Motivated Belief Updating and Rationalization of Information*

Christoph Drobner† Sebastian J. Goerg‡

January 30, 2024

Abstract

We study belief updating about relative performance in an ego-relevant task. Manipulating the perceived ego-relevance of the task, we show that subjects substantially overweight positive information relative to negative information because they derive direct utility from holding positive beliefs. This finding provides a behavioral explanation why and how overconfidence can evolve in the presence of objective information. Moreover, we document that subjects, who receive more negative information, downplay the ego-relevance of the task. These findings suggest that subjects use two alternative strategies to protect their ego when presented with objective information.

Keywords: Motivated beliefs, Optimistic belief updating, Overconfidence, Direct belief utility, Bayes' rule

JEL Codes: C91, D83, D84

*This experiment was pre-registered at the AEA RCT Registry (AEARCTR-0005121) and received IRB approval from the German Association for Experimental Economic Research e.V. (GfeW). We thank Yves Le Yaouanq, Kai Barron, Boon-Han Koh, and seminar participants at the ESA Meetings, IAREP/SABE Conference, BEWIP Seminar, BGPE Workshop, SPUDM Conference, GfeW Conference, YEM Conference, Matterhorn Symposium and VfS Conference for helpful comments and suggestions. We gratefully acknowledge financial support from the ExperimenTUM.

†Technical University Munich (TUMCS), UniDistance Suisse; Email: christoph.drobner@tum.de

‡Technical University Munich (TUMCS, SOM); Email: s.goerg@tum.de

1 Introduction

In standard decision theory, beliefs are unaffected by people's hopes and desires; instead new information is processed in a Bayesian manner. This Bayesian model is difficult to reconcile with empirical evidence on overconfidence, which often leads to sub-optimal decision-making. Examples include excessive entry in competitive markets (Camerer and Lovallo, 1999), distorted investment and merger decisions of managers and CEOs (Malmendier and Tate, 2005, 2008), and polarization in politics (Ortoleva and Snowberg, 2015). Furthermore, overconfident CEOs exhibit reduced responsiveness to performance feedback due to their optimistic financial outlook (Schumacher et al., 2020), while entrepreneurs' overconfident forecasts are associated with an increased risk of firm failures (Invernizzi et al., 2017). Whereas overconfident CEOs tend to explore novel technological avenues (Galasso and Simcoe, 2011), there's evidence that overconfidence in product selection can lead to inferior outcomes compared to random choices (Feiler and Tong, 2022). Thus, overconfidence is a common phenomenon, but a remaining puzzle is why and how overconfidence can evolve and persist in the presence of objective information.

We use a novel experimental design to provide causal evidence for the hypothesis that people overweight positive information relative to negative information because they derive direct utility from holding positive beliefs. Specifically, we study belief updating behavior in a *single event* (i.e., relative performance in an IQ test) and manipulate the perceived ego-relevance of this event (i.e., how much people care about their relative performance in the IQ test). Our results show that subjects overweight positive information relative to negative information when the perceived ego-relevance of the underlying event is increased. This finding provides a behavioral foundation for the persistence of overconfidence in ego-relevant settings despite the presence of objective information.

Previous experiments tested this *optimistic belief updating* hypothesis by comparing updating behavior between *different events*, which vary in their level of ego-relevance (Buser et al., 2018; Coffman et al., 2023; Coutts, 2019; Eil and Rao, 2011; Ertac, 2011; Grossman and Owens, 2012; Möbius et al., 2022). For instance, Coutts (2019) compares updating behavior in beliefs about other's (ego-neutral) versus own (ego-relevant) IQ scores. Taken together, this experimental evidence has produced a variety of mixed results with evidence in favor of and against the optimistic belief updating hypothesis (see Benjamin, 2019; Barron, 2021; Drobner, 2022, for reviews). One fundamental challenge of the methodology used in this literature is that *different events* vary in many dimensions, potentially confounding the causal relationship between ego-relevance and belief updating. For instance, ego-relevant and ego-neutral events may differ in the size and ambiguity of prior beliefs, making it difficult to distinguish optimistic belief updating from prior-biased inference such as base-rate neglect (see Barron, 2021, for a discussion). One goal of this paper is to resolve this identification problem by introducing exogenous variation in ego-relevance within a *single event* while holding other properties of the updating task fixed.

In our pre-registered experiments[1], subjects perform an IQ test and we elicit their beliefs about

[1]Pre-registered in the AEA RCT Registry (AEARCTR-0005121). Table A1 in Online Appendix A maps the pre-analysis plan to our paper.

the probability of scoring in the top half of the performance distribution. After the elicitation of initial beliefs, we provide subjects with different information about the importance of IQ tests. In the *High-Ego* treatment, subjects read an article containing scientific evidence arguing that IQ tests are a strong predictor for intelligence and future productivity. In the *Low-Ego* treatment, subjects read an article containing scientific evidence suggesting that IQ tests are not a valid measure for the complex phenomenon of intelligence. As a result, we argue that subjects in the *High-Ego* treatment perceive the IQ test as being more ego-relevant and consequently derive more direct belief utility than subjects in the *Low-Ego* treatment.[2] After the treatment manipulation, we provide subjects with two binary signals and elicit posterior beliefs about their relative performance in the IQ test. These signals are noisy but informative and we explicitly inform subjects that the true state of the world will not be resolved.

Overall, our results provide several important insights. First, we show that subjects update their beliefs more optimistically as direct belief utility increases. We provide several pieces of evidence in support of this finding: (*i*) we document more optimistic final beliefs in the *High-Ego* treatment compared to the *Low-Ego* treatment, (*ii*) we compare updating behavior to the Bayesian benchmark and show that subjects in the *High-Ego* treatment update their beliefs optimistically, while there is no such optimistic updating in the *Low-Ego* treatment, (*iii*) we show evidence for motivated errors as the propensity of updates that go in the opposite direction of the Bayesian prediction increases for negative signals in the *High-Ego* treatment, while it is independent of the valence of signals in the *Low-Ego* treatment. Taken together, these results provide causal evidence for the optimistic belief updating hypothesis and confirm a broad range of theoretical models with direct belief utility (Bénabou and Tirole, 2002; Möbius et al., 2022; Caplin and Leahy, 2019).[3] Moreover, these results complement the finding of a contemporaneous project by Kozakiewicz (2022), who introduces exogenous variation in ego-relevance by comparing updating behavior in response to either a realized signal or potential realizations of signals. In line with our results, Kozakiewicz (2022) documents a positive effect of direct belief utility on self-serving signal interpretations.

Second, we show that subjects alter their perceptions ex post about the ego-relevance of the IQ test depending on the valence of signals received. Exploiting the noisy signal structure, we provide causal evidence that subjects consider the IQ test as being less ego-relevant and they indicate exerting less effort in the IQ test as the number of negative signals increases. This finding complements evidence presented by Van der Weele and Siemens (2020) who find similar patterns in a self-signaling experiment, where subjects downplay the importance of doing well in a task if they receive negative performance feedback. Interestingly, we find that this ex-post rationalization of information is predominantly driven by the minority of subjects with pessimistic updating patterns

[2]Direct belief utility describes a hedonic value of holding a particular belief such as deriving ego utility (Köszegi, 2006) or anticipatory utility (Brunnermeier and Parker, 2005) from holding positive beliefs. To this end, direct belief utility is distinct from belief utility in the Bayesian model, which is purely instrumental and indirectly derived by making the best possible decision based on accurate beliefs.

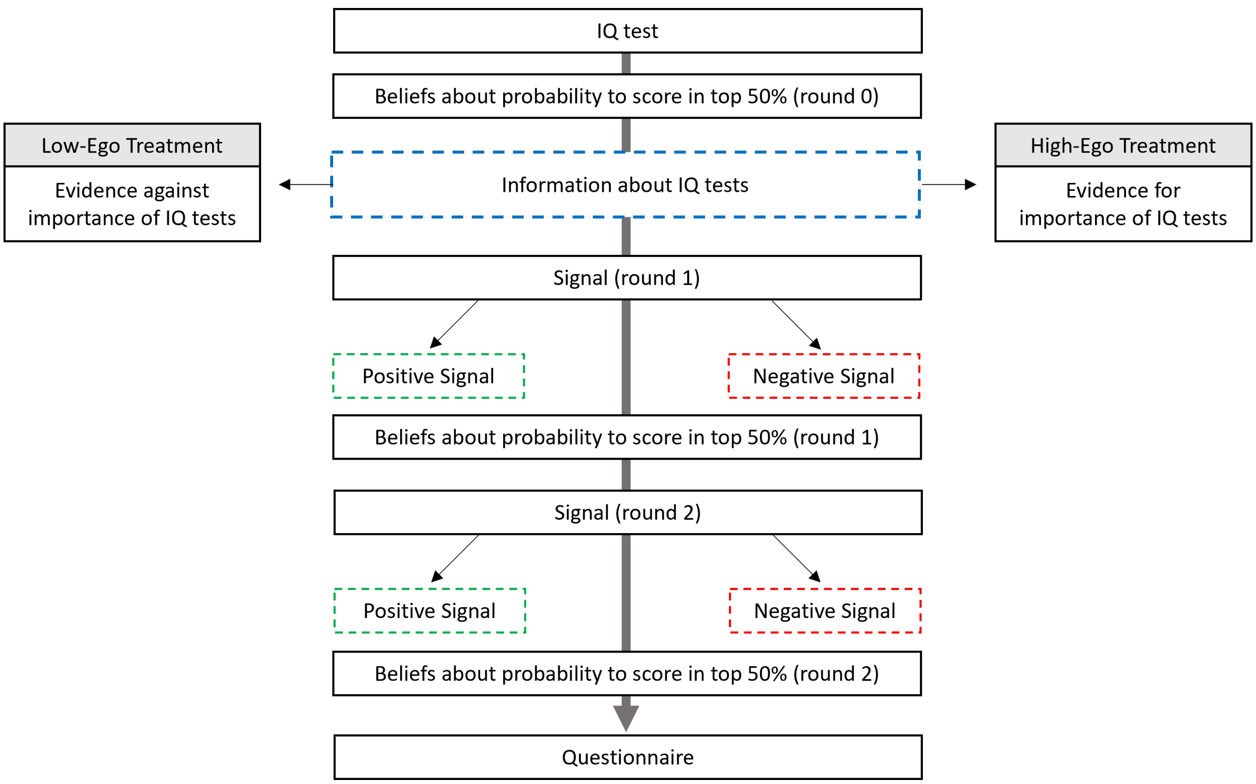
[3]Other behavioral predictions of this type of models include motivated memory (Zimmermann, 2020) and motivated information avoidance (Golman et al., 2017). In this paper, we focus on optimistic belief updating in the short run but the intuition of our results also applies to these related behavioral mechanisms.

in the belief updating task.

2 Experimental Design

Figure 1 illustrates our experimental design. To estimate the causal effect of direct belief utility on belief updating, the experiment requires i) a belief updating task and ii) exogenous variation in subjects' perceived ego-relevance of the underlying event. We capture these features by implementing the following experimental methodology: First, subjects performed an IQ-related test. Second, we elicited subjects' initial beliefs about their relative performance in the IQ test. Third, using a between-subjects design, we provided subjects with different information about the importance of IQ tests. Fourth, subjects received noisy but informative signals. Fifth, we elicited subjects' posterior beliefs. The last two stages were repeated such that subjects received two binary signals and reported their posterior beliefs twice.

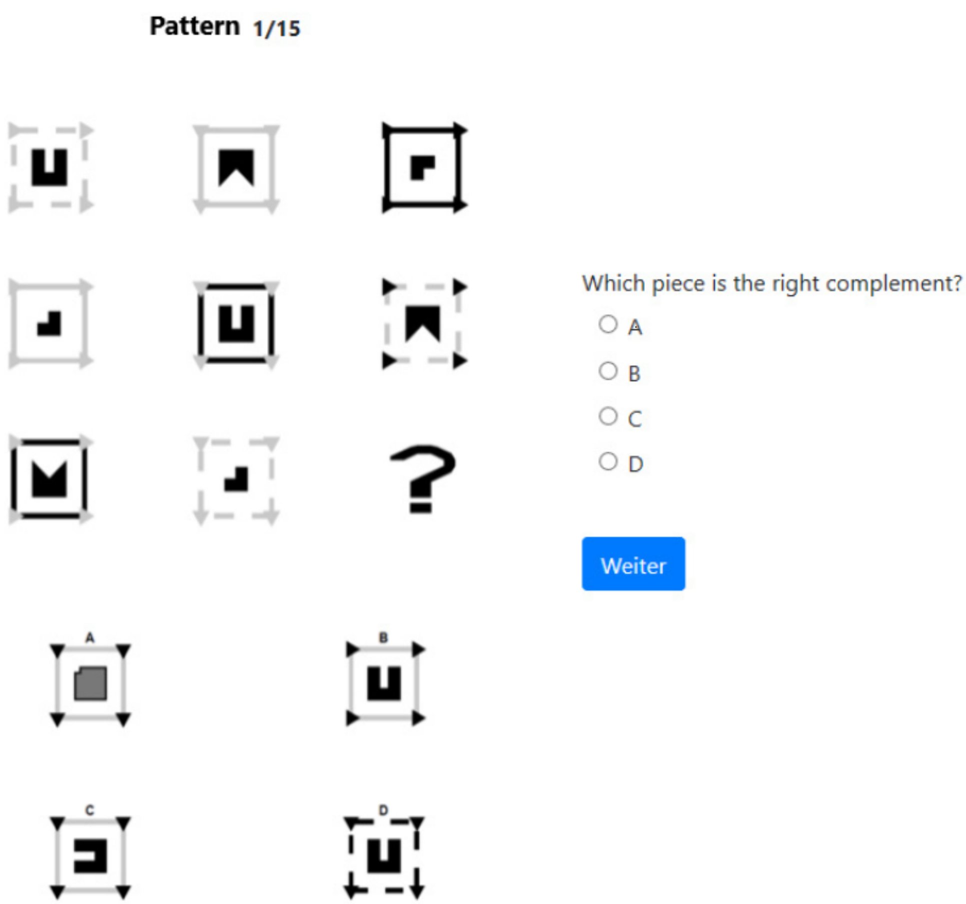
Figure 1: Experimental Design



One important aspect of the experimental design is that the treatment information was randomly assigned *after* the prior belief elicitation to rule out the possibility that other prior related errors such as base-rate neglect confound treatment differences in belief updating patterns. In addition, we explicitly informed subjects that the true state of the world remains uncertain during the course of the experiment. We implement this design feature as Drobner (2022) demonstrates that optimistic belief updating vanishes when subjects expect the immediate resolution of uncertainty. We now provide a detailed description of the different parts of the experiment.[4]

IQ test. Subjects performed a quiz with puzzles from Civelli and Deck (2018) that are similar to the Raven Progressive Matrix test, which is commonly used as an IQ test. Subjects saw a set of 15 puzzles and had 30 seconds each to choose the correct answer from a set of four possible answers as illustrated in Figure 2. Subjects received a piece-rate payment that varied between €0.1 and €0.5 for each correct answer in the test. The size of the payments was randomly selected for each question to obfuscate the relationship between payments and IQ test performance.

Figure 2: IQ Test Question



Belief elicitations. We elicited subjects' beliefs about the probability of scoring in the top half of the IQ test performance distribution in the session at three points at a time. In round 0, we elicited subjects' initial beliefs before receiving information. In round 1, we elicited subjects' beliefs after

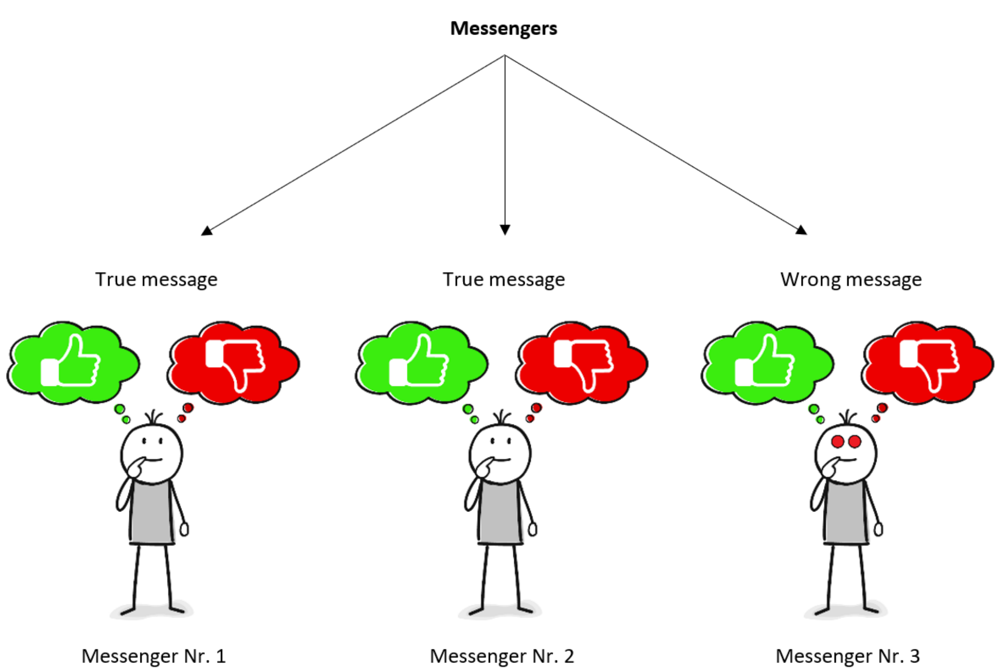
[4]Full experimental instructions are provided in Online Appendix D.

receiving the treatment information and the first binary signal about their relative performance. In round 2, we elicited subjects' beliefs after the receipt of the second binary signal about their relative performance. To incentivize truthful reporting, we implemented a variation of the Becker-DeGroot-Marschak (BDM) mechanism (Karni, 2009). We asked subjects to state the probability x which makes them indifferent between winning a monetary prize of €2 with probability x and winning the same monetary prize if they indeed performed in the top half of the performance distribution within the session. This mechanism ensures that truthful reporting maximizes expected utility from payments regardless of subjects' risk preferences (Trautmann and van de Kuilen, 2015).

Information about IQ tests. In a between-subjects design, we asked subjects to read an article that contains simplified and shortened information summarizing scientific papers with evidence about the importance of IQ tests. Subjects in the *High-Ego* treatment received an article with scientific evidence in favor of IQ tests as predictors for success and well-being. Specifically, the article highlighted strong correlations between IQ and ego-relevant future life outcomes such as income and health. Subjects in the *Low-Ego* treatment received an article with scientific evidence against the validity of IQ tests as a measure for intelligence.

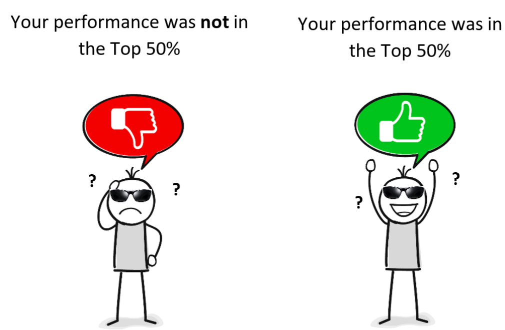
To incentivize careful reading of the articles, subjects were told that they would receive a question about the content of the article at some later stage in the experiment, providing the opportunity to win €2 if they answer the question correctly. Specifically, we asked subjects in the final questionnaire to choose the correct name of authors cited in these articles.

Figure 3: Signal Generating Process



Signals. Subjects received two binary signals containing either positive signals or negative signals about their relative performance in the IQ test. The signals were noisy but informative with an accuracy level $q = 66.67\%$. Following Coutts (2019), subjects were told that one messenger is randomly chosen from a set of three messengers to transmit the signal as illustrated in Figure 3. While two messengers always transmit a truthful signal, the third messenger always lies. The signal realization of both positive signals and negative signals is illustrated in Figure 4. While transmitting the signal, the messengers wore sunglasses such that individuals could not infer the reliability of the signal.

Figure 4: Signal Realization



Questionnaire. We asked subjects to rate the importance of their performance in the IQ test for their study and job success on a seven-point Likert scale. The ratings serve as proxies for subjects' perceived ego-relevance of the IQ test. In addition, we elicited subjects' self-reported effort in the IQ test on a seven-point Likert scale. We concluded the experiment with questions about the comprehensibility of the instructions and standard demographics.

Setting and sample size. The experiments were conducted with subjects from the laboratory for economic experiments at the Technical University Munich (ExperimenTUM) using both offline and online sessions due to the outbreak of COVID-19. We programmed the computerized experiments with the experimental software *otree* by Chen et al. (2016). Recruitment was automated using the online recruitment software ORSEE by Greiner (2015). A total of 419 subjects finished the experiment in 16 sessions (2 offline and 14 online).[5] The number of subjects in a session varied between 20 and 30.

3 Framework

In this section, we provide a stylized model of motivated beliefs in the context of our experimental setting to derive our main hypothesis. The framework follows Engelmann et al. (2023) by modeling

[5]Overall, 451 subjects participated, but 32 students dropped out during the online experiments.

the benefits and costs of belief distortions as a function of direct belief utility, instrumental belief utility, and cognitive costs of belief distortions. In our experiment, subjects form beliefs about the probability of scoring in the top half of the IQ test within the session. After observing a binary signal, subjects form beliefs $\hat{\mu}$ that may deviate from objective Bayesian beliefs μ.

In our framework, subjects choose the optimal belief $\hat{\mu}$, trading off the benefits and costs of belief distortions:

$$U = \underbrace{\alpha\hat{\mu}}_{Direct\,belief\,utility} + \underbrace{\frac{1}{2}(1 + 2\hat{\mu}\mu - \hat{\mu}^2)M}_{Instrumental\,belief\,utility} - \underbrace{\beta(\mu - \hat{\mu})^2}_{Cognitive\,costs} \tag{1}$$

Direct belief utility. The first term describes that subjects derive direct utility from beliefs $\hat{\mu}$ through motives such as ego-utility (Köszegi, 2006), self-esteem (Bénabou and Tirole, 2002) or anticipatory utility (Brunnermeier and Parker, 2005). The parameter α captures the perceived ego-relevance of the underlying event.[6]

Instrumental belief utility. The second term describes the monetary incentives for reporting beliefs $\hat{\mu}$ under the BDM mechanism that we used in the experiment.[7] The BDM mechanism implies that subjects maximize their chance of winning a monetary price M at $\hat{\mu} = \mu$.[8]

Cognitive costs of belief distortions. The third term describes that deviations of beliefs $\hat{\mu}$ from objective Bayesian beliefs μ are associated with cognitive costs of distorting reality (Bracha and Brown, 2012; Coutts et al., 2020).

Maximizing equation 1 results in the following optimal belief $\hat{\mu}$:

$$\hat{\mu} = \mu + \frac{\alpha}{M + 2\beta} \tag{2}$$

If $\alpha = 0$, subjects form beliefs according to Bayes' rule ($\hat{\mu} = \mu$). If $\alpha > 0$, subjects derive positive direct belief utility, resulting in inflated posterior beliefs in comparison to Bayesian beliefs ($\hat{\mu} > \mu$). In our experiment, we manipulate α by providing polarizing scientific information about the importance of IQ tests in *High-Ego* and *Low-Ego* treatments, respectively ($\alpha^{High-Ego} > \alpha^{Low-Ego}$). Consequently, we expect subjects in the *High-Ego* treatment to process information more optimistically than subjects in the *Low-Ego* treatment.

[6] For simplicity, we assume linearity in direct and instrumental belief utility because we only need monotonicity but not risk neutrality or other properties of von Neumann-Morgenstern utility theory to derive our main hypothesis.

[7] The formula is derived from Engelmann et al. (2023) and Hill (2017).

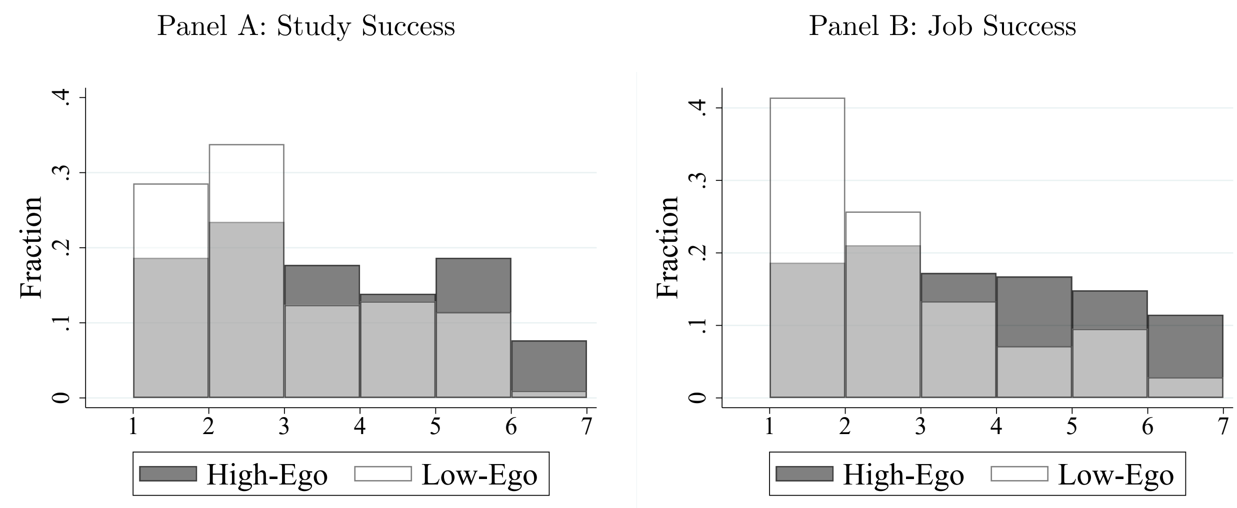
[8] For simplicity, we abstract from the fact that individuals may derive instrumental utility from the beliefs they hold about their relative IQ from decisions they make outside the laboratory because it does not affect the qualitative predictions of the framework.

4 Results

The results of our experiment are contingent on the assumption that subjects perceive the IQ test as being more ego-relevant in the *High-Ego* treatment compared to the *Low-Ego* treatment. To perform a manipulation check, we compare subjects' self-reported importance of the IQ test for study and job success measured on a Likert scale (1-very low importance, 7-very high importance) between *High-Ego* and *Low-Ego* treatments.

Figure 5 illustrates the ratings for study success (Panel A) and job success (Panel B) separately for *High-Ego* and *Low-Ego* treatments. It shows that subjects in the *High-Ego* treatment in fact rate the importance of the IQ test higher than subjects in the *Low-Ego* treatment for both study success (Wilcoxon rank-sum test, $p < 0.001$) and job success (Wilcoxon rank-sum test, $p < 0.001$).[9]

Figure 5: Manipulation Check



4.1 Aggregate Beliefs

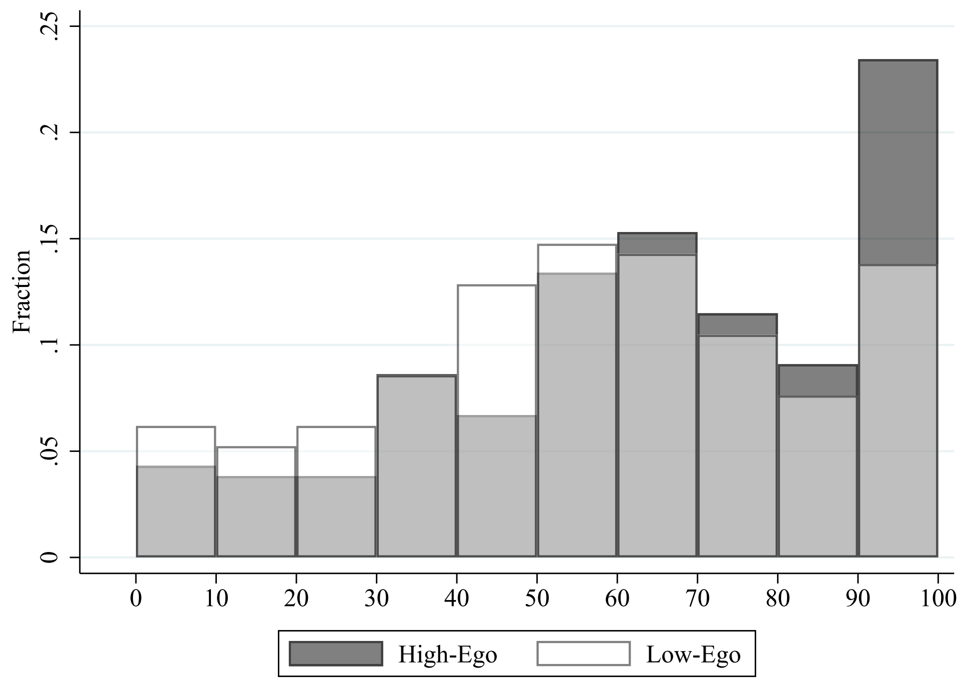
The main outcome variables from our experiment are subjects' beliefs about scoring in the top half of the IQ test within the session. Initial beliefs, measured *before* subjects received the treatment information about the importance of IQ tests, exhibit signs of overconfidence. Pooling data from both treatments, initial beliefs of being in the top half are on average 55.7% and, thus, significantly above 50% (Wilcoxon signed-rank test, $p < 0.001$). The same result holds when testing within the two treatments separately. In both treatments, initial beliefs are significantly above 50% (Wilcoxon signed-rank test, both $p < 0.05$). As expected, the distributions of initial beliefs do not differ significantly between *High-Ego* and *Low-Ego* treatments (Kolmogorov-Smirnov test, $p = 0.647$).

To study the effect of ego-relevance induced direct belief utility on belief updating we compare final beliefs between *High-Ego* and *Low-Ego* treatments. Final beliefs are measured *after* subjects

[9]The responses to the self-reported importance of the IQ test might be prone to experimenter demand effects. However, in Online Appendix B, we discuss why experimenter demand effects are only of minor concern for the main results of our experiment.

received the treatment information about the importance of IQ tests and the two noisy signals about their actual performance. Figure 6 depicts the distributions of final beliefs and shows that subjects in the *High-Ego* treatment form more optimistic final beliefs than subjects in the *Low-Ego* treatment (Wilcoxon rank-sum test, $p = 0.004$).

Figure 6: Distributions of Final Beliefs - High-Ego versus Low-Ego



In Table 1, we quantify the average treatment effect on final beliefs, accounting for potentially confounding imbalances between treatments. Specifically, in column 1 of Table 1 we regress final beliefs on a treatment dummy (1 if High-Ego, 0 if Low-Ego), controlling for initial beliefs, gender, and IQ test scores.[10] The estimated coefficient for the treatment dummy documents that final beliefs in the *High-Ego* treatment are on average 4.81 percentage points more optimistic than final beliefs in the *Low-Ego* treatment ($p = 0.026$).

One alternative interpretation of the treatment effect on final beliefs is that the treatment induces a level shift in beliefs rather than a difference in updating behavior. This conjecture would imply that we see similar treatment differences in final beliefs independent of the signal distribution. In column 2-4 of Table 1 we exploit the heterogeneity in signal distributions and estimate the treatment effects on final beliefs for different distributions of signals. Specifically, we run the regression analysis separately for subjects who received two negative signals, two mixed signals, or two positive signals. The results provide suggestive evidence that the treatment effect is mostly driven by the subjects who received two positive signals. This indicates that a mere level

[10]Online Appendix C1 shows that initial beliefs, gender, and IQ test scores do not differ significantly between treatments.

Table 1: Final Beliefs - High-Ego versus Low-Ego

Dependent Variable: Final Belief	(1) Full Sample	(2) Two Negative Signals	(3) Mixed Signals	(4) Two Positive Signals
High-Ego	4.807**	3.667	0.563	8.074**
	(2.155)	(3.363)	(2.091)	(3.238)
Initial Belief	0.708***	0.716***	0.700***	0.572***
	(0.055)	(0.096)	(0.070)	(0.086)
Female	-2.316	2.641	-0.484	-8.936***
	(2.179)	(3.367)	(2.180)	(3.146)
IQ Test Score	1.520***	0.019	-0.238	0.203
	(0.489)	(0.896)	(0.494)	(0.791)
Constant	2.554	-8.065	22.939***	42.028***
	(4.726)	(6.762)	(5.251)	(8.985)
Observations (Subjects)	419	109	194	116
R^2	0.407	0.445	0.512	0.425

Notes:
(i) Analysis uses OLS regressions with robust standard errors in parentheses.
(ii) Stars reflect significance levels, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

shift in beliefs that is independent of signals cannot explain the treatment effect on final beliefs.[11]

Result 1 *Initial beliefs are overconfident. Final beliefs in the High-Ego treatment are more optimistic than final beliefs in the Low-Ego treatment.*

4.2 Comparison to Bayesian Benchmark

We now extend the analysis and compare belief updating behavior to the normative benchmark of Bayes' rule using a structural empirical framework (Möbius et al., 2022). This structural framework provides several additional insights. First, in Section 4.1 we have shown that subjects in the *High-Ego* treatment form more optimistic final beliefs than subjects in the *Low-Ego* treatment, but this analysis remained agnostic about whether the belief updating process is generally optimistic or pessimistic in comparison to the Bayesian benchmark. Second, the structural framework allows a richer description of updating behavior because we include updating in both rounds after observing each binary signal. Third, it implicitly takes initial beliefs into account and hence controls for any between-subject differences in initial beliefs. Fourth, it allows a direct comparison of subjects' responsiveness to positive and negative signals, accounting for other deviations from Bayes' rule such as conservatism or base-rate neglect.

Following Möbius et al. (2022), we use a logit transformation to derive an augmented version of Bayes' rule with indicators for positive signals $I(s_t = P)$ and negative signals $I(s_t = N)$,

[11] In Online Appendix C3 we expand this discussion in the context of the structural framework used in the following section.

respectively:

$$logit(\hat{\mu}_t) = logit(\hat{\mu}_{t-1}) + I(s_t = P)log(\frac{q_P}{1-q_P}) + I(s_t = N)log(\frac{q_N}{1-q_N}) \tag{3}$$

Adding parameters δ, β_P, and β_N allows us to estimate the following empirical model, which nests Bayes' rule as a special case ($\delta = \beta_P = \beta_N = 1$):

$$logit(\hat{\mu}_{it}) = \delta logit(\hat{\mu}_{i,t-1}) + \beta_P I(s_{it} = P)log(\frac{q_P}{1-q_P}) + \beta_N I(s_{it} = N)log(\frac{q_N}{1-q_N}) + \epsilon_{it} \tag{4}$$

The parameters β_P and β_N represent subjects' responsiveness to positive and negative signals, respectively. Conservatism implies that subjects update too little in response to both positive and negative signals ($\beta_s < 1 \;\; \forall s \in \{P, N\}$). Optimistic belief updating is identified if subjects update their beliefs more strongly upon the receipt of positive signals compared to negative signals ($\beta_P > \beta_N$).

Table 2: Belief Updating

	(1)	(2)	(3)
Dependent Variable: Logit Belief	Pooled	High-Ego	Low-Ego
δ	0.877***	0.841***	0.899***
	(0.030)	(0.055)	(0.032)
β_P	0.716***	0.796***	0.642***
	(0.048)	(0.070)	(0.067)
β_N	0.557***	0.477***	0.619***
	(0.051)	(0.073)	(0.068)
Observations	715	348	367
R^2	0.703	0.677	0.728
$\beta_P - \beta_N$	0.159	0.318	0.023
P-value ($\beta_P = \beta_N$)	0.016	0.001	0.798
P-value [Chow test] for ($\beta_P - \beta_N$) (Regressions 2 and 3)			0.025

Notes:
(i) Analysis uses OLS regressions with robust standard errors clustered at the individual level.
(ii) Analysis includes two observations (belief updates) for each subject but excludes observations with boundary beliefs because the logit is not defined for 0 or 1.
(iii) Stars reflect significance levels, $*p < 0.10$, $**\,p < 0.05$, $***p < 0.01$.

Table 2 shows that the estimated coefficients for subjects' responsiveness to signals are significantly below one, providing evidence for conservatism. Pooling data from both treatments shows that subjects update their beliefs more strongly upon the receipt of positive signals compared to negative signals ($\beta_P > \beta_N,\ p = 0.016$). More importantly, however, this asymmetry in responsiveness to positive signals and negative signals is almost entirely driven by subjects in the *High-Ego* treatment. While subjects in the *High-Ego* treatment are substantially more responsive to positive signals ($\beta_P^{High-Ego} > \beta_N^{High-Ego}$, $p = 0.001$), there is no such optimistic updating in the *Low-Ego* treatment ($\beta_P^{Low-Ego} > \beta_N^{Low-Ego}$, $p = 0.798$). This treatment difference in the level of optimistic belief updating is confirmed by a Chow-test ($\beta_P^{High-Ego} - \beta_N^{High-Ego} > \beta_P^{Low-Ego} - \beta_N^{Low-Ego}$, $p = 0.025$).[12]

Result 2 *Subjects update their beliefs optimistically. Subjects in the High-Ego treatment update their beliefs more optimistically than subjects in the Low-Ego treatment.*

Table 3: Motivated Errors

Dependent Variable	Zero Update		Wrong Update	
	(1)	(2)	(3)	(4)
	High-Ego	Low-Ego	High-Ego	Low-Ego
Negative Signal	0.279**	0.054	0.436**	-0.028
	(0.131)	(0.118)	(0.203)	(0.223)
IQ Test Score	0.050	0.010	-0.097*	0.008
	(0.036)	(0.028)	(0.054)	(0.045)
Constant	-1.030***	-0.333	-0.742	-1.424***
	(0.373)	(0.283)	(0.497)	(0.463)
Observations	395	398	284	255
Pseudo R^2	0.011	0.001	0.067	0.000

Notes:
(i) Zero or wrong updates are dummy variables which are equal to 1 if subjects do not update in a given round or update in the wrong direction.
(ii) To provide a clean comparison to correct updates, the regression analysis of zero updates excludes wrong updates and the regression analysis of wrong updates excludes zero updates.
(iii) Analysis uses Probit regressions with clustered standard errors at the individual level in parentheses.
(iv) Stars reflect significance levels, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

In line with previous literature, 19.8% of our subjects never update their beliefs and 10.5% update their beliefs at least once in the opposite direction that Bayes' rule would imply (Möbius et al., 2022). In the following exploratory analysis, we analyze whether these zero or wrong updates can be attributed to noise or motivated errors, i.e., an extreme form of optimistic belief updating (Exley and Kessler, 2022). The idea of motivated errors in our setting is that people have a higher propensity for wrong and zero updates if they *i*) receive a negative signal and *ii*) belong to the *High-Ego* treatment. In Table 3, we regress a dummy variable for zero and wrong updates on a dummy for observing a negative signal and IQ test scores. Controlling for IQ test scores, the noisy signal structure allows us to estimate the causal effect of observing a negative signal on the propensity

[12] In Online Appendix C2 we provide several robustness checks. First, we replicate the analysis with restricted samples excluding subjects who do not update their beliefs in the direction of the Bayesian prediction. Second, we smooth boundary priors to run the regression analysis including the most optimistic and pessimistic subjects in the sample. Third, we address the potential endogeneity concern that arises when belief updating systematically differs between subjects ranked in the top half or the bottom half of the IQ test (see Barron, 2021). The robustness checks confirm the results in Table 2.

to form zero and wrong updates in a given round. Causality is established because, conditional on subjects' IQ test scores, whether they observe a positive or negative signal is completely random. The results in columns 1 and 2 show that the propensity of zero updates is positively affected by observing a negative signal in the *High-Ego* treatment ($p = 0.034$), while it has no effect in the *Low-Ego* treatment ($p = 0.648$). Likewise, the results in columns 3 and 4 show that the propensity for wrong updates is positively affected by observing a negative signal in the *High-Ego* treatment ($p = 0.032$), while it has no effect in the *Low-Ego* treatment ($p = 0.899$).

Result 3 *The propensity of wrong and zero updates is increasing for negative signals in the High-Ego treatment, while it is independent of the valence of signals in the Low-Ego treatment.*

4.3 Ex-Post Rationalization

One implicit assumption of the framework in Section 3 and the analysis so far is that ego-relevance induced direct belief utility affects the way people process information but not vice versa. We now relax this assumption and allow subjects to choose the ego-relevance of the IQ test depending on what type of signals they receive (i.e., they exert some control over the shape of their direct belief utility function).

To this end, we estimate how our proxies for ego-relevance, i.e. subjects' self-reported importance of the IQ test for study and job success, are affected by the number of negative signals received. In addition, we also test whether subjects rationalize negative signals by indicating lower effort provision.

Table 4: Ex-Post Rationalization

Dependent Variable	(1) Importance Study Success	(2) Importance Job Success	(3) Effort
Negative Signals	-0.306**	-0.285**	-0.266**
	(0.124)	(0.125)	(0.127)
IQ Test Score	0.094**	0.110***	0.178***
	(0.040)	(0.040)	(0.041)
Initial Belief	0.010**	0.004	0.012***
	(0.004)	(0.004)	(0.004)
High-Ego	0.679***	1.088***	0.130
	(0.177)	(0.182)	(0.178)
Observations (Subjects)	419	419	419
Pseudo R^2	0.033	0.043	0.039

Notes:
(i) Subjects' self-reported importance of the IQ test for study and job success as well as the indicated effort are measured on a seven-point Likert scale.
(ii) Analysis uses Ordered Logistic Regressions with standard errors in parentheses.
(iii) Stars reflect significance levels, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

In columns 1 and 2 of Table 4, we regress subjects' self-reported importance of the IQ test for study and job success on the number of negative signals received and IQ test scores. Following the identification strategy in Table 3, causality is established because conditional on subjects' IQ test scores, the number of negative signals received is completely random. The results show that subjects in fact rate the importance of the IQ test for study success ($p = 0.014$) and job success ($p = 0.023$) lower as the number of negative signals increases. One interpretation of this result is that subjects ex-post rationalize negative signals by downplaying the importance of the IQ test. An alternative interpretation is that people hold a certain belief about their intelligence and (rationally) update their beliefs about the reliability of the IQ test as a signal for intelligence depending on the valence of signals observed. However, the result in column 3 shows that subjects also indicate less effort provision in the IQ test when they observe more negative signals ($p = 0.036$), although we are controlling for IQ test scores. The latter result is difficult to reconcile with a rational belief updating process but rather confirms the ex-post rationalization interpretation.[13]

In Online Appendix C5 we demonstrate that ex-post rationalization is stronger among subjects with pessimistic belief updating patterns (compared to Bayes) and almost vanishes for subjects with neutral or optimistic belief updating patterns. This finding suggests that ex-post rationalization provides a substitute strategy for optimistic belief updating to explain away negative information. In other words, subjects have no reason to engage in optimistic belief updating if they find alternative ways to protect their ego utility.

Result 4 *Subjects rationalize negative signals about their relative performance ex-post by downplaying the importance of the IQ test and pretending that they did not exert much effort in the IQ test.*

5 Conclusion

We used experiments to demonstrate the importance of ego-relevance induced direct belief utility on belief updating behavior. As opposed to a comparison of belief updating between different events with varying ego-relevance, we manipulate the perceived ego-relevance in a single event. This design feature allows us to study the causal effect of ego-relevance on belief updating behavior while holding other properties of the updating task fixed.

Our results show that subjects update their beliefs more optimistically as direct belief utility increases. To this end, we even find evidence that subjects are more likely to update their beliefs in the opposite direction of the Bayesian prediction when they are confronted with information that negatively affects their direct belief utility. In addition, we show that subjects ex-post rationalize negative information by downplaying the ego-relevance of the underlying event. This ex-post rationalization is more prevalent among subjects with pessimistic belief updating patterns.

[13] Table 4 shows the regression analysis for the pooled data from both treatments. In Online Appendix C4 we run the regressions separately for *High-Ego* and *Low-Ego* treatments. The corresponding results indicate some differences in the magnitude of ex-post rationalization, which are, however, not statistically significant at any conventional level.

From a methodological perspective, our experimental manipulation of ego-relevance provides a portable paradigm to study interactions of direct belief utility with other biases in people's belief formation process. Our findings on ex-post rationalization are of relevance to researchers interested in identifying motivated beliefs. For them, it is important to constrain people's ability to downplay the ego-relevance of the event after receiving negative information because it undermines their motive for self-serving biases in belief formation.

From a practical perspective, our documented biases in information processing might adversely affect managerial decision-making. The negative impact of overconfidence on decision-making has been widely documented in the literature, and our results causally link higher overconfidence to settings with increased ego-relevance. Our findings suggest that decision environments designed to downplay the ego-relevance of a decision might result in less biased decision-making. An alternative strategy worth exploring involves implementing data-driven decision support systems, which should not be prone to people's ego-protecting biases in the processing of information.

References

BARRON, K. (2021): "Belief Updating: Does the 'Good-news, Bad-news' Asymmetry Extend to Purely Financial Domains?" *Experimental Economics*, 1–28.

BÉNABOU, R. AND J. TIROLE (2002): "Self-Confidence and Personal Motivation," *The Quarterly Journal of Economics*, 117, 871–915.

BENJAMIN, D. J. (2019): "Errors in probabilistic reasoning and judgment biases," in *Handbook of Behavioral Economics - Foundations and Applications 2*, Elsevier, vol. 2, 69–186.

BRACHA, A. AND D. J. BROWN (2012): "Affective decision making: A theory of optimism bias," *Games and Economic Behavior*, 75, 67–80.

BRUNNERMEIER, M. K. AND J. A. PARKER (2005): "Optimal expectations," *American Economic Review*, 95, 1092–1118.

BUSER, T., L. GERHARDS, AND J. VAN DER WEELE (2018): "Responsiveness to feedback as a personal trait," *Journal of Risk and Uncertainty*, 56, 165–192.

CAMERER, C. AND D. LOVALLO (1999): "Overconfidence and excess entry: An experimental approach," *American Economic Review*, 89, 306–318.

CAPLIN, A. AND J. V. LEAHY (2019): "Wishful thinking," *Working paper.*

CHEN, D. L., M. SCHONGER, AND C. WICKENS (2016): "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88–97.

CIVELLI, A. AND C. DECK (2018): "A Flexible and Customizable Method for Assessing Cognitive Abilities," *Review of Behavioral Economics*, 5, 123–147.

COFFMAN, K., M. R. COLLIS, AND L. KULKARNI (2023): "Stereotypes and belief updating," *Journal of the European Economic Association*, jvad063.

COUTTS, A. (2019): "Good News and Bad News are Still News: Experimental Evidence on Belief Updating," *Experimental Economics*, 109, 21.

COUTTS, A., L. GERHARDS, AND Z. MURAD (2020): "What to blame? Self-serving attribution bias with multi-dimensional uncertainty," *Working paper.*

DROBNER, C. (2022): "Motivated beliefs and anticipation of uncertainty resolution," *American Economic Review: Insights*, 4, 89–105.

EIL, D. AND J. M. RAO (2011): "The Good News-Bad News Effect: Asymmetric Processing of Objective Information about Yourself," *American Economic Journal: Microeconomics*, 3, 114–138.

ENGELMANN, J., M. LEBRETON, N. SALEM-GARCIA, P. SCHWARDMANN, J. J. VAN DER WEELE, AND L. A. CHANG (2023): "Anticipatory anxiety and wishful thinking," *Working paper.*

ERTAC, S. (2011): "Does self-relevance affect information processing? Experimental evidence on the response to performance and non-performance feedback," *Journal of Economic Behavior & Organization*, 80, 532–545.

EXLEY, C. L. AND J. B. KESSLER (2022): "Motivated Errors," *Working Paper.*

FEILER, D. AND J. TONG (2022): "From noise to bias: Overconfidence in new product forecasting," *Management Science*, 68, 4685–4702.

Galasso, A. and T. S. Simcoe (2011): "CEO overconfidence and innovation," *Management science*, 57, 1469–1484.

Golman, R., D. Hagmann, and G. Loewenstein (2017): "Information Avoidance," *Journal of Economic Literature*, 55, 96–135.

Greiner, B. (2015): "Subject pool recruitment procedures: organizing experiments with ORSEE," *Journal of the Economic Science Association*, 1, 114–125.

Grossman, Z. and D. Owens (2012): "An unlucky feeling: Overconfidence and noisy feedback," *Journal of Economic Behavior & Organization*, 84, 510–524.

Haaland, I., C. Roth, and J. Wohlfart (2023): "Designing information provision experiments," *Journal of economic literature*, 61, 3–40.

Hill, S. J. (2017): "Learning together slowly: Bayesian learning about political facts," *The Journal of Politics*, 79, 1403–1418.

Invernizzi, A. C., A. Menozzi, D. A. Passarani, D. Patton, and G. Viglia (2017): "Entrepreneurial overconfidence and its impact upon performance," *International Small Business Journal*, 35, 709–728.

Karni, E. (2009): "A Mechanism for Eliciting Probabilities," *Econometrica*, 77, 603–606.

Köszegi, B. (2006): "Ego Utility, Overconfidence, and Task Choice," *Journal of the European Economic Association*, 4, 673–707.

Kozakiewicz, M. (2022): "Belief-Based Utility and Signal Interpretation," *Working paper*.

Malmendier, U. and G. Tate (2005): "CEO overconfidence and corporate investment," *The Journal of Finance*, 60, 2661–2700.

——— (2008): "Who makes acquisitions? CEO overconfidence and the market's reaction," *Journal of Financial Economics*, 89, 20–43.

Möbius, M. M., M. Niederle, P. Niehaus, and T. S. Rosenblat (2022): "Managing self-confidence: Theory and experimental evidence," *Management Science*, 68, 7793–7817.

Ortoleva, P. and E. Snowberg (2015): "Overconfidence in political behavior," *American Economic Review*, 105, 504–35.

Schumacher, C., S. Keck, and W. Tang (2020): "Biased interpretation of performance feedback: The role of CEO overconfidence," *Strategic Management Journal*, 41, 1139–1165.

Trautmann, S. T. and G. van de Kuilen (2015): "Belief elicitation: A horse race among truth serums," *The Economic Journal*, 125, 2116–2135.

Van der Weele, J. J. and F. A. Siemens (2020): "Bracelets of pride and guilt? An experimental test of self-signaling," *Journal of Economic Behavior Organization*, 172, 280–291.

Zimmermann, F. (2020): "The dynamics of motivated beliefs," *American Economic Review*, 110, 337–361.

Zizzo, D. J. (2010): "Experimenter demand effects in economic experiments," *Experimental Economics*, 13, 75–98.

Online Appendix: Motivated Belief Updating and Rationalization of Information

Christoph Drobner and Sebastian J. Goerg

A Mapping of pre-analysis plan into paper

Table A1 provides a mapping of the results in the paper and the pre-registered hypotheses in the pre-analysis plan. The pre-analysis plan is available at the AEA RCT Registry (AEARCTR-0005121).

Table A1: Mapping of results and pre-registered hypotheses

Result in the paper	**Hypothesis in the pre-analysis plan**
Manipulation check result on page 8.	Hypothesis 2: Subjects' reported relevance of the IQ test for study success and job success is higher in the *High-Ego* treatment compared to the *Low-Ego* treatment.
Result 1 on page 10.	Hypothesis 1: Subjects hold overconfident prior beliefs.
Result 1 on page 10 and result 2 on page 12.	Hypothesis 4: Subjects in the *High-Ego* treatment update their beliefs more optimistically than subjects in the *Low-Ego* treatment.
Result 2 on page 12.	Hypothesis 3: Subjects update their beliefs optimistically compared to Bayes' rule.
Result 3 on page 13	Exploratory result - not pre-registered in the pre-analysis plan.
Result 4 on page 14	Hypothesis 5: Subjects ex-post rationalize negative feedback about their relative performance in the IQ test.

B Experimenter Demand Effects

One concern of our information treatment is the role played by experimenter demand effects (Haaland et al., 2023; Zizzo, 2010). We acknowledge that the results from our manipulation check in Section 4 could be partly explained by experimenter demand effects. For instance, some subjects may rate the IQ test as being more important in the *High-Ego* treatment because they anticipate that the experimenter wants them to answer this question accordingly.

However, we consider this not a major concern for the main conclusions of our experiment. First, our between-subjects design ensures that subjects were not aware of the treatment manipulation. To this end, it is unclear why an experimenter demand effect results in more optimistic belief updating in the *High-Ego* treatment compared to the *Low-Ego* treatment as we do not expect our subjects to anticipate the main objective of our experiment, i.e., measuring the effect of ego-relevance on belief updating behavior. In contrast, we explicitly tell subjects that they should report their most accurate beliefs, which would (if anything) trigger a more conservative treatment effect when subjects are susceptible to experimenter demand effects. Second, the majority of experimental sessions has been conducted online with almost no interaction between the researchers and the experimental subjects, which generally minimizes the concern for experimenter demand effects (Haaland et al., 2023; Zizzo, 2010). Third, we incentivized subjects to truthfully report their beliefs, which again generally reduces the concern for experimenter demand effects (Haaland et al., 2023).

C Robustness Checks

C.1 Baseline Balance

Figure 7 shows that the distributions of initial beliefs are not significantly different between *High Ego* and *Low Ego* treatments (Kolmogrov-Smirnov test, $p = 0.647$). Table C2 shows baseline balance between *High Ego* and *Low Ego* treatments with respect to gender and IQ test scores.

Figure 7: Distributions of Initial Beliefs

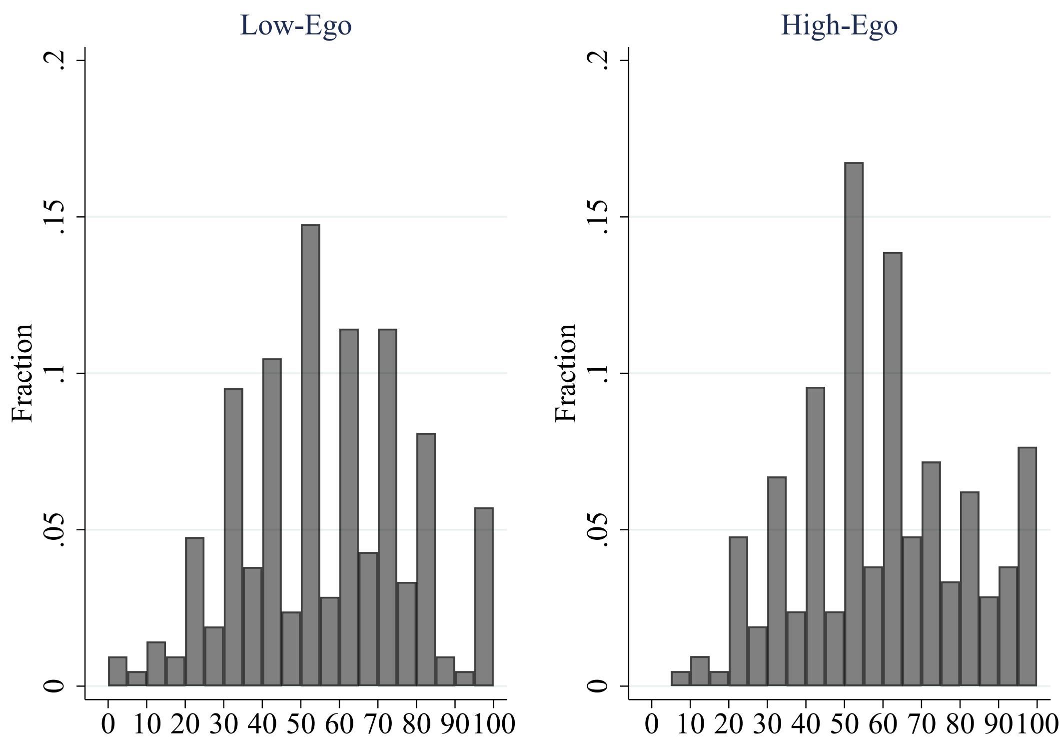


Table C2: Baseline Balance

Variable	High-Ego (N=209)	Low-Ego (N=210)	P-Value
Female	0.56	0.49	0.204 (Fisher's exact test)
IQ Test Score	9.71	9.33	0.708 (Kolmogrov-Smirnov test)

C.2 Robustness of Belief Updating

The following section provides several robustness checks of the regression analysis in Table 2. First, we replicate the analyses with restricted samples of subjects who do not update their beliefs in the direction of the Bayesian prediction. Second, we replicate the regression analysis by replacing boundary beliefs 0 and 1 with 0.01 and 0.99, respectively. Third, we address the potential endogeneity concern that arises when belief updating systematically differs between subjects who are ranked in the top half or the bottom half of the IQ test by interacting the right-hand side variables with a dummy for scoring in the top half. All robustness checks confirm the results in Table 2.

Table C3 replicates the regression analysis in Table 2 with a restricted sample of subjects who do not update their beliefs in the direction of the Bayesian prediction. Specifically, columns 1-3 show the regression analysis that excludes subjects who update their beliefs once in the opposite direction that Bayes' rule would imply (10.5% wrong updates), while columns 4-6 show the regression analysis that additionally excludes subjects who never update their beliefs (19.8% zero updates).[14]

Table C3: Belief Updating - Restricted Sample

Dependent	No Wrong Updates			No Wrong and No Zero Updates		
Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Logit Belief	Pooled	High-Ego	Low-Ego	Pooled	High-Ego	Low-Ego
δ	0.905***	0.887**	0.913***	0.909**	0.891	0.921*
	(0.030)	(0.055)	(0.031)	(0.041)	(0.068)	(0.047)
β_P	0.756***	0.828**	0.683***	0.949	0.995	0.899
	(0.050)	(0.072)	(0.070)	(0.054)	(0.074)	(0.081)
β_N	0.665***	0.599***	0.715***	0.827***	0.761***	0.877
	(0.051)	(0.073)	(0.068)	(0.057)	(0.082)	(0.077)
Observations	634	308	326	502	248	254
R^2	0.747	0.733	0.762	0.724	0.730	0.721
$\beta_P - \beta_N$	0.091	0.229	-0.032	0.122	0.234	0.022
P-value ($\beta_P = \beta_N$)	0.166	0.017	0.724	0.107	0.028	0.840
P-value [Chow test] for ($\beta_P - \beta_N$) (Regressions 2 and 3)						0.048
P-value [Chow test] for ($\beta_P - \beta_N$) (Regressions 5 and 6)						0.163

Notes:
(i) Analysis uses OLS regressions with robust standard errors clustered at the individual level.
(ii) Analysis includes two observations (belief updates) for each subject but excludes observations with boundary beliefs because the logit is not defined for 0 or 1.
(iii) Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

The results in column 1 document no significant difference between subjects' responsiveness to positive signals and negative signals at the aggregate level ($\beta_P > \beta_N, p = 0.166$). The results in columns 2 and 3 show that subjects in the *High-Ego* treatment update their beliefs more

[14] It is important to note that the analysis without zero updates excludes perfectly Bayesian subjects in the second round if they received a mixed sequence of signals.

strongly upon the receipt of positive signals ($\beta_G^{High-Ego} > \beta_N^{High-Ego}, p = 0.017$), while there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_N^{Low-Ego}, p = 0.724$). This treatment difference in the level of optimistic belief updating is confirmed by a Chow-test ($\beta_G^{High-Ego} - \beta_N^{High-Ego} > \beta_G^{Low-Ego} - \beta_N^{Low-Ego}, p = 0.048$). The results in column 4 show no significant difference between subjects' responsiveness to positive signals and negative signals at the aggregate level ($\beta_P > \beta_N, p = 0.107$). The results in columns 5 and 6 show that subjects in the *High-Ego* treatment update their beliefs more strongly upon the receipt of positive signals ($\beta_G^{High-Ego} > \beta_N^{High-Ego}, p = 0.027$), while there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_N^{Low-Ego}, p = 0.840$). However, this treatment difference in the level of optimistic belief updating is not confirmed by a Chow-test ($\beta_G^{High-Ego} - \beta_N^{High-Ego} > \beta_G^{Low-Ego} - \beta_N^{Low-Ego}, p = 0.163$). Overall, the results show that our treatment difference in the level of optimistic belief updating is robust when we exclude subjects with wrong and zero updates.

One disadvantage of the empirical framework used in Table 2 is the exclusion of subjects who hit the boundaries of the probability space 0 or 1, which excludes the most optimistic and pessimistic beliefs in our sample. Table C4 replicates the regression analysis by replacing boundary beliefs 0 and 1 with 0.01 and 0.99, respectively. The results show that our treatment difference in the level of optimistic belief updating is robust when we include beliefs on the boundaries of the probability space.

Table C4: Belief Updating - Including Boundary Priors

Dependent Variable: Logit Belief	(1) Pooled	(2) High-Ego	(3) Low-Ego
δ	0.853***	0.813***	0.888***
	(0.030)	(0.047)	(0.035)
β_P	1.133	1.344**	0.917
	(0.087)	(0.133)	(0.111)
β_N	0.743***	0.707***	0.754**
	(0.077)	(0.107)	(0.105)
Observations	838	418	420
R^2	0.681	0.669	0.702
$\beta_P - \beta_N$	0.390	0.637	0.163
P-value ($\beta_P = \beta_N$)	0.000	0.000	0.265
P-value [Chow test] for ($\beta_P - \beta_N$) (Regressions 2 and 3)			0.027

Notes:
(i) Analysis uses OLS regressions with robust standard errors clustered at the individual level.
(ii) Analysis includes two observations (belief updates) for each subject but.
(iii) Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

One potential endogeneity concern of the empirical framework used in Table 2 arises when belief updating systematically differs between subjects who are ranked in the top half or the bottom half of the IQ test because it affects the propensity of receiving positive signals and negative signals (see Barron, 2021, for an intriguing discussion). In Table C5, we address this potential endogeneity concern by interacting the right-hand side variables with a dummy for scoring in the top half. The results show that our treatment difference in the level of optimistic belief updating is robust when we rule out this potential endogeneity concern.

Table C5: Belief Updating - Controlling for State

Dependent Variable: Logit Belief	(1) Full Sample	(2) High-Ego	(3) Low-Ego
δ	0.997	1.080	0.935
	(0.073)	(0.103)	(0.079)
$Top * \delta$	-0.137*	-0.278**	-0.039
	(0.080)	(0.119)	(0.087)
β_P	0.789	0.948	0.622
	(0.137)	(0.176)	(0.189)
$Top * \beta_P$	-0.084	-0.170	0.021
	(0.146)	(0.191)	(0.202)
β_N	0.654	0.550	0.695
	(0.163)	(0.290)	(0.164)
$Top * \beta_N$	-0.112	-0.101	-0.087
	(0.172)	(0.298)	(0.180)
Observations	715	348	367
R^2	0.704	0.684	0.728
$(\beta_P + Top * \beta_P) - (\beta_N + Top * \beta_N)$	0.163	0.329	0.035
P-value $(\beta_P + Top * \beta_P = \beta_N + Top * \beta_N)$	0.019	0.001	0.729
P-value for $((\beta_P + Top * \beta_P) - (\beta_N + Top * \beta_N))$ (2 and 3)			0.033

Notes:
(i) Analysis uses OLS regressions with robust standard errors clustered at the individual level.
(ii) Analysis includes two observations (belief updates) for each subject but excludes observations with boundary beliefs because the logit is not defined for 0 or 1.
(iii) Stars reflect significance in a t-test of the null hypothesis that the interaction terms $Top * \delta$, $Top * \beta_P$, and $Top * \beta_N$ are different from zero, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

C.3 Belief Updating - Round 1 versus Round 2

In Table C6, we replicate the regression analysis in Table 2 of Section 4.2 separately for the first round of signals and the second round of signals. The qualitative results are similar in both rounds but we observe a stronger treatment effect in the first round. One explanation for this stronger treatment effect in round 1 could be a level shift in beliefs rather than a difference in updating behavior. However, the heterogeneity of the results in Table 1 of Section 4.1 for different distributions of signals suggests that a mere level shift in beliefs does not sufficiently explain our data. Alternatively, it is also plausible that there is no level shift in beliefs but a heterogeneous treatment effect on how people process information in round 1 and round 2 of the belief updating task (e.g., because the treatment shift in ego-relevance might be more salient in round 1). To summarize, we can rule out that a mere level shift of beliefs drives our results, but we cannot distinguish whether our effects are solely operating through differences in information processing or a combination of the latter with a level shift in beliefs.

Table C6: Belief Updating - Round 1 versus Round 2

$$logit(\hat{\gamma}_{it}) = \delta logit(\hat{\gamma}_{i,t-1}) + \beta_G log(\frac{p_{Gt}}{1-p_{Gt}}) + \beta_B log(\frac{p_{Bt}}{1-p_{Bt}}) + \epsilon_{it}$$

Dependent Variable: Logit Belief	Round 1 (1) Pooled	(2) High-Ego	(3) Low-Ego	Round 2 (4) Pooled	(5) High-Ego	(6) Low-Ego
δ	0.833***	0.805**	0.847***	0.921**	0.882*	0.947
	(0.049)	(0.094)	(0.046)	(0.038)	(0.062)	(0.051)
β_G	0.717***	0.758***	0.681***	0.717***	0.834	0.598***
	(0.061)	(0.091)	(0.083)	(0.074)	(0.105)	(0.106)
β_B	0.470***	0.317***	0.611***	0.645***	0.652***	0.630***
	(0.068)	(0.088)	(0.096)	(0.078)	(0.124)	(0.102)
Observations	369	181	188	346	167	179
R^2	0.707	0.681	0.737	0.703	0.684	0.724
$\beta_G - \beta_B$	0.246	0.440	0.070	0.071	0.183	-0.032
P-value ($\beta_G = \beta_B$)	0.006	0.000	0.581	0.511	0.279	0.825
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 2 and 3)						0.035
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 5 and 6)						0.336

Notes:
(i) Analysis uses OLS regressions with robust standard errors clustered at the individual level.
(ii) Analysis excludes observations with boundary beliefs 0 or 1.
(iii) Stars reflect significance levels, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

C.4 Ex-Post Rationalization - High Ego versus Low Ego

In Table C7, we replicate the regression analysis in Table 4 separately for *High-Ego* and *Low-Ego* treatments. All coefficients for negative signals have the same sign, but the results show that ex-post rationalization tends to be stronger in the *High-Ego* treatment if we consider subjects' beliefs about the importance of the IQ test for study success and job success as dependent variables, while it tends to be stronger in the *Low-Ego* treatment if we consider subjects' indicated effort as the dependent variable. However, Chow tests of the parameter estimates for negative signals provide no evidence for significant treatment differences in ex-post rationalization.

Table C7: Ex-Post Rationalization - High Ego versus Low Ego

Dependent variable	Importance study success		Importance job success		Effort	
	(1)	(2)	(3)	(4)	(5)	(6)
	High-Ego	Low-Ego	High-Ego	Low-Ego	High-Ego	Low-Ego
Negative Signals	-0.335**	-0.271	-0.413**	-0.164	-0.236	-0.303*
	(0.170)	(0.184)	(0.174)	(0.186)	(0.179)	(0.182)
IQ Test Score	0.072	0.107*	0.073	0.128**	0.192***	0.148**
	(0.059)	(0.056)	(0.059)	(0.057)	(0.061)	(0.057)
Initial Belief	0.008	0.012*	0.002	0.006	0.006	0.018***
	(0.006)	(0.007)	(0.059)	(0.007)	(0.006)	(0.007)
Observations	209	210	209	210	209	210
Pseudo R^2	0.015	0.028	0.015	0.020	0.031	0.047

Notes:
(i) Subjects' stated importance of the IQ test for study and job success as well as the indicated effort are measured on a seven-point Likert scale.
(ii) Analysis uses Ordered Logistic Regressions with standard errors in parentheses.
(iii) Stars reflect significance levels, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

C.5 Ex-Post Rationalization - Pessimistic versus Optimistic Subjects

In the following exploratory analysis we investigate whether ex-post rationalization of negative information is driven by optimistic or pessimistic subjects in the main belief updating task. Specifically, in Table C8 we replicate the regression analysis in Table 4 including a dummy for being pessimistic in the belief updating task, and an interaction term of the latter with the number of negative signals received. Subjects are classified as pessimistic if they hold more pessimistic final beliefs about their relative IQ performance than the Bayesian counterpart. Strikingly, the significantly negative interaction terms show that ex-post rationalization is stronger among the minority of subjects with pessimistic belief updating patterns and almost vanishes for subjects with neutral or optimistic belief updating patterns.

Table C8: Ex Post Rationalization - Pessimistic versus Optimistic Subjects

	(1)	(2)	(3)
Dependent Variable	Importance Study Success	Importance Job Success	Effort
Negative Signals	-0.118	-0.138	-0.032
	(0.163)	(0.163)	(0.167)
Pessimistic	0.349	0.192	0.448
	(0.293)	(0.292)	(0.297)
Negative Signals x Pessimistic	-0.491**	-0.415*	-0.587**
	(0.251)	(0.251)	(0.253)
IQ Test Score	0.093**	0.109***	0.181***
	(0.040)	(0.040)	(0.042)
Initial Belief	0.011**	0.005	0.013***
	(0.004)	(0.004)	(0.004)
High-Ego	0.670***	1.074***	0.134
	(0.178)	(0.182)	(0.179)
Observations	419	419	419
Pseudo R^2	0.036	0.046	0.043

Notes:
(i) Subjects' self-reported importance of the IQ test for study and job success as well as the indicated effort are measured on a seven-point Likert scale.
(ii) Analysis uses Ordered Logistic Regressions with standard errors in parentheses.
(iii) Stars reflect significance levels, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

D Experimental Instructions

Translated from the original instructions in German.

Welcome page

Welcome to this experiment! Please read the instructions carefully. You will be paid in this experiment according to your decisions and the decisions of other participants. In addition, you will receive a fixed payment of 4 euros.

The payment is anonymous and you will not receive any information about the payoffs of the other participants. At the end of the online experiment, you will be informed about your payoff and you will receive an individual code. Please make a note of the code; you will need the code at the payout. We will inform you by mail about the procedure and dates of payment as soon as we have clear information about the reopening of the TUM. In order to ensure an efficient process, please bring a signed printout of the receipt that we attached to the email yesterday.

Please note that the same conditions apply for participation in the online experiment as in the laboratory: At the computer in a quiet, undisturbed environment, preferably without external influences and distractions. If you have any questions, you can always return to the Zoom meeting and ask the experimenter a question.

Belief elictation explanation

In the course of this experiment, you will give your estimate for the probability of an uncertain event. The probability you then indicate will affect your payout. The payout mechanism is set up in such a way that you have the highest chance of receiving an additional payout of 2 Euros each time you truthfully state your best possible estimate.

In the section below we will explain the payout mechanism. For this purpose, we will use the event ”Germany wins the European Football Championship 2021” as an example. The example is purely for illustrative purposes and will be replaced by another event in the experiment.

Please enter the probability with which you believe that Germany will win the European Football Championship 2021 (Please choose an integer, e.g., $0, 1, 2, ..., 99, 100$).

After you have given your estimate, the computer will randomly select a number X between 0 and 100 in the background. Each number will be selected with equal probability. This will affect your payout as follows:

- If your reported probability is at least as high as the number X drawn by the computer, then you will receive 2 euros if Germany actually becomes the European champion.
- If your reported probability is lower than the number X drawn by the computer, then you will receive 2 euro with a probability of X% regardless of whether Germany becomes the European champion in 2021 or not.

According to this payment mechanism, it is always beneficial if you truthfully give your best estimate.

For example, assume that your true estimate for the probability of Germany winning the 2021 European Football Championship is 50% and you specify a probability of 30%. Then it is possible that the computer randomly draws the number X equal to 40. In this case, your probability of winning 2 Euros is 40%. If, on the other hand, you had indicated 50%, according to your true estimation you would win the 2 euros with a probability of 50% — namely exactly when Germany becomes the European champion.

Control questions:
To improve your understanding of the payout mechanism, we now ask you to answer some control questions. For this purpose, we will continue to use the example event ”Germany wins the European Football Championship 2021”. Your answers to these questions will not affect your payouts in the experiment. However, we will not progress to the next phase of the experiment until all participants have answered the questions correctly.

For the control questions, assume that your best estimate for the probability of Germany winning the 2021 European Championship is 30%. Now additionally assume that the computer has drawn the number X equal to 50.

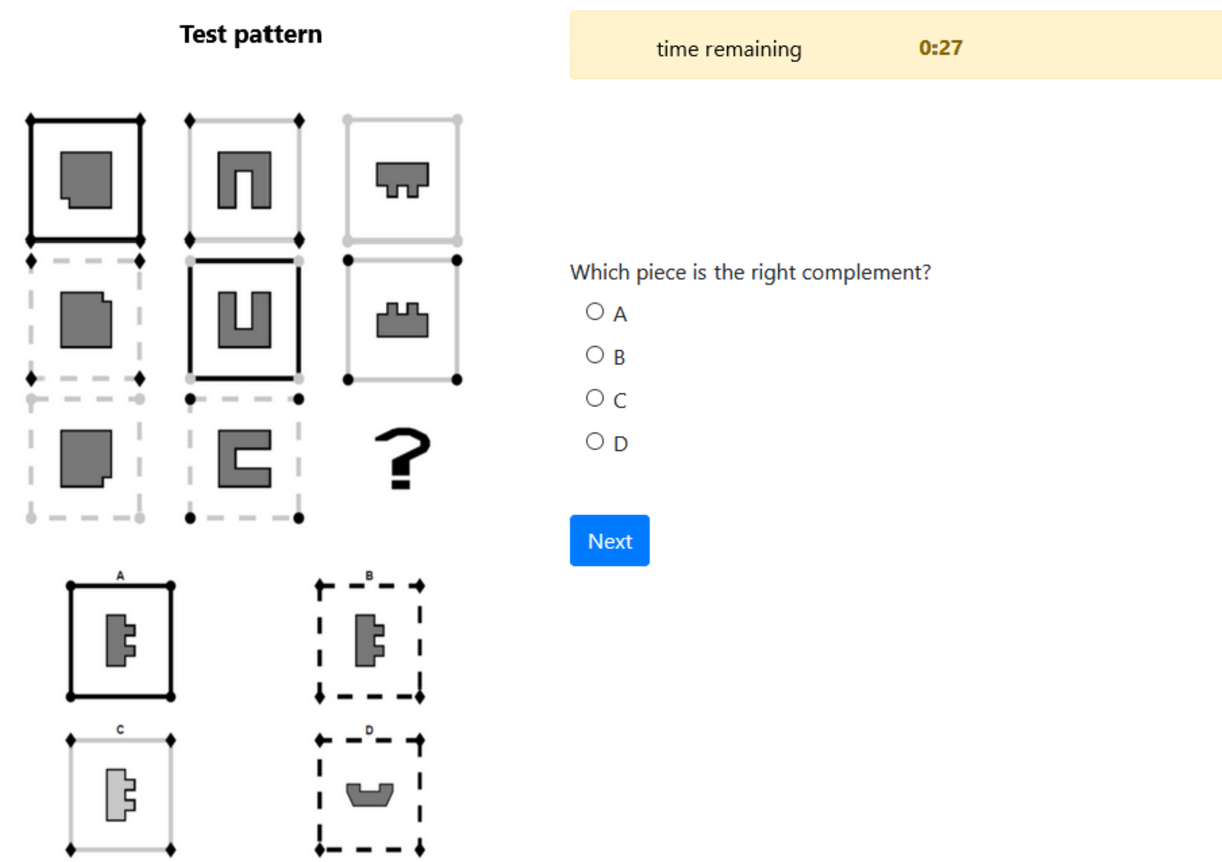
- What probability should you indicate such that you have the highest chance of a payment of 2 euros?
- What is your chance of winning 2 euros?
- Would you have had a higher probability to win 2 euros if you had a reported 60% probability instead of 30%?
  - Yes
  - No

Quiz

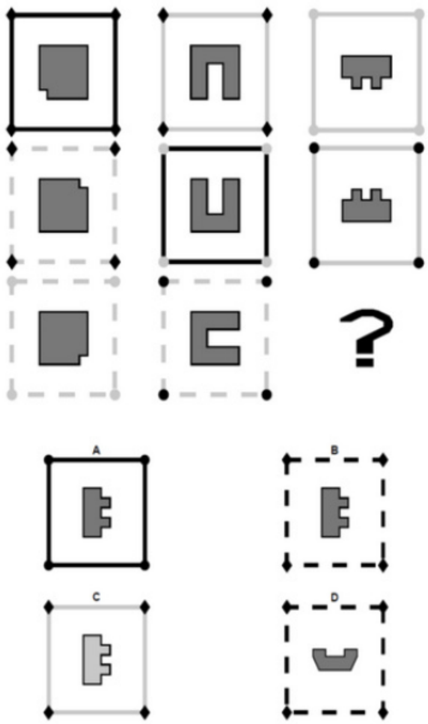
In the first part of the experiment we ask you to complete a quiz with 15 questions. You will see a pattern with one piece missing. Your task is to choose the correct piece from four suggestions and click on the Next button. You have 30 seconds to select the correct answer for each pattern and click the Next button.

For each correct answer in the quiz, you will receive one point. Each point is associated with an additional payment. The payment for each point is randomly selected by the computer for each question and varies from 10 cents to 50 cents per point.

On the following page, you have the possibility of answering a test question to get familiar with the format of the quiz!



Test pattern



The correct answer to the test question is **Answer A**.

Your task is to assign the suitable section of the four possible answers to the pattern below. You have 30 seconds each to do this. **Please note that you will only get the point for a correct answer if you click the Continue button after you have selected the correct answer.**

If you have understood the task, you can now start with the actual quiz.

Next

Prior belief elicitation

The test you have just taken is an intelligence test (IQ test).

The computer has ranked your performance in the IQ test relative to all participants in this session. Subsequently, we would like to ask you for your assessment of the probability that you were among the Top 50% of all participants in this session. In the course of the experiment, you will receive information about your relative performance and you will have the opportunity to revise your assessment.

For each estimate you make, you have the chance to win 2 Euros according to the same payout mechanism we explained at the beginning of the experiment. This means you maximize your payout if you make your best possible estimate.

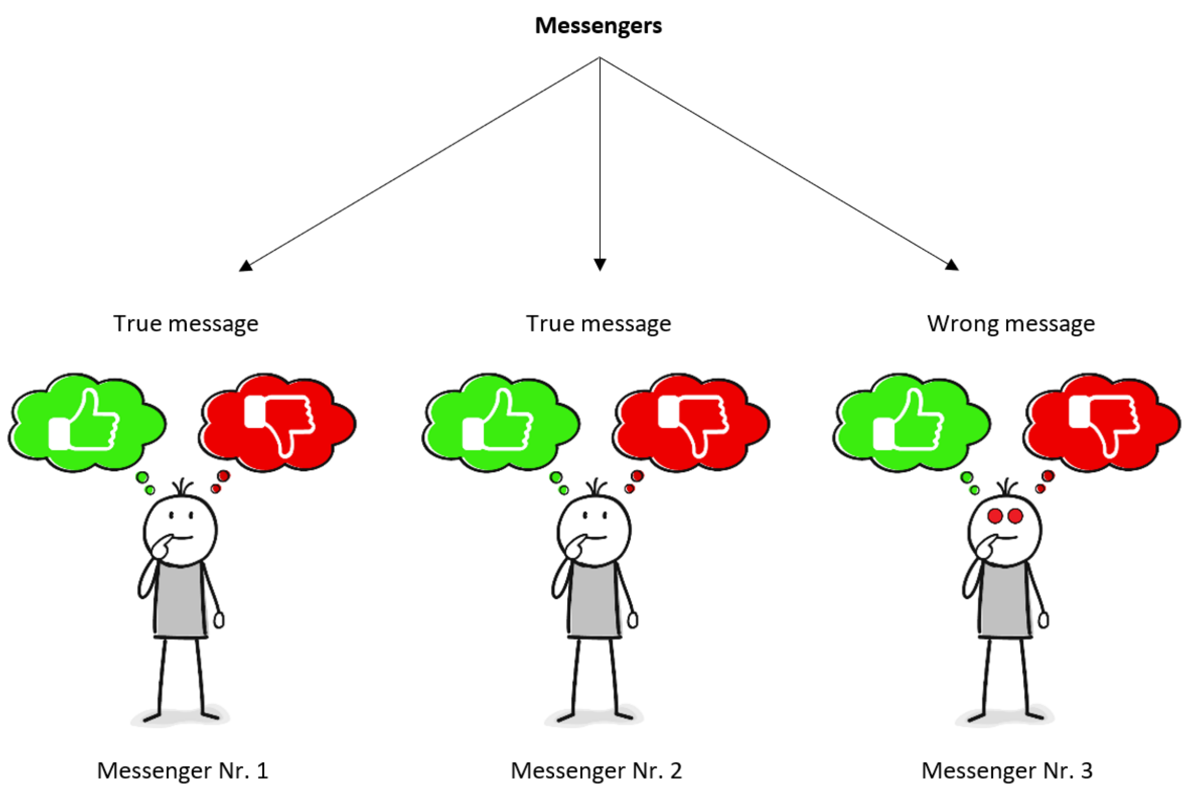
If two participants have the same number of points, the computer randomly determines which participant has the higher and the lower rank.

What is the probability you scored in the Top 50% in the IQ test among all the participants in this session?

Signal explanation

In the course of this experiment, you will twice receive information about your performance in the IQ test. You will receive either a positive message "Your performance was in the Top 50%" or a negative message "Your performance was not in the Top 50%".

The messages are provided by three messengers, which are shown in the figure below. However, not all of these messengers are trustworthy. While two messengers always tell the truth, one messenger always presents you with a false message about your score in the IQ test. The computer randomly selects one of the three messengers to deliver the messages and you will not be informed which messenger has been selected.



This means that you will receive a true message with two-thirds probability and a false message with one-third probability about your actual performance. However, it is also possible that you will receive two false messages.

After you have received the signal, you once again have the opportunity to give your estimate with which probability you have scored in the top 50% of all participants. In doing so, you have the opportunity to win 2 Euros according to the same payout mechanism that we explained at the beginning of the experiment. This means you maximize your payout if you make your best possible estimate.

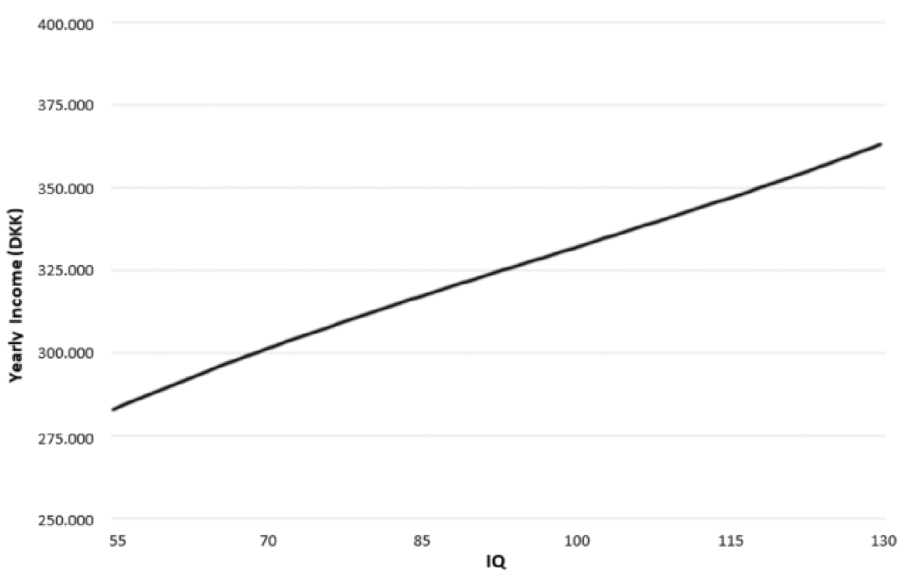
Information about IQ tests

Before you receive the first message about your score in the IQ test, you have two minutes to read an article with scientific evidence on the importance of IQ tests. At the end of the experiment, you will answer a question about the content of this article and you have the opportunity to receive an additional payment of 2 euros if you answer this question correctly.

High-Ego treatment

Numerous scientific studies have shown that intelligence tests have a very high significance for important areas of life (Gottfredson, 2003; Neisser et al., 1996; Strenze, 2007).
For example, longitudinal studies show a correlation coefficient of 0.5–0.6 between intelligence and educational achievement (Deary Johnson, 2010; Roth et al., 2015; Strenze, 2007), a correlation coefficient of 0.4–0.5 between intelligence and professional success (Gottfredson, 2003; Schmidt Hunter, 2004; Strenze, 2007), and a correlation coefficient of up to 0.4 between intelligence and income (Gottfredson, 2003; Strenze, 2007).
These results are confirmed by a recent long-term study from Denmark (Hegelund et al., 2018). The researchers have found that IQ test results are also related to important indicators in education and labor market research. For example, the probability of unemployment decreases significantly as IQ rises.
Figure 1 is from the study by Hegelund et al (2018) and illustrates the strong correlation between IQ test results and income based on a large database.

Figure 1: IQ and Yearly
(Hegelund et al., 2018)



*DKK=Danish crowns, 1 Euro corresponds to 7.5 DK

References:

Deary, I. J., Johnson, W. (2010). Intelligence and education: causal perceptions drive analytic processes and therefore conclusions. International Journal of Epidemiology, 39(5), 1362–1369.

Gottfredson, L. S. (2003).G, jobs and life. In H. Nyborg (Ed.). The scientific study of general intelligence: Tribute to Arthur R. Jensen (pp. 293–342). (1st ed.). Oxford: Elsevier Science Ltd.

Gottfredson, L. S., Deary, I. J. (2004). Intelligence predicts health and longevity, but why?. Current Directions in Psychological Science, 13(1), 1-4.

Hegelund, E. R., Flensborg-Madsen, T., Dammeyer, J., Mortensen, E. L. (2018). Low IQ as a predictor of unsuccessful educational and occupational achievement: A register-based study of 1,098,742 men in Denmark 1968–2016. Intelligence, 71, 46-53.

Lord, R. G., De Vader, C. L., Alliger, G. M. (1986). A meta-analysis of the relation between personality traits and leadership perceptions: An application of validity generalization procedures. Journal of applied psychology, 71(3), 402.

Neisser, U., Boodoo, G., Bouchard, T., Jr., Wade Boykin, A., Brody, N. J., Ceci, S., Urbina, S. (1996). Intelligence: Knowns and unknowns. American Psychologist, 51, 77–101.

Roth, B., Becker, N., Romeyke, S., Schäfer, S., Domnick, F., Spinath, F. M. (2015). Intelligence and school grades: A meta-analysis. Intelligence, 53, 118–137.

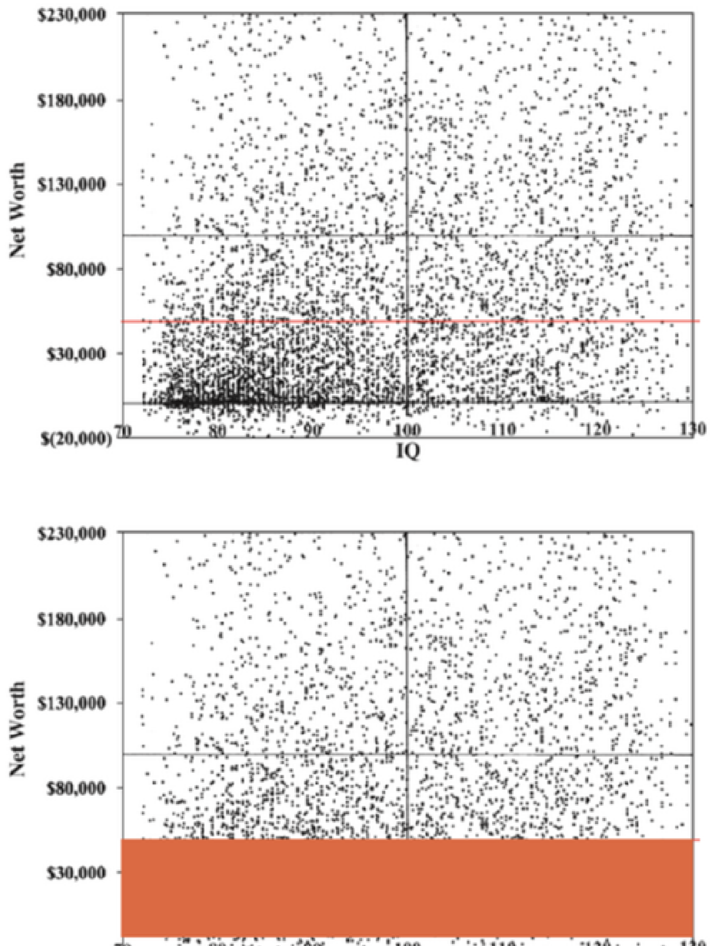
Schmidt, F. L., Hunter, J. (2004). General mental ability in the world of work: Occupational attainment and job performance. Journal of Personality and Social Psychology, 86(1), 162–173.

Strenze, T. (2007). Intelligence and socioeconomic success: A meta-analytic review of longitudinal research. Intelligence, 35(5), 401–426.

Low-Ego treatment

The scientist Nassim Taleb, researcher in the fields of statistics, epistemology, and financial mathematics, shows in his new research work that IQ measurements using IQ tests are not scientifically tenable and are only meaningful for some arbitrarily isolated mental abilities.
On the statistics front, Taleb argues that there is no correlation between higher IQ and income, and that the IQ test is a blunt, circular measuring tool that ignores unforeseen events at the end of the probability spectrum. IQ numbers emerge without regard to unexpected paradigm shifts. Therefore, they are almost ineffective under different conditions or will be ineffective in the future.

Figure 1: IQ and Net Worth
(Taleb, 2019)



* The figure shows that above $40,000 there is no correlation between IQ and net worth.

Figure 1 is from Taleb's article and illustrates that the correlation between IQ and net wealth in US dollars is only visible when people with very low wealth levels are included in the analysis. In contrast, there is no positive correlation between IQ and net wealth for people with medium to

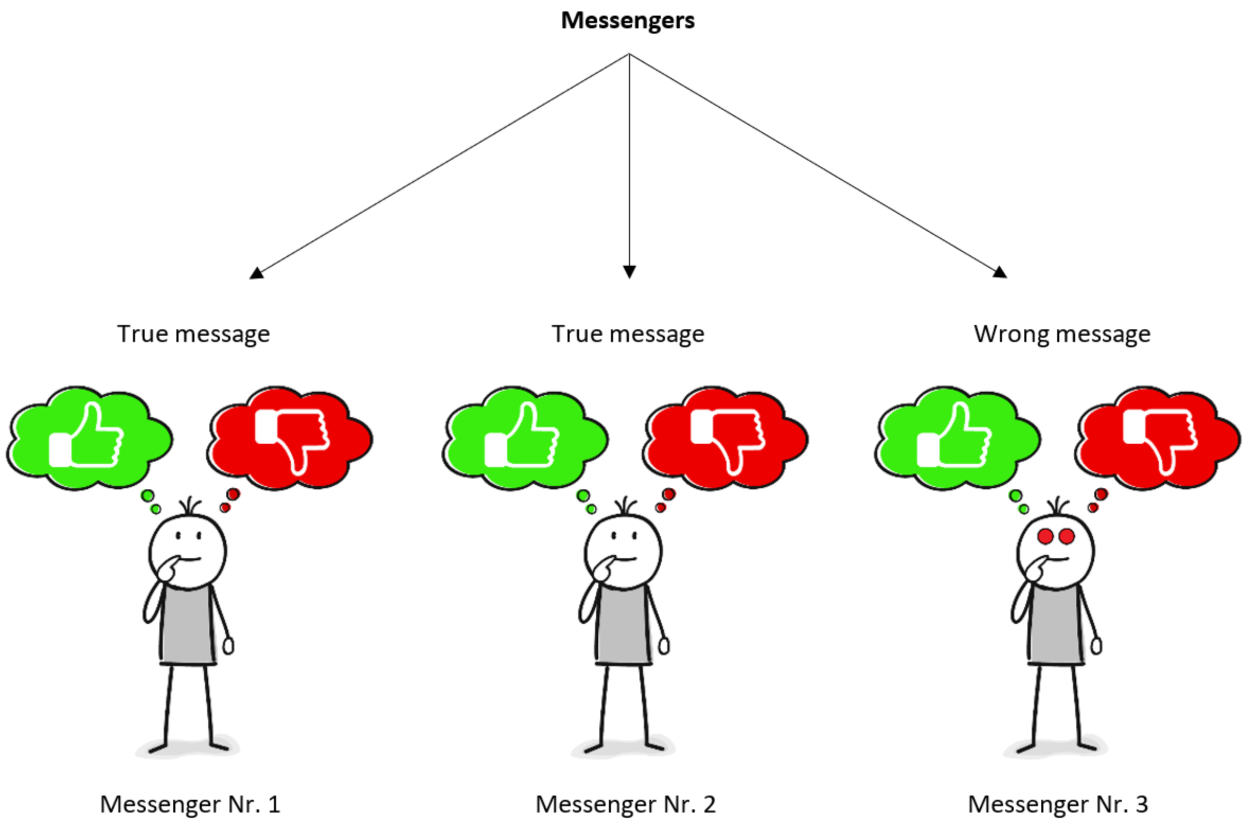
high wealth levels.
Taleb backs up his theses with plenty of probabilistic and statistical illustrative material. His data shows that the definition of intelligence used when measuring intelligence by IQ tests is too much reduced to domains that are not able to do justice to a complex phenomenon such as the human intellect in the living world. Taleb also shows that the test results of individual persons are subject to great fluctuations.

References:

Taleb, N. N. (2019). IQ is largely a pseudoscientific swindle.

Signal explanation 1

A messenger will now send you the first message about your score in the IQ test. For this purpose, the computer has randomly selected one of the three messengers.



However, in this experiment you will not learn which messenger transmitted the message. This means that you will never know for sure whether you have actually scored in the Top 50% of all participants of this session in the IQ test.

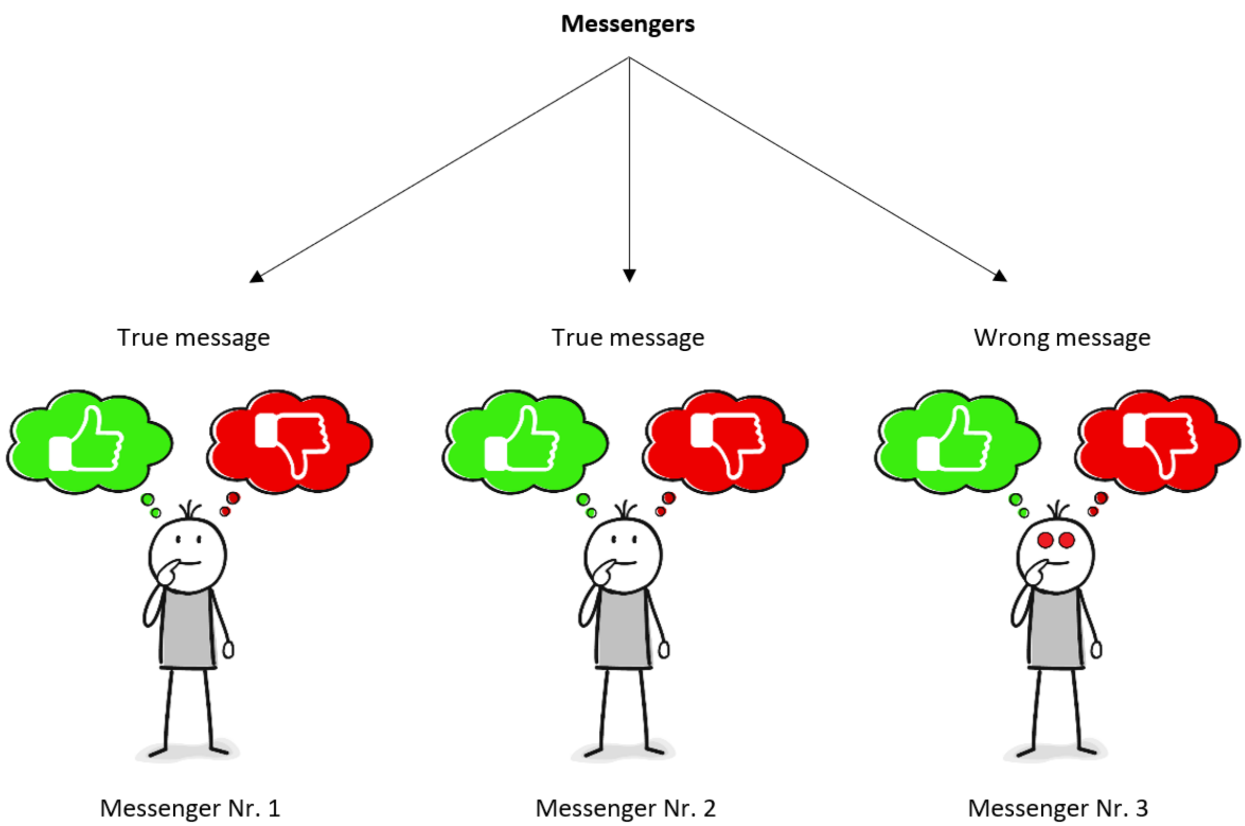
Signal realization 1

Posterior belief elicitation 1

What is the probability you scored in the Top 50% in the IQ test among all participants in this session?

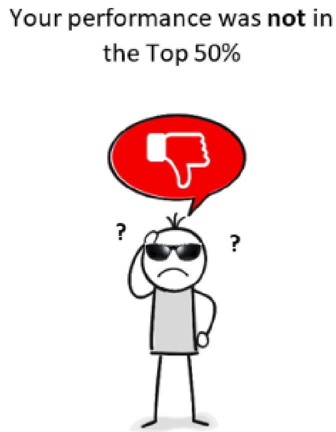
Signal explanation 2

A messenger will now send you the second message about your score in the IQ test. For this purpose, the computer has again randomly selected one of the three messengers.



However, in this experiment you will not learn which messenger transmitted the message. This means that you will never know for sure whether you have actually scored in the Top 50% of all participants of this session in the IQ test.

Signal realization 2



Posterior belief elicitation 2

What is the probability you scored in the Top 50% in the IQ test among all participants in this session?

Post-experimental questionnaire

In the following, we ask you to carefully read some questions and answer them truthfully:

- On a scale of 1 (not at all) to 7 (very much), how hard did you try to get the best possible score in the IQ test?
- On a scale of 1 (very low) to 7 (very high), how high do you rate the importance of your performance in the IQ test today for your success in studies?
- On a scale of 1 (very low) to 7 (very high), how high do you rate the importance of your performance in the IQ test today for your success at work?

The following question refers to the article about the importance of IQ tests that you have read in the course of this experiment. If you answer this question correctly, you will receive an additional payment of 2 euros.

High-Ego treatment: What are the names of the scientists who have shown that intelligent people have greater leadership potential?

- DeVader und Alliger
- Kovacs and Convay

Low-Ego treatment: What is the name of the scientist from the article about the importance of intelligence tests?

- Nassim Djabou
- Nassim Taleb

In the experiment, we asked you several times, with what probability you scored in the Top 50% of all participants of this session in the IQ test. Which of the following considerations applies to you?

- I have tried to give my best estimate.
- I did not think much and made an arbitrary estimate.
- I have given a higher probability than my actual estimate.
- I have given a lower probability than my actual estimate.

Were the instructions clear?

- Yes
- No, why?

Please fill in the following fields:

- Age:
- Gender:
- High school math grade:
- Field of study:

References

Barron, K. (2021): "Belief Updating: Does the 'Good-news, Bad-news' Asymmetry Extend to Purely Financial Domains?" *Experimental Economics*, 1–28.

Bénabou, R. and J. Tirole (2002): "Self-Confidence and Personal Motivation," *The Quarterly Journal of Economics*, 117, 871–915.

Benjamin, D. J. (2019): "Errors in probabilistic reasoning and judgment biases," in *Handbook of Behavioral Economics - Foundations and Applications 2*, Elsevier, vol. 2, 69–186.

Bracha, A. and D. J. Brown (2012): "Affective decision making: A theory of optimism bias," *Games and Economic Behavior*, 75, 67–80.

Brunnermeier, M. K. and J. A. Parker (2005): "Optimal expectations," *American Economic Review*, 95, 1092–1118.

Buser, T., L. Gerhards, and J. van der Weele (2018): "Responsiveness to feedback as a personal trait," *Journal of Risk and Uncertainty*, 56, 165–192.

Camerer, C. and D. Lovallo (1999): "Overconfidence and excess entry: An experimental approach," *American Economic Review*, 89, 306–318.

Caplin, A. and J. V. Leahy (2019): "Wishful thinking," *Working paper.*

Chen, D. L., M. Schonger, and C. Wickens (2016): "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88–97.

Civelli, A. and C. Deck (2018): "A Flexible and Customizable Method for Assessing Cognitive Abilities," *Review of Behavioral Economics*, 5, 123–147.

Coffman, K., M. R. Collis, and L. Kulkarni (2023): "Stereotypes and belief updating," *Journal of the European Economic Association*, jvad063.

Coutts, A. (2019): "Good News and Bad News are Still News: Experimental Evidence on Belief Updating," *Experimental Economics*, 109, 21.

Coutts, A., L. Gerhards, and Z. Murad (2020): "What to blame? Self-serving attribution bias with multi-dimensional uncertainty," *Working paper.*

Drobner, C. (2022): "Motivated beliefs and anticipation of uncertainty resolution," *American Economic Review: Insights*, 4, 89–105.

Eil, D. and J. M. Rao (2011): "The Good News-Bad News Effect: Asymmetric Processing of Objective Information about Yourself," *American Economic Journal: Microeconomics*, 3, 114–138.

Engelmann, J., M. Lebreton, N. Salem-Garcia, P. Schwardmann, J. J. van der Weele, and L. A. Chang (2023): "Anticipatory anxiety and wishful thinking," *Working paper.*

Ertac, S. (2011): "Does self-relevance affect information processing? Experimental evidence on the response to performance and non-performance feedback," *Journal of Economic Behavior & Organization*, 80, 532–545.

Exley, C. L. and J. B. Kessler (2022): "Motivated Errors," *Working Paper.*

Feiler, D. and J. Tong (2022): "From noise to bias: Overconfidence in new product forecasting," *Management Science*, 68, 4685–4702.

Galasso, A. and T. S. Simcoe (2011): "CEO overconfidence and innovation," *Management science*, 57, 1469–1484.

Golman, R., D. Hagmann, and G. Loewenstein (2017): "Information Avoidance," *Journal of Economic Literature*, 55, 96–135.

Greiner, B. (2015): "Subject pool recruitment procedures: organizing experiments with ORSEE," *Journal of the Economic Science Association*, 1, 114–125.

Grossman, Z. and D. Owens (2012): "An unlucky feeling: Overconfidence and noisy feedback," *Journal of Economic Behavior & Organization*, 84, 510–524.

Haaland, I., C. Roth, and J. Wohlfart (2023): "Designing information provision experiments," *Journal of economic literature*, 61, 3–40.

Hill, S. J. (2017): "Learning together slowly: Bayesian learning about political facts," *The Journal of Politics*, 79, 1403–1418.

Invernizzi, A. C., A. Menozzi, D. A. Passarani, D. Patton, and G. Viglia (2017): "Entrepreneurial overconfidence and its impact upon performance," *International Small Business Journal*, 35, 709–728.

Karni, E. (2009): "A Mechanism for Eliciting Probabilities," *Econometrica*, 77, 603–606.

Köszegi, B. (2006): "Ego Utility, Overconfidence, and Task Choice," *Journal of the European Economic Association*, 4, 673–707.

Kozakiewicz, M. (2022): "Belief-Based Utility and Signal Interpretation," *Working paper*.

Malmendier, U. and G. Tate (2005): "CEO overconfidence and corporate investment," *The Journal of Finance*, 60, 2661–2700.

——— (2008): "Who makes acquisitions? CEO overconfidence and the market's reaction," *Journal of Financial Economics*, 89, 20–43.

Möbius, M. M., M. Niederle, P. Niehaus, and T. S. Rosenblat (2022): "Managing self-confidence: Theory and experimental evidence," *Management Science*, 68, 7793–7817.

Ortoleva, P. and E. Snowberg (2015): "Overconfidence in political behavior," *American Economic Review*, 105, 504–35.

Schumacher, C., S. Keck, and W. Tang (2020): "Biased interpretation of performance feedback: The role of CEO overconfidence," *Strategic Management Journal*, 41, 1139–1165.

Trautmann, S. T. and G. van de Kuilen (2015): "Belief elicitation: A horse race among truth serums," *The Economic Journal*, 125, 2116–2135.

Van der Weele, J. J. and F. A. Siemens (2020): "Bracelets of pride and guilt? An experimental test of self-signaling," *Journal of Economic Behavior Organization*, 172, 280–291.

Zimmermann, F. (2020): "The dynamics of motivated beliefs," *American Economic Review*, 110, 337–361.

Zizzo, D. J. (2010): "Experimenter demand effects in economic experiments," *Experimental Economics*, 13, 75–98.