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Protecting the ego: Motivated information selection and updating ☆

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ABSTRACT

We investigate whether individuals self-select feedback that allows them to maintain their motivated beliefs. In our lab experiment, subjects can choose the information structure that gives them feedback regarding their rank in the IQ distribution (ego-relevant treatment) or regarding a random number (control). Although beliefs are incentivized, individuals are less likely to select the most informative feedback in the ego-relevant treatment. Instead, many individuals select information structures in which negative feedback is less salient. When receiving negative feedback with lower salience subjects update their beliefs less, but only in the ego-relevant treatment and not in the control. Hence, our results suggest that individuals sort themselves into information structures that allow them to misinterpret negative feedback in a self-serving way. Consequently, subjects in the IQ treatment remain on average overconfident despite receiving feedback.

1. Introduction

In many instances, individuals can choose the source from which they receive feedback about their ability. For example, politicians and executives can surround themselves with subordinates who give their honest opinion or loyalists who habitually praise the capabilities of their superior. In educational contexts, individuals select supervisors and mentors that differ in their feedback style. Similarly, college students select majors with more or less compressed grading distributions and thus differing informativeness of grades (Ahn et al., 2019; Sabot and Wakeman-Linn, 1991).

Standard models predict that individuals have a strict preference for choosing the most informative feedback source because this leads to more accurate beliefs and, in turn, better-informed decisions. However, if individuals have motivated beliefs, for example the desire to hold the belief that they have high ability (Bénabou and Tirole, 2002; Köszegi, 2006), they may prefer feedback structures that allow them to preserve this positive self-view.[1]

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[1] We are agnostic about whether individuals derive utility from holding themselves in high regard (Köszegi, 2006), whether they do so to gain a strategic advantage in persuading others (Von Hippel and Trivers, 2011), or to motivate themselves (Bénabou and Tirole, 2002). However, we note that holding inaccurate

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In this paper, we study individuals' preferences over feedback concerning their ability. Our experiment resembles the situation where a student can choose between two supervisors: supervisor A and supervisor B. The student knows that both supervisors aim to give clear, positive feedback when the student's performance is good. However, the student also knows that supervisor A usually tells the student clearly when she considers the work poor, while supervisor B abstains from giving any comment when she is critical about the student's work. Hence, not receiving feedback from supervisor B is in fact negative feedback, but it is framed in a way that is not explicit. If the student anticipates that this framing will allow to disregard potential negative feedback, the student may prefer supervisor B, which can lead to the formation and maintenance of overconfident beliefs.

We conduct the first lab experiment in which individuals can select the information structure that provides noisy feedback about their ability. We compare information selection when feedback is related to relative IQ test performance to a control condition, in which feedback relates to the draw of a random number. Feedback is instrumental since individuals are incentivized for the accuracy of their beliefs. Nonetheless, we find that many subjects in the IQ treatment do not choose the most informative feedback structure. Instead, our results suggest that they choose feedback that allows them to maintain their belief that they have high ability.

We provide evidence for a mechanism of ego protection so far unrecognized in the literature: When feedback is ego-relevant, individuals choose information structures in which negative feedback is less salient and, thus, potentially easier to misinterpret. We consider a signal to be less salient when it is framed in a neutral way (i.e., not linked to a positive or negative cue), although it carries either positive or negative information when its context is taken into account. In the experiment, a negative signal with high salience is presented as a red sign with the description "You are in the bottom half", while a negative signal with low salience is a gray sign with the description "…". Whereas the lower salience of feedback should not matter for a rational Bayesian updater, our results show that it leads individuals to update less in response to unpleasant news. When information is not ego-relevant, we do not find evidence for such asymmetric updating. Thus, the results are consistent with the explanation that individuals select feedback that allows them to distort their beliefs in a self-serving way.

The key feature of our design is that subjects can choose the information structure they receive feedback from. Information structures are presented in the form of two urns with varying compositions of positive and negative signals. Depending on whether the subject is in the top or bottom half of the distribution, signals are drawn from one urn or the other. This design allows us to vary the properties of the information structures and cleanly identify preferences for ego-relevant information. In particular, by varying the composition of signals in the urns, we vary the informativeness, salience, and skewness of feedback. *Informativeness* describes the noisiness of the signals. *Salience* refers to the way in which positive and negative signals are framed, holding informativeness constant. We vary the salience of feedback by framing it as either green/red signals with an explicit description (high salience) or gray signals without description (low salience). An information structure is *skewed* if positive signals are more or less informative than negative signals (Masatlioglu et al., 2017; Nielsen, 2020). For example, an information structure is positively skewed if a potential positive signal is more precise than a negative signal.

The incentivization of beliefs gives us a clear prediction for subjects in the control condition: we expect that subjects select the most informative feedback structure in order to maximize their expected payoff. In contrast, subjects who derive utility from the belief that they rank high in the IQ distribution may prefer an information structure that allows to maintain this belief—for example, by selecting feedback that is less informative, positively skewed, or makes negative feedback less salient (which potentially facilitates future belief distortion).

We find that individuals seek different information when the rank is ego-relevant versus when it is not. When the ego is at stake, subjects are more likely to choose information structures that are less informative (treatment difference of 13.5 percentage points) and that make negative feedback less salient (treatment difference of 26.4 percentage points). However, we find no evidence that subjects in the ego-relevant treatment are more likely to choose information structures that are positively skewed. Our findings are based on aggregate treatment differences in information structure choices, and reinforced when looking at within-individual choice patterns (in the control, we classify 89.3 percent of subjects as information maximizers, and in IQ only 65.5 percent). Furthermore, we find that subjects who are classified as avoiding information according to the Information Preference Scale by Ho et al. (2021) are more likely to choose an information structure that is less informative and features less salient negative feedback. We do not find evidence for heterogeneous information preferences by gender, cognitive ability, or prior beliefs.

Moreover, we find that the subsequent belief updating process is influenced by the information structure. Subjects in the IQ treatment react less to negative feedback than to positive feedback, but only when negative feedback is less salient. We find the first indication of this when subjects receive signals from the information structure that they self-select (endogenous treatment). The results are corroborated by a treatment in which subjects are exogenously placed into information structures to eliminate potential selection issues (exogenous treatment). Furthermore, in the control condition, subjects react similarly to positive and negative feedback irrespective of its salience. Therefore, asymmetric updating in the ego-relevant treatment is unlikely to be explained by difficulty in understanding less salient signals.

We assess explanations other than motivated reasoning for the treatment effects. The treatment variation in the ego-relevance of the state allows us to distinguish cognitive biases (i.e., general systematic errors regarding how people search and process new information, such as confirmation bias) from motivated biases (i.e., biases that are driven by a desire to hold positive views of oneself). We provide evidence that the treatment differences cannot be explained by cognitive biases such as confirmation-seeking or contradiction-seeking behavior, differences in cognitive ability, or confusion about the experimental design. Subjects' free-text

beliefs about ability is costly in many domains, for example, it leads to suboptimal management decisions (Malmendier and Tate, 2005) or over-entry into competition (Camerer and Lovallo, 1999).

explanations for their choices indicate that they make a "gut-level" decision to prefer positive-looking signals over explicit negative signals when feedback is ego-relevant.

Our results shed light on the conditions under which individuals with a desire to protect their ego can distort their beliefs. Bénabou and Tirole (2002) show in a two-selves model that it can be optimal for individuals to avoid or distort feedback when the belief in high ability has consumption or motivation value. However, since belief distortion in the model by Bénabou and Tirole (2002) is costly, manipulation of beliefs is only beneficial within the realms of the "reality constraints", implying that individuals cannot simply choose the beliefs they like. Our results suggest that selecting an information structures in which unpleasant feedback is easier to misinterpret can be one way to relax these reality constraints.

The idea that an individual selects an information structure that allows negative feedback to be interpreted in a self-serving way can be seen as a form of self-deception. It is a long-standing philosophical puzzle whether self-deception is possible at all, given that the same mind has to be the deceiver and the deceived (e.g., Mele, 2001). In the moral domain, Saccardo and Serra-Garcia (2020) find direct evidence for anticipated belief distortion. In their experiment, many advisors postpone acquiring the information whether the product they ought to recommend is beneficial for the advisee or not, thereby reducing the salience of the information. These subjects are also more likely to underrespond to the information when it is in conflict with their incentives and to behave ultimately in a self-serving way, showing that individuals are somewhat sophisticated about their future belief distortion. We find suggestive evidence that anticipated belief distortion also contributes to the maintenance of overconfident beliefs about intelligence. Our results show that subjects who select feedback that is less informative and in which negative feedback is less salient remain overconfident about their IQ rank over the course of the experiment. In contrast, subjects who receive explicit negative feedback are, on average, no longer overconfident at the end of the experiment.

Our findings contribute to the literature on how individuals process positive and negative feedback regarding their ego-relevant characteristics. Bénabou and Tirole (2016) argue that when ego-relevant beliefs are involved, people tend to process information differently depending on whether the information is more or less desirable.[2] For instance, people might tend to ignore or discount negative news, while more readily incorporating good news into their (posterior) beliefs.[3] However, the resulting experimental evidence on this mechanism – asymmetric updating – is mixed. On the one hand, Charness and Dave (2017), Eil and Rao (2011), and Möbius et al. (2014) find positive asymmetry in updating. On the other hand, a number of studies either find no asymmetry (Barron, 2021; Buser et al., 2018; Gotthard-Real, 2017; Grossman and Owens, 2012; Schwardmann and van der Weele, 2019) or even the opposite asymmetry (Coutts, 2019; Ertac, 2011; Kuhnen, 2015). Moreover, in a paper related to how errors in updating can be driven by motivated beliefs, Exley and Kessler (2019) find that people update their beliefs based on completely uninformative signals, but only when the signals carry positive information and the updating state is ego-relevant. Our paper helps explain the existing results by studying belief updating in different information structures. We show that asymmetric updating is only observed when the framing of the information structure allows subjects to interpret the signals in a self-serving way. In contrast, we do not observe asymmetric updating when positive and negative feedback is highly salient.

We complement the literature on information avoidance by giving subjects more control over the amount and type of feedback they receive.[4] Eil and Rao (2011) and Möbius et al. (2014) present experimental evidence that a considerable proportion of subjects who have received prior noisy information regarding their relative rank in ego-relevant domains (intelligence and attractiveness) have a negative willingness to pay to have their rank fully revealed. In contrast, subjects in our study *choose* the noisy signals that they would like to receive before any feedback is given. On the one hand, we find that subjects indeed choose less informative feedback when it is ego-relevant. On the other hand, they disregard unpleasant information using a mechanism that is so far unexplored in the literature: subjects in the ego-relevant treatment choose information structures that makes unpleasant feedback less salient.

Our results add novel insights about motivated cognition to the literature on how signal structures affect belief updating. While Epstein and Halevy (2019) and Fryer et al. (2019) find that ambiguous signals increase deviations from Bayes rule, Enke (2020) and Jin et al. (2021) illustrate that individuals find it difficult to interpret the lack of a signal. Enke et al. (2020) provide evidence that individuals update more in response to signals, which are framed with valenced cues that activate associative memory. In contrast to these experiments, we vary the ego-relevance of the state and show that the framing of signals affects whether subjects update asymmetrically.

Finally, our research adds a motivated beliefs perspective to the literature on information structure selection. Within this literature, several papers study preferences about the timing and skewness of information disclosure in settings where information structures have – in contrast to our experiment – no instrumental value (Falk and Zimmermann, 2016; Nielsen, 2020; Zimmermann, 2014). For example, Masatlioglu et al. (2017) find that individuals have a preference for positively skewed information sources; that is, information structures that resolve more uncertainty regarding the desired outcome than the undesired one. Some experimental papers study preferences over information structures in settings where information has instrumental value (but is not ego-relevant).

[2] Related literature on motivated reasoning studies the demand for and consumption of political news. This literature shows evidence that consumers prefer like-minded news (Garz et al., 2020; Gentzkow and Shapiro, 2010). Moreover, Chopra et al. (2019) show in a series of online experiments that people's demand for political news goes beyond the desire for acquiring more informative news.

[3] Selective recall of ego-relevant feedback is documented in the experiments of Chew et al. (2020) and Zimmermann (2020). Both papers find that negative feedback on IQ test performance is more likely to be forgotten, compared to positive feedback.

[4] For a review of the information avoidance literature, see the survey of Golman et al. (2017). In the health domain, Ganguly and Tasoff (2016) and Oster et al. (2013) provide empirical evidence that people avoid medical testing. In a financial context, Karlsson et al. (2009) and Sicherman et al. (2015) show that investors check their portfolios less often when the market is falling.

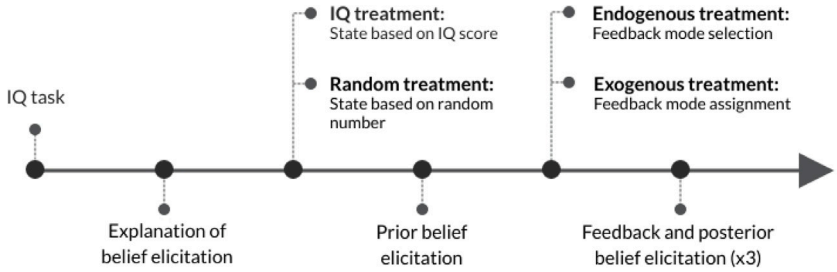


Fig. 1. Timeline of the experiment.

Charness et al. (2021) and Montanari and Nunnari (2019) study how people seek information from biased information structures and show that many individuals do not maximize the informativeness. Hoffman (2016) finds that businesspeople are on average too confident in their expert knowledge and underpay for instrumental information, possibly to avoid negative feedback. We show that the tendency to select less informative feedback is more pronounced in ego-relevant domains and can be one driver for the prevalence of overconfident beliefs.

The remainder of this paper is organized as follows. In Section 2, we describe our experimental design, which comprises two treatment variations: ego-relevance of the rank and endogenous/exogenous information structure allocation. In Section 3, we present our experimental results. First, we study how participants select their preferred information structures depending on the ego-relevance of the rank. Second, we study subsequent belief updating. In Section 4, we discuss our findings, and in Section 5 we conclude.

2. Experimental design

To investigate whether individuals choose information structures that protect their ego, we design an experiment that contains (1) exogenous variation in the ego-relevance of beliefs; (2) choices between different information structures; and (3) elicitation of updating behavior within different information structures.

In a 2×2 between-subject design, we vary, on the one hand, whether subjects receive feedback about their relative rank in IQ test performance (IQ treatment) or about a random number (random treatment). This treatment variation allows us to study the impact of motivated beliefs on preferences over feedback. On the other hand, we vary whether subjects receive signals from the information structure they selected into (endogenous treatment) or from an information structure they are exogenously assigned to (exogenous treatment). The latter treatment variation allows us to study how subjects update their beliefs with and without self-selection into feedback.

2.1. Overview

Fig. 1 presents an overview of the experiment. In the beginning, all subjects perform an incentivized IQ test. They have 10 min to solve 20 matrices from the Raven Advanced Progressive Matrices (APM) test. They can earn £2.00 per correct answer out of three randomly chosen matrices. Although the IQ performance is only relevant for subjects in the IQ treatment in the later stages of the experiment, all subjects solve the IQ quiz. This ensures that there are no systematic differences in fatigue, timing, or average earnings between treatments.

In the remainder of the experiment, subjects are asked to express their beliefs about the state of the world, which is either related to their rank in the IQ test (IQ treatment) or to the draw of a random number (random treatment). First, we explain the matching probabilities method to the subjects (Karni, 2009), so that they know that they maximize their chance of winning a £6.00 prize by stating their true beliefs (see Online Appendix A). Next, subjects are informed whether the belief questions refer to their IQ score or their random number and are asked for their prior beliefs. Afterwards, subjects in the endogenous treatment choose the feedback mode they would like to receive signals from, while subjects in the exogenous treatment are shown the feedback mode assigned to them. Feedback modes are presented in the form of urns with a varying composition of signals, as explained below. Finally, three rounds of feedback are drawn from the respective mode. We elicit subjects' posterior beliefs, allowing us to study how subjects update their beliefs in response to receiving signals.

At the end of the experiment, either the IQ task or the belief elicitation is randomly selected for payout. If the belief elicitation is chosen, one out of the four beliefs (one prior and three posteriors) is randomly selected for payout. Thereby, we aim to exclude any hedging motives that could lead to a reported belief about IQ performance that differs from the true belief (cf. Blanco et al., 2010; Azrieli et al., 2018). Screenshots of the experimental instructions are provided in Online Appendix G.

Subjects are incentivized to give their true beliefs, so a payoff-maximizing subject would always choose the most informative feedback mode and update according to Bayes rule. However, in the IQ treatment, subjects' motives to maximize payout can conflict with the desire to protect their beliefs about their (relative) ability. For instance, subjects may be willing to accept a smaller expected payoff in order to not impair their belief that they are in the top of the intelligence distribution. If that is the case, we expect a treatment difference in information structure selection and/or updating behavior depending on whether the beliefs are ego-relevant.

2.2. Treatments

2.2.1. IQ and random treatment

We vary the ego-relevance of beliefs by randomizing subjects into an IQ treatment and a random treatment at the individual level. Consistent with previous research, we argue that rank in the IQ treatment is ego-relevant (e.g., Eil and Rao, 2011), and that subjects care more for their IQ rank than their random number. We assume that further deviations from the rational benchmark are constant between the IQ and random treatments (this assumption is discussed in Section 4).

IQ treatment. In the IQ treatment, we inform subjects that the second part of the experiment is related to their relative performance in the IQ test they completed in the beginning. We tell them that the computer divides participants in their session into two groups: one group of subjects whose score is in the top half of the score distribution and the other with scores in the bottom half. The task is to assess whether their IQ performance is in the top or bottom half of the distribution, compared to all other participants in their session. To increase the ego-relevance of the IQ treatment (Drobner and Goerg, 2021), we explicitly tell subjects that the APM test is commonly used to measure fluid intelligence and that high scores in this test are regarded as a good predictor for academic and professional success, occupation, income, health, and longevity (Sternberg et al., 2001; Gottfredson and Deary, 2004).

Random treatment. In the random treatment, subjects are shown a randomly drawn number between 1 and 100. We tell subjects that three other numbers between 1 and 100 (with replacement) were drawn. These numbers are not shown to them. Their task is to assess whether the number they are given is in the top or bottom half of the distribution among these four numbers. The four numbers are randomized at the individual level and ties are broken randomly. The task is deliberately designed to generate variation in prior beliefs.[5] If subjects were not given the drawn number or if we compared their number against many numbers, we would have expected a degenerate prior distribution instead.

In Fig. A.1, we plot the prior distribution by treatment. As expected, the prior distribution in the random treatment is centered around 50 percent, while priors in the IQ treatment are left-skewed with more mass in the top half of the distribution. Hence, in the analysis, we include priors as a covariate and use a matching strategy to ensure that the differences in priors do not drive differences in feedback choice.

2.2.2. Endogenous and exogenous treatment

Moreover, we vary whether subjects endogenously select or are exogenously assigned a feedback mode. The rationale for the exogenous treatment is that it allows us to study updating behavior absent self-selection. In contrast, in the endogenous treatment, subjects in different feedback modes have, on average, different preferences over information structures, which could affect updating behavior.

Endogenous treatment. In the endogenous treatment, subjects make five pairwise choices between feedback modes. Figures G.16 to G.18 in Online Appendix G illustrate the choice situations. In each of the five choice situations, we vary the properties of the feedback modes, as explained in detail in the next section. Afterwards, one out of the five feedback mode choices is randomly selected and the choice of the subject is implemented. Before receiving signals, each subject is shown the selected feedback mode from which they would receive the signals.

Exogenous treatment. In the exogenous treatment, subjects are not asked to choose a feedback mode—instead, assignments are exogenous. In particular, following the IQ test, subjects are randomly allocated to receive ego or non-ego relevant feedback from one of the feedback modes.

2.3. Feedback modes

Table 1 shows the information structures in the experiment. Information structures consist of two urns with 10 balls each. A ball drawn from an urn in the selected information structure constitutes a signal. If an individual's IQ score or random number is in the top (bottom) half of the distribution, balls are drawn from the upper (lower) urn with replacement. This design allows us to cleanly vary the properties of the information structure in a way that is transparent to the subjects.

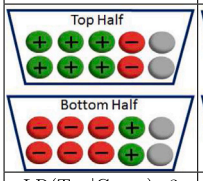
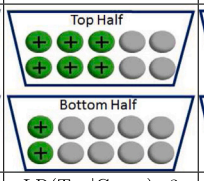
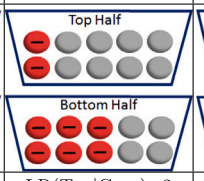
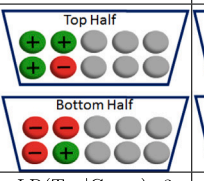
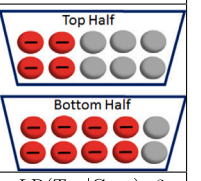
Depending on the information structure, subjects can receive up to three different types of (noisy) signals. Subjects in the IQ (random) treatment can either receive a green signal with a plus (+) sign and the description "You are in the top half" ("Your number is in the top half"), a red signal with a minus (-) sign and the description "You are in the bottom half" ("Your number is in the bottom half"), or a gray signal with the description "...". Figure G.8 in the online appendix shows how the signals are introduced in the instructions.

On the same page, we explain that the informational content of the respective signal depends on the feedback mode and the state. For example, subjects are told that in feedback mode A, they are more likely to get the green (+) signal if they are in the top half of the distribution and that they are more likely to get the red (-) signal if they are in the bottom half of the distribution.[6]

[5] In the endogenous treatment, the standard deviation of prior beliefs in the random treatment turns out to be 25.065, compared to 19.993 in the IQ treatment. Hence, the random treatment generates similar variance compared to the IQ treatment.

[6] In the endogenous treatment, we explain these characteristics by always using one feedback mode choice as an example. We use three different examples, as illustrated in Figures G.9 to G.11 in the online appendix, and check if the presented example matters for choices in Online Appendix C. In the exogenous treatment, we explain the signals using the participant's assigned feedback mode: see the screenshot in Figure G.12.

Table 1
Feedback modes.

Mode A	Mode B	Mode C	Mode D	Mode E
				
LR(Top|Green)=3	LR(Top|Green)=3	LR(Top|Grey)=2	LR(Top|Green)=3	LR(Top|Grey)=3
LR(Top|Red)=1/3	LR(Top|Grey)=1/2	LR(Top|Red)=1/3	LR(Top|Red)=1/3	LR(Top|Red)=1/2
Prob(No Info)=1/5	Prob(No Info)=0	Prob(No Info)=0	Prob(No Info)=3/5	Prob(No Info)=0

Notes: The table shows the feedback modes that can be selected in the experiment. Depending on the state (top or bottom half), a signal is drawn from the upper or lower urn. LR(State|Signal) describes the likelihood ratio of the signal concerning the state and is a measure for its informativeness. For example, LR(Top|Green(+)) is the likelihood of receiving a green (+) signal when being in the top half divided by the likelihood of receiving a green (+) signal when in the bottom half. Prob(No Info) describes the probability of receiving a non-informative signal.

Subjects have to correctly answer comprehension questions about these features before they can proceed. In all feedback modes, the green (+) signal increases the posterior that one is in the top half and the red (-) signal increases the posterior that one is in the bottom half. Depending on the feedback mode, the gray signal can be positive, negative, or non-informative feedback.

Information structures differ in their informativeness, skewness, and framing. Informativeness describes how noisy a feedback mode is. Note that a perfectly informative feedback structure could feature only green (+) signals in the top urn and only red (-) signal in the bottom urn. We introduce noise by, for example, adding red (-) signals to the top urn or uninformative gray signals to either urn. The informativeness of signals in our experiment can be described first by their likelihood ratio (LR) and second by the probability of receiving a non-informative signal. Both of these properties are given in the bottom panel of Table 1. The further away the likelihood ratio is from unity, the more informative the signal and the more it shifts the posterior belief of a Bayesian updater (e.g., the negative signal in Mode A is more informative than the negative signal in Mode B).[7] The probability of receiving a non-informative signal only applies to Modes A and D, in which gray signals are not informative (hence, Mode A is more informative than D).

We call an information structure positively skewed if the positive signals are more informative in terms of their likelihood ratio than the negative signals (as in Modes B and E) and negatively skewed if the negative signals are more informative (as in Mode C).

Finally, information structures differ in their feedback salience. Since the color gray is typically not associated with positive or negative states and the description is not explicit, we say that positive or negative feedback in the form of gray signals is *less salient*. For example, in Mode B negative feedback is less salient, while in Modes C and E positive feedback is less salient.

2.4. Feedback mode choices

Subjects make five pairwise choices between information structures. By carefully varying the information structures they can choose from, we are able to elicit whether subjects have preferences for informativeness, salience, or skewness of feedback depending on its ego-relevance. Every subject in the endogenous treatment makes all five choices. To control for order effects, we vary the order of information structure choices (cf. Online Appendix C).

Baseline Choice: Mode A vs Mode B In the baseline choice, subjects choose between two feedback modes that vary in informativeness, skewness, and salience. First, Mode A is more informative than Mode B. Second, while Mode A gives balanced positive and negative feedback depending on the state, Mode B is positively skewed and negative feedback is less salient (i.e., negative feedback is framed as gray signals). Hence, if more subjects choose Mode B in the IQ treatment compared to the random treatment, we can interpret this as evidence that subjects protect their ego by choosing an information structure that gives less informative and positively skewed signals and where negative feedback is less salient.

Using the remaining feedback mode choices, we aim to disentangle the underlying preferences for informativeness, salience, and skewness.

Informativeness Choice: Mode A vs Mode D First, individuals might want to avoid information if it is ego-relevant. The choice between Modes A and D isolates a preference for informativeness. In both feedback modes, the skewness and salience of signals is held constant, only the probability of receiving a completely uninformative (gray) signal varies. Hence, subjects who have a preference for avoiding information prefer Mode D over Mode A.

[7] In fact, a likelihood ratio of one implies that the signal is fully uninformative about the underlying state.

Salience Choice: Mode B vs Mode E Second, individuals could have a preference for the salience of feedback, for example, for reducing the salience of negative feedback if information is ego-relevant. This could be due to an aversion to explicit negative feedback, or due to anticipation of differential updating behavior (cf. results of updating in Section 3.2). To test for salience preferences, we let subjects choose between Modes B and E, which have the same informativeness and skewness but only differ in the salience of positive and negative feedback (in Mode B negative feedback is less salient and in Mode E positive feedback is less salient).

Skewness over Salience Choice: Mode A vs Mode E Third, we investigate whether individuals have a preference for positive skewness. We test individuals' preferences for positive skewness relative to their preference for feedback salience. Therefore, we consider the choice between Modes A and E together with the baseline choice between Modes A and B. If subjects' choices are driven by a preference for positive skewness, they would prefer both Mode E and Mode B over Mode A.

Baseline Reversed Choice: Mode A vs Mode C Finally, we also check if individuals have a preference for a negatively skewed information structure with less salient positive feedback (Mode C).

2.5. Updating behavior

Besides information structure selection, we also analyze the updating behavior of subjects and how it interacts with the feedback mode. During the updating stage, subjects receive three consecutive signals from one of the feedback modes. After each signal, subjects are asked to report their posterior beliefs. Further, each time they receive a signal and are asked about their beliefs, subjects can view a picture of the feedback mode urns from which they receive information by clicking a button (see Figure G.19 in the online appendix for a screenshot of the choice situation).

Our main interest is to understand differences in updating across feedback modes and according to the ego-relevance of the task. For this reason, we specifically focus on Modes A and B and their interaction with the ego-relevance of the task. On the one hand, a comparison in updating behavior across Modes A and B in the random treatment will allow us to understand whether differences in the information structure drive cognitive biases (i.e., general deviations from Bayes rule). On the other hand, a comparison of updating across IQ and random treatment will allow us to study the extent of motivated biases in updating (i.e., deviations from Bayes rule specific to ego-relevant feedback).

2.6. Debriefing

In the last part of the experiment, we ask subjects a battery of questions. First, we ask subjects to complete the Information Preferences Scale by Ho et al. (2021), which is a 13-item questionnaire that measures an individual's desire to obtain or avoid information that has an instrumental value but is also unpleasant. The scale measures information preferences in three domains: consumer finance, personal characteristics, and health. Second, we ask subjects to complete the Gneezy and Potters (1997) risk elicitation task. Specifically, each subject receives £1.00 and has to decide how much of this endowment to invest in a risky project with a known probability of success. The risky project returns 2.5 times the amount invested with a probability of one-half and nothing with the same probability. We also ask them a non-incentivized general willingness to take risks question (Dohmen et al., 2011). Third, we ask subjects to answer two questions in free-form text and they receive £0.50 for their answers. We ask them to advise a hypothetical subject who would be performing the feedback mode choices and updating task. In the endogenous treatment, we additionally ask them to explain their motives for choosing the feedback modes across the five choice situations. Finally, we ask subjects a series of demographic questions including age, gender, and nationality.

2.7. Experimental procedure

The experimental sessions were conducted from June to October 2019 in the Economics Laboratory of Warwick University, United Kingdom. Overall, we recruited 445 subjects through the Sona recruitment system to take part in the experiment. We conducted 14 sessions (216 subjects) for the endogenous treatment and 15 sessions (229 subjects) for the exogenous treatment. Sessions lasted an average of 60 min. Participants earned an average payment of £11.00, including the show-up fee of £5.00. We conducted the experiment using oTree (Chen et al., 2016). Descriptive statistics of the sample are provided in Table A.1.

In each session, subjects were randomly assigned a cubicle and general instructions were read aloud. The remaining instructions were provided onscreen. In both the endogenous and exogenous sessions, it was randomly determined whether the cubicle belonged to the IQ or random treatment. Moreover, in the exogenous treatment, it was randomly determined if the cubicle was allocated to Modes A or B.

3. Results

Our analysis proceeds in two steps: First, we investigate treatment differences between IQ and random in feedback mode choices. Second, we analyze how subjects update in response to signals from the feedback modes.

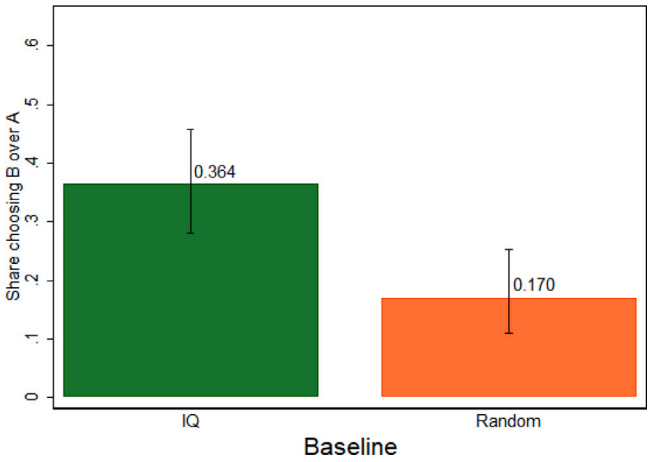


Fig. 2. Share choosing Mode B over A in baseline choice. (Notes: The plot shows the fraction of subjects who prefer Mode A over B in the baseline choice by treatment. In contrast to Mode A, Mode B is less informative, positively skewed, and makes negative feedback less explicit. The 95% confidence intervals (Wilson) are shown by the bar. In the IQ treatment, there are $N = 110$ subjects and in random treatment $N = 106$.)

3.1. Information selection

We first focus on the baseline choice between Modes A and B that vary in informativeness, salience, and skewness. While Mode A gives balanced feedback, Mode B gives less informative, positively skewed signals with less salient negative feedback. Hence, choosing Mode B is costly because subjects are paid based on the accuracy of their posterior beliefs and Mode B provides less information.

Fig. 2 illustrates the percentage of subjects who prefer to receive signals from Mode B over Mode A. While only 17.0 percent of subjects in the random treatment choose Mode B over Mode A, 36.4 percent in the IQ treatment prefer Mode B. The difference of 19.4 percentage points is statistically significant (t-test, $p = 0.001$; Wilcoxon rank-sum test, $p = 0.001$).

In order to disentangle preferences for informativeness, salience, and skewness, we elicit subjects' preferences over information structures in four additional choice situations. Fig. 3 plots the results. In the informativeness choice, subjects can choose between Mode A and Mode D, where both give balanced feedback but where Mode D is less informative than Mode A. The top left panel of Fig. 3 shows that a higher proportion of subjects in IQ choose the less informative Mode D over Mode A. The difference of 13.5 percentage points is statistically significant (t-test, $p = 0.002$; Wilcoxon rank-sum test, $p = 0.002$). Hence, the results suggest that subjects in the IQ treatment do indeed have a preference for less information compared to subjects in the random treatment.

In the salience choice, subjects choose between Mode B, in which negative feedback is less salient, and Mode E, in which positive feedback is less salient. We find that, in the IQ treatment, significantly more subjects exhibit a preference for less salient negative feedback, compared to the random treatment (difference of 26.5 percentage points, t-test, $p < 0.001$; Wilcoxon rank-sum test, $p < 0.001$). Since the informativeness and skewness of the feedback modes are held constant, we expect subjects in the random treatment to be indifferent. Indeed, the share of 52.8 percent choosing Mode E in the random treatment is not significantly different from 50 percent (t-test, $p = 0.563$). In contrast, in the IQ treatment only 26.4 percent choose Mode E, which is significantly lower than the 50 percent predicted by indifference (t-test, $p < 0.001$). Hence, we infer that people care about the salience of signals when it concerns ego-relevant information.

In the skewness over salience choice, we give subjects the choice between Mode A and Mode E. Mode E – just like Mode B – gives positively skewed information, but gives explicit negative feedback and less salient positive feedback. We find that fewer subjects prefer Mode E over Mode A in the IQ treatment than in the random treatment. Taken together with our findings from the baseline choice, we conclude that subjects' preference for Mode B in the IQ treatment is not driven by a preference for positive skewness. The difference in framing of Mode E is enough to overturn the treatment difference from the baseline choice, which suggests that the preference for positive skewness is not as strong as the preference against explicit negative signals.[8]

Finally, in the baseline reversed choice, we let subjects decide between Mode A and Mode C. Mode C gives less informative, negatively skewed signals with less salient positive feedback. In contrast to the baseline choice, we do not find a statistically significant difference between treatments with fewer subjects in IQ choosing Mode C (difference of 5.2 percentage points, t-test, $p = 0.299$; Wilcoxon rank-sum test, $p = 0.298$). This result suggests that subjects do not prefer less informative feedback modes in the IQ treatment if the feedback mode is negatively skewed and makes positive feedback less salient.

[8] Although the informativeness of Modes B and E are the same, we find different levels in the random treatment for the baseline choice and the skewness over salience choice. In Online Appendix C, we find evidence that this could be because some subjects do not understand without further explanation which feedback mode is more informative. When we explain that Mode B and Mode E are less informative than Mode A, the levels in the random treatment are very similar.

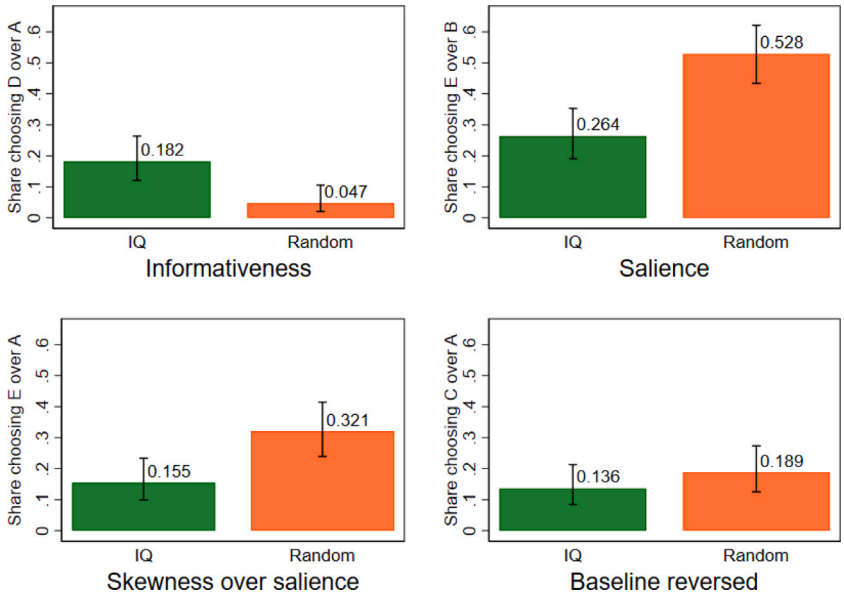


Fig. 3. Selection of feedback mode by choice situation. (Notes: The plot shows the fraction of subjects who prefer one feedback mode over the other in the respective choice by treatment. Informativeness: Mode D is less informative than Mode A. Salience: Mode E makes negative feedback less salient than Mode B. Skewness over salience: Mode E is positively skewed and less informative than Mode A, but makes positive feedback less salient. Baseline reversed: Mode C is negatively skewed, less informative than Mode A, and makes positive feedback less salient. The 95% confidence intervals (Wilson) are shown by the bar. In the IQ treatment, there are $N = 110$ subjects and in random treatment $N = 106$.)

Robustness. In Table A.2 in the appendix, we regress the five feedback mode choices on the IQ treatment dummy and various control variables. Controlling for demographics, prior beliefs, IQ scores and risk preferences does not alter the results in terms of treatment differences in feedback mode choices. In Table A.3, we perform a nearest-neighbor matching (with replacement) with respect to priors. By matching subjects in IQ to subjects with similar priors in the random treatment, we control for differences in the prior distributions non-parametrically. However, the treatment effects turn out to be very similar compared to the main analysis.

In the main analysis, we test treatment differences in five information structure choices. We account for multiple hypothesis testing in Table A.4 in the appendix. To control for the family-wise error rate, we calculate p-values based on the procedure by List et al. (2019) and report p-values using Holm (1979) and Bonferroni adjustment. None of the adjustments change our assessment of the effects' statistical significance.

3.1.1. *Information selection — Within individual*

So far we have looked at aggregate treatment differences in separate choices and analyzed what we can learn from them. We now examine the within-subject choice patterns. To perform this within-analysis, we suppose that each subject has a fixed preference over information structures (conditional on the treatment) and chooses information structures according to this preference. In line with our experimental design, we focus on three preferences for information structures: maximize the informativeness, seek positive skewness, and reduce salience of negative feedback/increase salience of positive feedback. We estimate the fraction of subjects who consistently choose information structures that conform to these preferences.[9]

First, we calculate the fraction of subjects who make choices according to each of these preferences and the fraction of subjects who make choices that do not conform to one of these preferences. Second, we allow subjects to make mistakes and estimate which of the preferences can best explain subjects' choice patterns using a finite mixture model. Hence, we estimate the share of preference types and the amount of implementation noise (γ) necessary to classify subjects. The estimation strategy is described in detail in Online Appendix B.

In Table 2, we compare the relative prevalence of the implied preferences by treatment. In the first two columns, we present the empirically observed fraction of subjects who adhere to a given preference when they are not allowed to make mistakes. In the third and fourth columns, we show the estimated fractions using the finite mixture model. Note that 26.4 percent of subjects in the IQ and 36.8 percent in the random treatment are not classified if we do not allow for mistakes. In contrast, in the finite mixture model we use maximum likelihood to assign to every subject the preference that describes her choice pattern best.

[9] "Maximum information" predicts that subjects make choices according to $A \succ B, C, D, E$, "Positive skewness" predicts $B \succ A; E \succ A; A \succ C$, and "Salience of feedback" predicts $B \succ A; A \succ C, E; B \succ E$. Note that subjects can follow more than one preference but we assume that they have one dominant preference when these preferences conflict.

Table 2
Share of subjects revealing a consistent preference by treatment.

Preferences	No Mistakes		Maximum Likelihood		
	IQ	Random	IQ	Random	Difference
Maximum information	0.409	0.538	0.655***	0.893***	−0.238***
			(0.059)	(0.043)	(0.072)
Salience of feedback	0.327	0.057	0.345***	0.000	0.345***
			(0.059)	(0.001)	(0.059)
Positive skewness	0.000	0.038	0.000	0.107	−0.107**
					(0.045)
Variance of error term (γ)			0.492***	0.585***	
			(0.046)	(0.050)	
Not classified	0.264	0.368			
N	110	106	110	106	

Notes: The table shows the share of subjects who choose feedback modes consistent with the respective preference. Maximum information prescribes $A \succ B, C, D, E$. Positive skewness prescribes $B \succ A; A \succ C; E \succ A$. Salience of feedback means to seek explicit positive feedback but avoid explicit negative feedback and prescribes $B \succ A; A \succ C, E; B \succ E$. In No Mistakes, we calculate the share without allowing for implementation mistakes. In Maximum Likelihood, we estimate the share allowing for implementation noise γ. The share of "Positive skewness" is implied since the shares have to sum to 1. Standard errors in parentheses are bootstrapped with 1,000 replications. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

First, consider the strategy to maximize the informativeness of information structures. There are fewer subjects in the IQ treatment who consistently maximize the informativeness than in the random treatment. When using the finite mixture model, the share increases from 40.9 to 65.5 percent in IQ and from 53.8 to 89.3 percent in the random treatment, suggesting that many subjects aim to maximize the informativeness of signals but make mistakes.[10] The treatment difference of 23.8 percent is statistically significant.

Second, there are significantly more subjects in the IQ than in the random treatment who exhibit a preference for reducing the salience of negative feedback but not of positive feedback. While more than 30 percent of subjects follow such a preference in IQ, there are few to none who are categorized as such in the random treatment. For the salience of feedback, we find the largest treatment difference, at a statistically significant 34.5 percentage points.

Finally, there are only a few subjects who consistently choose feedback modes that are positively skewed. In particular, there are no subjects in the IQ and 3.8 percent of subjects in the random treatment. In the finite mixture model, the share in the random treatment increases to 10.7 percent. However, note that it only requires three consistent choices to be attributed to this preference (in contrast to four for the other preferences). Overall, the results do not suggest that subjects choose positively skewed feedback to protect their ego.

To sum up, the within-individual choices support our findings from the individual information structure choices. When looking at internally consistent choice patterns, subjects in IQ prefer less informative feedback modes as well as modes in which positive feedback is explicit but negative feedback less salient. Moreover, we find few subjects who have a preference for positive skewness but, if anything, the share is higher in the random than in the IQ treatment.

3.1.2. Heterogeneity in information structure selection

We investigate heterogeneity in information structure selection based on self-reported information preferences, gender, prior beliefs, and performance in the IQ quiz. We focus on the baseline choice as it combines all three potential channels of ego protection: informativeness, skewness, and salience.

Information preference scale. In the post-experimental questionnaire, subjects are asked to answer the Information Preference Scale (IPS) by Ho et al. (2021).[11] The scale consists of 13 scenarios from different domains (health, consumer finance, personal life) in which an individual can receive potentially unpleasant information (the items are shown in Online Appendix D). The respondent has to indicate her preference on a 4-point scale from "Definitely don't want to know" to "Definitely want to know".

In the first column of Table 3, we regress the choice of Mode B in the baseline choice on the IQ treatment indicator, an indicator if a subject scores above the median in the IPS scale, and an interaction of the two variables. The statistically significant interaction term implies that individuals, who are information seeking according to the IPS scale, are less likely to avoid information and choose less salient negative feedback in the IQ treatment. Moreover, the IPS scale is not associated with information structure choice in the random treatment, as illustrated by the small and statistically insignificant main coefficient of the IPS variable.

[10] In Online Appendix C, we exploit the order in which feedback modes are presented and find suggestive evidence that the difference is, to a large degree, driven by subjects who do not understand that Mode E reveals less information than Mode A.

[11] Ho et al. (2021) design and validate the Information Preference Scale in order to measure an individual's trait to obtain or avoid information. They show that it correlates strongly with related scales and that it even predicts information avoidance in the political domain, a domain not represented in the scale itself.

Table 3
Heterogeneity in baseline choice.

	(1) IPS Scale	(2) Gender	(3) Prior Beliefs	(4) IQ Score
IQ treatment	0.323***	0.243**	0.196**	0.182**
	(0.083)	(0.107)	(0.073)	(0.091)
IPS (Info seeking)	0.064			
	(0.074)			
IPS (Info seeking) × IQ treatment	−0.259**			
	(0.117)			
Female		−0.121		
		(0.079)		
IQ treatment × Female		−0.064		
		(0.127)		
Low prior			−0.060	
			(0.073)	
IQ treatment × Low prior			−0.028	
			(0.125)	
Low IQ				0.018
				(0.074)
IQ treatment × Low IQ				0.020
				(0.120)
Constant	0.140***	0.244***	0.191***	0.159***
	(0.046)	(0.068)	(0.048)	(0.056)
R2	0.075	0.076	0.054	0.049
N	216	216	216	216

Notes: The table shows heterogeneous treatment effects of the IQ treatment on the choice of Mode B in the baseline choice by IPS Scale, Gender, Prior beliefs, and IQ score. IPS (Info seeking) is an indicator for subjects who score in the top half of the Information Preference Scale (Ho et al., 2021). Low prior indicates if a subject reports a prior below 50 and Low IQ indicates if a subject has not scored more than the median in the IQ quiz. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Gender. In the second column of Table 3, we regress the choice of Mode B in the baseline choice on the IQ treatment indicator interacted with a dummy variable that indicates whether a subject is female. However, since the interaction term is small and far from statistically significant, we conclude that there is no evidence for heterogeneous treatment effects by gender in the experiment.

Prior beliefs. In the third Column of Table 3, we investigate whether the effect of the ego-relevant treatment is different depending on the reported prior beliefs. "Low Prior" indicates that an individual reports a prior that is lower than 50%, while the reference group reports a prior above or equal to 50%. We do not observe that subjects with priors below 50% are affected differently by the treatment compared to individuals with priors above 50%.[12]

IQ score. Finally, in the last column of Table 3, we analyze whether there is a differential treatment effect for subjects who performed better or worse in the IQ quiz. "Low IQ" indicates that a subject has correctly solved the same number or fewer of the Raven matrices than the median (12). The statistically insignificant and small interaction term suggests that there is no differential treatment effect depending on the performance in the IQ task (i.e., their measured cognitive ability).

3.1.3. Information selection and overconfidence

After subjects made the five information structure choices, one of these choices was randomly selected and the corresponding decision of the subject was implemented. Before analyzing belief updating in detail, we check descriptively how the selected information structure relates to the development of overconfident beliefs about the IQ rank.

In Fig. 4, we plot how the average beliefs in the IQ treatment evolve, depending on the feedback mode from which subjects receive signals. Although the sample becomes quite small when conditioning on the selected feedback mode (n=66 in Mode A and n=26 in Mode B), some interesting patterns emerge. We observe that in the IQ treatment, subjects are *overconfident* in their prior beliefs: on average, they report a likelihood higher than 50% of being in the top half of the IQ distribution, both in Mode A (t-test, $p = 0.003$) and in Mode B (t-test, $p = 0.001$).[13] Subjects in Mode A and Mode B start out with similar priors, but while the average beliefs of subjects in Mode A seem to converge toward 50% after receiving signals, the beliefs in Mode B remain constant.[14]

[12] Although not statistically significant, the main coefficient of the prior is negative, which is consistent with confirmation-seeking behavior. In Section 4, we discuss confirmation-seeking behavior in more detail.

[13] Benoît et al. (2015) show that true overconfidence is observed when the average stated probability to be in the top 50% of the distribution is significantly larger than 50%.

[14] In fact, after three rounds of feedback, subjects in Mode A have an average belief that is statistically indistinguishable from 50% (t-test, $p = 0.806$), while subjects in Mode B have an average belief that is still significantly larger than 50% (t-test, $p = 0.002$). The difference between Mode A and B in final posterior minus prior is statistically significant (Welch's unequal variances t-test, $p = 0.022$; Wilcoxon exact rank-sum test, $p = 0.007$).

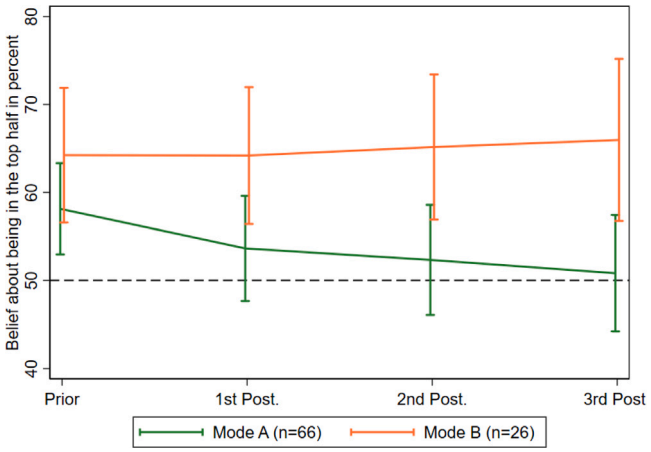


Fig. 4. Beliefs before and after signals by feedback mode (endogenous/IQ treatment). (Notes: The plot shows the average prior and posterior beliefs from the endogenous/IQ treatment for the selected feedback mode. Subjects are overconfident, if the average belief about being in the top half is larger than 50 percent. The whiskers represent 95% confidence intervals.)

These results suggest that selecting an information structure that is less informative and makes negative feedback less salient indeed leads to maintaining overconfident beliefs in the IQ treatment. Moreover, in Online Appendix F, we show that this pattern is not observed in the random treatment. These descriptive patterns motivate us to investigate belief updating by information structure in more detail in the next section.

3.2. Belief updating

We aim to investigate how subjects process the signals they receive from different feedback modes. First, we introduce the estimation framework for analyzing potential deviations from Bayesian updating. Then, we analyze updating in both the endogenous and exogenous treatment. While subjects in the endogenous treatment receive signals from the self-selected feedback mode, subjects in the exogenous treatment are allocated to a feedback mode.

3.2.1. Estimation framework

We follow the approach developed by Grether (1980) and Möbius et al. (2014) to estimate updating behavior. The framework allows individuals to put different weights on the prior and the positive or negative signals they may receive, nesting the Bayesian benchmark as a special case. In the case of binary signals, Bayes rule can be written in the following form:

$$logit(\mu_t) = logit(\mu_{t-1}) + \mathbb{1}(s_t = pos) ln(LR_{pos}) + \mathbb{1}(s_t = neg) ln(LR_{neg}) \tag{1}$$

where μ_t is the belief at time t and LR_k is the likelihood ratio of the signal $s_t = k \in \{pos, neg\}$.

To estimate the model, we add an error term and attach coefficients to the prior and to the positive and negative signals an individual receives:

$$\begin{aligned} logit(\mu_{it}) \; = \; & \delta^{\text{prior}} logit(\mu_{i,t-1}) \\ & + \beta^{\text{pos}} \mathbb{1}(s_{it} = pos) ln(LR_{pos}) + \beta^{\text{neg}} \mathbb{1}(s_{it} = neg) ln(LR_{neg}) + \epsilon_{it} \end{aligned} \tag{2}$$

where δ^{prior} captures the weight of the prior while β^{pos} and β^{neg} measure the responsiveness to positive and negative signals, respectively. ϵ_{it} captures non-systematic errors in updating. A Bayesian updater would exhibit $\delta^{\text{prior}} = \beta^{\text{pos}} = \beta^{\text{neg}} = 1$.

The estimated β coefficients in the random treatment (i.e., where the state is not ego-relevant) inform us how updating behavior deviates from the Bayesian benchmark. Following the literature on belief updating, we interpret these deviations as being driven by "cognitive" biases, while the differential updating across ego-relevant and non-ego relevant states allows us to identify "motivated" biases in processing information. In particular, we test whether there is asymmetric updating ($\beta^{pos} \neq \beta^{neg}$). For example, subjects in the ego-relevant treatment might have a desire to put more weight on positive rather than negative signals when forming their posteriors.

Moreover, we investigate whether there are cognitive or motivated biases across information structures. Hence, we investigate whether the properties of an information structure have implications for updating behavior.

Table 4
Updating across feedback modes and treatments (exogenous treatment).

	(1) IQ Mode A	(2) IQ Mode B	(3) Random Mode A	(4) Random Mode B
δ^{prior}	0.814**	0.896***	0.716***	0.779***
	(0.085)	(0.046)	(0.066)	(0.061)
β^{Pos}	0.623***	0.482***	0.839	0.758
	(0.120)	(0.077)	(0.127)	(0.174)
β^{Neg}	0.568***	0.244***	0.767*	0.938
	(0.124)	(0.088)	(0.125)	(0.142)
Wald p-value ($\beta^{\text{Pos}} = \beta^{\text{Neg}}$)	0.715	0.028	0.685	0.325
R2	0.640	0.781	0.697	0.730
N	165	165	171	186
Chow p-value ($\delta_{\text{A}}^{\text{prior}} = \delta_{\text{B}}^{\text{prior}}$)	0.398		0.480	
Chow p-value ($\beta_{\text{A}}^{\text{Pos}} = \beta_{\text{B}}^{\text{Pos}}$)	0.321		0.710	
Chow p-value ($\beta_{\text{A}}^{\text{Neg}} = \beta_{\text{B}}^{\text{Neg}}$)	0.035		0.367	

Notes: The table shows regression results of Eq. (2) in the exogenous treatment, separately by IQ and random treatment and Modes A and B. We regress the posterior belief on the prior belief and the signal's likelihood ratio, interacted with an indicator if the signal is positive or negative. The model does not include a constant. Stated beliefs of 100 are replaced with 99 and beliefs of 0 with 1, respectively. Standard errors clustered on subject level in parentheses. Stars indicate whether the coefficient is statistically different from 1. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

3.2.2. Updating in the endogenous treatment

First, we briefly consider belief updating in the endogenous treatment. Here, subjects receive signals from the feedback mode they chose in the randomly selected choice situation. We restrict the analysis to Modes A and B to allow comparisons with the exogenous treatment.

A word of caution may be necessary here as the analysis of belief updating in the endogenous treatment can only be seen as suggestive for two main reasons: First, subjects self-select into feedback modes, that is, subjects in Mode A and B may not be comparable. Second, there are relatively few subjects who end up receiving signals from Mode B. In the IQ treatment, 26 subjects update according to Mode B, and in the random treatment there are only 19 subjects (in contrast, 66 subjects in the IQ treatment and 61 subjects in the random treatment end up in Mode A).[15]

Table A.5 in the appendix presents the estimation results of Eq. (2) separately by treatment and feedback mode. In Mode A, we do not find evidence for asymmetric updating in either treatment since the coefficients β^{Pos} and β^{Neg} are of similar magnitude and we cannot reject the null hypothesis that they are equal (Wald tests, $p = 0.620$ in IQ and $p = 0.928$ in random). In Mode B, in contrast, we observe that β^{Pos} is larger than β^{Neg}, both in the IQ and the random treatment. However, as noted above, due to the small number of subjects in Mode B, we lack the statistical power to reject the null hypothesis that the coefficients are equal. The minimum detectable difference in coefficients is 0.598 for the IQ treatment and 0.622 in the random treatment (for $p < 0.05$ at 80% power), which is well above the differences that we find (0.349 in IQ and 0.204 in random).[16]

To have more statistical power and to exclude self-selection into feedback modes, we now turn our focus to belief updating in the exogenous treatment.

3.2.3. Updating in the exogenous treatment

In the exogenous treatment, subjects are randomly assigned to Modes A or B. In the IQ treatment, 55 (55) subjects update according to Mode A (B), and in the random treatment 57 (62) subjects update according to Mode A (B).

In Table 4, we display the estimation results for the exogenous treatment. As before, we do not find evidence for asymmetric updating in Mode A. In both IQ and random treatment the coefficients β^{Pos} and β^{Neg} are of similar magnitude and are not significantly different from each other (Wald tests, $p = 0.715$ in IQ and $p = 0.685$ in random).

However, we find asymmetric updating in Mode B in the IQ treatment: when information is ego-relevant and negative signals are less salient (i.e., framed as gray signals), subjects update less in response to negative than in response to positive signals. The updating coefficient for positive signals is about twice as large as for negative signals and the coefficients differ significantly (Wald test, $p = 0.028$). However, this is not the case when feedback is not ego-relevant: in the random treatment, subjects update, if anything, more in response to negative, less salient feedback, but the difference in coefficients is not statistically significant (Wald test, $p = 0.325$).

[15] Part of the reason for this imbalance is the fact that Mode A features in four choice situations and Mode B only in two, such that the probability is twice as high that a choice is drawn, in which Mode A could have been selected.

[16] To calculate the minimum detectable difference (MDD), we recode the independent variables such that one coefficient indicates the difference between the positive and negative updating coefficients. The p-value on this variable is equivalent to the Wald test p-value reported in the bottom of Table A.5. The standard error of this coefficient times 2.8 gives us the minimum detectable difference that would be necessary to find a statistically significant coefficient at the 0.05 level with 80% power. The idea behind the factor 2.8 is the following: For the t-test to be significant, the coefficient has to be 1.96 standard errors away from zero. To have a 80% probability of drawing a t-value greater than 1.96, the "true" t-statistic has to be 1.96+0.84=2.8, with 0.84 being the inverse normal at the 80th percentile (see, e.g., Ioannidis et al., 2017).

Table 5
Differences in final posterior beliefs between IQ and random treatment using nearest-neighbor matching (exogenous treatment).

	(1) Mode A	(2) Mode B
1 Neighbor	−2.609	11.746**
	(5.976)	(5.743)
2 Neighbors	−0.490	11.971**
	(5.615)	(5.668)
5 Neighbors	0.813	11.334**
	(5.385)	(5.684)
N	107	103

Notes: The table shows average treatment effects for final posterior beliefs between IQ and random treatment. The analysis is based on nearest neighbor matching on priors with replacement. We require subjects to be matched to at least 1, 2, or 5 neighbors by minimizing the absolute distance in priors. To ensure common support, we trimmed 5 observations in Mode A (1 from IQ and 4 from random) and 14 observations in Mode B (14 from random), which were above the maximum prior or below the minimum prior in the respective other treatment. Standard errors in parentheses are based on Abadie and Imbens (2006). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In the exogenous treatment, we have more statistical power compared to the endogenous treatment. However, to detect more subtle differences in updating, we would need a larger sample size. The minimum detectable difference in coefficients at 80% power is 0.422 (IQ) and 0.494 (random) in Mode A, while it is 0.295 (IQ) and 0.506 (random) in Mode B. It is notable that we are relatively well powered for detecting a difference in the IQ treatment in Mode B, but that we have less statistical power to detect a difference in the random treatment. However, since our subjects in the random treatment update, if anything, *more* in response to negative feedback, we still interpret it as suggestive evidence in favor of a motivated bias in updating (instead of a cognitive bias).

This interpretation is also supported by results from Chow tests in the bottom of Table 4. Subjects update significantly less in response to negative feedback in Mode B when signals are ego-relevant ($p = 0.035$). However, when information is not ego-relevant, the difference is not statistically significant ($p = 0.367$).

The previous analysis studies updating in a Bayesian framework that takes prior beliefs and signal informativeness into account. However, since it is derived from Bayes' rule it imposes a lot of structure. To control for differences in prior beliefs between treatments in a more flexible way, we follow a nearest-neighbor matching strategy. We compute the treatment difference in final posterior beliefs after matching subjects in IQ and control based on their prior beliefs. First, we trim the prior belief distribution to ensure common support between treatments.[17] Next, individuals are matched to at least 1, 2, or 5 neighbors in the other treatment by minimizing the distance in priors. The average treatment effect is calculated by comparing the average final posterior in one treatment to the posteriors of the neighbors in the other treatment.

Table 5 presents the results of the matching exercise. In Mode A, we observe that after three rounds of signals there are no significant differences in posterior beliefs between individuals in the IQ and random treatment. However, in Mode B, in which negative feedback is less salient, subjects in the IQ treatment are 11.33 to 11.97 percentage points more likely to believe that they are in the top half at the end of the experiment. Put differently, subjects in Mode A who start out with similar priors end up with similar posteriors in the IQ and random treatment. Only in Mode B do they arrive at different posteriors, depending on whether feedback is ego-relevant.

Taken together, the results suggest that subjects' belief formation is driven by motivated reasoning, as subjects update asymmetrically only in the IQ treatment. However, while individuals might have a preference for forming confident beliefs about themselves, our results show that this does not always seem to be possible. In fact, our results suggest that asymmetric updating arises only in the information structure that features negative signals that are less salient and, thus, easier to misperceive. In the next section, we further discuss and interpret our experimental results.

4. Discussion

Our experimental findings show systematic differences across treatments in the way subjects choose between different feedback modes. We interpret these results as evidence for preferences over information structures driven by motivated reasoning (individuals' desire to have high opinions of themselves and self-enhancement motives).

We now discuss whether treatment differences could alternatively be explained by cognitive biases. In doing so, we follow the key features that distinguish motivated thinking from cognitive failures according to Bénabou and Tirole (2016).

[17] For example, in Mode B the lowest prior in the IQ treatment is 20, while there are 14 observations in the random treatment with a prior below 20 (see Fig. A.1(b)). We drop these 14 observations as they have no counterpart in the IQ treatment. Trimming is described as an important pre-processing step, e.g., in Imbens (2015).

4.1. Endogenous directionality

A distinct feature of motivated reasoning is that it is directed toward some end (for example, the belief that one is highly intelligent). In contrast, general failures in cognitive reasoning that depend on one's prior beliefs, like confirmation-seeking and contradiction-seeking behavior, can go in either direction.

Confirmation-seeking behavior, or confirmation bias, is the tendency to search for, interpret, favor, and recall information in a way that confirms preexisting beliefs.[18] On the contrary, contradiction-seeking behavior is the tendency to favor information that goes against one's prior beliefs. In a non-ego-relevant setting, Charness et al. (2021) find that many individuals choose information structures that confirm their prior beliefs, but relatively few subjects can be classified as contradiction-seeking.[19]

In our experiment, confirmation-seeking could potentially explain treatment differences in information structure selection, as individuals in the IQ treatment have slightly higher priors on average. For instance, confirmation-seeking subjects with high priors could prefer Mode B since it is less informative about the negative state. However, even when controlling for prior beliefs, we see that subjects in the ego-relevant treatment are more likely to choose Mode B compared to those in the random treatment. In fact, all treatment differences hold when controlling for prior beliefs in regressions (Table A.2) and when employing a matching strategy on priors (Table A.3).

Finally, it is relevant to note that, in the informativeness choice, the treatment difference cannot be explained by confirmation- or contradiction-seeking behavior. Taken together, these results show that confirmation bias falls short of explaining the treatment differences in the information selection stage of our experiment.

4.2. Bounded rationality

4.2.1. Cognitive ability

Cognitive errors in processing and interpreting information depend on individuals' cognitive ability and analytical sophistication. That is, more able and more analytically sophisticated agents are less prone to cognitive biases. On the other hand, motivated reasoning does not necessarily imply a negative correlation.

By taking into account participants' abstract reasoning ability, measured by their IQ scores, our results do not seem to be driven by cognitive ability. Two pieces of evidence support this conclusion. First, individuals across treatment groups do not vary in their cognitive ability.[20] Second, our treatment differences in feedback mode selection are robust to controlling for individuals' cognitive ability (see Table A.2 in the appendix).

4.2.2. Confusion

Our experimental design features some rather complex elements and thus might have affected participants' understanding. To tackle this we paid close attention to the way we presented the experimental instructions. We also ensured understanding by letting participants answer comprehension questions (see screenshots in Figures G.2, G.4, and G.15 in the online appendix). Moreover, participant confusion is unlikely to affect our conclusions as it is held constant across treatments.

Furthermore, if we look at the informativeness choice, in which the information structures only differ in the likelihood of receiving an uninformative signal and where we held constant their skewness and framing, we see that less than five percent of subjects in the random treatment make the suboptimal choice. This finding is reassuring as it implies that subjects understood our experimental instructions and were sufficiently incentivized to make well thought-out decisions.

4.3. Emotional involvement: Heat vs light

Bénabou and Tirole (2016) argue that motivated beliefs evoke and trigger emotional reactions, whereas cognitively driven biases do not. While we do not measure participants' emotions in the experiment, we find some suggestive evidence for emotions arising in the IQ treatment in the free-text questions.

In the post-experimental questionnaire, we asked subjects to explain how they chose between feedback modes. In the IQ treatment, we find that many subjects report a "gut-level" response to select the more positive-looking feedback and avoid explicit negative (red) signals.[21] In Online Appendix E, we conduct a quantitative content analysis of the free-text responses. We enlisted three research assistants, who had no information about the treatment variation, to code the free-text responses according to a

[18] See Nickerson (1998) for a review of the psychological literature on confirmation bias.

[19] In the random treatment, we find some support for confirmation-seeking as a cognitive bias. In the baseline choice we find that subjects with a high prior are slightly more likely to choose Mode B (although the difference is not statistically significant) and in the baseline reversed choice they are less likely to choose Mode C (t-test, $p = 0.068$). However, in the skewness over framing choice, subjects with high priors are slightly less likely to choose Mode E (t-test, $p = 0.238$), speaking against confirmation-seeking behavior. In general, our experiment is not designed to provide conclusive evidence regarding confirmation-seeking behavior since the information structures vary both in framing and informativeness. It is an interesting question for future research how confirmation-seeking individuals trade off informativeness and salience of feedback.

[20] Mean IQ score in the IQ treatment is 11.34, while it is 11.41 in the random treatment. We cannot reject the H0 that IQ scores are significantly different between IQ and random (t-test, $p = 0.882$; Wilcoxon rank-sum test, $p = 0.780$).

[21] Subjects who chose Mode B in the IQ treatment stated, for example, "I always chose the feedback that looked the more positive. For example, with the most green dots/the less red dots", "My mind told me to avoid red and go for green", "I took a preference for those featuring green, motivational I guess?", etc.

pre-defined codebook (shown in Online Appendix E.1). A coding is counted if at least two out of the three research assistants coded a response in the same way.

In Table E.1 in the online appendix, we find that subjects in the IQ treatment are more likely to state that they preferred the feedback mode that featured more green signals (Fisher's exact test, $p = 0.001$) and less red signals (Fisher's exact test, $p = 0.060$) compared to the random treatment. Subjects in the random treatment are more likely to state that they made their selection according to the feedback's informativeness (Fisher's exact test, $p = 0.013$). We do not find a statistically significant treatment difference for any of the other explanations (e.g., ease of understanding feedback, confirmation of prior belief). In Table E.2, we find that the stated preference for more green/less red signals and for more information is indeed correlated with observed behavior.

5. Conclusion

This paper documents an experiment to study individuals' preferences toward information structures and subsequent belief updating when information is ego-relevant or not. Our results from the information selection stage show that individuals in the ego-relevant treatment are more likely to choose feedback modes that are less informative and that make negative feedback less salient, compared to the control. The results from the belief updating stage indicate that individuals' belief formation is asymmetric (i.e., individuals respond more to positive news than to negative news), but only in the ego-relevant condition and when the negative feedback is less salient, and therefore easier to misperceive. These findings are consistent with individuals selectively choosing information structures that allow them to protect their ego.

Our results suggest that while individuals might have a motivated tendency to process information differently depending on its valence, their ability to do so depends on the "reality constraints" in the environment. We provide evidence that the framing and salience of feedback is one dimension of "reality constraints" that limits individuals' ability to nurture motivated beliefs. Zimmermann (2020) shows that raising the incentives to recall negative feedback can constitute another "reality constraint". Similarly, Drobner (2022) shows that subjects, who are informed that uncertainty about the ego-relevant state will be resolved at the end of the experiment are less likely to update in a motivated way. This raises a question for future research regarding other dimensions in the environment that may constrain individuals from maintaining motivated beliefs and how consciously people engage in motivated thinking.

We find that subjects update symmetrically when feedback is made explicit, but that they update asymmetrically when negative feedback is less salient. In light of the mixed evidence on asymmetric updating in the literature, it would be interesting to study in more detail how the propensity to update asymmetrically depends on the framing and style of feedback. Moreover, future research could investigate how subjects choose between information structures, in which no asymmetric updating was found.

Taken together, our findings suggest that motivated information selection might play an important role in producing overconfident beliefs. Indeed, it is often the case that in our everyday life, we can choose our information sources and exert some control over the type of signals that we receive. This can help us protect ourselves from having to adjust our ego-relevant beliefs downwards. Further research could investigate in real-world settings how preferences over information structures impact how individuals sort into feedback environments, for example, in educational contexts.

While overconfidence is costly in some settings, it may be beneficial in others, for example, for motivational purposes or when trying to persuade others. Therefore, it depends on the context whether institutions should restrict or enhance individuals' ability to select their feedback sources. Future studies could investigate how much discretion over feedback sources is optimal in educational or professional environments.

Appendix A. Additional tables and figures

See Tables A.1–A.5 and Fig. A.1

Table A.1
Descriptive statistics.

	Endogenous		Exogenous	
	IQ	Random	IQ	Random
Age (Mean)	20.973	21.830	20.236	20.168
	(2.960)	(4.095)	(2.933)	(2.304)
Female (Share)	0.664	0.613	0.618	0.529
	(0.475)	(0.489)	(0.488)	(0.501)
Native English speakers (Share)	0.427	0.377	0.364	0.370
	(0.497)	(0.487)	(0.483)	(0.485)
Studying (Share)	0.964	0.972	0.955	0.975
	(0.188)	(0.167)	(0.209)	(0.157)
First year students (Share)	0.455	0.481	0.545	0.504
	(0.500)	(0.502)	(0.500)	(0.502)
IQ puzzles solved (Mean)	11.336	11.406	10.964	10.924
	(3.425)	(3.397)	(3.038)	(3.051)
N	110	106	110	119

Notes: The table shows descriptive statistics of the experimental dataset. Standard deviations are in parentheses.

Table A.2
Information structure choices controlling for covariates.

	(1)	(2)	(3)	(4)	(5)	(6)
Baseline	0.194***	0.191***	0.178***	0.193***	0.189***	0.164***
	(0.059)	(0.060)	(0.059)	(0.059)	(0.058)	(0.061)
Informativeness	0.135***	0.138***	0.132***	0.134***	0.132***	0.128***
	(0.042)	(0.045)	(0.043)	(0.042)	(0.042)	(0.045)
Framing	−0.265***	−0.266***	−0.243***	−0.265***	−0.263***	−0.239***
	(0.064)	(0.066)	(0.065)	(0.065)	(0.065)	(0.068)
Skewness over framing	−0.166***	−0.130**	−0.163***	−0.165***	−0.167***	−0.122**
	(0.057)	(0.059)	(0.057)	(0.057)	(0.058)	(0.058)
Baseline reversed	−0.052	−0.038	−0.049	−0.053	−0.052	−0.038
	(0.050)	(0.052)	(0.050)	(0.050)	(0.051)	(0.053)
Demographics		✓				✓
Prior			✓			✓
IQ score				✓		✓
Risk					✓	✓
N	216	216	216	216	216	216

Notes: The table shows the coefficient of the IQ treatment dummy in the regression of the feedback mode choice on the respective covariates. Demographics comprises controls for gender, age, years of study, and whether English is the native language. The risk measure is by Gneezy and Potters (1997). Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3
Information structure choices using nearest-neighbor matching by prior.

	(1) 1 Neighbor	(2) 2 Neighbors	(3) 5 Neighbors
Baseline	0.227***	0.225***	0.189***
	(0.065)	(0.067)	(0.062)
Informativeness	0.136***	0.142***	0.135***
	(0.050)	(0.049)	(0.050)
Salience	−0.250***	−0.238***	−0.219***
	(0.069)	(0.068)	(0.065)
Skewness over framing	−0.159***	−0.145**	−0.150***
	(0.058)	(0.057)	(0.055)
Baseline reversed	−0.076	−0.070	−0.058
	(0.049)	(0.048)	(0.047)
n	215	215	215

Notes: The table shows average treatment effects for information structure choices between IQ and random treatment. The analysis is based on nearest neighbor matching on priors with replacement. We require subjects to be matched to at least 1, 2, or 5 neighbors by minimizing the absolute distance in priors. To ensure common support, we trimmed 1 observation in the random treatment, which was below the minimum prior in the IQ treatment. Standard errors in parentheses are based on Abadie and Imbens (2006). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4
Information structure choices applying multiple testing correction.

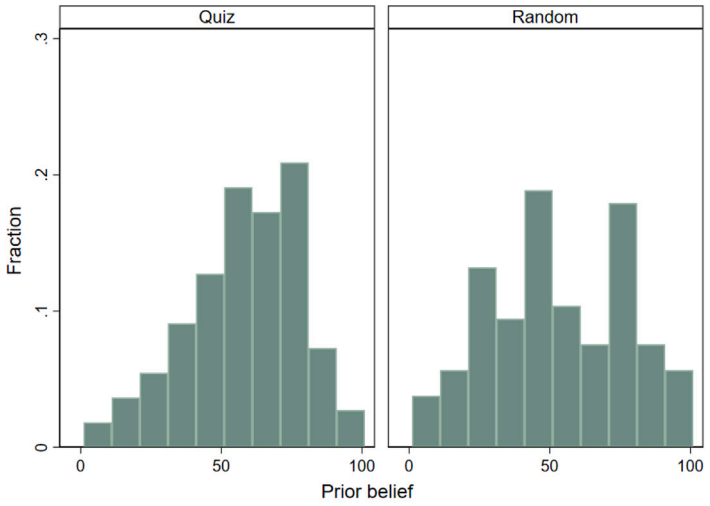
	Difference	*p*-values			
		Unadjusted	MHT	Holm	Bonferroni
Baseline	0.194	0.001	0.004	0.004	0.006
Informativeness	0.135	0.002	0.005	0.005	0.009
Salience	−0.265	0.000	0.000	0.001	0.001
Skewness over framing	−0.166	0.003	0.007	0.007	0.017
Baseline reversed	−0.052	0.300	0.300	0.300	1.000

Notes: The table shows treatment differences in information structure choices between IQ and random treatment, together with unadjusted *p*-values and *p*-values corrected for multiple hypothesis testing. All *p*-values are calculated using the Stata package mhtexp with 10,000 bootstrap replications (List et al., 2019). MHT uses the procedure proposed by List et al. (2019) that builds on Romano and Wolf (2010) to control the familywise error rate. Holm multiplies the smallest unadjusted *p*-value by the number of hypotheses, the second smallest by the number of hypotheses minus 1 etc. Bonferroni multiplies all unadjusted *p*-values by the number of hypotheses.

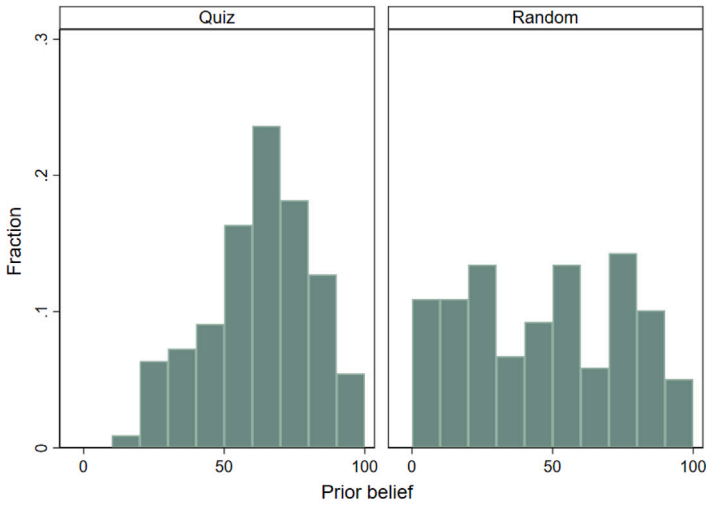
Table A.5
Updating across feedback modes and treatments (endogenous treatment).

	(1) IQ Mode A	(2) Random Mode A	(3) IQ Mode B	(4) Random Mode B
δ^{prior}	0.767***	0.650***	0.828	0.832
	(0.076)	(0.070)	(0.107)	(0.163)
β^{Pos}	0.603***	0.781	0.541**	0.408***
	(0.135)	(0.157)	(0.198)	(0.178)
β^{Neg}	0.527***	0.763*	0.191***	0.205***
	(0.111)	(0.131)	(0.084)	(0.272)
Wald p-value ($\beta^{\text{Pos}} = \beta^{\text{Neg}}$)	0.620	0.928	0.114	0.372
R2	0.684	0.651	0.809	0.646
N	198	183	78	57

Notes: The table shows regression results of Eq. (2) in the endogenous treatment, separately by IQ and random treatment and Modes A and B. We regress the posterior belief on the prior belief and the signal's likelihood ratio, interacted with an indicator if the signal is positive or negative. The model does not include a constant. Stated beliefs of 100 are replaced with 99 and beliefs of 0 with 1, respectively. Standard errors clustered on subject level in parentheses. Stars indicate whether the coefficient is statistically different from 1. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



(a) Endogenous treatment



(b) Exogenous treatment

Fig. A.1. Prior beliefs in deciles by treatment. (Notes: The plot shows the distribution of prior beliefs to be in the top half of the distribution by treatment.)

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2021.104007.

References

Abadie, A., Imbens, G.W., 2006. Large sample properties of matching estimators for average treatment effects. Econometrica 74 (1), 235–267.

Ahn, T., Arcidiacono, P., Hopson, A., Thomas, J.R., 2019. Equilibrium grade inflation with implications for female interest in STEM majors, NBER Working Paper 26556.

Azrieli, Y., Chambers, C., Healy, P., 2018. Incentives in experiments: A theoretical analysis. J. Polit. Econ. 126 (4), 1472–1503.

Barron, K., 2021. Belief updating: Does the 'good-news, bad-news' asymmetry extend to purely financial domains? Exp. Econ. 24, 31—58.

Bénabou, R., Tirole, J., 2002. Self-confidence and personal motivation. Q. J. Econ. 117 (3), 871–915.

Bénabou, R., Tirole, J., 2016. Mindful economics: The production, consumption, and value of beliefs. J. Econ. Perspect. 30 (3), 141–164.

Benoît, J.-P., Dubra, J., Moore, D.A., 2015. Does the better-than-average effect show that people are overconfident? two experiments. J. Eur. Econom. Assoc. 13 (2), 293–329.

Blanco, M., Engelmann, D., Koch, A., Normann, H., 2010. Belief elicitation in experiments: Is there a hedging problem? Exp. Econ. 13 (4), 412–438.

Buser, T., Gerhards, L., van der Weele, J., 2018. Responsiveness to feedback as a personal trait. J. Risk Uncertain. 56 (2), 165–192.

Camerer, C., Lovallo, D., 1999. Overconfidence and excess entry: An experimental approach. Amer. Econ. Rev. 89 (1), 306–318.

Charness, G., Dave, C., 2017. Confirmation bias with motivated beliefs. Games Econom. Behav. 104, 1–23.

Charness, G., Oprea, R., Yuksel, S., 2021. How do people choose between biased information sources? Evidence from a laboratory experiment. J. Eur. Econom. Assoc. 19 (3), 1656–1691.

Chen, D.L., Schonger, M., Wickens, C., 2016. oTree—An open-source platform for laboratory, online, and field experiments. J. Behav. Exp. Finance 9, 88–97.

Chew, S.H., Huang, W., Zhao, X., 2020. Motivated false memory. J. Polit. Econ. 128 (10), 3913–3939.

Chopra, F., Haaland, I., Roth, C., 2019. Do people value more informative news?. https://www.cesifo.org/DocDL/cesifo1_wp8026.pdf (retrieved 01/12/2022).

Coutts, A., 2019. Good news and bad news are still news: Experimental evidence on belief updating. Exp. Econ. 22 (2), 369–395.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. J. Eur. Econom. Assoc. 9 (3), 522–550.

Drobner, C., 2022. Motivated beliefs and anticipation of uncertainty resolution. Am. Econ. Rev.: Insights forthcoming.

Drobner, C., Goerg, S.J., 2021. Motivated belief updating and rationalization of information. https://www.econstor.eu/handle/10419/243173 (retrieved 11/22/2021).

Eil, D., Rao, J.M., 2011. The good news-bad news effect: asymmetric processing of objective information about yourself. Am. Econ. J. Microecon. 3 (2), 114–138.

Enke, B., 2020. What you see is all there is. Q. J. Econ. 153 (3), 1363–1398.

Enke, B., Schwerter, F., Zimmermann, F., 2020. Associative memory and belief formation. https://benjamin-enke.com/pdf/Memory.pdf (retrieved 10/29/2020).

Epstein, L., Halevy, Y., 2019. Hard-to-interpret signals. https://yoram-halevy.faculty.economics.utoronto.ca/wp-content/uploads/SignalAmbiguity.pdf (retrieved 07/26/2019).

Ertac, S., 2011. Does self-relevance affect information processing? Experimental evidence on the response to performance and non-performance feedback. J. Econ. Behav. Organ. 80 (3), 532–545.

Exley, C.L., Kessler, J.B., 2019. Motivated errors. https://www.dropbox.com/s/fqb32hb1g7e6vrm/ExleyKessler_MotivatedErrors.pdf (retrieved 07/26/2019).

Falk, A., Zimmermann, F., 2016. Beliefs and utility: Experimental evidence on preferences for information. IZA Discussion Paper No. 10172.

Fryer, R.G., Harms, P., Jackson, M.O., 2019. Updating beliefs when evidence is open to interpretation: Implications for bias and polarization. J. Eur. Econom. Assoc. 17 (5), 1470–1501.

Ganguly, A., Tasoff, J., 2016. Fantasy and dread: the demand for information and the consumption utility of the future. Manage. Sci. 63 (12), 4037–4060.

Garz, M., Sood, G., Stone, D.F., Wallace, J., 2020. The supply of media slant across outlets and demand for slant within outlets: Evidence from US presidential campaign news. Eur. J. Political Econ. 63 (101877).

Gentzkow, M., Shapiro, J.M., 2010. What drives media slant? Evidence from US daily newspapers. Econometrica 78 (1), 35–71.

Gneezy, U., Potters, J., 1997. An experiment on risk taking and evaluation periods. Q. J. Econ. 112 (2), 631–645.

Golman, R., Hagmann, D., Loewenstein, G., 2017. Information avoidance. J. Econ. Lit. 55 (1), 96–135.

Gottfredson, L.S., Deary, I.J., 2004. Intelligence predicts health and longevity, but why? Curr. Dir. Psychol. Sci. 13 (1), 1–4.

Gotthard-Real, A., 2017. Desirability and information processing: An experimental study. Econom. Lett. 152, 96–99.

Grether, D.M., 1980. Bayes rule as a descriptive model: The representativeness heuristic. Q. J. Econ. 95 (3), 537–557.

Grossman, Z., Owens, D., 2012. An unlucky feeling: Overconfidence and noisy feedback. J. Econ. Behav. Organ. 84 (2), 510–524.

Ho, E., Hagmann, D., Loewenstein, G., 2021. Measuring information preferences. Manage. Sci. 67 (1), 126–145.

Hoffman, M., 2016. How is information valued? Evidence from framed field experiments. Econ. J. 126, 1884–1911.

Holm, S., 1979. A simple sequentially rejective multiple test procedure. Scand. J. Stat. 6 (2), 65–70.

Imbens, G.W., 2015. Matching methods in practice. Three examples. J. Hum. Resour. 50 (2), 373–419.

Ioannidis, J.P.A., Stanley, T.D., Doucouliagos, H., 2017. The power of bias in economics research. Econ. J. 127, F236–F265.

Jin, G.Z., Luca, M., Martin, D., 2021. Is no news (perceived as) bad news? An experimental investigation of information disclosure. Am. Econ. J. Microecon. 13 (2), 141–173.

Karlsson, N., Loewenstein, G., Seppi, D., 2009. The ostrich effect: Selective attention to information. J. Risk Uncertain. 38 (2), 95–115.

Karni, E., 2009. A mechanism for eliciting probabilities. Econometrica 77 (2), 603–606.

Köszegi, B., 2006. Ego utility, overconfidence, and task choice. J. Eur. Econom. Assoc. 4 (4), 673–707.

Kuhnen, C.M., 2015. Asymmetric learning from financial information. J. Finance 70 (5), 2029–2062.

List, J.A., Shaikh, A.M., Xu, Y., 2019. Multiple hypothesis testing in experimental economics. Exp. Econ. 22, 773–793.

Malmendier, U., Tate, G., 2005. CEO overconfidence and corporate investment. J. Finance 60 (6), 2661–2700.

Masatlioglu, Y., Orhun, A.Y., Raymond, C., 2017. Intrinsic information preferences and skewness. http://econweb.umd.edu/~masatlioglu/Masatlioglu_Orhun_Raymond.pdf (retrieved 10/01/2019).

Mele, A.R., 2001. Self-Deception Unmasked. Princeton University Press, Princeton, NJ.

Möbius, M., Niederle, M., Niehaus, P., Rosenblat, T., 2014. Managing self-confidence: Theory and experimental evidence. https://web.stanford.edu/~niederle/Mobius.Niederle.Niehaus.Rosenblat.paper.pdf (retrieved 07/26/2019).

Montanari, G., Nunnari, S., 2019. Audi alteram partem: An experiment on selective exposure to information. http://www.salvatorenunnari.eu/mn_selectexposure.pdf (retrieved 12/15/2019).

Nickerson, R.S., 1998. Confirmation bias: A ubiquitous phenomenon in many guises. Rev. Gen. Psychol. 2 (2), 175–220.

Nielsen, K., 2020. Preferences for the resolution of uncertainty and the timing of information. J. Econom. Theory 189, 105090.

Oster, E., Shoulson, I., Dorsey, E., 2013. Limited life expectancy, human capital and health investments. Amer. Econ. Rev. 103 (5), 1977–2002.

Romano, J.P., Wolf, M., 2010. Balanced control of generalized error rates. Ann. Statist. 38, 598–633.
Sabot, R., Wakeman-Linn, J., 1991. Grade inflation and course choice. J. Econ. Perspect. 5 (1), 159–170.
Saccardo, S., Serra-Garcia, M., 2020. Cognitive flexibility or moral commitment? Evidence of anticipated belief distortion. https://ssrn.com/abstract=3676711 (retrieved 08/02/2021).
Schwardmann, P., van der Weele, J., 2019. Deception and self-deception. Nat. Hum. Behav. 3 (10), 1055–1061.
Sicherman, N., Loewenstein, G., Seppi, D.J., Utkus, S.P., 2015. Financial attention. Rev. Financ. Stud. 29 (4), 863–897.
Sternberg, R.J., Grigorenko, E.L., Bundy, D.A., 2001. The predictive value of IQ. Merrill-Palmer Q. 47 (1), 1–41.
Von Hippel, W., Trivers, R., 2011. The evolution and psychology of self-deception. Behav. Brain Sci. 34 (1), 1.
Zimmermann, F., 2014. Clumped or piecewise? Evidence on preferences for information. Manage. Sci. 61 (4), 740–753.
Zimmermann, F., 2020. The dynamics of motivated beliefs. Amer. Econ. Rev. 110 (2), 337–361.