhil and Andrei Shleifer, "The Market for News," *American Economic Review*, 2005, *95* (4), 1031–1053.

Nickerson, Raymond S, "Confirmation Bias: A Ubiquitous Phenomenon in Many Guises," *Review of General Psychology*, 1998, *2* (2), 175.

Nielsen, Kirby, "Preferences for the Resolution of Uncertainty and the Timing of Information," *Journal of Economic Theory*, 2020, *189*, 105090.

Peterson, Erik, Sharad Goel, and Shanto Iyengar, "Partisan Selective Exposure in Online News Consumption: Evidence from the 2016 Presidential Campaign," *Political Science Research and Methods*, 2021, *9* (2), 242–258.

Quattrociocchi, Walter, Antonio Scala, and Cass R Sunstein, "Echo Chambers on Facebook," *Discussion Paper No. 877, Harvard Law School*, 2016.

Sears, David O and Jonathan L Freedman, "Selective Exposure to Information: A critical Review," *Public Opinion Quarterly*, 1967, *31* (2), 194–213.

Skov, Richard B and Steven J Sherman, "Information-Gathering Processes: Diagnosticity, Hypothesis-Confirmatory Strategies, and Perceived Hypothesis Confirmation," *Journal of Experimental Social Psychology*, 1986, *22* (2), 93–121.

Slowiaczek, Louisa M, Joshua Klayman, Steven J Sherman, and Richard B Skov, "Information Selection and Use in Hypothesis Testing: What is a Good Question, and What is a Good Answer?," *Memory & Cognition*, 1992, *20* (4), 392–405.

Snowberg, Erik and Leeat Yariv, "Testing the Waters: Behavior across Participant Pools," *American Economic Review*, 2021, *111* (2), 687–719.

Tappin, Ben M, Leslie van der Leer, and Ryan T McKay, "The Heart Trumps the Head: Desirability Bias in Political Belief Revision," *Journal of Experimental Psychology: General*, 2017, *146* (8), 1143.

Tversky, Amos and Daniel Kahneman, "Belief in the Law of Small Numbers.," *Psychological Bulletin*, 1971, *76* (2), 105.

Vicario, Michela Del, Alessandro Bessi, Fabiana Zollo, Fabio Petroni, Antonio Scala, Guido Caldarelli, H Eugene Stanley, and Walter Quattrociocchi, "The Spreading of Misinformation Online," *Proceedings of the National Academy of Sciences*, 2016, *113* (3), 554–559.

Viscusi, W Kip and Charles J O'Connor, "Adaptive Responses to Chemical Labeling: Are Workers Bayesian Decision Makers?," *American Economic Review*, 1984, *74* (5), 942–956.

Zimmermann, Florian, "Clumped or Piecewise? Evidence on Preferences for Information," *Management Science*, 2014, *61* (4), 740–753.

Appendix A: Proofs

Proof of Proposition 1 Assume the DM observes an r signal from **Blue**. The posterior belief $Pr(R|r, \mathbf{Blue})$ is computed via Bayes Rule:

$$Pr(R|r, \mathbf{Blue}) = \frac{Pr(R) \cdot Pr(r, \mathbf{Blue}|R)}{Pr(R) \cdot Pr(r, \mathbf{Blue}|R) + Pr(B) \cdot Pr(r, \mathbf{Blue}|B)} = \frac{(1-\pi)(1-\lambda_B)}{(1-\pi)(1-\lambda_B)} = 1$$

Thus, the signal is fully revealing and implies the highest possible expected payoff. It follows $a^*(r, \mathbf{Blue}) = R$. On the other hand, after observing b from **Blue**, action B yields a higher payoff than R provided that $Pr(B|b, \mathbf{Blue}) > Pr(R|b, \mathbf{Blue})$, that is provided

$$\frac{\pi}{\lambda_B + \pi(1-\lambda_B)} > \frac{\lambda_B(1-\pi)}{\lambda_B + \pi(1-\lambda_B)}$$

which can be restated as $\lambda_B < \frac{\pi}{1-\pi}$ and the inequality always holds for $\pi > 0.5$.

Proof of Proposition 2 When the DM observes a b signal from **Red**, it updates $Pr(B|b, \mathbf{Red}) = \frac{(1-\lambda_R)\pi}{(1-\lambda_R)\pi} = 1$. It immediately follows $a^*(b, \mathbf{Red}) = B$. When the DM observes r from **Red**, it is optimal to guess R whenever

$$Pr(R|r, \mathbf{Red}) > Pr(B|r, \mathbf{Red}) \iff \frac{1-\pi}{1-(1-\lambda_R)\pi} > \frac{\pi\lambda_R}{1-(1-\lambda_R)\pi}$$

which can be re-arranged as $\lambda_R < \frac{1-\pi}{\pi}$, as we wanted to show.

Lemma 1 (Expected Utility from Blue Source) $\mathbb{E}[\boldsymbol{Blue}] = 1-(1-\pi)\lambda_B \in [\pi, 1]$ *is increasing in* π *and decreasing in*

Proof of Lemma 1

The DM's posterior belief that she is making the correct guess is $Pr(\theta = R|r, \mathbf{Blue}) = 1$ following a contradictory signal; and $Pr(\theta = B|b, \mathbf{Blue}) = \frac{\pi}{\pi+(1-\pi)\lambda_B}$ following a confirmatory signal. Weighing these posterior beliefs with the unconditional distribution of signals by this source, we get the following expected payoff:

$$
\begin{aligned}
\mathbb{E}[\textbf{Blue}] &= [\pi + (1-\pi)\lambda_B] \frac{\pi}{\lambda_B + \pi(1-\lambda_B)} + (1-\pi)(1-\lambda_B) \\
&= \frac{\pi^2 + (1-\pi)\pi\lambda_B + (1-\pi)(1-\lambda_B)[\lambda_B + \pi(1-\lambda_B)]}{\lambda_B + \pi(1-\lambda_B)} \\
&= \frac{\pi^2 + (1-\pi)[\pi\lambda_B + (1-\lambda_B)\lambda_B + \pi(1-\lambda_B)^2]}{\lambda_B + \pi(1-\lambda_B)} \\
&= \frac{\pi^2 + (1-\pi)\pi\lambda_B + (1-\pi)(1-\lambda_B)[\lambda_B + \pi(1-\lambda_B)]}{\lambda_B + \pi(1-\lambda_B)} \\
&= \frac{\pi[\lambda_B + \pi(1-\lambda_B)] + (1-\pi)(1-\lambda_B)[\lambda_B + \pi(1-\lambda_B)]}{\lambda_B + \pi(1-\lambda_B)} \\
&= \pi + (1-\pi)(1-\lambda_B) \\
&= 1 - (1-\pi)\lambda_B \in [\pi, 1]
\end{aligned}
$$

$\mathbb{E}[\textbf{Blue}]$ is clearly increasing in π and decreasing in λ_B.

Lemma 2 (Expected Utility from Red Source) *If $\lambda_R \geq \frac{1-\pi}{\pi}$, $\mathbb{E}[\boldsymbol{Red}] = \pi$. If, instead, $\lambda_R < \frac{1-\pi}{\pi}$, $\mathbb{E}[\boldsymbol{Red}] = 1 - \pi\lambda_R \in [\pi, 1]$, decreasing in π and in λ_R.*

Proof of Lemma 2 When $\lambda_R \geq \frac{1-\pi}{\pi}$, signals from **Red** are uninformative and therefore ignored. It follows that, in this case, the expected payoff is equal to

$$
\begin{aligned}
\mathbb{E}[\textbf{Red}] &= \pi(1-\lambda_R) + [(1-\pi) + \pi\lambda_R] \left[\frac{\pi\lambda_R}{1-(1-\lambda_R)\pi}\right] \\
&= \mathbb{E}_{Pr(\theta|b,\textbf{Red})}[u(\theta|b)] + \mathbb{E}_{Pr(\theta|r,\textbf{Red})}[u(\theta|b)] \\
&= \mathbb{E}_{Pr(\theta|s,\textbf{Red})}\left[\mathbb{E}[u(\theta|b)|s, \textbf{Red}]\right] \\
&= \mathbb{E}_{\pi}\left[u(\theta|b)\right] \text{ by LIE} \\
&= \pi
\end{aligned}
$$

On the other hand, when $\lambda_R < \frac{1-\pi}{\pi}$, the DM follows any signal received from **Red**. In this case, her posterior belief that she is making the correct guess is $Pr(\theta = R|r, \textbf{Red}) =$

$\frac{1-\pi}{\pi\lambda_R+(1-\pi)}$ following a contradictory signal; and $Pr(\theta = B|b, \mathbf{Red}) = 1$ following a confirmatory signal. Weighing these posterior beliefs with the unconditional distribution of signals by this source, we get the following expected payoff:

$$\begin{aligned}
\mathbb{E}[\mathbf{Red}] &= \pi(1-\lambda_R) + [(1-\pi) + \pi\lambda_R]\left(\frac{1-\pi}{1-(1-\lambda_R)\pi}\right) \\
&= \frac{\pi(1-\lambda_R) - \pi^2(1-\lambda_R)^2 + (1-\pi)^2 + \pi(1-\pi)\lambda_R}{1-(1-\lambda_R)\pi} \\
&= \frac{\pi(1-\lambda_R)[1-\pi(1-\lambda_R)] + (1-\pi)[1-\pi+\pi\lambda_R]}{1-(1-\lambda_R)\pi} \\
&= \pi(1-\lambda_R) + (1-\pi) \\
&= 1 - \pi\lambda_R \in [1-\pi, 1]
\end{aligned}$$

$\mathbb{E}[\mathbf{Red}]$ is clearly decreasing in π and in λ_R.

Proof of Proposition 3 We distinguish two cases, namely $\lambda_R < \frac{1-\pi}{\pi}$ and $\lambda_R \geq \frac{1-\pi}{\pi}$.

First consider the case where $\lambda_R \geq \frac{1-\pi}{\pi}$, i.e. signals from **Red** are uninformative. Using the previous results, the DM prefers **Blue** over **Red** as long as

$$\mathbb{E}[\mathbf{Blue}] \geq \mathbb{E}[\mathbf{Red}] \iff 1-(1-\pi)\lambda_B \geq \pi \iff 1-\pi \geq (1-\pi)\lambda_B \iff 1 \geq \lambda_B$$

which always holds by construction. Hence if $\lambda_R \geq \frac{1-\pi}{\pi}$, the DM chooses to access source **Blue**.

Consider next the case $\lambda_R < \frac{1-\pi}{\pi}$. In this range signals from **Red** are informative and always followed. The DM prefers **Blue** over **Red** whenever

$$\mathbb{E}[\mathbf{Blue}] \geq \mathbb{E}[\mathbf{Red}] \iff 1-(1-\pi)\lambda_B \geq 1-\pi\lambda_R \iff \lambda_R \geq \frac{1-\pi}{\pi}\lambda_B$$

In particular, the DM accesses source **Red** when $\lambda_R < \frac{1-\pi}{\pi}\lambda_B$ and Blue otherwise.

Putting together the two cases, the result in the proposition follows.

Appendix B: Additional Figures and Tables

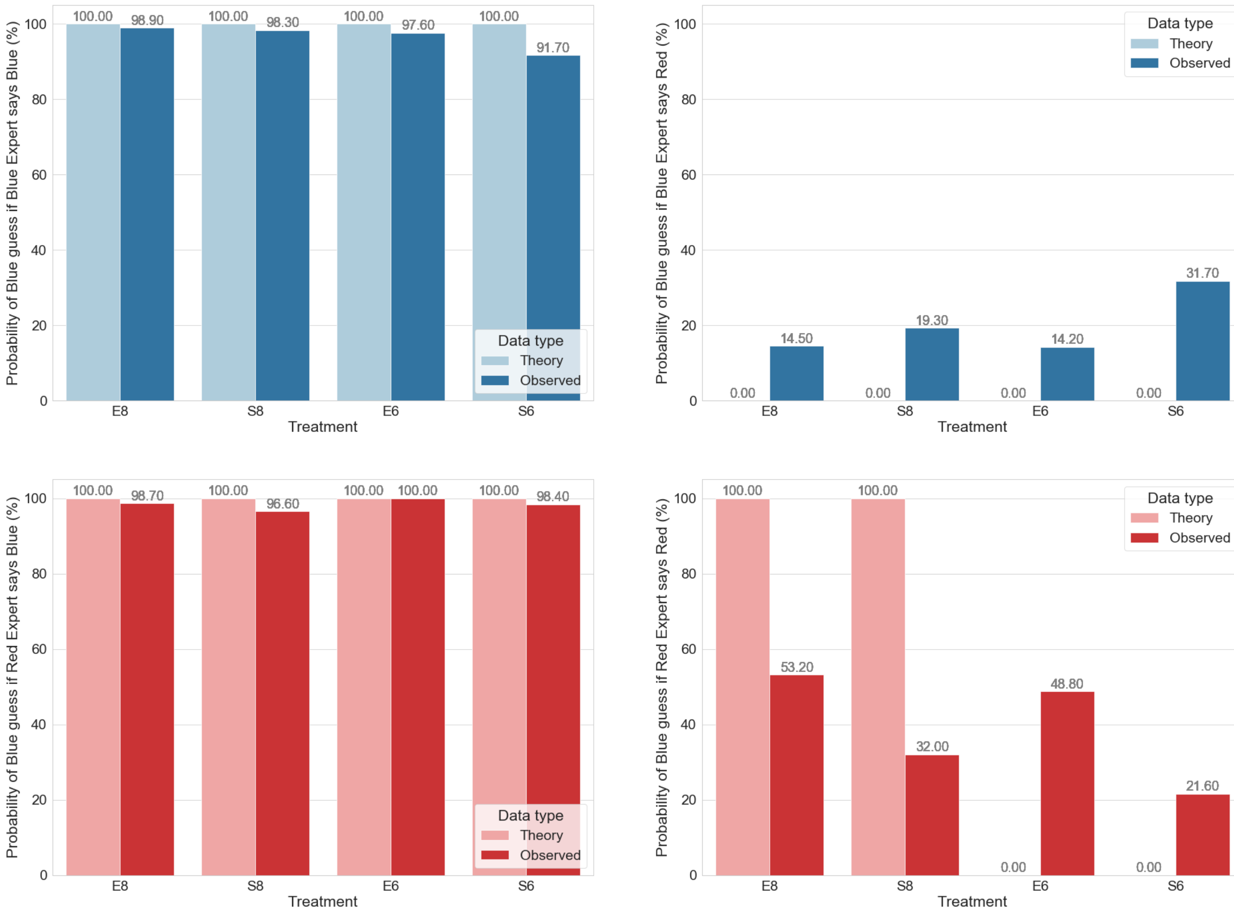


Figure 3: Guess on the State by Treatment and Information Set: Theory vs. Observed Data

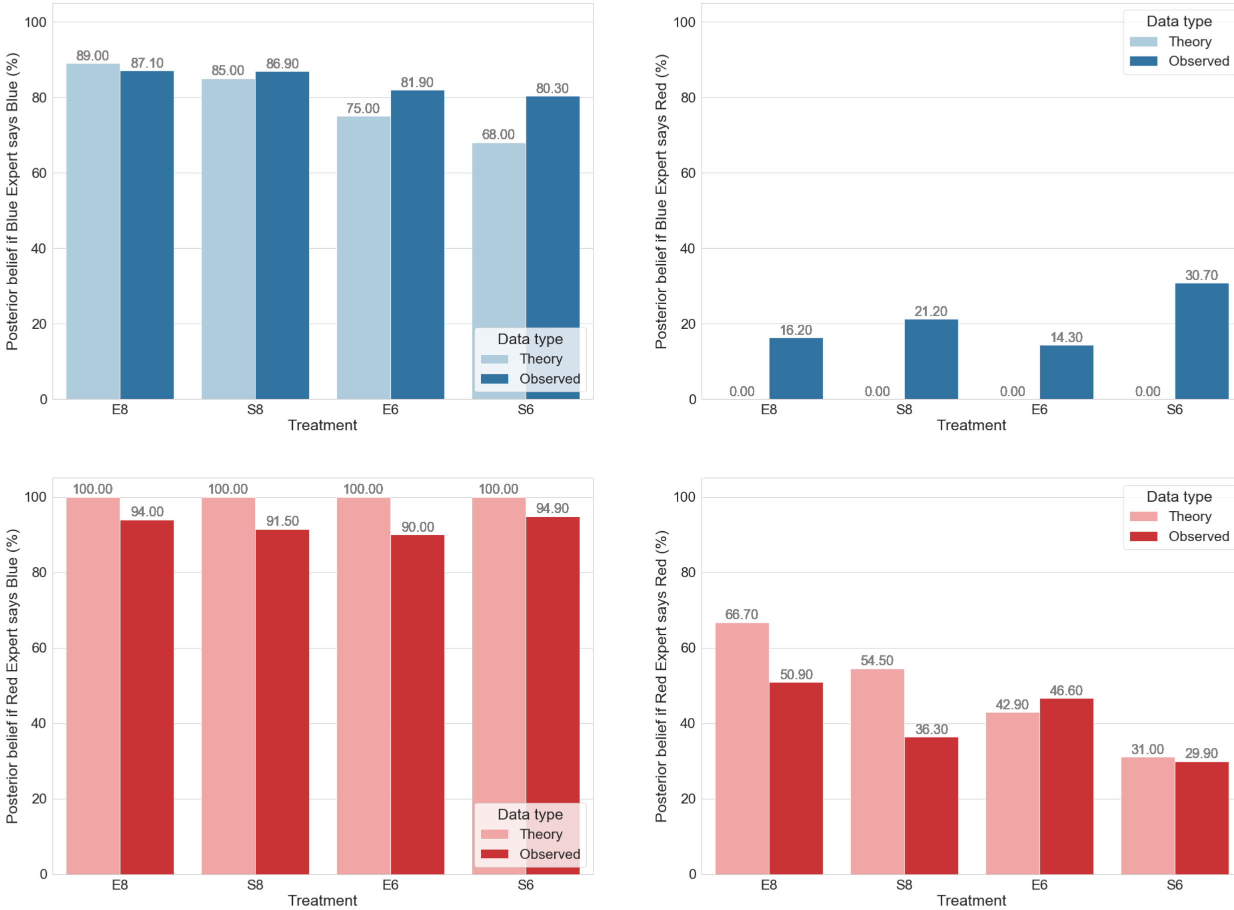


Figure 4: Posterior Beliefs by Treatment and Information Set: Theory vs. Observed Averages

E8	Round 1	Round 2	Round 3	Round 4	Round 5
% Chooses Blue Expert	69.8	66.0	66.0	73.6	75.5
% Guesses Blue Ball if B Says b	97.3	100.0	97.1	100.0	100.0
% Guesses Blue Ball if B Says r	10.8	8.6	20.0	17.9	15.0
% Guesses Blue Ball if R Says b	100.0	94.4	100.0	100.0	100.0
% Guesses Blue Ball if R Says r	43.8	44.4	50.0	57.1	76.9
Mean Posterior if B Says b	87.1	88.7	85.5	87.4	86.5
Mean Posterior if B Says r	12.4	11.6	18.5	19.1	18.9
Mean Posterior if R Says b	92.3	90.7	97.2	96.8	93.1
Mean Posterior if R Says r	43.2	48.1	49.3	53.9	63.5
S8	Round 1	Round 2	Round 3	Round 4	Round 5
% Chooses Blue Expert	25.5	25.5	17.0	25.5	27.7
% Guesses Blue Ball if B Says b	100.0	100.0	100.0	100.0	92.3
% Guesses Blue Ball if B Says r	8.3	25.0	12.5	16.7	30.8
% Guesses Blue Ball if R Says b	94.3	100.0	97.4	97.1	94.1
% Guesses Blue Ball if R Says r	25.7	31.4	33.3	31.4	38.2
Mean Posterior if B Says b	90.0	84.0	89.7	88.8	83.1
Mean Posterior if B Says r	16.9	24.2	9.4	20.4	30.5
Mean Posterior if R Says b	90.3	94.2	92.2	92.0	88.5
Mean Posterior if R Says r	31.7	34.0	36.1	37.5	42.5
E6	Round 1	Round 2	Round 3	Round 4	Round 5
% Chooses Blue Expert	72.5	58.8	62.7	66.7	70.6
% Guesses Blue Ball if B Says b	100.0	100.0	96.9	94.1	97.2
% Guesses Blue Ball if B Says r	13.5	16.7	9.4	14.7	16.7
% Guesses Blue Ball if R Says b	100.0	90.5	84.2	88.2	100.0
% Guesses Blue Ball if R Says r	50.0	47.6	42.1	47.1	60.0
Mean Posterior if B Says b	84.4	83.5	81.6	79.3	80.6
Mean Posterior if B Says r	14.1	15.5	10.2	13.8	17.9
Mean Posterior if R Says b	98.2	89.4	81.3	86.8	98.0
Mean Posterior if R Says r	48.2	46.8	41.9	46.3	51.5
S6	Round 1	Round 2	Round 3	Round 4	Round 5
% Chooses Blue Expert	30.0	16.0	30.0	22.0	22.0
% Guesses Blue Ball if B Says b	86.7	100.0	86.7	90.9	100.0
% Guesses Blue Ball if B Says r	33.3	25.0	13.3	45.5	45.5
% Guesses Blue Ball if R Says b	100.0	92.9	100.0	100.0	100.0
% Guesses Blue Ball if R Says r	17.1	28.6	22.9	23.1	15.4
Mean Posterior if B Says b	76.9	91.6	78.8	75.1	83.8
Mean Posterior if B Says r	30.7	27.5	18.7	41.4	38.9
Mean Posterior if R Says b	96.0	90.8	95.4	96.4	96.2
Mean Posterior if R Says r	29.1	32.0	28.9	29.7	29.2

Table 5: Observed Outcomes by Treatment and Round, All Subjects

E8	1+ Correct Answers (N = 53)	2+ Correct Answers (N = 49)	3 Correct Answers (N = 29)
% Chooses Blue Expert	70.7	70.2	73.8
% Guesses Blue Ball if B Says b	97.0	98.8	100.0
% Guesses Blue Ball if B Says r	0.0	15.1	11.2
% Guesses Blue Ball if R Says b	95.1	98.6	97.4
% Guesses Blue Ball if R Says r	48.8	54.8	65.8
Mean Posterior if B Says b	82.6	87.1	87.0
Mean Posterior if B Says r	0.9	14.6	12.6
Mean Posterior if R Says b	94.5	95.1	93.2
Mean Posterior if R Says r	49.0	51.7	60.9
S8	**1+ Correct Answers (N = 47)**	**2+ Correct Answers (N = 41)**	**3 Correct Answers (N = 15)**
% Chooses Blue Expert	24.3	22.4	18.7
% Guesses Blue Ball if B Says b	98.2	97.8	100.0
% Guesses Blue Ball if B Says r	19.3	15.2	7.1
% Guesses Blue Ball if R Says b	96.6	96.9	98.4
% Guesses Blue Ball if R Says r	32.0	34.6	31.1
Mean Posterior if B Says b	86.9	86.9	83.0
Mean Posterior if B Says r	21.2	19.1	9.6
Mean Posterior if R Says b	91.5	91.7	90.7
Mean Posterior if R Says r	36.3	37.7	35.0
E6	**1+ Correct Answers (N = 51)**	**2+ Correct Answers (N = 42)**	**3 Correct Answers (N = 28)**
% Chooses Blue Expert	66.3	65.2	70.7
% Guesses Blue Ball if B Says b	97.6	97.8	97.0
% Guesses Blue Ball if B Says r	14.2	6.6	0.0
% Guesses Blue Ball if R Says b	91.9	93.2	95.1
% Guesses Blue Ball if R Says r	48.8	52.1	48.8
Mean Posterior if B Says b	81.9	82.6	82.6
Mean Posterior if B Says r	14.3	7.6	0.9
Mean Posterior if R Says b	90.0	92.6	94.5
Mean Posterior if R Says r	46.6	48.3	49.0
S6	**1+ Correct Answers (N = 48)**	**2+ Correct Answers (N = 41)**	**3 Correct Answers (N = 22)**
% Chooses Blue Expert	22.1	20.0	11.8
% Guesses Blue Ball if B Says b	90.6	90.2	84.6
% Guesses Blue Ball if B Says r	28.3	34.1	7.7
% Guesses Blue Ball if R Says b	98.4	99.4	100.0
% Guesses Blue Ball if R Says r	21.4	20.1	14.4
Mean Posterior if B Says b	80.0	82.3	74.2
Mean Posterior if B Says r	28.1	29.3	5.8
Mean Posterior if R Says b	95.1	97.2	98.7
Mean Posterior if R Says r	29.8	29.0	26.9

Table 6: Observed Outcomes by Performance in Comprehension Quiz, All Rounds

Equal Reliability, Prior = 0.8 (E8)	N	Observed	Theory
Mean Posterior if B Says b	186	87.1	88.9
Mean Posterior if B Says r	186	16.2	0
Mean Posterior if R Says b	79	94.0	100
Mean Posterior if R Says r	79	50.9	66.7

Skewed Reliability, Prior = 0.8 (S8)	N	Observed	Theory
Mean Posterior if B Says b	57	86.9	85.1
Mean Posterior if B Says r	57	21.2	0
Mean Posterior if R Says b	178	91.5	100
Mean Posterior if R Says r	178	36.3	54.5

Equal Reliability, Prior = 0.6 (E6)	N	Observed	Theory
Mean Posterior if B Says b	169	81.9	75.0
Mean Posterior if B Says r	169	14.3	0
Mean Posterior if R Says b	86	90.0	100
Mean Posterior if R Says r	86	46.6	42.9

Skewed Reliability, Prior = 0.6 (S6)	N	Observed	Theory
Mean Posterior if B Says b	60	80.3	68.2
Mean Posterior if B Says r	60	30.7	0
Mean Posterior if R Says b	190	94.9	100
Mean Posterior if R Says r	190	29.9	31.0

Table 7: Posterior Beliefs (from Confidence Statements) by Treatment.

Appendix C: Experimental Instructions

Experimental instructions were delivered in the initial screens of the experiment. We report here the complete text and figures of these screens, including the comprehension quiz and the practice round. Page titles, as they appeared on the participants' screen, are in bold.

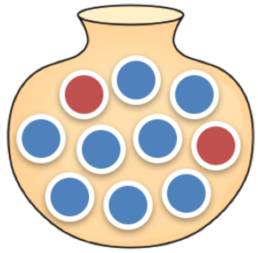
WELCOME

Welcome! Thank you for agreeing to participate in this experiment! This is an experiment designed to study how people make decisions. The whole experiment will last around 10 minutes. In addition to your participation fee, you will be able to earn a bonus payment. Your bonus payment will depend on your choices so, please, read the instructions carefully. We will use only one decision to determine your bonus payment but all decisions are equally likely to be selected so all choices matter. The instructions describe how your choices affects your earnings. They are composed of three pages and include a comprehension question at the end of each page. Please, devote at least 5 minutes to the instructions and the comprehension questions. Once you start the experiment, we require your complete and undistracted attention. When you are ready to start, please click the button below.

INSTRUCTIONS/1: YOUR TASK

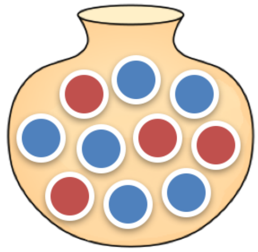
TREATMENT E8 AND S8 ONLY

In each round, there will be a jar, like the one you see below, containing 8 **BLUE** balls and 2 **RED** balls.



Treatment E6 and S6 Only

In each round, there will be a jar, like the one you see below, containing 6 **BLUE** balls and 4 **RED** balls.



The computer will randomly draw ONE ball out of this jar. All balls are equally likely to be drawn. In each round, your task will be to guess whether the ball drawn by the computer is **BLUE** or **RED**. Before proceeding to the next page, please answer the comprehension question below: Without any additional information, what do you know about the ball drawn by the computer?

- It is more likely that it is **BLUE**
- It is more likely that it is **RED**
- It is just as likely that it is **BLUE** as that it is **RED**

Please spend at least 30 seconds on this page. Read the instructions carefully! :-)

FEEDBACK/1

Correct!

Treatment E8 and S8 Only

The urn contains 10 balls in total: 8 **BLUE** balls and 2 **RED** balls. The computer draws one ball completely at random: each of the 10 balls is equally likely to be drawn. This means that there are 8 chances out of 10 that the computer draws a **BLUE** ball and 2 chances out of 10 that the computer draws a **RED** ball.

Treatment E6 and S6 Only

The urn contains 10 balls in total: 6 **BLUE** balls and 4 **RED** balls. The computer draws one ball completely at random: each of the 10 balls is equally likely to be drawn. This means that there are 6 chances out of 10 that the computer draws a **BLUE** ball and 4 chances out of 10 that the computer draws a **RED** ball.

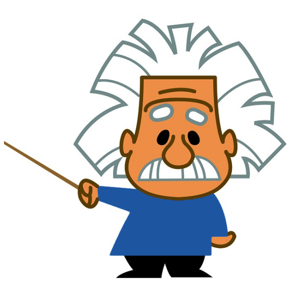
Thus, without any additional information, you know that the ball is more likely to be **BLUE**.

INSTRUCTIONS/2: GETTING ADVICE

Before you make your assessment, you can consult an expert. The expert you consult might be informed about the ball drawn by the computer. If he knows the color, he will report it to you. If he does not know the color, he will simply report to you his preferred color. There are 10 **BLUE** experts and 10 **RED** experts. You choose whether you want to hear from a BLUE expert or a RED expert. If you choose a BLUE expert, the computer randomly picks one BLUE expert to advise you. If you choose to hear from a RED expert, the computer randomly picks one RED expert.

If you get advice from a **BLUE** expert:

Treatment E6 and E8 Only



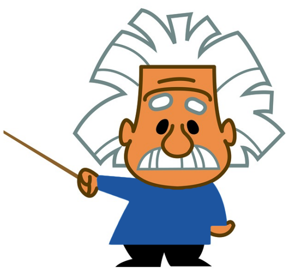
- 5 out of 10 **BLUE** experts are informed about the ball

- If the ball is BLUE:
  - An informed BLUE expert says "The ball is BLUE"
  - An uninformed BLUE expert says "The ball is BLUE"
- If the ball is RED:

– An informed BLUE expert says "The ball is RED"

– An uninformed BLUE expert says "The ball is BLUE"

TREATMENT S6 AND S8 ONLY



- 3 out of 10 **BLUE** experts are informed about the ball
- If the ball is BLUE:
  - An informed BLUE expert says "The ball is BLUE"
  - An uninformed BLUE expert says "The ball is BLUE"
- If the ball is RED:

– An informed BLUE expert says "The ball is RED"

– An uninformed BLUE expert says "The ball is BLUE"

If you get advice from a **RED** expert:

TREATMENT E6 AND E8 ONLY

- 5 out of 10 **RED** experts are informed about the ball
- If the ball is BLUE:
  - An informed RED expert says "The ball is BLUE"
  - An uninformed RED expert says "The ball is RED"

  If the ball is RED:
  - An informed RED expert says "The ball is RED"
  - An uninformed RED expert says "The ball is RED"

TREATMENT S6 AND S8 ONLY

- 7 out of 10 **RED** experts are informed about the ball
- If the ball is BLUE:
  - An informed RED expert says "The ball is BLUE"
  - An uninformed RED expert says "The ball is RED"

  If the ball is RED:
  - An informed RED expert says "The ball is RED"
  - An uninformed RED expert says "The ball is RED"

Before proceeding to the next page, please answer the comprehension question below:

If a **BLUE** expert says "The ball is **RED**", which of the following is true?

- You know for sure that the ball is **BLUE**

- You know for sure that the ball is **RED**
- The ball is more likely to be **RED** but you do not know this for sure.
- The ball is more likely to be **BLUE** but you do not know this for sure.

FEEDBACK/2

Correct!

A BLUE expert says "The ball is RED" only if he is informed and the ball is, in fact, RED. In all other cases, he says "The ball is BLUE". This means that, if you get advice from a BLUE expert, and he says "The ball is RED", then you know for sure that the ball is RED.

Treatment E6 and E8 Only
Remember that not all BLUE experts are informed (only 5 out of 10).

Treatment S6 and S8 Only
Remember that not all BLUE experts are informed (only 3 out of 10).

Similarly, a RED expert says "The ball is BLUE" only if he is informed and the ball is, in fact, BLUE. In all other cases, he says "The ball is RED". This means that, if you get advise from a RED expert, and he says "The ball is BLUE", then you know for sure that the ball is BLUE.

Treatment E6 and E8 Only
Remember that not all RED experts are informed (only 5 out of 10).

Treatment S6 and S8 Only
Remember that not all RED experts are informed (only 7 out of 10).

INSTRUCTIONS / 3: GUESS THE COLOR AND EARN MONEY!

After you choose what expert to consult, but before you are revealed his message, you will be asked to make your best guess about the color of the ball, depending on what you will hear from the expert. Since you can receive two different messages, you will be asked two questions:

- What is your guess about the color of the ball, if the expert says “The ball is **BLUE**”?
- What is your guess about the color of the ball, if the expert says “The ball is **RED**”?

After you submit your answers, the computer will report you the expert’s message and will use as your guess for this round the answer to the corresponding question. For example, if the expert you consulted says “The ball is **BLUE**”, the computer will use as your guess the answer you gave to the first question above. If, instead, the expert says ”The ball is **RED**”, the computer will use as your guess the answer you gave to the second question above.

Your guess will determine your bonus payment in the following way:

- You will earn \$1 if your guess matches the true color of the ball.
- You will earn \$0 if your guess does not match the true color of the ball.

In addition, you will be asked how confident you are of each of your guesses, on a scale between 0 and 100. For example, 0 indicates that you think it is just as likely that you are right or wrong (that is, you think that it is just as likely that the ball is **BLUE** or **RED**), while 100 indicates that you are sure you picked the right color (that is, you think you know for sure whether the ball is **BLUE** or **RED**). These assessments do not affect your bonus payment but it is very important to us that you make your choice carefully and that you report to us what you really believe.

Before proceeding to the next page, please answer the comprehension question below:

Consider this example. Your guesses are that the ball is BLUE if the expert says BLUE; and that the ball is RED if the expert says RED. The expert says “The ball is BLUE”? and the true color of the ball is BLUE. What is your bonus payment in this round?

- \$1 because you guessed BLUE and it coincides with the actual color of the ball.

- $0.50 because only one of your two guesses coincides with the actual color of the ball.
- $0 because you guessed RED and it doesn't coincides with the actual color of the ball.

Please spend at least 60 seconds on this page. Read the instructions carefully! :-)

FEEDBACK/3

Correct!

Only one guess matters for your bonus payment. The guess that matters depends on the message you receive from the expert. Since you do not know what message you will receive, make both guesses carefully.

If the expert says "The ball is **BLUE**", the guess that matters for your bonus payment is the answer to the question: What is your guess about the color of the ball, if the expert says "The ball is **BLUE**"? If the expert says "The ball is **RED**", the guess that matters for your bonus payment is the answer to the question: What is your guess about the color of the ball, if the expert says "The ball is **RED**"?

In this example, the expert said BLUE; your guess, conditional on the expert saying BLUE, was BLUE and, thus, your guess for this round was: BLUE. The ball randomly drawn by the computer was BLUE too. This means that your guess coincided with the ball drawn by the computer and, thus, you earned $1. You earn $0 if your guess does not match the color of the ball.

GET READY FOR THE GAME!

You will play 5 rounds of this game. The computer will randomly pick one round to determine your bonus payment but all rounds are equally likely to be selected so all choices matter. In each round, there are a new jar with 10 balls, 10 new BLUE Experts, and 10 new RED Experts. The chance the computer draws a RED ball or a BLUE ball from the jar, as well as the chance that the expert you consult is informed or uninformed are not affected in any way by what happened in the previous rounds.When you are ready to start with Round 1, please click the button below.

Please spend at least 30 seconds on this page. Read the instructions carefully! :-)

PRACTICE ROUND - WHOSE ADVICE DO YOU WANT?

TREATMENT E8 AND S8 ONLY
There is a jar containing 8 **BLUE** balls and 2 **RED** balls.

TREATMENT E6 AND S6 ONLY
There is a jar containing 6 **BLUE** balls and 4 **RED** balls.

The computer has randomly drawn **ONE** ball out of this jar.

Your task is to guess whether the ball drawn by the computer is BLUE or RED.

Before you make your guess, you can get advice from a **BLUE** or a **RED** expert.

If you get advice from a **BLUE** expert:

- If the ball is BLUE:
  - An informed BLUE expert says "The ball is BLUE"
  - An uninformed BLUE expert says "The ball is BLUE"

- If the ball is RED:
  - An informed BLUE expert says “The ball is RED”
  - An uninformed BLUE expert says “The ball is BLUE”

If you get advice from a **RED** expert:

- If the ball is BLUE:
  - An informed RED expert says “The ball is BLUE”
  - An uninformed RED expert says “The ball is RED”

  If the ball is RED:
  - An informed RED expert says “The ball is RED”?
  - An uninformed RED expert says “The ball is RED”?

TREATMENT E6 AND E8 ONLY Remember that 5 out of 10 BLUE experts are informed and 5 out of 10 RED experts are informed.

TREATMENT S6 AND S8 ONLY Remember that 3 out of 10 BLUE experts are informed and 7 out of 10 RED experts are informed.

Which expert do you want to hear from?

PRACTICE ROUND - GUESS THE COLOR! (EXAMPLE)

You decided to consult a **BLUE** Expert.

(a) Blue Expert

(b) Red Expert

What is your guess about the color of the ball, if the expert says "The ball is BLUE"?

On a scale from 0 to 100, how confident are you about this guess? For example, 0 means that you think it is just as likely that you are right or wrong and 100 means you are sure your guess is correct.

What is your guess about the color of the ball, if the expert says "The ball is RED"?

On a scale from 0 to 100, how confident are you about this guess? For example, 0 means that you think it is just as likely that you are right or wrong and 100 means you are sure your guess is correct.

PRACTICE ROUND - RESULTS (EXAMPLE)

You decided to consult a **BLUE** Expert.

This expert reported "The ball is **BLUE**".

Your guess, given the expert's report, was: **BLUE**.

The ball randomly drawn by the computer in this round was **BLUE**.

Your earnings in this round are $1.00.

When you are ready to start with the first of the paid rounds, please click the button below.