How Do People Choose Between Biased Information Sources? Evidence from a Laboratory Experiment

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Abstract

We report an experiment designed to measure, for the first time, how (and how well) subjects choose between biased sources of instrumentally valuable information. Subjects choose between two information sources with opposing biases in order to inform their guesses of a binary state. By varying the nature of the bias, we vary whether it is optimal to consult sources biased towards or against subjects' prior beliefs. We find that subjects frequently choose sub-optimal information sources, and that these mistakes can be described by a handful of well-defined decision rules. Most common among these is a confirmation-seeking rule that guides subjects to systematically choose information sources that are biased towards their priors. Analysis of post-experiment survey questions suggest that subjects follow these rules intentionally and find them normatively appealing. Combined with incentivized belief data and post-experiment cognitive tests, this suggests that mistakes like confirmation-seeking are driven by fundamental errors in reasoning about the informativeness of biased information sources.

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1 Introduction

Modern decision-makers frequently must choose between competing sources of information (e.g. news sources, policy analysts, medical or financial advisors, scientific papers, product reviews) – a task that is complicated by the fact that in many (perhaps most) contexts, available information sources are *biased* in some way (i.e. in favor of some ideology, product, theory etc.). The question of *how* people choose between information sources in the face of such bias has become an important topic of discussion in recent years and a popular answer is that people are prone to consult sources that are biased in support of their own prior beliefs. Indeed, this type of "confirmation-seeking" behavior is often blamed for contemporary problems like information-bubbles, echo-chambers, conspiracy theories and product lock-in.[1] To date, however, there is little direct evidence on how people choose between biased information sources or whether these choices tend to be characterized by confirmation-seeking.

In this paper, we report an experiment designed to measure, for the first time, how (and how well) subjects choose between biased sources of instrumentally valuable information. Our experimental design is simple and deliberately abstract, removing motivational and reputational factors that might influence this type of choice in the field and thus allowing us to cleanly measure how well subjects *reason* through such decisions. We repeatedly provide subjects with a prior over a stochastic state of the world ("green" or "orange") and pay them for correctly guessing the state. Before guessing, subjects first choose one of two computerized information structures from which to receive a signal about the state. A key feature of the design is that subjects can see that each information structure is biased towards one of the two states, and we vary the nature of this bias across problems: in one set of problems, we induce bias by *commission* (generated by the possibility that the signal is false), while in others, we induce bias by *omission* (generated by the possibility that a signal revealing the state is not produced).[2]

By varying the nature of the bias, we are able to identify patterns in how decision makers seek

[1] Prior (2007), Pariser (2011) and Sunstein (2018) provide a discussion of the literature on the topic in the context of political information. Gentzkow & Shapiro (2011) and Iyengar & Hahn (2009) and recently Jo (2017) show evidence of selective exposure. Empirical literature studying the determinants of media bias find bias to be mostly demand driven (Gentzkow & Shapiro (2010)); and there is evidence to suggest that biased news sources can have an impact on voting behavior. (See DellaVigna & Kaplan (2007), Martin & Yurukoglu (2017), Adena et al. (2015) and Durante et al. (2017) .)

[2] See Gentzkow et al. (2015) for further discussion of categorization of bias. Bias by commission is related to cheap-talk games as in Crawford & Sobel (1982) and persuasion games as in Kamenica & Gentzkow (2011); bias by omission is related to disclosure games as in Milgrom & Roberts (1986)).

out information. As we show in Section 2, an optimizing decision maker chooses the information structure biased towards her prior when the bias is by commission, but does the exact opposite when the bias is by omission. In contrast, we identify a confirmation-seeking decision maker as one who consistently chooses the information structure biased towards her prior. Other salient decision rules such as "contradiction-seeking" (always choose the information structure biased against your prior) and "certainty-seeking" (choose the information structure most likely to give unambiguous signals) are likewise naturally identifiable under our design.

Finally, in addition to measuring choices over information structures and guessing behavior about the state, we elicit subjects' *beliefs* about the likelihood of each state as a function of the signals provided by the information structures they selected. In half of our sessions, we go further by including an additional sequence of decision problems in which subjects are *exogenously* assigned each of the possible information structures and asked to report guesses and beliefs for every possible signal (we will call these exogenous assignments "EX" decisions). These additional problems allow us to characterize how subjects value each of the information structures presented to them in the earlier *endogenous* ("END") decision problems (in which subjects chose between information structures). With this type of data, we can directly assess the "true costs" associated with choosing the wrong information structures and assess the relationship between subjects' interpretation of information (guesses and posterior beliefs induced by each information structure) and their choices over information structures.

In the aggregate, we find that subjects have substantial difficulty identifying the optimal information structure, and that these mistakes are heavily weighted in a confirmation-seeking direction. These results do not seem to be driven by weak incentives or confusion about the nature of the task: subjects do quite well in similar control problems in which information structures can be Blackwell ranked. Furthermore, individual level analysis reveals choices over information structures to be fundamentally different from what we would predict for a confused decision maker choosing randomly. Importantly, these mistakes come at a significant cost in guessing accuracy: subjects choosing the optimal information structure improve their guessing accuracy (relative to following their prior) about 7 times more than subjects choosing the sub-optimal information structure.

At the individual level, subjects tend to employ consistent decision rules. Simple exercises to type subjects and estimation results from a finite-mixture model both suggest that most subjects use one of the four decision rules described above (optimal, confirmation-seeking, contradiction-seeking and certainty-seeking) and that virtually no subjects would be successfully typed using these methods if they were simply randomizing their decisions or noisily implementing the optimal rule.

Confirmation-seeking types are as common in our data as optimal types, while contradiction-seeking types are half as common (with certainty-seeking types less common still). Although subjects of all types learn a significant amount from the information they receive (i.e. significantly improve their guessing accuracy relative to simply following their prior), optimal types learn about twice as much as other types do.

Data on beliefs and guesses (from the EX decision block in which we exogenously assign information structures) suggest that these mistakes are not due to subjects' inability to make effective use of optimal structures or to form accurate beliefs conditional on the signals. For instance, the data are not consistent with the hypothesis that subjects choose sub-optimal information structures because they correctly anticipate that they will be unable to make effective use of the signals they receive from optimal information structures: subjects of *all* types consistently make substantially better guesses using signals from optimal than from sub-optimal information structures. Likewise the data do not support the hypothesis that subjects make mistakes because they falsely believe sub-optimal information structures produce posterior beliefs that lead to more accurate guesses than optimal structures: variation in the expected value subjects attribute to information structures (when we elicit beliefs) does almost nothing to explain variation in the way subjects choose between information structures. Thus, although types vary in their ability to make accurate guesses and form accurate beliefs (optimal types are particularly accurate, confirmation-seeking types particularly inaccurate), these variables have little power to explain patterns of information-structure choice.

Likewise, the abstract and transparent setting of our experiment rules out traditional explanations for behaviors like confirmation-seeking such as *motivated beliefs* (people get utility from receiving information that confirms their prior)[3] or reputational concerns about quality of the information source (i.e. people trust information sources aligned with their prior).[4,5] Our design effectively shuts down motivated beliefs by exposing subjects to decision problems in which prior beliefs are over abstract states and change too much over the course of the experiment for subjects to credibly form preferences to maintain their prior beliefs. (By contrast, the extant literature on confirmation bias in psychology, political science and economics is focused on settings in which people have non-randomly assigned prior beliefs and thus there is scope for motivated beliefs over

[3]Confirmation bias is considered to be especially prevalent with established beliefs and emotionally significant issues. See Rabin & Schrag (1999) for a discussion of this literature. Charness & Dave (2017) also provides a recent overview.

[4]See Gentzkow et al. (2015) for a review.

[5]See Fryer et al. (2018) for a recent literature review of theoretical models of confirmation bias. Che & Mierendorff (2017) study when a confirmatory learning strategy is optimal in a dynamic model of information acquisition.

information.) It also removes reputational channels by providing subjects with clear, unambiguous information about the signal distribution associated with competing information structures.

If mistakes in choices over information structures we observe in the data cannot be explained by (i) mistakes in the interpretation of signals or (ii) traditional mechanisms like motivated beliefs and reputations, why do subjects make these mistakes? The data suggest a simple explanation: subjects employ easy-to-implement, appealing rules of thumb that involve directly matching (or anti-matching) the bias of information structures to prior beliefs. Survey questions and incentivized advice questions support this interpretation of the data, suggesting that subjects tend to be aware of the bias-based decision rules they employ and, moreover, that they typically believe these decision rules to be good strategies in the experiment. Indeed, subjects frequently provide strikingly thoughtful (but mistaken) probabilistic justifications for the use of these mistaken "bias matching" decision rules. Finally, the data suggest that subjects lean on these rules because they have difficulty navigating the internal logic of these types of decisions: subjects are more likely to turn to sub-optimal heuristics if they also performed poorly on incentivized cognitive tests.

Our results thus point to an essentially *cognitive mechanism* underlying behaviors like confirmation-seeking that has not previously been discussed in the literature. This new explanation for errors in choices over information sources may, in turn, be important for designing policies and institutions to avoid the negative consequences of confirmation-seeking such as information bubbles, media echo chambers and product lock-in. Moreover, while popular alternative mechanisms for confirmation-seeking, such as motivated beliefs and reputational concerns about information source quality, also play a plausible role in how individuals acquire information in political contexts, they are likely to play a smaller role in contexts like product choice or financial and medical advice. The fact that we find strong evidence for confirmation-seeking behavior in the highly abstract setting of our experiment suggests that that these sub-optimal patterns of decision making might apply in a much broader set of contexts than the ideological and political ones in which they are typically discussed.

Unlike our experiment, the existing literature on choices over information structures has focused on settings in which information does not have instrumental value. Nielsen (2018), Zimmermann (2014) and Falk & Zimmermann (2017) study preferences over the timing and concentration of information and how that can change with one's prior. Closest to our work, but still focusing on non-instrumental information, Masatlioglu et al. (2017) find strong preference for *positive skewness*; that is, they find that subjects prefer information structures which rule out more uncertainty about the desired outcome (while tolerating uncertainty about the undesired outcome) compared to those which rule out more uncertainty about the undesired outcome (while tolerating uncertainty about the desired outcome). By contrast, in our setting, choices over information structures have clear payoff consequence, and subjects have no *ex-ante* reason to differentiate between the states. Ambuehl (2017) reports the only other experiment we are aware of in which subjects choose between sources of information with instrumental value, though that experiment studies a very different question (the effects of incentives on information sources selected) and setting (the decision of whether or not to eat an insect) than ours.

Less directly, our paper contributes to an emerging literature studying biases in learning and demand for information, mostly focusing on deviations from the Bayesian paradigm in belief updating.[6] Eil & Rao (2011), Burks et al. (2013) and Mobius et al. (2011) find that subjects asymmetrically update beliefs in response to objective information about themselves, over-weighting positive feedback relative to negative.[7,8,9]Ambuehl & Li (2018) study demand for information and find that individuals differ consistently in their responsiveness to information.[10] In field settings involving medical and financial decisions, Oster et al. (2013) and Sicherman et al. (2015) find evidence for information avoidance, where agents trade-off instrumental information with the desire to hold on to optimistic beliefs. Focusing on the endogenous design of information structures, Fréchette et al. (2018) study the role of commitment.

Also relevant is a recent literature highlighting subjects' difficulties updating beliefs in the face of selection issues in signal distributions which have a relationship to some of our findings. This literature finds that many subjects neglect missing information (Enke (2017)), suffer from *correlation neglect* (e.g. Enke & Zimmermann (2017)) and show insufficient skepticism about failures by other subjects to disclose information (Jin et al. (2015)).[11]

[6] See Camerer (1998) and Benjamin et al. (2016) for more comprehensive literature reviews.

[7] Eliaz & Schotter (2010) identify a *confidence effect*: the desire to increase one's posterior belief by ruling out "bad news" even when information has no instrumental value. In another setting in which information has no instrumental value, Loewenstein et al. (2014) study diverse motives driving the preference to obtain or avoid information. Zimmermann (2018) studies motivated beliefs in the presence of feedback.

[8] Charness & Levin (2005) study how people make choices in environments where Bayesian updating and reinforcement learning push behavior in opposite directions.

[9] In social settings, Weizsäcker (2010), Andreoni & Mylovanov (2012) and recently Eyster et al. (2018) study failures in learning and persistence of disagreement.

[10] Ambuehl & Li (2018) find undervaluation of high-quality information, and a disproportionate preference for information that may yield certainty. Although they make up a small share of our data, we also find some such certainty-seeking behavior in our environment.

[11] For further literature on this topic, we refer the reader to Eyster & Rabin (2005), Gabaix & Laibson (2006), Mullainathan et al. (2008), Heidhues et al. (2016), and Ngangoue & Weizsacker (2018).

The remainder of the paper is organized as follows. In Section 2 we describe the theoretical setting and generate a set of predictions. In Section 3 we discuss our experimental design and in Section 4 we describe how this design allows us to identify distinct decision rules in the data at the individual level. In Section 5 we present the results of the experiment. We close the paper in Section 6 with a concluding Discussion.

2 Theoretical framework

Suppose there is an unobserved state of the world $\theta \in \Theta := \{L, R\}$ (called the left and right state) and an agent must submit a guess $a \in \Theta$ of the state. That is, the preferences of the agent conditional on the state θ and action $a \in \Theta$ can be represented by the following utility function:

$$u(a \mid \theta) = \begin{cases} 1, & \text{if } a = \theta \\ 0, & \text{if } a \neq \theta \end{cases}$$

The agent has an *ex-ante* prior belief p_0 over the probability that $\theta = R$ and may receive a signal s from an information structure to inform her guess. An information structure σ is a stochastic mapping from the state space to a set of signals $S := \{l, n, r\}$.

In this section we analyze how an agent should assess the relative informativeness (discussed in Section 2.2) of two information structures that differ in their relative *biases* (as defined in Section 2.1) in providing signals of the state.

2.1 Bias

We first operationalize the notion of bias using a partial order introduced by Gentzkow et al. (2015). Let $p(s \mid \sigma, p_o)$ denote the Bayesian posterior belief that $\theta = R$ conditional on receiving signal s from information structure σ for an agent with prior p_o. Two information structures, σ and σ', are said to be *consistent* if they have the same support, i.e. produce the same type of signals, and the signals are ordered in the same way in terms of the posteriors they generate.[12] Note that, conditional on the prior, any information structure can be associated with the distribution of posteriors it generates. Let $\mu(\sigma|\sigma')$ denote the distribution of posteriors when an agent believes signals come from σ when they are actually generated by σ'.

[12] Formally, for any two signals s and s', $p(s \mid \sigma, p_o) > p(s' \mid \sigma, p_o)$ if and only if $p(s \mid \sigma', p_o) > p(s' \mid \sigma', p_o)$.

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

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

Table 1: Two symmetrically-biased information structures with bias by commission *Notes: Each cell represents the probability of a signal being generated conditional on θ, $0 < \lambda < 1$. (For example, the information structure presented on the right-hand side produces signal r with probability 1 when the state is R, and with probability $1-\lambda$ when the state is L.*

Definition 1. *(Gentzkow et al. (2015))*
σ' is biased to the right (that is towards R) of σ if

(i) σ and σ' are consistent, and

(ii) $\mu(\sigma|\sigma')$ first-order stochastically dominates $\mu(\sigma|\sigma)$.

This definition provides only a partial order on information structures but, by focusing on the distribution of posteriors, it allows us to consider (and compare) different types of bias.

The literature has emphasized two main forms of bias.[13] First, information structures can be biased through the possibility of false reports. This is bias by *commission*, which mirrors the kind of false reporting in cheap-talk models of Crawford & Sobel (1982). Table 1 provides an example of two information structures that can provide signals l or r that noisily indicate states L and R respectively. Bias arises in this case through the possibility that the information structure sends a "false" signal conditional on the state of the world (i.e. sending signal l when the state is R or signal r when the state is L). Notice that, following Definition 1, the information structure shown on the right-hand side in Table 1 is *biased to the right* of the information structure that is depicted on the left-hand side.[14]

Second, information can be biased through the possibility that the state will not be *revealed*. This is bias by *omission*, and mirrors the strategic transmission of information modeled in disclosure

[13]See DellaVigna & Hermle (2017) for empirical analysis of bias by omission vs. commission in movie reviews. Gentzkow et al. (2015) provides an overview of the literature and includes discussion of a third type of bias, bias by filtering, which captures bias introduced by selection when information sources are constrained by the dimensionality of signal space.

[14]By construction, the information structure on the right-hand side is more likely to produce r signals (and hence less likely to produce l signals). With both information structures, the r signal produces a higher posterior than the l signal. Hence if an agent believed that signals were coming from the information structure on the left-hand side, switching to the right-hand side would lead to a first order stochastic shift in the distribution of posteriors.

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

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

Table 2: Two symmetrically-biased information structures with bias by omission *Notes: Each cell represents the probability of a signal being generated conditional on θ, $0.5 < \lambda_l < \lambda_h < 1$. (For example, the information structure presented on the right-hand side produces signal r with probability λ_h and n with probability $1 - \lambda_h$ when the state is R.)*

games (e.g. Milgrom & Roberts (1986)). The information structures depicted in Table 2 provide an example. Note that in both information structures, the signals r and l are fully revealing of states R and L respectively, while the n signal can be thought of as a failure to produce a signal. Differences in bias in this case arise from differences in how often the information structure reveals the state conditional on the state of the world. As in the *commission* case analyzed above, following Definition 1, the information structure that is depicted on the right-hand side in Table 2 is biased to the right of the information structure that is depicted on the left-hand side.[15,16]

2.2 Informativeness

How do the pairs of information structures depicted in Tables 1 and 2 differ in terms of *informativeness*? That is, in each case, which information structure would an agent optimally choose if she could receive only one signal from one information structure? Our main interest is in analyzing how the optimal structure choice is related to the biases of the available information structures and the prior of the agent. Our experimental design builds on the insight that the answer critically depends on the nature of the bias.

Remark 1. *If two information structures are symmetrically-biased by commission, it is optimal to receive a signal from the structure biased in the same direction as one's prior.*

Importantly the reasoning behind Remark 1 does not require Bayesian inference or even probability calculations. Note, first, that an information structure creates value for an agent only by

[15] With both information structures, the r, n and l signals are ranked in the natural way in terms of the posteriors they generate. And, by construction, the information structure on the right-hand side, relative to the one on the left-hand side, shifts distribution of signals from l to n and from n to r.

[16] Note that for any λ and p_0, the two information structures in Table 1 are also ranked in terms of the Monotone likelihood ratio property. This is not true for every λ_h, λ_l, for the information structures presented in Table 2, but the parameters we choose will guarantee this ordering.

increasing the accuracy of her guess and this only happens if the agent can make use of the information provided to sometimes guess against her prior. Thus, in this simple setting (with binary signals and binary state of the world), an information structure can create value if and only if the agent follows the recommendation of the information structure (i.e. guesses L in response to signal l). The challenge facing the decision maker is that both information structures sometimes send incorrect signals and the two structures differ precisely in which states they make such false reports. The information structure on the left-hand side of Table 1 sends the agent a false report and thus induces the incorrect action with $1-\lambda$ probability when the state is R and, due to symmetry, induces the incorrect action with $1-\lambda$ probability when the state is L with the information structure on the right-hand side. Remark 1 follows simply from noticing that an agent would naturally prefer an information source that generates mistakes in the state of the world that is less likely to occur.[17]

Remark 2. *If two information structures are symmetrically-biased by omission, it is optimal to receive a signal from the structure biased in the opposite direction as one's prior.*

Again the reasoning behind Remark 2 does not require Bayesian beliefs or probabilistic sophistication. Suppose $p_0 > 0.5$, which implies that in the absence of any further information, the agent would guess the state to be R. New information can improve an agent's payoff - by increasing his guessing ability - to the extent that it induces the agent to sometimes guess differently. Since the r and l signals are fully revealing, they automatically suggest guesses of R and L, respectively. The only remaining issue is which action the agent prefers to take upon getting the n signal. Note that the n signal from the information structure on the left-hand side (in Table 2) must induce the R guess - we started with a right-leaning prior and the signal pushes beliefs further to the right. This is because the n signal is more likely to be generated conditional on the state being R, rather than L. This means that an agent consuming this information structure will only make a guessing mistake when the state is L and the n signal is generated which happens with probability $(1-p_0)(1-\lambda_h)$. No matter how an agent decides to make use of the n signal from the information structure on the right-hand side, the probability of making a mistake would be higher than had she chosen the information structure on the left: guessing R conditional on n induces a mistake with probability $(1-p_0)(1-\lambda_l)$ and guessing L instead implies a mistake with probability $p_0(1-\lambda_h)$,

[17] Notice that this type of observation is robust to introducing a *neutral* information structure that is normalized appropriately. For example, it could be that this type of information structure is equally likely to send misleading signals (with probability $\frac{1-\lambda}{2}$ in either state of the world). This highlights how the intuition to "go with the neutral source" can be misguided.

with both values larger than $(1-p_0)(1-\lambda_h)$ for an agent with a right-leaning prior.[18] Hence, it is always optimal to go with the information structure on the left-hand side for an agent with a right-leaning prior.[19]

In summary, an agent choosing optimally among information structures will choose information sources biased in the same direction as her prior when bias is by commission, but will choose to do the opposite (i.e. choose sources biased in the opposite direction as her prior) when bias is by omission.

3 Design

The goal of our experiment is to (i) *measure* subjects' ability to discern between more and less informative information structures and (ii) to identify the types of decision rules individual subjects use in this type of choice. Our experimental design directly mirrors the decision setting described in the previous section. In each of as many as 26 decision problems, subjects were shown an urn on their computer screen consisting of 20 balls colored orange or green in varying proportions and were asked to guess the color of a single ball drawn randomly from the urn. To inform their guesses, subjects first chose one of a pair of computerized advisors, from which to receive a signal ("orange", "green" or "null") about the ball drawn. Subjects were fully informed of the probabilities with which each advisor would provide each signal as a function of the true color of the ball drawn from the urn.

The experiment consisted of two *decision blocks*. In each of the 14 rounds of the main "Endogenous Advisors" (or "END") block, we presented subjects with a pair of advisors that differed in their signal structures and asked the subject to choose an advisor from which to receive a signal. After choosing an advisor, subjects were then asked to guess the color of the ball and to submit a likelihood that the ball was green vs. orange as a function of *each possible signal* their chosen advisor might send (that is, we used a version of the strategy method, e.g. Brandts & Charness (2011)). Over the course of the 14 rounds we varied the menu of advisors and the composition of

[18] In the former case, $(1-p_0)(1-\lambda_h) < (1-p_0)(1-\lambda_l)$ since $\lambda_h > \lambda_l$, and in the latter case, $(1-p_0)(1-\lambda_h) < p_0(1-\lambda_l)$ since $p_0 > 0.5$.

[19] Note that a *naive* agent who does not consider the n signal to carry any information would also choose the optimal information structure here. Such an agent would be taking a short cut in reaching that conclusion. An agent of this type with a right-leaning prior would always guess R conditional on n, which would imply incorrect guesses only when the state is L, with probability $1-\lambda_h$ when using the information structure on the left, and with probability $1-\lambda_l$ when using the information structure on the right.

the urn (and therefore the subject's prior beliefs). Subjects received no feedback from decision-to-decision and states and signals and payments were determined only at the end of the experiment. These design choices limit the degree to which intrinsic preferences over information driven by psychological motives can affect subject's choices over information structures.[20]

In six of the decision rounds of the END block subjects faced advisors with bias by commission, choosing between the advisors shown in Table 1, with $\lambda = 0.7$. In another six decision rounds, subjects faced advisors with bias by omission, choosing between the advisors shown in Table 2, with $\lambda_h = 0.7$ and $\lambda_l = 0.3$. In each case we varied the priors (likelihood of a green ball being drawn) between $p_0 \in \{\frac{4}{20}, \frac{5}{20}, \frac{6}{20}, \frac{14}{20}, \frac{15}{20}, \frac{16}{20}\}$.[21,22] We randomized the order of bias-type and, within type, the order of the prior thoroughly across sessions and subjects.[23] Finally, in the last two decision rounds of the END block, subjects faced what we refer to as the "Blackwell problems," designed to assess subjects' comprehension of the decision environment. In these problems, the two advisors presented to the subjects were biased in the same direction, and could be easily ranked via Blackwell ordering.[24]

In order to measure how subjects' guesses and beliefs were shaped by their advisors, we ran half of our subjects through an additional diagnostic decision block called "Exogenous Advisors"

[20]A growing theoretical literature including Kreps & Porteus (1978), Grant et al. (1998), Caplin & Leahy (2001), Kőszegi & Rabin (2009), Dillenberger & Segal (2017), Brunnermeier & Parker (2005) studies intrinsic preferences for the timing, concentration and skewness of information.

[21]We chose these values for the prior for the following reason. We wanted to maximize the difference between the informativeness of the two information structures biased in the opposite direction in the problems with bias by commission and omission questions. Clearly, this difference disappears as the prior converges to 0.5 since the agent has no reason to favor one information structure over the other. Similarly, as the prior converges to 1, the agent is able to guess almost perfectly even without any further information, so value of *any* information structure vanishes. We choose priors in this range to balance these counteracting forces.

[22]Alternatively (and equivalently), we might have instead varied values for $\lambda, \lambda_h, \lambda_l$ keeping p_0 constant. We chose to vary p_0 because (i) we hypothesized that it was easier for subjects to internalize information about the prior and (ii) in order to prevent subjects from becoming attached to their prior belief, potentially introducing scope for motivated reasoning.

[23]Specifically we randomized at the subject level whether the first set of 6 problems corresponded to the problems with bias by commission or the problems with bias by omission. Then, within question-type, we randomized (again at the subject level) the order of the prior the subject faced.

[24]In these questions, the advisors were both biased towards the orange color. Specifically, the probability of receiving the orange signal conditional on the color of the ball being orange was 1 for both advisors and the probability of receiving the orange (green) signal conditional on the color of the ball being green was 0.7 (0.3) for one advisor and 0.3 (0.7) for the other. These advisor could be Blackwell ranked in the sense that one could be written as a garbling of the other one. The prior on the color of the ball being green was either 0.3 or 0.7. The order of these questions was also randomized at the subject level.

(or “EX”) following the END block. Instead of asking subjects to choose between advisors as in END, in each of the 12 rounds of EX we *assigned* subjects one of the four advisors from Table 1 and Table 2 (again with $\lambda = 0.7$, $\lambda_h = 0.7$ and $\lambda_l = 0.3$) and asked them to guess the color of the ball and submit likelihoods of green vs. orange for each possible signal the advisor might send. For each of the four advisors we varied the prior p_0 between $\{\frac{4}{20}, \frac{5}{20}, \frac{6}{20}\}$. The order of the resulting 12 choices were again randomly sequenced for each session and subject.

At the end of the experiment, subjects were asked to complete a survey that included questions on demographic information, cognitive ability and over-confidence, political attitudes and media habits, as well as questions on the subjects' learning strategy in the experiment. We also asked subjects to write down (free-form text) advice to another subject who would participate in this experiment on how to choose between the different information structures.

Responses to the decision blocks and the survey were incentivized in the following way. The most significant portion of subjects' payoff was linked to their guesses about the state. One of the decision rounds from the END block was chosen randomly, and conditional on the state and the advisor chosen by subject, a random signal was generated. The subject earned \$10 if her guess for this signal matched the state (\$0 otherwise). Another information-choice problem was chosen randomly to determine payment for beliefs. The subject's belief response to this question (conditional on the state, the advisor chosen, and the realized state) determined the likelihood (according to the Binary Scoring Rule) of winning \$1.[25] In the sessions that included the EX block, subjects faced additional incentives as in the END block, where they had a chance to earn \$10 based on their guess in a randomly-selected round, and \$1 depending on their answers to the belief question in another randomly-selected round. In addition, subjects were paid \$5 for show up, \$2 for filling out the survey and could earn up to \$2.5 from the cognitive ability questions in the survey. We also incentivized the advice question in the survey. Subjects were told that advice written down by three randomly-selected subjects would be shown to another subject in each session and the subject who wrote down the advice chosen to be “most useful” would receive an additional \$1.[26]

We ran the experiment using 344 subjects over 18 sessions at the EBEL laboratory at UC Santa Barbara between January and June 2018. All of the sessions included the END decision block; 9

[25] The advantage of this over other traditional mechanisms is that it does not rely on risk neutrality to be incentive-compatible. We implement this following a method proposed by Wilson & Vespa (2018). We removed hedging motives between the belief responses and guesses by randomly determining the state independently for each case.

[26] Martínez-Marquina et al. (2018) uses a similar incentive structure for advice data.

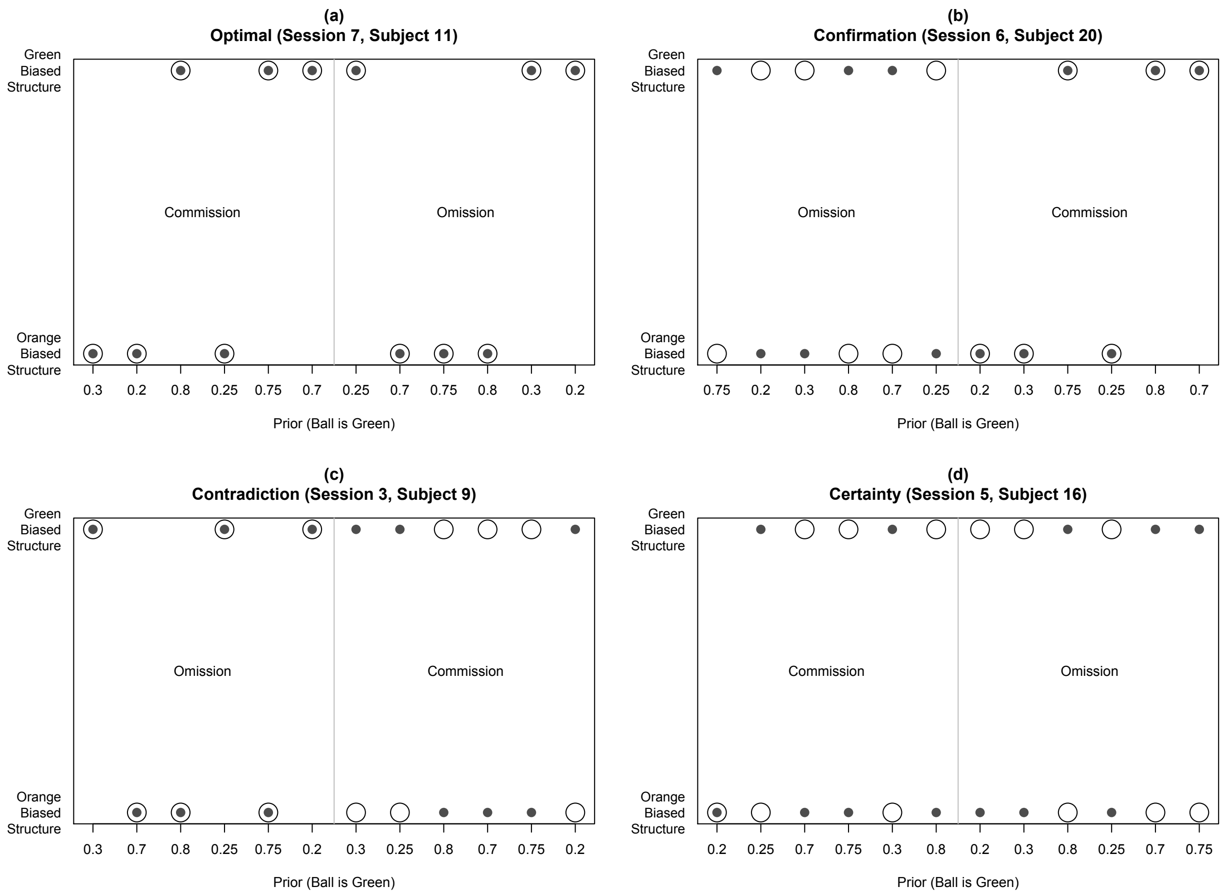

Figure 1: Identifying Decision Rules *Notes: Graphs compare actual choices over information structures to optimal behavior. The sequence of problems encountered by each subject is denoted on the x-axis (numbers indicate prior). Hollow dots show the optimal choice in each case and solid dots show the subject's actual choices.*

sessions (158 subjects) also included the EX block.[27] Detailed instructions with examples were read out loud to explain how the different information structures can be understood.[28,29] As a result of the payoff structure implemented, subjects earnings varied from \$7.50 to \$31.75 (average \$21.5).

4 Identifying Decision Rules Using the Design

The experiment outlined in Section 3 was designed not only to assess how well subjects choose between information structures, but also to facilitate identification of alternative sub-optimal be-

[27]Sessions were computerized using *Qualtrics*. Sessions with only the END block lasted 80min, while those with the EX block went for 110min.

[28]See Online Appendix F for screenshots from the experiment and a copy of the instructions and the survey.

[29]We also highlighted to the subjects every time the set of possible advisors changed. Subjects were allowed to spend as much time as needed on each decision.

havioral rules like confirmation-seeking that are often raised in popular discussion.

As we outline in Section 2.2, a subject using an optimal[30] decision rule (an "Optimal" type subject) will choose the information structure biased in the same direction as her prior when the bias is by commission and will choose the structure biased in the opposite direction of her prior when it is by omission. Panel (a) of Figure 1 illustrates a subject who uses a pure optimal rule by plotting an example from our dataset. From left to right we plot the sequence of decisions the subject faced in the END block of the experiment (recall that this ordering is randomized across subjects) and below the x-axis we list the subject's prior for that decision. The y-axis represents the information structures biased towards the orange vs. green state. Hollow dots show the optimal choice in each case and solid dots show the subject's actual choices. These two dots always overlap for an Optimal type. Importantly, matching the optimal pattern of behavior involves a very precise pattern of choice that would be very difficult to stumble upon by chance.

The design also allows us to crisply identify several salient decision rules that depart from optimality. A subject using a consistent "confirmation-seeking" rule (a "Confirmation" type) will always – in problems both with bias by commission and omission – choose an information structure that is biased *in the same direction as her prior*. A subject using the opposite "contradiction-seeking" rule (a "Contradiction" type) will instead always choose an information structure biased *in the opposite direction* of her prior. Panels (b) and (c) show examples of subjects from our dataset employing each of these rules; note that each type makes perfectly optimal decisions for one bias-type (by commission or omission) and perfectly sub-optimal decisions for the other. It is important to emphasize that each of these rules leave no less distinctive a fingerprint than an optimal rule and are equally difficult to implement by chance.

Finally, after designing the experiment, we discovered that a fourth decision rule was readily identified using our design. A subject seeking to maximize her chances of receiving a signal that identifies the states with certainty (a "Certainty" type) will do exactly the opposite of an Optimal decision maker, choosing an advisor that contradicts her prior in the problems with bias by commission and an advisor that confirms her prior in the problems with bias by omission. Panel (d) shows an example subject from our dataset.

To summarize, we can identify types of subjects employing different decision rules in the experi-

[30]Throughout the paper we define an information structure as "optimal" if it provides signals that are more informative (enables an agent to maximize guessing accuracy), as described in Section 2.2. A decision rule is optimal in this sense if it always leads to a choice of an optimal information structure. Such a rule will also be optimal in the sense of utility maximization for any subject (at least) with expected utility preferences.

ment by examining how the information structure-bias favored by a subject (towards or against her prior) changes with the bias-type (commission or omission). We can identify four decision rules: Optimal, Confirmation-seeking, Contradiction-seeking and Certainty-seeking. These patterns are distinctive and they are extremely unlikely to arise by chance. Thus, the experiment is designed to allow us to distinguish the use of these decision rules from one another and from other behaviors such as random decision-making.

5 Results

In Section 5.1 we report aggregate results and provide evidence showing that (i) subjects frequently choose sub-optimal information structures, (ii) that these mistakes tend towards confirmation-seeking information structures and are highly non-random and (iii) that these mistakes come at a high cost to guessing accuracy. In Section 5.2 we type subjects according to the rules discussed in Section 4 and report that Confirmation types are as common as Optimal types. In Section 5.3 we use data from the EX decision block to examine how types differ in their guessing behavior while in Section 5.4 we use the same data to show that differences in the accuracy of beliefs cannot explain the rules subjects use. Finally, in Section 5.5 we use survey results and incentivized cognitive tests to show that subjects are frequently conscious of the rules they use and are more likely to use sub-optimal rules when less cognitively capable.

5.1 Aggregate Results

Figure 2 plots the aggregate rate at which subjects chose the optimal information structure (in the END decision block) for each bias-type (Bias by commission, Bias by omission and Blackwell) and prior-strength (0.7,0.75 and 0.8).[31] In our control Blackwell problems, subjects choose the optimal information structure 89% of the time, significantly more often than under non-Blackwell problems ($p < 0.001$). This high rate of optimal choice assures us that subjects understand how to interpret the experimental interface and instructions and are sufficiently motivated to make considered decisions in the experiment.

This high rate of optimal information-structure choice collapses when the two information struc-

[31] Priors are symmetrically arrayed around 0.5 in the design: $p_0 \in \{\frac{4}{20}, \frac{5}{20}, \frac{6}{20}, \frac{14}{20}, \frac{15}{20}, \frac{16}{20}\}$. The "prior-strength" normalizes the direction in terms of precision: $\max\{p_0, 1 - p_0\}$. Regression results confirm that subject behavior is not different across these colors. All tests reported in the text are based on probit (for binary variables) or linear (for continuous variables) regressions clustered at the subject level.

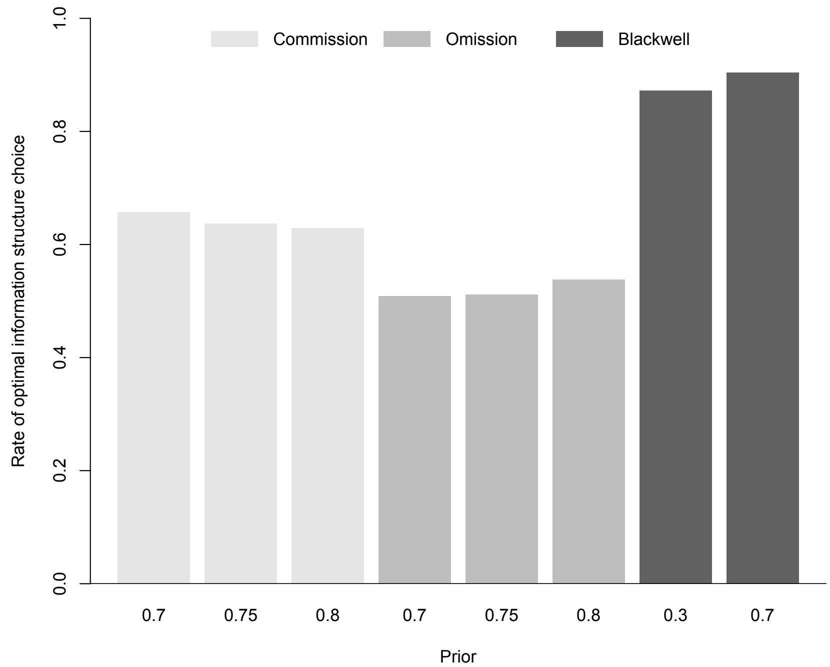

Figure 2: Frequency of choosing the optimal information structure by prior and question type

tures cannot be Blackwell ranked. With bias by commission, subjects choose the optimal information structure only 64% of the time and under bias by omission, this rate drops significantly ($p < 0.001$) to 52%, a rate not much better than chance. These mistake rates do not vary much by the strength of the prior.

Importantly, these high mistake rates come at a great cost in terms of state-guessing accuracy. To show this, Figure 3 plots average *learning* by subjects: the change in the probability of correctly guessing the state relative to simply following the prior. On the left side of the Figure we plot (broken down by bias-type and prior-strength) learning by subjects who chose the optimal information structure and, on the right, learning for those who chose the sub-optimal one. In white we plot the learning a perfectly rational Bayesian subject would exhibit – an upper bound on the amount of learning possible conditional on the information structure chosen – while the shaded bars plot the average learning by actual subjects in the experiment.

The results show that subjects learn dramatically less (improve upon their priors to a much smaller degree) in the aggregate after choosing sub-optimal than after choosing optimal information structures. Part of this is a result of subjects making much less use of information provided by sub-optimal rather than optimal structures (the shaded bars are smaller relative to the white bars

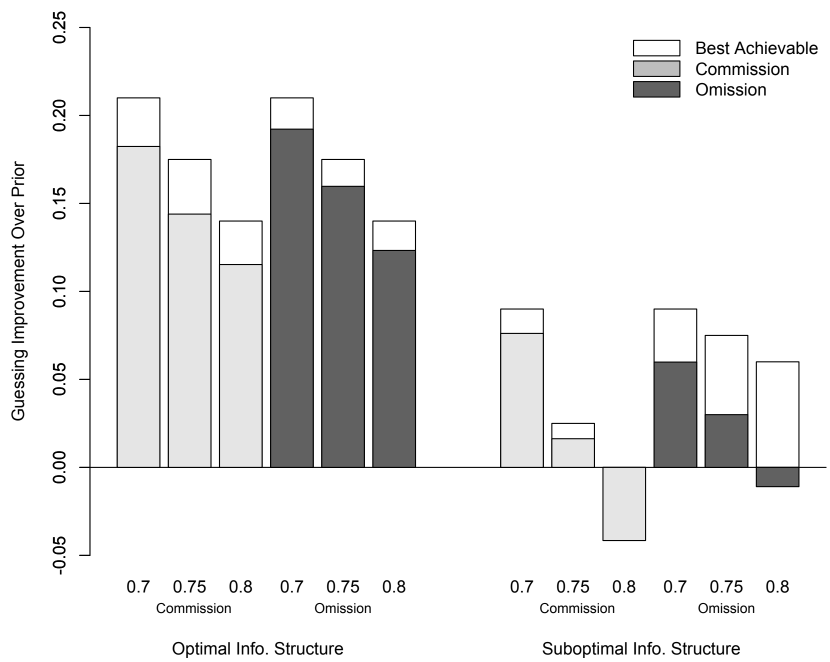

Figure 3: Guessing accuracy relative to prior by information-structure choice, prior and bias-type.

with sub-optimal than with optimal structures).[32] Indeed, in some decision rounds where the prior strength was 0.8, subjects who choose the sub-optimal structures actually make worse guesses than they would by simply following their priors.[33] But much of this is a direct consequence of structure choice: white bars (the maximum amount of possible learning) are much lower with sub-optimal than with optimal information structures.[34]

We summarize the findings so far in a first Result:

Result 1. *Subjects frequently choose sub-optimal information structures, leading to severe failures in learning.*

Are these high mistake rates in choices over information structures driven by consistent decision rules (such as those outlined in Section 4), or are they driven by random errors in choice? To answer

[32]The overall difference in difference – guessing accuracy relative to best achievable conditional on information structure choice – is highly significant ($p < 0.001$).

[33]As the Bayesian benchmark indicates, when the prior strength was 0.8 and the bias-type was commission, the optimal guess was always equal to the ex-ante most likely state (regardless of the signal from the sub-optimal information structure). In contrast, if the bias-type was omission, due to the disclosure environment, there was always opportunity for learning.

[34]Interpreting these results is complicated in part by self selection: subjects choose their information structures, which might lead to biased estimates of the causal impact of structures on learning. This is one of the motivations for the EX treatment, which removes this potential source of bias. See Section 5.3 below.

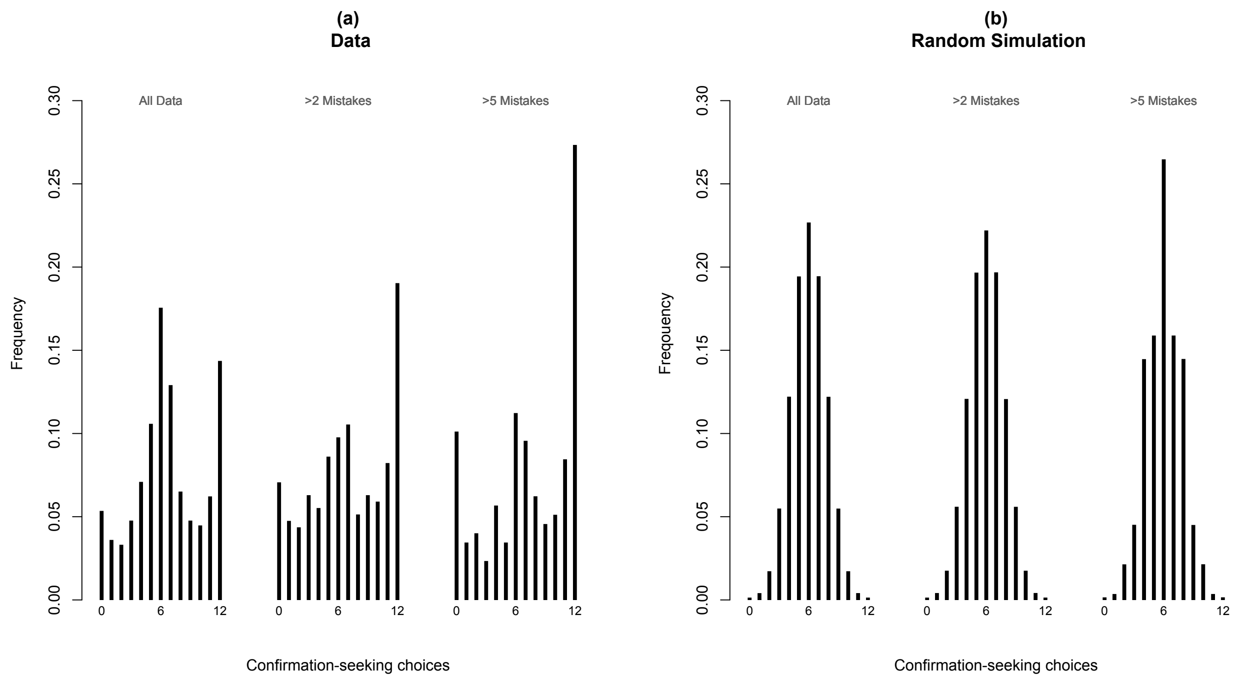

Figure 4: Frequency of information-structure choices that coincide with confirmation-seeking *Notes: "All Data" refers to the full data set. "> 2 Mistakes" ("> 5 Mistakes") is the subset of subjects that make more than 2 (5) mistakes relative to the optimum in choosing an information structure. Random Simulation is for* 10^7 *subjects who are assumed to choose randomly between information structures.*

this question, we count the number of times each subject chooses information structures that are biased towards their priors. Panel (a) plots histograms of this measure across subjects for the full dataset ("All Data") and for the subset of subjects that make more than 2 ("> 2 Mistakes") and more than 5 mistakes ("> 5 Mistakes") relative to the optimum, out of the 12 problems they encounter, in choosing an information structure.

Focusing first on "All Data," there are concentrations of subjects at 12 and 0, corresponding to subjects that consistently make confirmation-seeking choices (choices of structures biased towards their priors) or contradiction-seeking choices, respectively. There is also a concentration of subjects at 6, which could be driven by optimal choice (recall that optimal behavior requires confirmation-seeking choices in only the six problems of bias by commission) but could also be a result of random decision-making (subjects whose six confirmation-seeking choices are not concentrated in problems of bias by commission as they would be for an optimal decision-maker). In order to focus on the nature of *mistakes* we filter out near-optimal subjects by examining the subset of subjects that make at least 3 and at least 6 mistakes relative to the optimum. When we consider only subjects that make more than two mistakes in their choices over information structures, the mode at 6 shrinks and confirmation-seeking choice becomes the salient mode. When we consider

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	-

Table 3: Type shares

subjects that make more than a handful of mistakes (> 5 mistakes) pure confirmation-seeking and contradiction-seeking behavior become dominant. This exercise suggests that the mode at 6 in the full dataset includes a number of near-optimizing subjects and that confirmation-seeking behavior is a particularly strongly represented decision rule.

In order to better interpret these results, panel (b) conducts the same exercise for thousands of simulated subjects, programmed to make iid random choices. The results here are strikingly different: pure confirmation-seeking and contradiction-seeking subjects are completely absent, with confirmation-seeking choices concentrated around 6 and the distribution changing little as we focus on subsets making mistakes. The exact same pattern emerges in simulations using an alternative benchmark of a Noisy Optimal decision maker who implements the Optimal rule but with random errors: confirmation-seeking choices for Noisy Optimal types should be centered at 6 with pure confirmation-seeking and contradiction-seeking choices almost never occurring. These aggregate results suggest that choices (and mistakes) in our experiment are far from random but are instead driven by heterogenous subjects using confirmation-seeking decision rules, optimal decision rules and, to a lesser extent, contradiction-seeking choice rules. We report this as a second result:

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.*

5.2 Types and Heterogeneity

Figure 4 suggests that subjects use non-random decision rules but that these rules are quite heterogeneous across subjects. While some subjects seem to use near-optimal rules, some others systematically choose advisors biased towards their priors. In order to better understand the internal consistency of subjects' decision rules and study the prevalence of various rules in the subject population, we conduct an exercise to sort individuals into types. In particular we examine the degree to which subjects employ (perhaps with a small number of errors) rules from the taxonomy described in Section 4.

In Table 3, we classify subjects according to the types described in Section 4 based on their choices over information structures. In the first column, we look at the share of subjects whose choices are perfectly consistent with the four types of behavior we discussed in Section 4. We observe that behavior for 31% of the population fits perfectly one of these categories. As a benchmark, in the last row, we present what these shares would be on a random sample - a large set of simulated subjects who randomly pick between the advisors. In this case, in contrast, the categories considered capture less than 0.1% of the population.[35] We replicate this analysis allowing for choices to differ from the signature behavior associated with the categories in one choice - second column - or two choices - third column. The share of subjects who are classified goes up to 52% with one mistake and 71% with two mistakes, although the associated values on a random sample remain very low.

In order to validate this typing we estimate a finite-mixture model whose results are reported in the last column of Table 3. We parameterize the mixture model in the following way. We denote the population share of the different types by $\omega_{op}, \omega_{cf}, \omega_{ct}, \omega_{ce}$, and we allow the total share of these types to be weakly less than 1. The remaining share of the population is assumed to be randomly choosing between the information structures. We also allow for implementation noise denoted by $\kappa \in [0, 0.5)$. That is, each type, in each problem, chooses the information structure associated with his type's signature decision rule with $1 - \kappa$ probability. The advantage of this approach is that we do not need to take an ex-ante position on how flexible we should be with the classification method. This falls out of the estimation as an output - that is, we search for the implementation noise measure that best explains the data. In summary, we estimate $\omega_{op}, \omega_{cf}, \omega_{ct}, \omega_{ce}$ and κ on 344×12 decisions. The last column in Table 3 reports precisely the estimated values for the type shares. The estimated κ is 9.7%, broadly consistent with 11.2% frequency for sub-optimal choice in the Blackwell questions.[36] Moreover, the estimated κ value (probability of deviating from the

[35] An alternative benchmark is a Noisy Optimal agent – an Optimal type who makes an error in each choice with some probability p ($p = 0.5$ is just the iid random decision maker shown in Table 3). This benchmark generates type distributions that fundamentally differ from those observed in the data. For instance, if we allow two errors from each type's signature behavior, Noisy Optimal types would be categorized as Optimal 69%, 91%, 98% and 99.8% of the time (conditional on being classified) with p of 0.4, 0.3, 0.2 and 0.1, respectively. By contrast, in the data, subjects are categorized as Optimal types under this error allowance only 35% of the time.

[36] If we look at this rate – frequency of choosing the sub-optimal advisor chosen in the Blackwell questions – among those subjects who are classified (with ≤ 2 errors), it goes down to 9.1%.

prescribed path) is slightly higher than the 6.9% we observe among those subjects who are classified (with ≤ 2 errors), which is consistent with a higher share of the population being classified with the mixture model.

The type-classifying results reported in Table 3 reveal that, however we look at the data, the type distribution within classified subjects tells a clear story. There are as many subjects whose behavior is best explained as confirmation seeking as there are subjects displaying optimal behavior. Looking over the results from the different classification models represented by the different columns in this table, we see significant shifts in the share of the subject population that can be classified. But, among those who are classified, the share corresponding to either optimal or confirmation-seeking behavior is always high, making up 70-75% of the population. There is also some evidence for contradiction- and certainty-seeking behavior, although the fraction of subjects classified in these categories is consistently smaller relative to optimal and confirmation-seeking behavior.

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.*

5.3 Guessing Accuracy

In order to better understand why subjects use these decision rules, we next examine how subjects of different types differ in the way they make use of the information they receive.[37] First, and most importantly, we look at how types differ in the accuracy of their guessing behavior, revisiting data reported in Figure 3. Since we use the strategy method, we know how each subject in each decision round will guess conditional on each of the signals she could receive. This allows us to calculate expected guessing accuracy, α, for each subject for each round. We focus on subjects' *learning* – the improvement in guessing accuracy subjects achieve relative to simply guessing based on their prior beliefs. Figure 5 normalizes across bias-types and priors by plotting the average value of

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

(where α^{Opt} is the expected guessing accuracy conditional on optimality of the information structure and guesses) in gray. This learning measure is maximized at 1 for subjects who both (i) receive signals from optimal information structures (defined on the pair of information structures presented in each round of the END block) and (ii) make optimal guesses for each signal they could

[37] For the remainder of the paper, when comparing different types, we will use the ≤ 2 error classification and focus on the problems where the information structures cannot be Blackwell ranked.

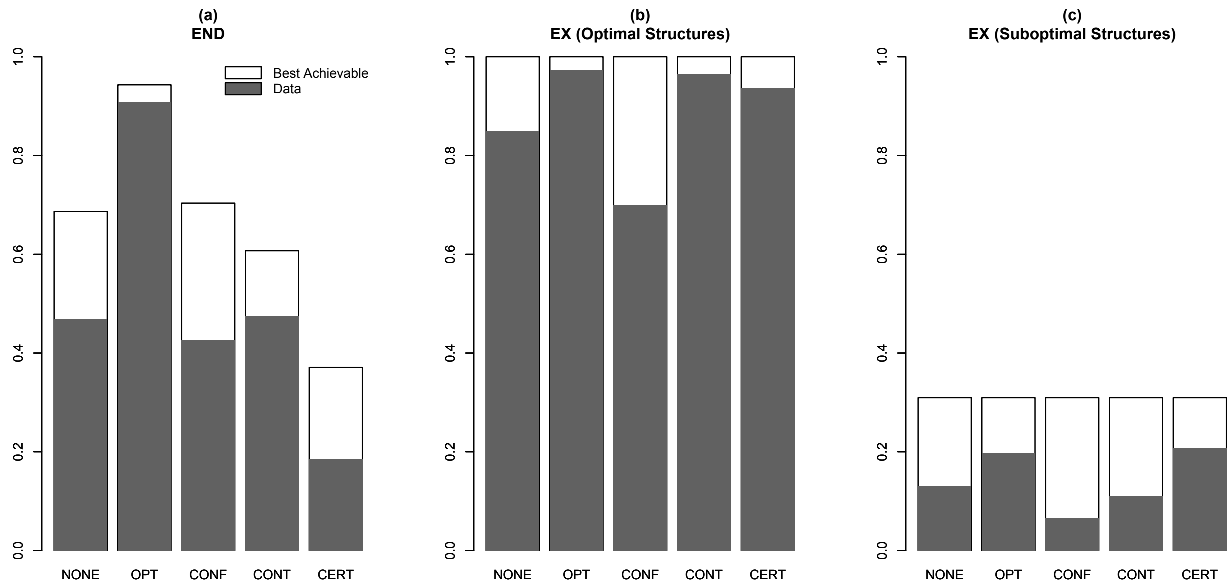

Figure 5: Learning by type

receive from this information structure. In white we plot, for reference, the maximum value of this statistic achievable conditional on the information structure from which the subject received signals (averaged across subjects).

Panel (a) of Figure 5 plots data from the END block (the same data plotted in Figure 3), broken down by type. Focusing on the gray bars (actual, observed learning based on guessing behavior), it is clear that Optimal types learn considerably more than subjects using sub-optimal decision rules: Optimal subjects achieve 91% of possible improvement in guessing accuracy (relative to the prior) compared to the 43%-48% for Confirmation/Contradiction types and 19% for Certainty types. Examining the white bars, we find that much (though not all) of this difference is driven by the fact that Optimal types are learning from more informative structures – the white bar is much higher for Optimal types than for other types. Importantly, however, the difference between the height of gray and the height of white bars in Figure 5 is much smaller for Optimal types than it is for other types (particularly Confirmation and Certainty types), suggesting that Optimal types also do a better job of interpreting and using their information. Despite these differences, values for learning are significantly different from zero in almost all cases implying that on average subjects are able to make use of signals to improve their guessing accuracy regardless of how they choose between information structures.[38]

[38]The only exception is that confirmation-seeking types do not learn anything significant from suboptimal advisors (though they do learn significantly from optimal advisors).

Interpreting learning data from the END treatment is complicated by the fact that subjects self-select into the different information structures. In particular, the exercise tells us nothing about what subjects would have done with signals from the information structures they rejected. Panels (b) and (c) show guessing data from the EX block that was designed to overcome exactly this type of concern, by asking every subject to submit guesses for every one of the information structures available in the END block.[39] In each of these EX panels in Figure 5 we classify subjects according to their choices over information structures in the END block, and then examine their guessing behavior in the EX block when they are assigned optimal (panel b) vs. sub-optimal (panel c) information structures from reach round of the END block.[40,41]

The results show a striking pattern. First, *all types* learn substantially more when they are assigned the optimal information structure relative to the case when they are assigned the sub-optimal one (gray bars in panel b are much higher than gray bars in panel c). The Bayesian benchmark in white highlights that most of the decline in learning is due to the change in the information structure, not changes in guessing behavior conditional on the information structure. When assigned an optimal information structure, Contradiction and Certainty types make almost as much use of information as Optimal types but Confirmation types make considerably worse use of information. Subjects of all types seem to have much more difficulty making use of information from sub-optimal than optimal structures (gray bars are much more similar to white bars for optimal structures than for sub-optimal structures). Here, too, Confirmation types are an outlier, making worse use of information from sub-optimal structures than do subjects of other types.

Data from the EX block also gives us a measure of the "true cost" of not choosing the optimal information structure in the END block, by allowing us to form a counterfactual measure of what learning would be like if subjects *had* selected the optimal information structures. In order to conduct this exercise, we replace each subject's guessing behavior, whenever they chose the sub-optimal information structure, with their guessing behavior for the optimal information structure (taken from their choices in the EX block). In this counterfactual, learning substantially improves for all types, with learning measures rising from 93% to 98% for Optimal, from 41% to 77% for Confirmation types, from 41% to 88% for Contradiction types and from 21% to 94% for Certainty

[39]Recall that the EX task was assigned in only half of our sessions.

[40]Note that white bars mechanically extend to 1 in the former case and much lower in the latter.

[41]Conditioning on the information structure and controlling for the prior, there is generally no statistical difference between how different types behave (in terms of guesses and stated beliefs) between the decision rounds in the END and EX blocks. The few exceptions are: Certainty types learn more in the EX block from suboptimal information structures in the bias-by-omission problems; Contradiction types state less accurate beliefs in the EX block when assigned the optimal information structure in the bias-by-commission problems.

types. This suggests that subjects are not avoiding optimal information structures because they correctly foresee personal difficulties in interpreting optimal structures – subjects of all types would have been substantially better off by choosing optimal information structures and they sacrifice significant guessing accuracy by failing to do so.

Overall, Figure 5 suggests that (i) most of the variation in learning across subjects is driven by variation in information structure (gray bars in panel c are much smaller than those in panel b), (ii) all subjects make significant use of information they receive from their information structures (gray bars are positive for every type in all three panels, $p < 0.001$) but (iii) Confirmation types make less use of information than other types of subjects (gray bars are lower for Confirmation types in panels b and c). In Online Appendix B, we use the EX block data to show that these patterns also hold separately for bias-by-commission and bias-by-omission problems (that is, the results are universal across problems).

We collect these observations as a further result:

Result 4. *All types learn significantly better 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.*

5.4 Beliefs and Information Structure Choices

In addition to guessing the state, subjects were incentivized to submit beliefs about the likelihoods of the state (in both END and EX blocks). Panel (a) of Figure 6 shows the average (absolute) difference between these submitted beliefs and the beliefs a Bayesian would form upon receiving signals from the same information structure (for this we use data from the EX task where we have, for each subject, elicitation for every information structure).[42,43] As with the learning/guessing accuracy results from the previous subsection, Optimal types make better use of information than the other types and confirmation-seeking types stand out as forming the worst beliefs (those with the greatest deviation from Bayesian benchmarks).[44]

[42] Formally, the Figure plots $\sum_s \pi_s |p_s - p_s^{Bay}|$ where p_s^{Bay} is the Bayesian posterior and p_s is the stated posterior of the subject conditional on signal s and π_s is the probability of receiving signal s.

[43] Results are broadly similar for the END treatment but as we discuss above, self-selection into information structure makes these beliefs more difficult to interpret.

[44] Both Optimal and Confirmation types are statistically different from others ($p < 0.05$), and the difference between these two types is highly significant ($p < 0.001$). Nonetheless, there is substantial variation among all types. For example, focusing on the top quartile of the data (in terms of accuracy of beliefs), we see that among those only 34% of subjects are Optimal types. (The ratio goes up to 50% among classified types).

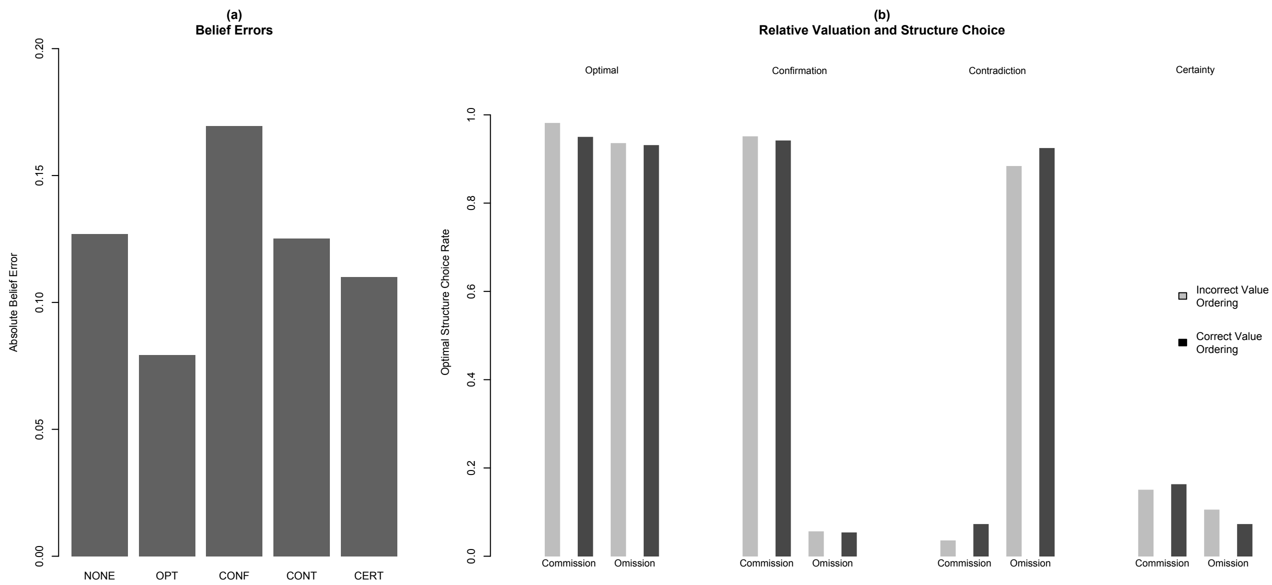

Figure 6: Belief Errors and Information Structure Choice by Type *Notes: Incorrect (Correct) Value Ordering refers to problems in which a subject's expected value for the optimal information structure (implied by the beliefs the subject submits for this structure in the EX block) is lower than the expected value for the sub-optimal information structure.*

There is a relationship between mistakes in choices over information structures and mistakes in beliefs, but do the latter *cause* the former? Do subjects choose sub-optimal information structures *because* they mistakenly believe these structures will provide more useful signals? If so, we would expect variation in the accuracy of beliefs across subjects and decisions to predict when subjects make mistakes in their choices over information structures. To examine this, we can calculate the *expected value* of each information structure σ implied by the beliefs subject i submits for this structure in the EX block. Formally,

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

where π_s is the probability of receiving signal s and p_s is the stated posterior of the subject conditional on that signal.[45,46] Suppose among two information structures $\overline{\sigma}$ and $\underline{\sigma}$ the former is optimal and the latter sub-optimal. That is, an agent with Bayesian beliefs would consider $\overline{\sigma}$ to be of higher value than $\underline{\sigma}$. Under the hypothesis that mistakes in choices over information structures are driven by mistaken beliefs (deviations from Bayesian updating), we would expect $\underline{\sigma}$ to be chosen

[45]The value is equivalent to the subject's expected guessing accuracy in that problem when receiving signals from this information structure. When subjects' stated beliefs coincide with the Bayesian posteriors, this value is equivalent to the Bayesian value.

[46]Recall that subjects directly observe the prior and the signal distribution conditional on each state when making their choices.

over $\overline{\sigma}$ much more frequently when subject i states beliefs such that $V(\underline{\sigma}) > V(\overline{\sigma})$ and less frequently when $V(\underline{\sigma}) < V(\overline{\sigma})$. Panel (b) of Figure 6 shows, for each subject type (Optimal, Confirmation etc.) and bias-type (commission or omission) the proportion of optimal choices (selections of $\overline{\sigma}$) in cases in which subjects' beliefs imply (i) a correct value ordering ($V(\underline{\sigma}) < V(\overline{\sigma})$, in black) versus (ii) an incorrect value ordering ($V(\underline{\sigma}) \geq V(\overline{\sigma})$, in gray).

The results cast serious doubt on the hypothesis that mistaken beliefs drive usage of sub-optimal decision rules (confirmation, contradiction and certainty seeking behavior). For both bias-type problems, the rates of optimal structure choice are *no higher* when beliefs generate a correct value ordering than when they generate an incorrect value ordering in the two most common types (Optimal and Confirmation).[47] This is true even though there is substantial variation in value orderings in each of these subject-type/bias-type combinations (a full 35% of Confirmation types have the correct value ordering even for bias-by-omission problems in which subjects almost never choose the correct structure). Contradiction types are slightly more likely to choose the correct advisor when value orderings are correct. However, even here these likelihood differences do almost nothing to explain the large drops in rates of optimal structure choice in the bias-by-omission case relative to the bias-by-commission case (or the reverse for Confirmation types).

We conclude that although types differ to some degree in the accuracy of their beliefs, these differences do little to explain observed patterns in subjects' mistakes in choosing between 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.*

In Online Appendix C, we conduct further analysis using the belief data showing, in particular, that there is no evidence that Confirmation types, in updating their beliefs, underweigh signals that oppose their priors relative to signals that reinforce their prior. To the contrary, while subjects are overall conservative in their updating behavior, all types in the experiment tend to *overweigh* signals that oppose the prior relative to those that reinforce their prior. This further reinforces our conclusion that biased processing of information is not a primary determinant of the decision rules subjects adopt to choose between information structures.

[47] This suggests that even Optimal types, to a large extent, don't rely on conditional beliefs to identify the optimal information structure. This is consistent with how subjects describe their decision rules in the Advice task.

5.5 Self Awareness and Cognitive Ability

As shown in the previous section, variation in subjects's ability to make use of their signals does not explain their mistakes in choosing between information structures. Instead, these mistakes seem to be driven mostly by subjects consistently matching (Confirmation types) or anti-matching (Contradiction types) the biases in information structure to their priors. In order to better understand how consciously subjects employ these rules, we asked subjects to describe and justify their strategies. Specifically, at the end of the experiment we asked subjects to provide free-form advice (including explanation/justification) to a prospective participant in the experiment, and provided a monetary bonus for the advice judged most useful by their peers. The results confirm that subjects *intentionally* engage in this "bias matching" and, moreover, that they believe bias matching strategies are the optimal way of choosing between information structures.

Subjects provided strikingly detailed (and often sophisticated) descriptions of how they made their choices (about 70% of subjects gave us clear, operationalizable descriptions of how they made their choices). These descriptions reveal that most subjects choose information structures by (i) explicitly identifying the direction of bias of each information structure and (ii) choosing the information structure whose bias either matches (confirmation-seeking) or anti-matches (contradiction-seeking) the *ex-ante* more likely state (i.e. the prior provided for the task). Furthermore, it is clear from these descriptions that subjects commonly find these heuristics normatively appealing and rational, with many subjects making attractive arguments for the probabilistic sophistication of their approaches (in a few cases subjects even explicitly claim that confirmation-seeking is Bayesian!).

For instance, confirmation-seeking subjects frequently argue that it is optimal to maximize the likelihood of receiving signals that match the state and that this can be accomplished by selecting information structures that give accurate signals in the *a priori* more likely state.[48] Contradiction-seeking subjects commonly argue that information is most useful if it improves accuracy on the *a priori* less likely state and advise choosing the information structure that provides the most accurate signals on this state.[49] Both of these lines of justification have some statistical sophistication

[48] For example: "The advice I have is to 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."

[49] For example: "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 BECAUSE / / - for the color that has the least amount of ball, it is unlikely to be the chosen color so you want the advisor to tell if the color is ever chosen (in other words, 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."

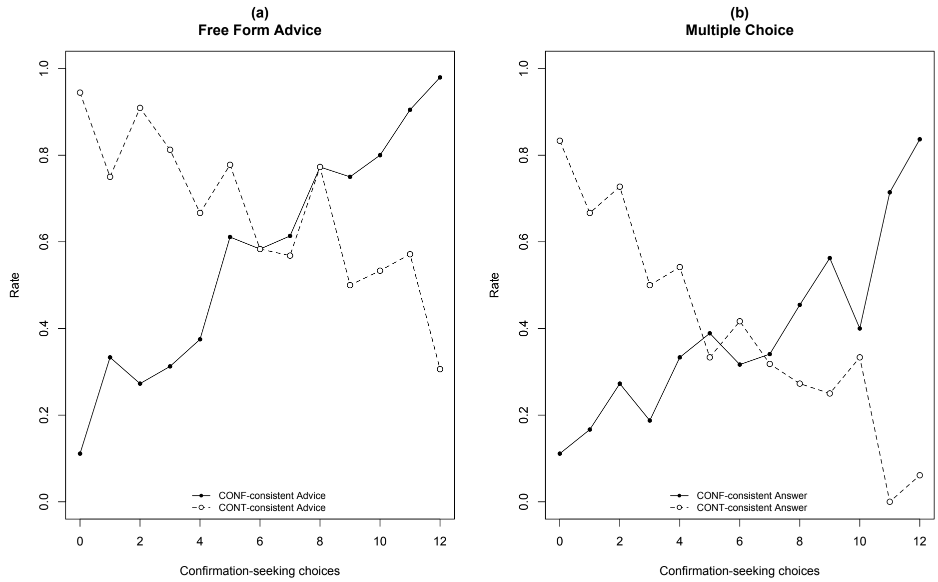

Figure 7: Relationship between confirmation-seeking choices and self-reported strategies. *Notes: CONF (CONT) -consistent advice/choice refers to free form advice (panel a) or multiple choice answer (panel b) that we have coded as consistent with confirmation (contradiction) seeking reasoning.*

underlying them, but ignore fundamental elements of reasoning needed to avoid incorrect guesses in both bias-type problems. Optimal types often explicitly (and correctly) discuss the instrumental value of receiving signals about the *a priori* less likely state, but also emphasize that such signals are most useful when they fully reveal the state (which differs from contradiction-seeking advice which simply emphasizes receiving signals of the less likely state with high likelihood).[50] (We give some canonical examples of advice given by different types in Online Appendix D).

Importantly, subjects' advice matches their behavior in the experiment quite well. We coded subjects' advices according to their consistency with the decision rules described in Section 4: CONF-consistent, CONT-consistent, OPT-consistent, CERT-consistent or NONE[51] (in ambiguous cases we coded advice as consistent with more than one rule). In Figure 7 (a), we plot the rate at which subjects submitted CONF-consistent and CONT-consistent advice as a function of the number of confirmation-seeking choices subjects made in the experiment. The results show a

[50]For example: "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 range 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."

[51]We coded subjects as NONE if they provided non-serious or indecipherable advice.

strong positive relationship between CONF-consistent advice and confirmation-seeking choices, with Confirmation types almost always giving advice coded as CONF-consistent. Likewise, there is a strong negative relationship between CONT-consistent advice and confirmation-seeking choices, with Contradiction types almost always giving advice coded as CONT-consistent.[52] (Optimal types also give advice coded as OPT-consistent nearly 75% of the time, though OPT advice is subtler and sometimes more difficult to differentiate from other types of advice). Regressions (reported in Online Appendix E) show that *for all four types* advice-consistency (i) strongly predicts type (e.g. CONF-consistency strongly increases the odds of being a Confirmation type) but (ii) does not predict other types (e.g. CONF-consistency does not increase the odds of being an Optimal type).

As a robustness check, after the advice question we asked subjects to classify their information structure decisions by choosing one of the following from a multiple choice list: (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." In Figure 7 (b) we plot the rates at which subjects chose a CONF description (1) or CONT description (2) again as a function of the number of confirmation-seeking choices. Again, we find an extremely strong relationship, with confirmation-seeking subjects usually choosing the CONF description (and almost never choosing the CONT description) and contradiction-seeking subjects doing the reverse. These choices, too, are highly predictive of subject types (see Online Appendix E).

These results confirm that subjects are aware of the decision rules they are using and, moreover, are using them because they believe they are payoff enhancing. This, in turn, suggests that in our experiment, bias-matching strategies like confirmation-seeking are driven by mistakes in reasoning rather than preferences, random choices or the application of simple habits. We report this as a further result.

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

Finally, after eliciting advice, we administered a multi-part, incentivized cognitive test including

[52] Optimal and Certainty types cannot be distinguished as clearly on Figure 7 (both types make between 4 and 7 confirmation-seeking choices). Notably, in panel (b), where answers are most crisply coded, many subjects who make between 4 and 7 confirmation-seeking choices provide neither CONF or CONT-consistent answers to the survey (CONF-consistent and CONT-consistent sum to less than 1).

the Wason selection task (which tests deductive reasoning and is often associated with confirmation bias), three Raven matrix questions (of varying difficulty, measuring abstract reasoning), three non-standard variations on cognitive reflection test questions (which measures tendencies to override initial responses to questions) and three Belief Bias questions (measuring ability to evaluate logical arguments).[53] We use probit regressions (detailed in Online Appendix E) to estimate how predictive these measures are of the likelihood that subjects employ each of the four decision rules (Optimal, Confirmation etc.). Most importantly, we find that high Belief Bias and Wason scores are highly predictive ($p < 0.01$) and Raven score is marginally predictive ($p < 0.10$) of being typed as Optimal.[54,55,56] This suggests that subjects are less likely to use sub-optimal decision rules the stronger their cognitive abilities are.[57]

Result 7. *Subjects with high measured cognitive abilities are less likely to employ sub-optimal decision rules.*

6 Discussion

Our experiment provides some of the first direct evidence on how people choose between biased information sources and the motivations behind those choices. Subjects make frequent (and costly) mistakes in choosing between biased information structures, but these mistakes are not random. Indeed, patterns in choices over information structures are distinctive enough that we can categorize

[53] Thomson & Oppenheimer (2016) provides detailed discussion of these cognitive ability measures; Cosmides (1989) studies the Wason selection task.

[54] Conversely, mistakes on the Wason selection task are marginally predictive of being a confirmation-seeking type ($p < 0.10$) and having an analytical major of study is predictive of being a contradiction-seeking type and against being a Confirmation type ($p < 0.05$ in both cases).

[55] We also ran versions of these regressions that include two measures on self-perception. The first looks at self-confidence. We ask two questions to subjects on how well they think they have done in the cognitive ability questions: one is a simple guess on the number of questions they answered correctly, and the second is an assessment on how well they have done relative to others. The second is a measure on how closely the subject identifies with the following statement: "It is very important to me to hold strong opinions." Results show that self-confidence is predictive of being an optimal type ($p < 0.05$). The results from the first regressions remain.

[56] Ranking subjects in terms of their overall scores for the cognitive ability questions, we observe share of Optimal and Confirmation types in the top (bottom) quartile to be 52% (13%) and 14% (30%) respectively. Furthermore, among those subjects who solved the Wason task correctly 51% were Optimal and 12% were Confirmation. These shares change to 21% and 27% for the remainder of the data.

[57] Our survey also included several questions about political attitudes and media habits. However, we had too little variation in these measures relative to our sample size to conduct credible hypothesis tests with this data. Details are provided in Online Appendix E.

most subjects as implementing one of a handful of decision rules. The most common of these is a confirmation-seeking rule that arises in the subject population about as frequently as optimal rules. Less common are contradiction-seeking and certainty-seeking rules.

Why do most subjects use decision rules like confirmation-seeking rather than behaving optimally? Our experimental design and data provides some perspective.

First, our experiment was designed to rule out, *ex ante*, the most common explanations offered for confirmation-seeking behavior such as *motivated beliefs* (people have a *preference* for reinforcing closely held beliefs) or *reputational concerns* (people trust information sources that conform with their prior beliefs). By studying an environment in which (i) prior beliefs are over abstract states (the color of a ball drawn from an urn) and (ii) change radically from decision to decision over the course of the experiment (so that subjects are unlikely to be attached to beliefs about any one state over the course of the experiment) we effectively eliminate the scope for motivated beliefs to generate confirmation-seeking behavior. To the best of our knowledge, our experiment is the first to document confirmation bias in an environment in which priors are exogenously assigned, so that motivated reasoning is not a plausible explanation for the bias. Likewise, the design removes reputational concerns by providing subjects with exact signal distributions for each information structure they might choose.

Second, our results indicate that the use of sub-optimal decision rules is linked to difficulty in evaluating competing biases in information structures, and not due to subjects being confused about the instructions or underwhelmed by the incentives. When we conduct control tasks in which incentives and framing are identical but information structures are instead biased in the *same direction* (hence Blackwell ranked), subjects make highly optimal choices.

Third, by eliciting subjects' posterior beliefs over all information structures and signals, we are able to assess and ultimately rule out errors in Bayesian updating as the primary driver of mistakes in choices over information structures. In particular, we find that subjects are not much more likely to choose optimal information structures when their beliefs are accurate enough to correctly rank information structures than when they are not. The explanatory power of beliefs over patterns of choices are dwarfed by the explanatory power of the direction of the bias (towards or against the prior) in information structures. That is, when subjects make mistakes, they seem to be responding to the biases themselves (relative to priors) rather than the relative beliefs induced by information structures.

Fourth, subjects are able to accurately describe the rules they employed in the experiment and often provide highly sophisticated (but typically mistaken) justifications for using these rules. These descriptions and justifications indicate that subjects find decision rules like confirmation-seeking normatively appealing and that the resulting patterns of mistakes in choosing between information sources are founded in simple mistakes in reasoning.

Finally, a set of incentivized cognitive questions, conducted post-experiment, suggest that use of non-optimal decision rules is linked to cognitive ability. Subjects who perform well on cognitive tests that measure logical reasoning (Wason selection tasks and Belief Bias tasks) are significantly more likely to use optimal decision rules.

Taken together, our results suggest an essentially cognitive explanation for failures to optimally navigate bias when choosing between information sources – one that differs from standard explanations in popular discussion. People use sub-optimal decision rules like confirmation-seeking because it is cognitively difficult to correctly assess the relative informativeness of biased information sources. Rules that involve matching (or anti-matching) biases in information to prior beliefs are appealing to subjects, and subjects deploy these rules because they mistakenly believe they will result in good outcomes.

Our experiment was partly motivated by popular concern that biases in selecting sources of political information (particularly confirmation-seeking biases) are responsible for the proliferation of echo chambers, information bubbles and ultimately increased political polarization in recent years. Our finding that confirmation-seeking behavior is, in part, rooted in a simple error in *reasoning*, may have implications for policy responses to these type of phenomena. On the negative side, to the degree that behaviors like confirmation-seeking are driven by reasoning errors, policies aimed at improving trust in news sources (for instance calls for the development of fact checking websites) or at reversing motivated-reasoning (for instance by reframing policies in conciliatory ways) might not completely remove the negative social effects of these errors. On the positive side, to the degree that cognitive mistakes drive these behaviors, there may be scope for interventions that improve people's learning and reasoning habits – policies that would be ineffective if confirmation-seeking were driven purely by reputational and motivated reasoning mechanisms. Moreover, our results show a surprising de-linkage between people's ability to select optimal information sources and their ability to make use of optimal information sources: our subjects are capable of making effective use of optimal information sources even when they are unable to select optimal information sources in the first place. This may suggest that policies designed to expose people to information that they would not voluntarily seek out themselves might be particularly effective in encouraging the formation of accurate beliefs.[58] Future experiments that build on our design by studying whether (and under what circumstances) cognitive training, provision of information and framing can eliminate these types of errors is an important next step in this research agenda.

Finally, our finding that confirmation-seeking behavior may be driven (at least in part) by errors in reasoning suggests that confirmation-seeking may have much greater scope than the news/political domain in which they are generally discussed. To the degree that motivated beliefs alone drive errors like confirmation-seeking, we might expect such errors to arise largely in contexts in which subjects have closely held beliefs (such as political ideology). However, to the degree that these errors arise from errors in reasoning we might expect them also to arise in less affectively-loaded domains such as choices between competing product reviews, financial advisors, academic disciplines and sources of medical advice.

[58] In a similar spirit, Sunstein has argued that for social media platforms should adopt an "architecture of serendipity", creating chance encounters with people and ideas we might not choose to engage with.

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Online Appendix for

How Do People Choose Between Biased Information Sources? Evidence from a Laboratory Experiment

Gary Charness Ryan Oprea Sevgi Yuksel

CONTENTS:

A. Further analysis on design

B. Further analysis on learning

C. Further analysis on beliefs

D. Examples from classification of advice

E. Further analysis on survey

F. Screenshots

G. Instructions

A Further analysis on design

Remark 3. *The two information structures in Table 1 are ranked in terms of the Monotone likelihood ratio property.*

Proof. Let π_s^1 (π_s^2) denote the probability of observing signal s from the information structure on the left (right) hand side of Table 1. Clearly,

$$\frac{\pi_r^2}{\pi_r^1} = \frac{(1-p_0)(1-\lambda)+p_0}{p_0(1-\lambda)} > \frac{(1-p_0)\lambda}{(1-p_0)+p_0(1-\lambda)} = \frac{\pi_l^2}{\pi_l^1}$$

□

Remark 4. *The two information structures in Table 2 are ranked in terms of the Monotone likelihood ratio property for* $(\lambda_h, \lambda_l) = (0.7, 0.3)$.

Proof. Let π_s^1 (π_s^2) denote the probability of observing signal s from the information structure on the left (right) hand side of Table 2. We would like to show:

$$\frac{\pi_r^2}{\pi_r^1} = \frac{\lambda_h}{\lambda_l} > \frac{\pi_n^2}{\pi_n^1} > \frac{\lambda_l}{\lambda_h} = \frac{\pi_l^2}{\pi_l^1}$$

$$\frac{\pi_n^2}{\pi_n^1} = \frac{(1-p_0)(1-\lambda_l)+p_0(1-\lambda_h)}{(1-p_0)(1-\lambda_h)+p_0(1-\lambda_l)} = \frac{1-\lambda_l+(\lambda_l-\lambda_h)p_0}{1-\lambda_h+(\lambda_h-\lambda_l)p_0}$$

The first inequality can be written as $\lambda_h - \lambda_h^2 + (\lambda_h^2 - \lambda_h\lambda_l)p_0 > \lambda_l - \lambda_l^2 + (\lambda_l^2 - \lambda_h\lambda_l)p_0$ which is equivalent to $\lambda_h - \lambda_l > (\lambda_l^2 - \lambda_h^2)(1-p_0)$. Similarly, the second inequality can be written as $\lambda_h - \lambda_l > (\lambda_l^2 - \lambda_h^2)p_0$. Note $\lambda_h - \lambda_l > (\lambda_l^2 - \lambda_h^2)$ when $\lambda_h, \lambda_l = (0.7, 0.3)$ which is sufficient for the result. □

B Further analysis on learning

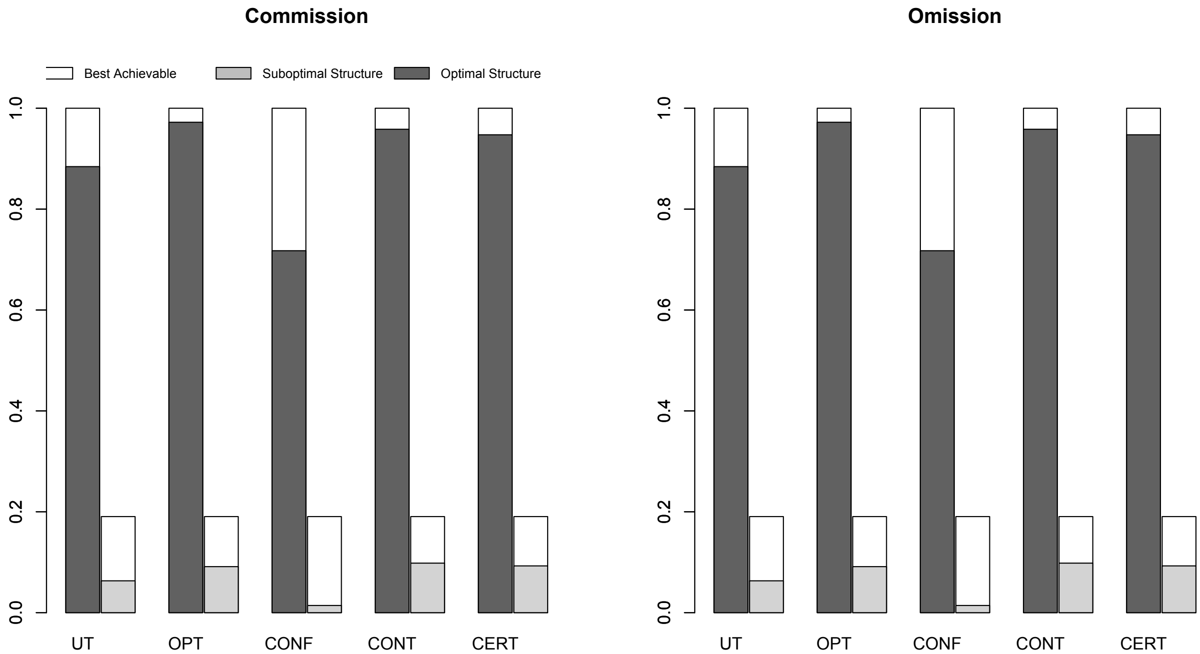


Figure 8: Learning by type separated by bias-type

C Further analysis on beliefs

We look at how biased stated beliefs are relative to the prior. A necessary condition for Bayesian updating is that the expected posterior should equal to the prior. We calculate $\sum_s \pi_s p_s - p_0$ for each subject and problem to see how much it deviates from zero. As noted before, in analyzing the data, we have relabeled the states in each of the questions such that subjects can be considered to start with a prior $p_0 > 0.5$ in all questions.[59] We call a subject to have *negative bias* in a question if $\sum_s \pi_s p_s < p_0$. A negative bias implies that in updating beliefs, relative to the Bayesian benchmark, a subject is overweighing signals that are contradictory to their prior relative to those that are reinforcing of their prior. We see overwhelming evidence for native bias in updating. Focusing on stated beliefs in the EX block, optimal types show negative bias in 74% of the questions. The corresponding values for confirmation and contradiction seeking types is 78% and 89%.[60] This finding indicates that, at least on how they state their beliefs, subjects are not attached to their prior and are willing to state opinions to the contrary. Furthermore, we observe the relative ranking of these biases to be linked nicely to the classification categories. Subjects displaying confirmation seeking behavior in their information-structure choice also form beliefs that are most likely to lean in the direction of their prior, and those displaying contradiction seeking behavior form beliefs that are most leaning in the opposite direction.

To understand why beliefs are generally biased and significantly different for all types from the Bayesian benchmark, we generate a measure of *responsiveness to information* for different types of signals by calculating for each subject and problem the following variable:[61]

$$p_s = p_0 + \alpha_s(p_s^{Bay} - p_0)$$

Note that $\alpha_s = 1$ corresponds to perfect Bayesian updating, $\alpha_s < 1$ suggests under-responsiveness to information, and $\alpha_s > 1$ suggests over-responsiveness to information. Once again, we normalize the questions to always set $p_0 > 0.5$, so that we can interpret r to be the prior reinforcing signal

[59] Without this relabeling, this analysis would be testing if subjects form beliefs that are systematically biased towards the *orange* or *green* state as presented in the design (we vary which state is more likely according to the prior.) We don't find any bias in this case which confirms that subjects did not treat these states differently, but made decisions based only on which state was more likely.

[60] For certainty seeking types, the value is 75%. For untyped subjects, the value is 79%.

[61] The literature usually focuses on logistic representation of Bayes' rule to construct a measure of responsiveness. (See Mobius et al. (2011) and Ambuehl & Li (2018) and references cited there for an overview of this). However, the type of information structures we include in our experiment, where there are fully revealing signals which give log likelihood ratios of zero or infinity, are not conducive to this type of analysis. For these reasons, to illustrate the main features of the data, we use a very simple measure.

Type	α_r	α_l	α_n
Optimal	0.81	1.07	0.91
Confirmation	0.30	0.92	0.55
Contradiction	0.50	1.04	1.08
Certainty	0.68	1.11	0.86

Table 4: Responsiveness to information

($p_r^{Bay} > p_0$), and l to be the prior opposing signal ($p_l^{Bay} < p_0$). We focus on data from the EX block, where subjects were assigned information structures to facilitate the comparison between the different types.

A few observations stand out in Table 4. First, consistent with our analysis on *negative bias* above, in relative terms, subjects are more responsive to prior opposing signals, that is $\alpha_l > \alpha_r$ for all types ($p < 0.01$). Second, Optimal types are most responsive to signals that are reinforcing of one's prior, and surprisingly Confirmation types are the least responsive to these signals.[62] Third, Confirmation types have substantial difficulty internalizing the informational content of failing to receive signals. While the value for α_n is significantly different from 0 ($p < 0.01$), suggesting that, in aggregate, there is some learning as a consequence of receiving this signal, the value is also significantly different from 1 ($p < 0.01$).[63,64]

[62]For all types α_r is significantly different than 1 ($p < 0.01$). Optimal and Certainty types are over-responding to contradictory signals with α_l significantly different than 1 ($p < 0.05$ for optimal , and $p < 0.01$ for Certainty types). Confirmation types are marginally under-responding to these signals ($p < 0.10$).

[63]For Optimal types, it is also marginally different from 1 ($p < 0.10$).

[64]Recent literature has documented similar problems with interpreting failure to receive signals in different settings. See Jin et al. (2015) and Enke (2017) for a discussion on this.

D Examples from classification of advice

Classification	Advice
OPT-consistent	First, if the advisor only gives your advice on Orange or Green, you can choose the advisor who tends to choose the color of the ball that has more proportion. For example, there are more orange than green in the basket, you should choose the advice who are more likely to say orange because once he said green, it must be a green ball that will be chosen, otherwise, if he says orange, it will be more likely to be an orange ball because green ball has less chance to let him to say orange. / / Second, if the advisor also says nothing. Similar to the previous one, you may want the advisor to tends to keep quiet on when the color that has more proportion. If there is more orange than green, you may want him to keep more quiet on orange rather than green.
OPT-consistent	Choose the least ambiguous advice. If there are fewer green balls than orange balls, choose the adviser that can give you a response so that you know for certain the ball is green. Also, choose the adviser who will give the lower percent of the ambiguous advice to the less frequent ball colour. / / If the response ”orange” from the adviser could mean either orange or green, choose the adviser who would is more likely to advise orange for the ball colour that is more frequent. The same goes for if saying nothing is an ambiguous response. / / The fewer of one colour there is, the less ambiguous you want the advice for that colour to be. The more of a colour there is, the more ambiguous it should be, as there is a greater chance of it being that coloured ball.
OPT-consistent	When picking an advisor, check the ratio of green to orange balls in the box above. If there is a majority colored ball, choose the advisor that will only say the minority color when it is picked. For example, when there is 10 orange balls vs 5 green balls, the orange balls are the majority. You should then chose the advisor that will say green only when green is pulled, that way you will know for sure that ball is green. If the advisor says orange and there is a possibility that the ball is green or orange, the risk is minimized since there is already a majority color of orange.
CONF-consistent	Look at the balls in the basket and see which one is highest, then look at which advisor leans more towards that color.
CONF-consistent	If there are more green ball than orange ball in the box, you should pick the one that more likely to say green; on the other hand, if there are more orange ball than green ball in the box, you should pick the one who will more likely to say orange.
CONF-consistent	Go with the advisor who is most certain about the more probabilistic outcome.
CONF-consistent	Run the numbers in your head. The ball’s have probabilities that are multiples of five so they’re easy, and the advisors are generally multiples of ten so they’re easy too. Then see which advisors will give you the highest probability of telling the ’truth’ and go with them.
CONF-consistent	You want to maximize the chance that the advisor will give you correct advice. To do this you should pick the advisor that gives you a 100% or at the very least gives you a higher chance of the correct color for the majority of balls. For example if there are 14 orange and 6 green. Pick the advisor that says 100% of saying orange if ball chosen is orange and like 70% chance of saying green if the ball chosen is green. This increases the chance of you getting the right answer.
CONF-consistent	When the amount of the orange balls is greater than the amount of the green balls, choose the advisor that gives more accurate information of the orange ball; / otherwise, choose the advisor that can give more accurate information of the green ball.

Classification	Advice
CONT-consistent	If there are more orange balls than green balls, pick the advisor that has a greater chance of saying green balls. Even if there are less green balls than orange balls which means there is a greater chance of an orange ball getting picked, if the advisor says there is a greater percentage of receiving a green ball, then it is most likely so since the advisor is more accurate with the ball being green than it is being orange.
CONT-consistent	Because many pairings of advisors had opposite likelihoods of truthfully disclosing the color of the ball, it makes sense to choose the advisor who is more likely to tell the truth about the color of ball which appears fewer times in the bag. For example, if there are 16 orange balls and 4 green balls, the advisor who tells the truth more often about the number of green balls is who you would be apt to choose, because regardless of possible deception about the number of orange balls, you are more likely to draw orange balls and thus answer more questions correctly.
CONT-consistent	Choose the advisor that has the greatest possibility of telling you the correct color of the ball. / / To do so, first determine how many of each color ball are in the basket. If there are a lot of orange, choose the advisor who is more likely to say green when the ball is green. If there are a lot of green, choose the advisor who is more likely to say orange when the ball is orange. This is because the ball is more likely to be the majority color and you would rather the advisor be more correct when the lesser probability color is chosen. / / Do a similar strategy when the advisors can say nothing. You would rather be more sure of when the lessor probable color occurs as it will occur less often.
CERT-consistent	1) Decide for each adviser if there is information that you can know with 100% certainty / / 2) Find the most likely color of the ball and pick the adviser that tells you that color with 100% certainty / / 3) If both advisers do this (ex: when they both say a color, they are certain its right, but they could also say nothing for both colors) look at which adviser will give you an answer for the most likely color more often and pick that advisor.

E Further analysis on survey

	OPT	CONF	CONT	CERT
OPT-consistent advice	0.724***	-0.716***	-0.0207	-0.0382
	(0.180)	(0.219)	(0.217)	(0.247)
CONF-Consistent advice	-0.574***	1.983***	-0.944***	-0.290
	(0.211)	(0.362)	(0.266)	(0.259)
CONT-Consistent advice	-0.556**	0.642*	0.575**	-0.471
	(0.235)	(0.359)	(0.281)	(0.304)
CERT-Consistent advice	0.121	-0.721**	0.0358	0.926***
	(0.227)	(0.334)	(0.262)	(0.272)
Constant	-0.505**	-1.852***	-1.160***	-1.250***
	(0.203)	(0.353)	(0.257)	(0.236)
Observations	344	344	344	344

Standard errors in parentheses. ***1%, **5%, *10% significance.

OPT: Optimal; CONF: Confirmation; CONT: Contradiction; CERT: Certainty

Table 5: Probit Regression of the Probability of Being Each Type

	OPT	CONF	CONT	CERT
Self-declared confirmation strategy	-0.0610	1.308***	-1.013***	-0.200
	(0.167)	(0.204)	(0.216)	(0.216)
Self-declared neutral strategy	-0.130	0.654***	-1.102***	-0.0876
	(0.201)	(0.241)	(0.290)	(0.252)
Constant	-0.630***	-1.505***	-0.655***	-1.240***
	(0.123)	(0.176)	(0.123)	(0.152)
Observations	344	344	344	344

Standard errors clustered (at the subject level) in parentheses. ***1%, **5%, *10% significance.

OPT: Optimal; CONF: Confirmation; CONT: Contradiction; CERT: Certainty

Table 6: Probit Regression of the Probability of Being Each Type

	OPT		CONF		CONT		CERT	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Wason Task	0.655***	0.663***	-0.526*	-0.538*	-0.439	-0.407	0.00270	-0.0643
	(0.216)	(0.219)	(0.278)	(0.280)	(0.329)	(0.330)	(0.298)	(0.308)
Belief Bias Score	0.241***	0.219***	-0.0720	-0.0605	0.0638	0.0723	-0.0322	-0.0363
	(0.0816)	(0.0826)	(0.0719)	(0.0729)	(0.0878)	(0.0889)	(0.0920)	(0.0947)
Raven Score	0.204*	0.146	-0.105	-0.0881	0.0375	0.0472	0.188	0.207
	(0.115)	(0.118)	(0.108)	(0.110)	(0.132)	(0.133)	(0.142)	(0.146)
CRT Score	0.0831	0.0813	-0.144	-0.135	-0.00672	-0.0190	0.0687	0.0831
	(0.120)	(0.121)	(0.111)	(0.112)	(0.133)	(0.134)	(0.155)	(0.155)
Male	0.114	0.0621	0.239	0.260	-0.336*	-0.311	0.101	0.0658
	(0.157)	(0.160)	(0.155)	(0.159)	(0.192)	(0.195)	(0.197)	(0.203)
Analytical Major	0.218	0.175	-0.398***	-0.383**	0.407**	0.434**	0.0888	0.0659
	(0.156)	(0.158)	(0.154)	(0.155)	(0.185)	(0.188)	(0.194)	(0.198)
Values Strong Opinions		0.00783		-0.0175		0.123		-0.183**
		(0.0668)		(0.0662)		(0.0817)		(0.0837)
Confidence		1.042**		-0.434		-0.405		0.0537
		(0.479)		(0.459)		(0.540)		(0.596)
Constant	-2.125***	-2.594***	0.189	0.416	-1.436***	-1.633***	-1.957***	-1.460**
	(0.434)	(0.526)	(0.369)	(0.462)	(0.452)	(0.581)	(0.525)	(0.619)
Observations	344	344	344	344	344	344	344	344

Standard errors in parentheses. ***1%, **5%, *10% significance.

OPT: Optimal; CONF: Confirmation; CONT: Contradiction; CERT: Certainty

Table 7: Probit Regression of the Probability of Being Each Type

	OPT	CONF	CONT	CERT
Errors on comprehension questions	-0.489***	0.273***	-0.0497	-0.0525
	(0.0993)	(0.0651)	(0.0852)	(0.0883)
Constant	-0.382***	-0.936***	-1.140***	-1.299***
	(0.0909)	(0.0979)	(0.109)	(0.116)
Observations	344	344	344	344

Standard errors in parentheses. ***1%, **5%, *10% significance.

OPT: Optimal; CONF: Confirmation; CONT: Contradiction; CERT: Certainty

Table 8: Probit Regression of the Probability of Being Each Type

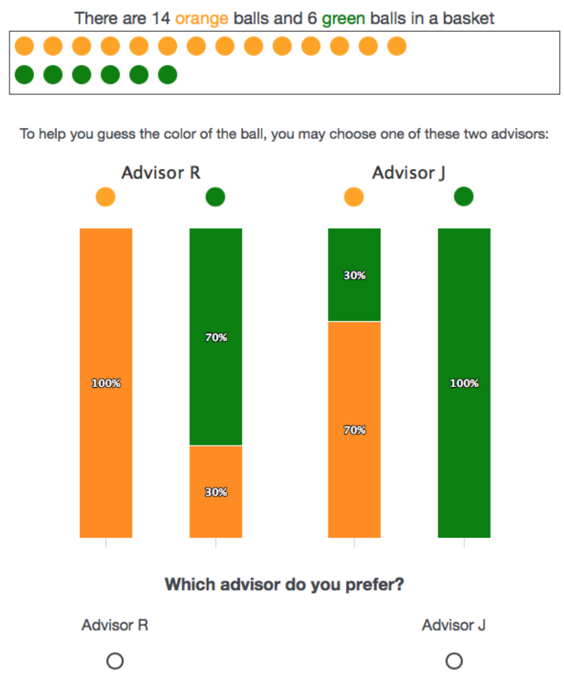
	OPT	CONF	CONT	CERT
Ideology	-0.129	0.127	-0.0385	-0.0838
	(0.129)	(0.128)	(0.153)	(0.165)
Partisanship	0.0808	0.156	0.00976	-0.109
	(0.103)	(0.102)	(0.122)	(0.132)
Political engagement	-0.0468	0.0430	0.0342	-0.0419
	(0.0506)	(0.0512)	(0.0580)	(0.0650)
Political Informedness	0.0558	-0.0697	0.0681	-0.0446
	(0.0715)	(0.0715)	(0.0869)	(0.0917)
Trust news	0.0760	-0.108*	0.0790	-0.0292
	(0.0626)	(0.0650)	(0.0746)	(0.0831)
Attentive to news sources	0.0971	-0.257***	0.0761	0.185
	(0.0989)	(0.0965)	(0.120)	(0.130)
Constant	-1.181***	0.366	-2.070***	-1.519**
	(0.435)	(0.412)	(0.550)	(0.592)
Observations	344	344	344	344

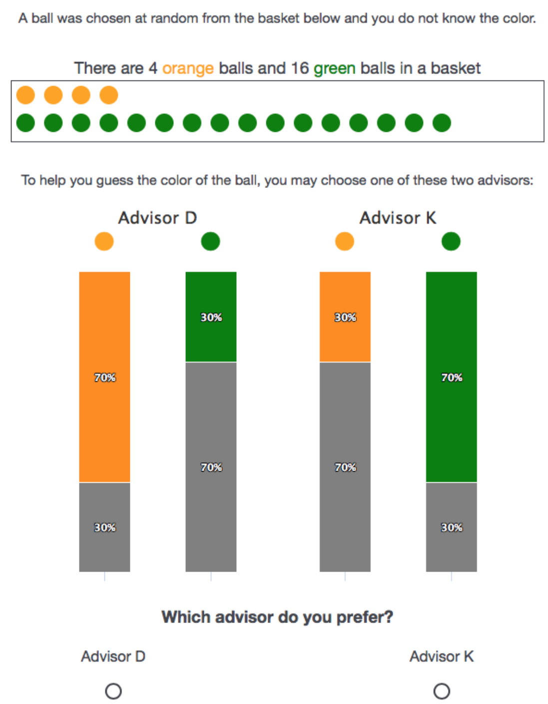
Standard errors in parentheses. ***1%, **5%, *10% significance.

OPT: Optimal; CONF: Confirmation; CONT: Contradiction; CERT: Certainty

Table 9: Probit Regression of the Probability of Being Each Type

F Screenshots





G Instructions

INSTRUCTIONS

*You are about to participate in an experiment in the economics of decision-making. Follow these instructions carefully. In this experiment, you can earn a **CONSIDERABLE AMOUNT OF MONEY**, which will be **PAID TO YOU IN CASH** at the end of the experiment.*

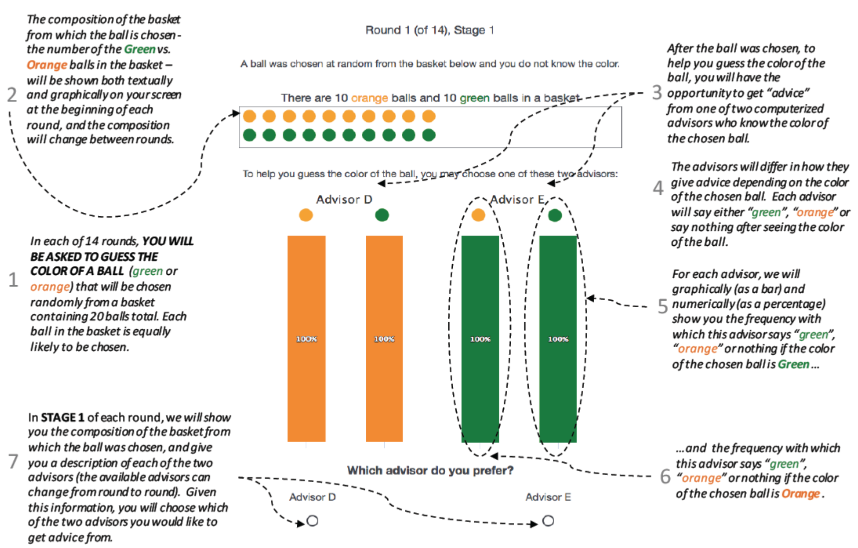
*After the instruction period, **we will ask you questions to check that you understand how the experiment works**. You should be able to answer all these questions correctly. You will not be able to participate in the experiment before you answer all questions correctly.*

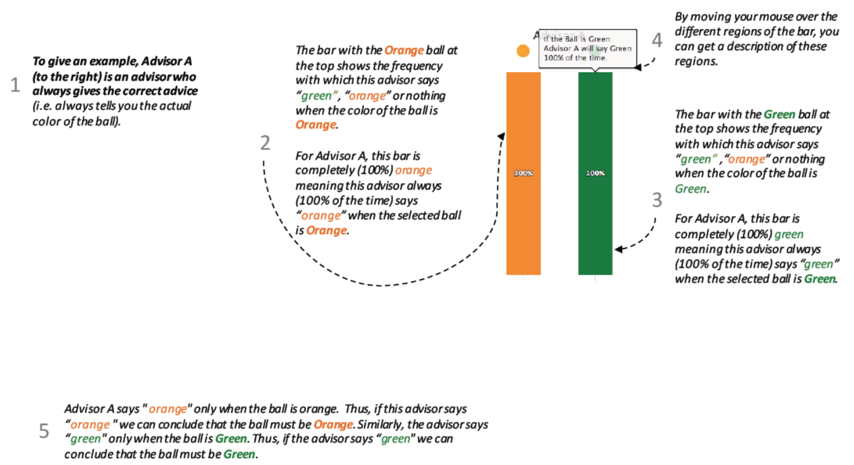
This experiment has two parts; these instructions are for the first part. Once this part is over, instructions for the second part will be given to you. Your decisions in this part have no influence on the other part.

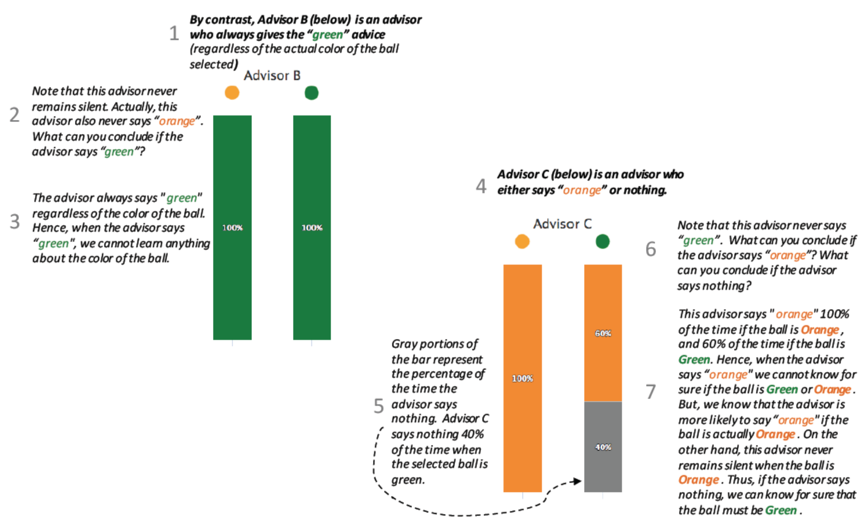
*The first part consists of **14 rounds**. You will only be paid for **2 rounds** from the first part which will be randomly determined at the end of the experiment. Each round is equally likely to be selected.*

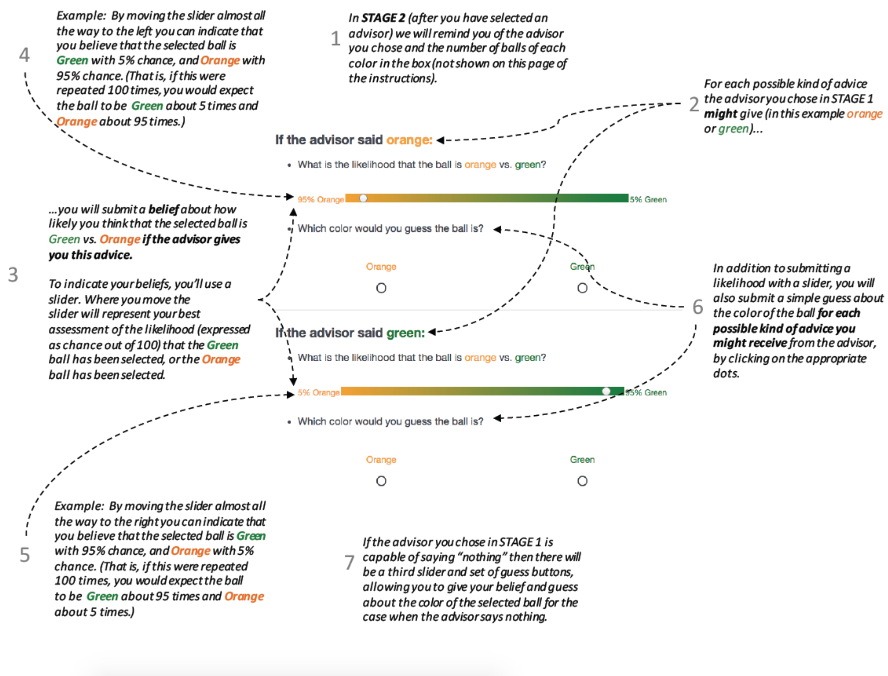
There is also a survey at the end of the experiment, and you will also receive additional payment for completing the survey.

1

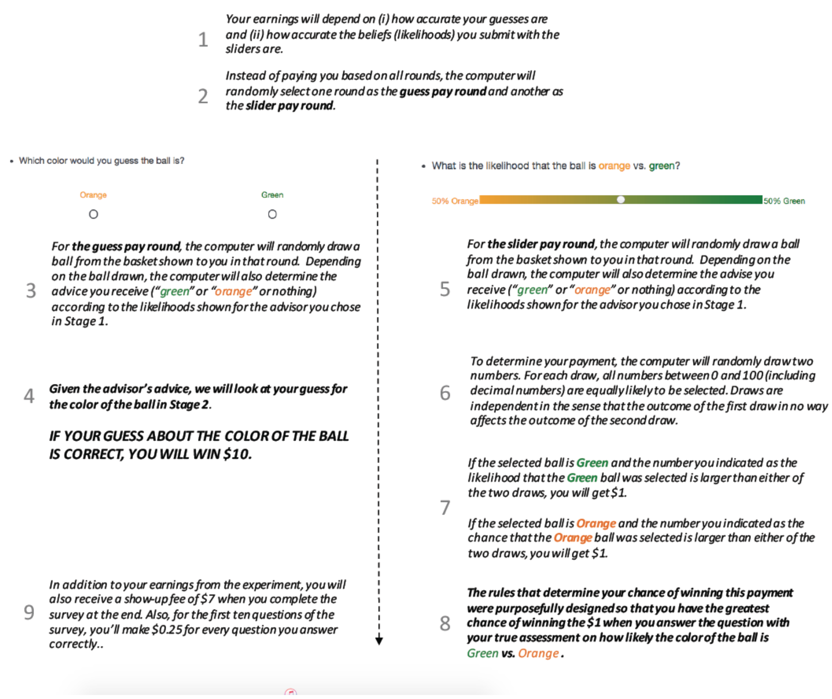



1 To give an example, Advisor A (to the right) is an advisor who always gives the correct advice (i.e. always tells you the actual color of the ball).
2 The bar with the Orange ball at the top shows the frequency with which this advisor says "green", "orange" or nothing when the color of the ball is Orange.
For Advisor A, this bar is completely (100%) orange meaning this advisor always (100% of the time) says "orange" when the selected ball is Orange.
If the Ball is Green
Advisor A will say Green
100% of the time
100%
100%
4 By moving your mouse over the different regions of the bar, you can get a description of these regions.
3 The bar with the Green ball at the top shows the frequency with which this advisor says "green", "orange" or nothing when the color of the ball is Green.
For Advisor A, this bar is completely (100%) green meaning this advisor always (100% of the time) says "green" when the selected ball is Green.
5 Advisor A says "orange" only when the ball is orange. Thus, if this advisor says "orange" we can conclude that the ball must be Orange. Similarly, the advisor says "green" only when the ball is Green. Thus, if the advisor says "green" we can conclude that the ball must be Green.


1 By contrast, Advisor B (below) is an advisor who always gives the "green" advice (regardless of the actual color of the ball selected)
Advisor B
2 Note that this advisor never remains silent. Actually, this advisor also never says "orange". What can you conclude if the advisor says "green"?
3 The advisor always says "green" regardless of the color of the ball. Hence, when the advisor says "green", we cannot learn anything about the color of the ball.
100%
100%
4 Advisor C (below) is an advisor who either says "orange" or nothing.
Advisor C
100%
60%
40%
5 Gray portions of the bar represent the percentage of the time the advisor says nothing. Advisor C says nothing 40% of the time when the selected ball is green.
6 Note that this advisor never says "green". What can you conclude if the advisor says "orange"? What can you conclude if the advisor says nothing?
7 This advisor says "orange" 100% of the time if the ball is Orange, and 60% of the time if the ball is Green. Hence, when the advisor says "orange" we cannot know for sure if the ball is Green or Orange. But, we know that the advisor is more likely to say "orange" if the ball is actually Orange. On the other hand, this advisor never remains silent when the ball is Orange. Thus, if the advisor says nothing, we can know for sure that the ball must be Green.



1 In STAGE 2 (after you have selected an advisor) we will remind you of the advisor you chose and the number of balls of each color in the box (not shown on this page of the instructions).
2 For each possible kind of advice the advisor you chose in STAGE 1 might give (in this example orange or green)...
3 ...you will submit a belief about how likely you think that the selected ball is Green vs. Orange if the advisor gives you this advice.
To indicate your beliefs, you'll use a slider. Where you move the slider will represent your best assessment of the likelihood (expressed as chance out of 100) that the Green ball has been selected, or the Orange ball has been selected.
4 Example: By moving the slider almost all the way to the left you can indicate that you believe that the selected ball is Green with 5% chance, and Orange with 95% chance. (That is, if this were repeated 100 times, you would expect the ball to be Green about 5 times and Orange about 95 times.)
5 Example: By moving the slider almost all the way to the right you can indicate that you believe that the selected ball is Green with 95% chance, and Orange with 5% chance. (That is, if this were repeated 100 times, you would expect the ball to be Green about 95 times and Orange about 5 times.)
6 In addition to submitting a likelihood with a slider, you will also submit a simple guess about the color of the ball for each possible kind of advice you might receive from the advisor, by clicking on the appropriate dots.
7 If the advisor you chose in STAGE 1 is capable of saying "nothing" then there will be a third slider and set of guess buttons, allowing you to give your belief and guess about the color of the selected ball for the case when the advisor says nothing.
If the advisor said orange:
What is the likelihood that the ball is orange vs. green?
95% Orange
5% 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?
5% Orange
95% Green
Which color would you guess the ball is?
Orange
Green



1 Your earnings will depend on (i) how accurate your guesses are and (ii) how accurate the beliefs (likelihoods) you submit with the sliders are.
2 Instead of paying you based on all rounds, the computer will randomly select one round as the guess pay round and another as the slider pay round.
Which color would you guess the ball is?
Orange
Green
3 For the guess pay round, the computer will randomly draw a ball from the basket shown to you in that round. Depending on the ball drawn, the computer will also determine the advice you receive ("green" or "orange" or nothing) according to the likelihoods shown for the advisor you chose in Stage 1.
4 Given the advisor's advice, we will look at your guess for the color of the ball in Stage 2.
IF YOUR GUESS ABOUT THE COLOR OF THE BALL IS CORRECT, YOU WILL WIN $10.
9 In addition to your earnings from the experiment, you will also receive a show-up fee of $7 when you complete the survey at the end. Also, for the first ten questions of the survey, you'll make $0.25 for every question you answer correctly..
What is the likelihood that the ball is orange vs. green?
50% Orange
50% Green
5 For the slider pay round, the computer will randomly draw a ball from the basket shown to you in that round. Depending on the ball drawn, the computer will also determine the advise you receive ("green" or "orange" or nothing) according to the likelihoods shown for the advisor you chose in Stage 1.
6 To determine your payment, the computer will randomly draw two numbers. For each draw, all numbers between 0 and 100 (including decimal numbers) are equally likely to be selected. Draws are independent in the sense that the outcome of the first draw in no way affects the outcome of the second draw.
7 If the selected ball is Green and the number you indicated as the likelihood that the Green ball was selected is larger than either of the two draws, you will get $1.
If the selected ball is Orange and the number you indicated as the chance that the Orange ball was selected is larger than either of the two draws, you will get $1.
8 The rules that determine your chance of winning this payment were purposefully designed so that you have the greatest chance of winning the $1 when you answer the question with your true assessment on how likely the color of the ball is Green vs. Orange.

INSTRUCTIONS FOR PART 2

1 *The second part of the experiment consists of 12 rounds and is very similar to the first part. In every round, you will be asked to guess the color of a ball that will be chosen randomly from a basket.*

2 *The only difference is that you will not be able to choose between advisors. Instead , the advisor will be given to you by the computer. Everything else will be the same.*

*Similar to part 1, you will only be paid for two rounds. The computer will randomly select one round as the **guess pay round** and another as the **slider pay round**.*

- Which color would you guess the ball is?

Orange ○ Green ○

3 *As before, for **the guess pay round**, the computer will randomly draw a ball from the basket shown to you in that round. Depending on the ball drawn, the computer will also determine the advice you receive ("green" or "orange" or nothing) according to the likelihoods shown for the advisor given to you in that round.*

4 ***Given the advisor's advice, we will look at your guess for the color of the ball.***

IF YOUR GUESS ABOUT THE COLOR OF THE BALL IS CORRECT, YOU WILL WIN $10.

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

50% Orange —— 50% Green

5 *For **the slider pay round**, the computer will randomly draw a ball from the basket shown to you in that round. Depending on the ball drawn, the computer will also determine the advise you receive ("green" or "orange" or nothing) according to the likelihoods shown for the advisor given to you in that round.*

6 *As before, you will have a chance to win $1 depending on your stated likelihood that the ball is Green **vs.** Orange for this advice. You can go back to the original instructions for how this payment is determined.*

7 ***To remind you, the rules that determine your chance of winning this payment were purposefully designed so that you have the greatest chance of winning the $1 when you answer the question with your true assessment on how likely the color of the ball is** Green **vs.** Orange **.***

8 *Finally, to remind you, in addition to your earnings from the experiment, you will also receive a show-up fee of $7 when you complete the survey at the end. Also, for the first ten questions of the survey, you'll make $0.25 for every question you answer correctly..*