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ABSTRACT

Motivated Belief Updating and Rationalization of Information*

We study belief updating about relative performance in an ego-relevant task. Manipulating the perceived ego-relevance of the task, we show that subjects update their beliefs optimistically because they derive direct utility flows 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 received more bad signals, downplay the ego-relevance of the task. Taken together, these findings suggest that subjects use two alternative strategies to protect their ego when presented with objective information.

JEL Classification: C91, D83, D84

Keywords: motivated beliefs, optimistic belief updating, overconfidence, direct belief utility, Bayes' rule, ex-post rationalization

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* 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).

1 Introduction

In many important domains of life, people make decisions based on their beliefs about themselves and their future prospects. During this process, people regularly obtain and interpret new information. For instance, people make preventative healthcare investments based on noisy information about their health status or financial investors make portfolio choices upon the receipt of noisy financial market information. In standard economic theory, beliefs serve only as a guide for accurate decision making and new information is processed in a Bayesian manner. This Bayesian model is difficult to reconcile with empirical evidence on overconfident beliefs, which lead 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 Geoffrey, 2005, 2008), and polarization in politics (Ortoleva and Snowberg, 2015). One puzzle in the economics literature is why and how overconfidence can evolve in the presence of objective information.

We use a novel experimental design to provide causal evidence for the hypothesis that people process new information optimistically because they derive direct utility flows from holding positive beliefs. Specifically, we study belief updating behavior in a *single event* and manipulate the perceived ego-relevance of this event. Our results show that subjects process information more optimistically when the perceived ego-relevance of the underlying event is increased. Previous experimental literature in economics 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; Coutts, 2019; Eil and Rao, 2011; Ertac, 2011; Grossman and Owens, 2012; Möbius et al., forthcoming). For instance, Coutts (2019) compares updating behavior in beliefs about other's (ego-neutral) versus own (ego-relevant) IQ scores. Taken together, the 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). The goal of this paper is to resolve this methodological 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, subjects perform an IQ test and we elicit their beliefs about 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. 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 at any point. We do this because Drobner (2022) shows in a related experiment that optimistic belief updating is only activated if subjects expect no immediate resolution of uncertainty.

We assume that our exogenous manipulation of ego-relevance results in a shift in direct belief utility within a single event. 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 beliefs.[1] To this end, direct belief utility is distinct from indirect belief utility in expected utility theory, which is only indirectly derived by making the best

[1]Note that other more instrumental reasons such as maintaining personal motivation (Bénabou and Tirole, 2002) or persuasive motives (Von Hippel and Trivers, 2011; Schwardmann and van der Weele, 2019; Solda, 2020) can also be the driver of direct belief utility.

possible decision based on accurate beliefs.[2] In the context of our experiment, we argue that subjects in the *High-Ego* treatment derive more direct belief utility than subjects in the *Low-Ego* treatment because they perceive the IQ test as being more ego-relevant.

Overall, our results provide three important insights. First, our main result shows that subjects update their beliefs more optimistically as direct belief utility increases. We provide several pieces of evidence in support of this result. We document more optimistic final beliefs in the *High-Ego* treatment compared to the *Low-Ego* treatment without relying on a Bayesian benchmark. Specifically, we show that final beliefs in the *High-Ego* treatment are on average 4.8 percentage points more optimistic than final beliefs in the *Low-Ego* treatment. In addition, we use a structural Bayesian framework to show that subjects in the *High-Ego* treatment update their beliefs optimistically, while there is no such optimistic updating in the *Low-Ego* treatment. This result provides causal evidence for the optimistic belief updating hypothesis and confirms a broad range of theoretical models with direct belief utility (Bénabou and Tirole, 2002; Möbius et al., forthcoming; Caplin and Leahy, 2019). For instance, Möbius et al. (forthcoming) model optimistic belief updating as an optimal strategy to balance the counteracting forces of direct and indirect utility from beliefs, while Caplin and Leahy (2019) model optimistic belief updating as an optimal trade-off between direct belief utility and the cognitive costs of distorting reality.[3] Moreover, this result complements the finding of a contemporaneous project by Kozakiewicz (2021), who studies the effect of direct belief utility on signal interpretation. In contrast to our direct manipulation of ego-relevance, Kozakiewicz (2021) introduces exogenous variation in ego-relevance by comparing updating behavior in response to either a realized

[2]Previous literature often used the term belief-based utility to describe direct belief utility. We use the term direct belief utility because it provides a clear distinction to indirect belief utility while belief-based utility literally comprises both direct and indirect belief utility.

[3]Other behavioral predictions of this type of models include selective recall (Chew et al., 2020; Enke et al., 2022; Huffman et al., 2022; Zimmermann, 2020) and information avoidance (Golman et al., 2017, 2022). 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.

signal or potential realizations of signals. In line with our result, Kozakiewicz (2021) documents a positive effect of direct belief utility on self-serving signal interpretations.

Second, we find in an exploratory analysis that part of the treatment difference in optimistic belief updating between *High-Ego* and *Low-Ego* treatments can be attributed to motivated errors. Specifically, the propensity of updates that go in the opposite direction of the Bayesian prediction increase for bad signals in the *High-Ego* treatment, while it is independent of the valence of signals in the *Low-Ego* treatment. This result is in line with findings of Exley and Kessler (2022) who document that subjects make motivated errors to justify selfish actions.

Third, we show that subjects ex post alter their perceptions 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 bad 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 in an exploratory analysis that this ex-post rationalization of information is predominantly driven by the minority of subjects with pessimistic updating patterns in the belief updating task.

Taken together, our findings highlight that subject use two substitute strategies to interpret objective information in self-serving manners. One class of subjects forms overconfident beliefs because they process objective information optimistically. Another class of subjects manipulates the extent to which these beliefs enter the utility function directly by adjusting their perceptions about the ego-relevance of the underlying event depending on the valence of information. Both strategies allow subjects to protect their ego when confronted with objective information.

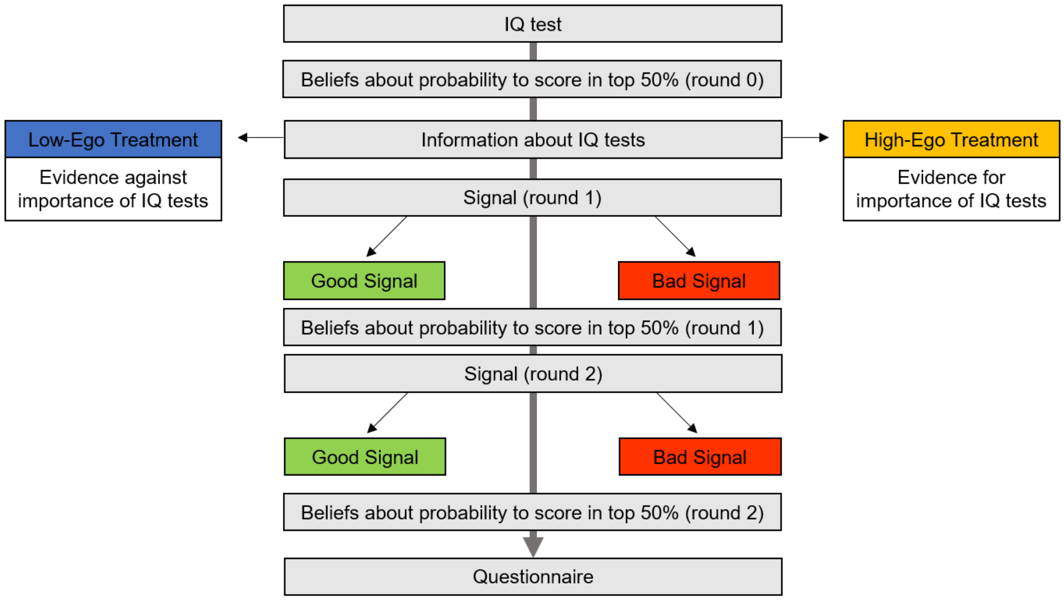
The remainder of this paper proceeds as follows: Section 2 describes the experimental design. Section 3 introduces a stylized framework of motivated beliefs to derive the main hypotheses of this paper. Section 4 discusses the results and Section 5 concludes.

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 the probability of scoring in the top half of the performance distribution in the session. Third, using a between-subject design, we provided subjects with different information about the importance of IQ tests. Fourth, subjects received noisy but informative signals about their relative performance. Fifth, we elicited subjects' posterior beliefs about the probability of scoring in the top half of the performance distribution in the session. The last two stages were repeated such that subjects received two binary signals and reported their posterior beliefs twice.

One important aspect of the experimental design is that the treatment information was randomly assigned at the individual level *after* the prior belief elicitation to rule out the possibility that other prior related errors such as *base-rate neglect* or *confirmation bias* 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 because Drobner (2022) shows in a related experiment that optimistic belief updating is vanished when subjects expect the immediate resolution of uncertainty. To accommodate this design feature, we aimed to obfuscate the relationship between payments and the true state of the world while maintaining the desirable properties of fully incentivized decisions. For instance, subjects only received the total payments of the experiment without information about the earnings in different parts of the experiment. We

Figure 1: Experimental design



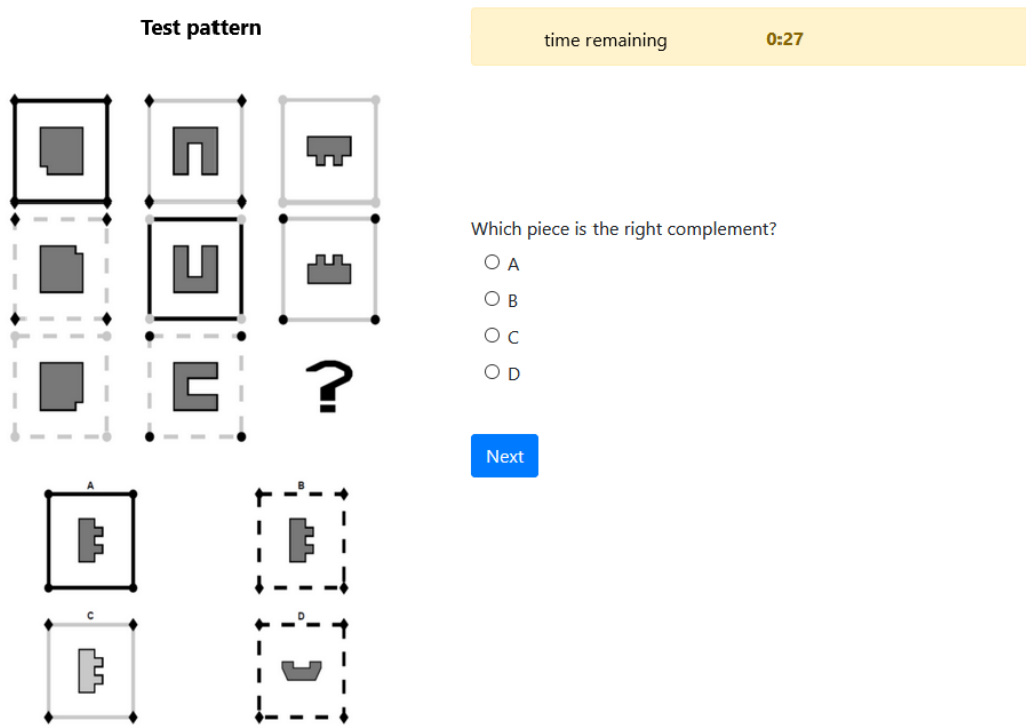
now provide a detailed description of the different stages in the experiment.[4]

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 for each puzzle 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 the final payment for the experiment and the true state of the world.

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 the re-

[4]Full experimental instructions are provided in Appendix C.

Figure 2: IQ test question



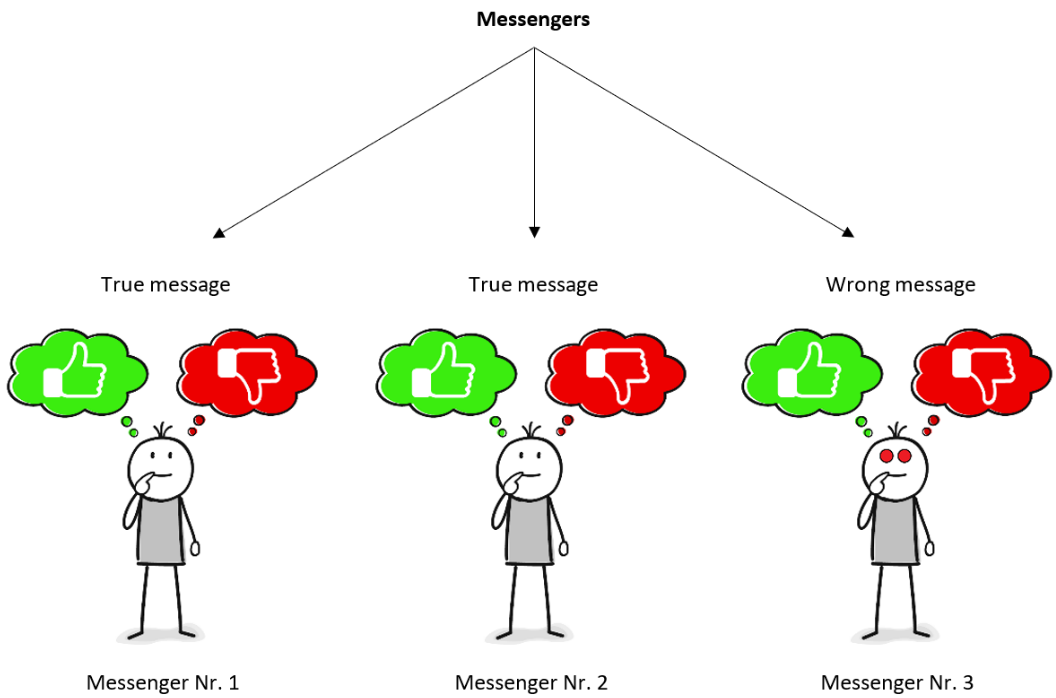
ceipt of treatment information and the first binary signal about their relative performance. In round 2, we elicited subjects' beliefs after the receipt of the second binary signal about their relative performance. To incentivize truthful reporting, we implemented a variation of the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964) proposed by Grether (1981), Allen (1987), and 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 monetary payoffs regardless of subjects' risk preferences. We explained the belief elicitation method in the beginning of the experiment for an unrelated event including some control questions to enhance subjects' understanding of the incentive structure.

Information about IQ tests. In a between-subject design, we asked subjects to read different articles with scientific 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 highlights 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.

Signals. Subjects received two binary signals containing either good signals or bad signals about their relative performance in the IQ test. We have explicitly chosen two signals because it allows us to investigate the belief updating process for different distributions of signals but still ensures that subjects do not learn their true rank with certainty (Drobner, 2022). Figure 3 illustrates the signal generating process. The signals were noisy but informative with an accuracy level of 66.67%. Following Coutts (2019), we aimed to provide an intuitive explanation of the signal informativeness. To this end, 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 message about the true state of the world, the third messenger always lies. The signal realization of both good signals and bad signals is illustrated in Figure 4. While transmitting the signal, the messengers wear sunglasses such that individuals cannot infer the reliability of the signal.

Questionnaire. In the post-experimental questionnaire, we asked subjects to report their stated beliefs about the importance of their performance in the

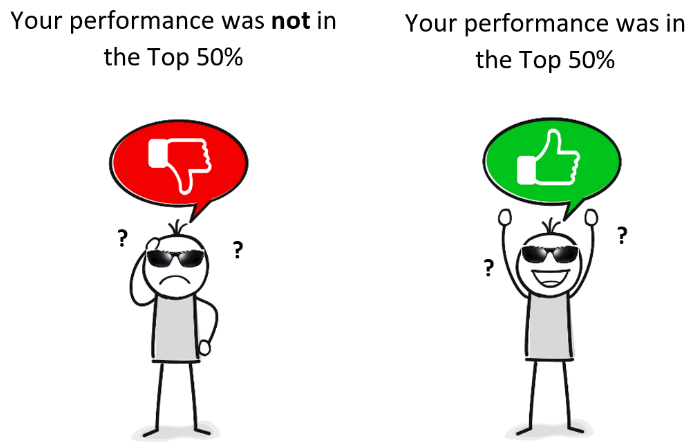
Figure 3: Signal generating process



IQ test for their study and job success on a seven-point Likert scale. These beliefs serve as our proxies for subjects' perceived ego-relevance of the IQ test. The purpose of this proxy is twofold. First, we use it as a sanity check whether our treatment manipulation results in a shift in direct belief utility. Second, it allows us to investigate whether subjects ex-post rationalize information by manipulating their perceived ego-relevance of the IQ test depending on the valence of information they received. In addition, we elicited subjects' self-reported effort in the IQ test on a seven-point Likert scale (1-very low effort, 7-very high effort). This measure allows us to investigate whether subjects ex-post rationalize an increasing number of bad signals with lower effort in the IQ test. Finally, we concluded the survey with questions about the comprehensibility of the instructions and standard demographics.

Setting and sample size. The experiments were conducted with partici-

Figure 4: Signal realization



pants 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.[5] 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 (2004). A total of 419 subjects finished the experiment in 16 sessions (2 offline and 14 online).[6] The number of subjects in a session varied between 20 and 30.

3 Framework and Hypotheses

In this section, we provide a stylized model of motivated beliefs in the context of our experimental setting to derive our main hypotheses. The framework follows Engelmann et al. (2022) by modeling the benefits and costs of belief distortions as a function of direct belief utility, instrumental belief utility, and

[5]Appendix B.10 provides evidence that the conditions in the online sessions were similar to those in the laboratory.

[6]We planned to have exactly 210 subjects in each treatment as pre-registered in the AEA RCT Registry (AEARCTR-0005121). Overall, 451 subjects participated in the experiments, but 32 students voluntarily dropped out or lost the connection during the experiments. As a result, we ended up with 209 subjects in the *High-Ego* treatment and 210 subjects in the *Low-Ego* treatment.

cognitive costs of belief distortions. In our experiment, subjects form beliefs about the probability of scoring in the top half of the performance distribution of an IQ test. Let p_{st} be the informativeness of the binary signal $s \in \{G, B\}$ in rounds $t \in \{1, 2\}$ about scoring in the top half of the performance distribution. Writing out Bayes' rule, the objective Bayesian belief is given by:

$$\gamma_{st} = \frac{p_{st}\gamma_{t-1}}{p_{st}\gamma_{t-1} + (1 - p_{st})(1 - \gamma_{t-1})}. \tag{1}$$

In our framework, subjects may form beliefs $\hat{\gamma}_{st}$ that deviate from objective Bayesian beliefs (Caplin and Leahy, 2019). Similar to Gervais and Odean (2001) and Coutts et al. (2020), subjects follow Bayes' rule but subconsciously choose the informativeness $\hat{p}_{st} \in \{0, 1\}$ of the binary signal about scoring in the top half of the performance distribution:

$$\hat{\gamma}_{st} = \frac{\hat{p}_{st}\gamma_{t-1}}{\hat{p}_{st}\gamma_{t-1} + (1 - \hat{p}_{st})(1 - \gamma_{t-1})}. \tag{2}$$

Choosing the optimal signal informativeness $\hat{p}_{st} \in \{0, 1\}$ emerges from an optimization problem, trading off the benefits and costs of belief distortions:

$$U = \underbrace{\alpha\hat{\gamma}_{st}}_{Direct\, belief\, utility} + \underbrace{\frac{1}{2}\left(1 + 2\hat{\gamma}_{st}\gamma_{st} - \hat{\gamma}_{st}^2\right) M}_{Instrumental\, belief\, utility} - \underbrace{\beta\left(\gamma_{st} - \hat{\gamma}_{st}\right)^2}_{Cognitive\, costs} \tag{3}$$

Direct belief utility. First, subjects derive direct utility from beliefs $\hat{\gamma}_{st}$ 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.

Instrumental belief utility. Second, we incentivized subjects to report their beliefs $\hat{\gamma}_{st}$ using a BDM mechanism. The BDM mechanism implies that subjects maximize their chance of winning a monetary price M if their reported beliefs $\hat{\gamma}_{st}$ coincide with objective Bayesian beliefs γ_{st} (Engelmann et al., 2022).

Cognitive costs of belief distortions. Third, deviations of beliefs $\hat{\gamma}_{st}$ from objective Bayesian beliefs γ_{st} are associated with cognitive costs of distorting reality (Bracha and Brown, 2012; Coutts et al., 2020; Engelmann et al., 2022).

Plugging equations (1) and (2) into equation (3), choosing the optimal signal informativeness $\hat{p}_{st}$ results in the following first-order condition:

$$\frac{\delta U}{\delta \hat{p}_{st}} = \frac{p_{st}\gamma_{t-1}}{p_{st}\gamma_{t-1} + (1-p_{st})(1-\gamma_{t-1})} - \frac{\hat{p}_{st}\gamma_{t-1}}{\hat{p}_{st}\gamma_{t-1} + (1-\hat{p}_{st})(1-\gamma_{t-1})} + \frac{\alpha}{M+2\beta} = 0 \tag{4}$$

If $\alpha = 0$, subjects do not misinterpret the binary signal ($\hat{p}_{st} = p_{st}$) and form beliefs according to Bayes' rule ($\hat{\gamma}_{st} = \gamma_{st}$). If $\alpha > 0$, subjects derive positive direct belief utility and overweight the informativeness of the binary signal about scoring in the top half ($\hat{p}_{st} > p_{st}$), resulting in inflated posterior beliefs in comparison to Bayesian beliefs ($\hat{\gamma}_{st} > \gamma_{st}$). In the context of our experiment, we assume that subjects derive positive direct belief utility from holding confident beliefs about their relative performance in the IQ test ($\alpha > 0$). Based on our framework, we propose that subjects process information optimistically in comparison to the normative benchmark of Bayes' rule.

Hypothesis 1 *Subjects update their beliefs optimistically in comparison to Bayesian updating.*

Equation (4) shows that the chosen informativeness $\hat{p}_{st}$ of the binary signal about scoring in the top half and the resulting belief $\hat{\gamma}_{st}$ are increasing by the perceived ego-relevance α. 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 ($\alpha^{High-Ego} > \alpha^{Low-Ego}$). Based on our framework, we propose that subjects in the *High-Ego* treatment process information more optimistically than subjects in the *Low-Ego* treatment.

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

4 Results

The main objective of our experiment is to evaluate how an exogenous shift of direct belief utility affects subjects' belief updating process about their relative performance in the IQ test.[7] Assuming that ego-relevance induces direct belief utility, 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. Throughout the analysis, we use subjects' stated beliefs about the importance of the IQ test for study and job success measured on a Likert scale (1-very low importance, 7-very high importance) as proxies for ego-relevance.

Figure 5: Manipulation Check

Panel A: Study Success Panel B: Job Success

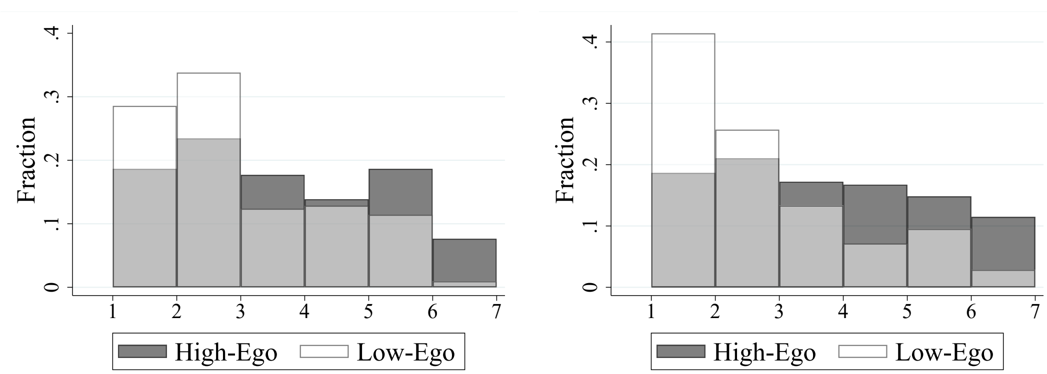


Figure 5 illustrates the distributions of stated beliefs about the importance of the IQ test for study success (Panel A) and job success (Panel B) separately for *High-Ego* and *Low-Ego* treatments. The different distributions between treatments provide visual evidence that subjects in fact perceive the IQ test as being more ego-relevant in the *High-Ego* treatment compared to the *Low-Ego*

[7]Table 7 in Appendix A maps the pre-analysis plan to our results.

treatment. Specifically, subjects in the *High-Ego* treatment state substantially higher beliefs about the importance of the IQ test 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, $p < 0.001$).[8]

Result 1 *Subjects in the High-Ego treatment perceive the IQ test as being more ego-relevant than subjects in the Low-Ego treatment.*

4.1 Aggregate Beliefs

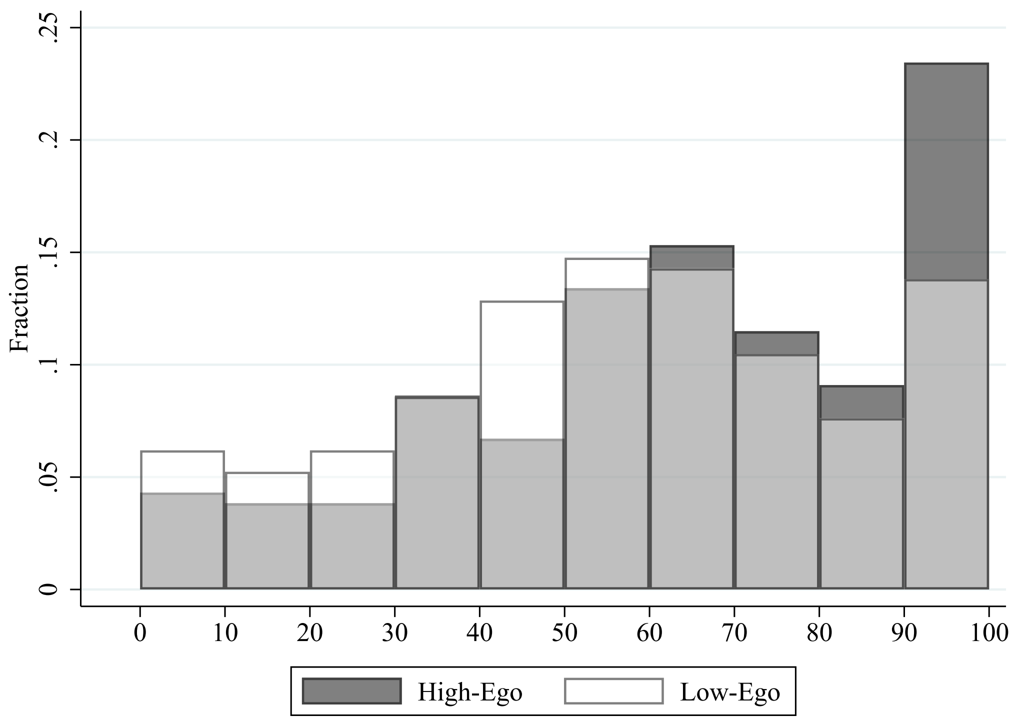
To provide a general overview of belief updating behavior, we describe the beliefs about relative performance in the IQ test at the aggregate level without relying on a Bayesian benchmark. Initial beliefs, measured *before* subjects received the treatment information about the importance of IQ tests, 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, $p < 0.001$).[9]

Figure 6 shows the distributions of final beliefs separately for *High-Ego* and *Low-Ego* treatments. Final beliefs are measured *after* subjects received the treatment information about the importance of IQ tests and the two noisy signals about their actual performance. The different distributions of final beliefs between treatments provide visual evidence that subjects in the *High-Ego* treatment form more optimistic final beliefs than subjects in the *Low-Ego* treatment. Specifically, final beliefs in the *High-Ego* treatment are on average 61.5% while final beliefs in the *Low-Ego* treatment are with an average of 53.8% significantly lower (Wilcoxon rank-sum test, $p = 0.004$). These test results are confirmed when testing for differences between distributions using a one-sided test for stochastic dominance and separateness of the two distributions

[8] All non-parametric tests are two-sided if not stated otherwise.

[9] 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, $p = 0.647$). See Figure 7 in Appendix B.1 for the whole distributions of initial beliefs.

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



(Schmid and Trede, 1996, $p = 0.002$).[10] Interestingly, initial and final beliefs do not differ significantly in the *Low-Ego* treatment (Wilcoxon signed-rank test, $p = 0.972$), but in the *High-Ego* ($p = 0.007$).

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.[11] The estimated coefficient for the treatment dummy documents that final beliefs in the *High-Ego* treatment are on average 4.81 percentage points

[10]Following Imas (2014), we compute the p-value using Monte-Carlo simulations with 100,000 repetitions. We would like to thank Alex Imas for providing the code. Figure 8 in Appendix B.3 shows the CDFs of final beliefs in both treatments.

[11]Appendix B.2 shows that our treatment groups are relatively balanced according to initial beliefs, gender, and IQ test scores but we include the controls as an additional robustness check. Appendix B.4 describes gender differences in initial and final beliefs.

more optimistic than final beliefs in the *Low-Ego* treatment ($p = 0.026$).

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

Dependent Variable: Final Belief	(1) Full Sample	(2) Two Bad Signals	(3) Mixed Signals	(4) Two Good 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 in a t-test of the null hypothesis that coefficients are equal to 0, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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 good signals, two mixed signals, or two bad signals. The results provide suggestive evidence that the treatment effect is stronger for subjects who received two good signals. However, we cannot reject equality of the coefficient estimates for the treatment dummy for subjects who received two good signals versus subjects who received two mixed signals or two bad signals ($p = 0.141$).

Result 2 *Pooled initial beliefs are overconfident. Final beliefs in the High-Ego treatment are on average more optimistic than final beliefs in the Low-Ego treatment.*

4.2 Comparison to Bayesian benchmark

In this section, we compare belief updating behavior to the normative benchmark of Bayes' rule using a structural empirical framework (Möbius et al., forthcoming). The reason for doing so is threefold. 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 take into account updating behavior in both rounds after observing each binary signal. Third, it allows a direct comparison of subjects' responsiveness to good signals and bad signals, which accounts for other deviations from Bayes' rule such as conservatism or base-rate neglect.

The objective Bayesian posterior belief γ_{st} is a function of the prior γ_{t-1} and the informativeness of the signal p_{st} for any signal $s \in \{G, B\}$. Specifically, the objective Bayesian posterior belief γ_{st} in response to a good signal ($s = G$) is defined as:

$$\gamma_{Gt} = \frac{p_{Gt}\gamma_{t-1}}{p_{Gt}\gamma_{t-1} + (1 - p_{Gt})(1 - \gamma_{t-1})} \tag{5}$$

while the objective Bayesian posterior belief γ_{st} in response to a bad signal ($s = B$) is defined as:

$$\gamma_{Bt} = \frac{p_{Bt}\gamma_{t-1}}{p_{Bt}\gamma_{t-1} + (1 - p_{Bt})(1 - \gamma_{t-1})} \tag{6}$$

Following Möbius et al. (forthcoming), we use a logit transformation to derive an augmented version of Bayes' rule with indicators for good signals $I(s = G)$ and bad signals $I(s = B)$, respectively:

$$logit(\gamma_t) = logit(\gamma_{t-1}) + I(s = G)log(\frac{p_{Gt}}{1 - p_{Gt}}) + I(s = B)log(\frac{p_{Bt}}{1 - p_{Bt}}) \quad (7)$$

Adding parameters δ, β_G, and β_B allows us to estimate the following empirical model, which nests Bayes' rule as a special case ($\delta = \beta_G = \beta_B = 1$):

$$logit(\hat{\gamma}_{it}) = \delta logit(\hat{\gamma}_{i,t-1}) + \beta_G log(\frac{p_{Gt}}{1 - p_{Gt}}) + \beta_B log(\frac{p_{Bt}}{1 - p_{Bt}}) + \epsilon_{it} \quad (8)$$

The parameter δ tests the invariance assumption of Bayes' rule which implies that a change in logit beliefs only depends on past signals and not the prior. This assumption holds, if the parameter δ equals one. Deviations from invariance include base-rate neglect ($\delta < 1$) and confirmation bias ($\delta > 1$). Base-rate neglect implies that subjects update their beliefs as if their priors are closer to one-half and confirmation bias implies that subjects update their beliefs as if their priors are closer to the boundaries zero or one (Barron, 2021). The parameters β_G and β_B represent subjects' responsiveness to good and bad signals, respectively. Conservatism implies that subjects update too little in response to both good and bad signals ($\beta_s < 1 \ \ \forall s \in \{G, B\}$) and overresponsiveness implies that subjects update too much in response to both good and bad signals ($\beta_s > 1 \ \ \forall s \in \{G, B\}$). Optimistic belief updating is identified if subjects update their beliefs more strongly upon the receipt of good signals compared to bad signals ($\beta_G > \beta_B$).[12]

Table 2 shows the results of the corresponding regression analysis using the full sample and separately for *High-Ego* and *Low-Ego* treatments. The parameter estimates for δ are similar across all samples and significantly below one,

[12]It is important to note that the framework is agnostic for beliefs that hit the boundaries of the probability space because the logit is not defined for 0 or 1.

Table 2: Belief Updating

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

	(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_G	0.716***	0.796***	0.642***
	(0.048)	(0.070)	(0.067)
β_B	0.557***	0.477***	0.619***
	(0.051)	(0.073)	(0.068)
Observations	715	348	367
R^2	0.703	0.677	0.728
$\beta_G - \beta_B$	0.159	0.318	0.023
P-value ($\beta_G = \beta_B$)	0.016	0.001	0.798
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 2 and 3)			0.025

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 in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

suggesting that subjects update exhibit base-rate neglect. Moreover, the estimated coefficients for subjects' responsiveness to signals β_s for $s \in \{G, B\}$ are significantly below one, showing that subjects update their beliefs conservatively in comparison to Bayes' rule. Pooling data from both treatments shows that subjects on average update their beliefs more strongly to good signals than bad signals ($\beta_G > \beta_B, p = 0.016$). More importantly, however, this asymmetry in responsiveness to good signals and bad signals is almost entirely driven by subjects in the *High-Ego* treatment. While subjects in the *High-Ego* treatment update their beliefs more strongly upon the receipt of good signals ($\beta_G^{High-Ego} > \beta_B^{High-Ego}, p = 0.001$), there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_B^{Low-Ego}, p = 0.798$). This treatment difference in the level of optimistic belief updating is confirmed by a Chow-test

$(\beta_G^{High-Ego} - \beta_B^{High-Ego} > \beta_G^{Low-Ego} - \beta_B^{Low-Ego}, p = 0.025)$.[13]

Result 3 *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 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% false updates), while columns 4-6 show the regression analysis that additionally excludes subjects who never update their beliefs (19.8% zero updates).[14] The results in column 1 document no significant difference between subjects' responsiveness to good signals and bad signals at the aggregate level ($\beta_G > \beta_B, p = 0.166$). The results in columns 2 and 3 show that subjects in the *High-Ego* treatment update their beliefs more strongly upon the receipt of good signals ($\beta_G^{High-Ego} > \beta_B^{High-Ego}, p = 0.017$), while there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_B^{Low-Ego}, p = 0.724$). This treatment difference in the level of optimistic belief updating is confirmed by a Chow-test ($\beta_G^{High-Ego} - \beta_B^{High-Ego} > \beta_G^{Low-Ego} - \beta_B^{Low-Ego}, p = 0.048$). The results in column 4 show no significant difference between subjects' responsiveness to good signals and bad signals at the aggregate level ($\beta_G > \beta_B, p = 0.107$). The results in columns 5 and 6 show that subjects in the *High-Ego* treatment update their beliefs more strongly upon the receipt of good signals ($\beta_G^{High-Ego} > \beta_B^{High-Ego}, p = 0.027$), while there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_B^{Low-Ego}, p = 0.840$). However, this treatment difference in the level of optimistic belief updating is not confirmed by a Chow-test ($\beta_G^{High-Ego} - \beta_B^{High-Ego} > \beta_G^{Low-Ego} - \beta_B^{Low-Ego}, p = 0.163$).

One interesting question that arises from this reduced treatment effect in the restricted sample is whether this difference can be attributed to motivated

[13] In Appendix B.7, we provide an exploratory analysis of belief updating for different sequences of signals. In Appendix B.8, we provide an exploratory analysis of belief updating for round 1 and round 2, respectively.

[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.

Table 3: Belief Updating - Restricted Sample

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

Dependent Variable: Logit Belief	No Wrong Updates (1) Pooled	(2) High-Ego	(3) Low-Ego	No Wrong and No Zero Updates (4) Pooled	(5) High-Ego	(6) 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_G	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_B	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
$\beta_G - \beta_B$	0.091	0.229	-0.032	0.122	0.234	0.022
P-value ($\beta_G = \beta_B$)	0.166	0.017	0.724	0.107	0.028	0.840
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 2 and 3)						0.048
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 5 and 6)						0.163

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 in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

zero or wrong updates. The basic idea of motivated zero and wrong updates is that people have a higher propensity of wrong and zero updates if they *i*) receive a bad signal and *ii*) belong to the *High-Ego* treatment. In Table 4, we use probit regressions of a dummy for zero and wrong updates on a dummy for a bad signal observed in a given round separately for *High-Ego* and *Low-Ego* treatments. 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. The results in columns 1 and 2 provide suggestive evidence that the propensity of zero updates is positively affected by observing a bad signal in the *High-Ego* treatment ($p = 0.086$), while it does not differ significantly from zero in the *Low-Ego* treatment ($p = 0.692$). However, this difference in the coefficient estimates for the bad signal dummy is not significantly different between *High-Ego* and *Low-Ego* treatments (Chow-test, $p = 0.309$). The results in columns 3 and 4 show stronger evidence for motivated wrong updates. Specifically, subjects' propensity for wrong updates is positively affected by observing a bad signal in the *High-Ego* treatment ($p = 0.015$), while it does not differ significantly from zero in the *Low-Ego* treatment ($p = 0.837$). This difference in the coefficient estimates for the bad signal dummy is significantly different between *High-Ego* and *Low-Ego* treatments (Chow-test, $p = 0.047$). This analysis suggests that part of our treatment effect in the full sample can be attributed to motivated errors.

Table 4: Motivated Errors

Dependent Variables:	Zero Updates		Wrong Updates	
	(1)	(2)	(3)	(4)
	Low-Ego	High-Ego	Low-Ego	High-Ego
Bad Signal	0.046	0.222*	-0.030	0.570***
	(0.116)	(0.129)	(0.221)	(0.206)
Constant	-0.240**	-0.517***	-1.349***	-1.706***
	(0.098)	(0.010)	(0.156)	(0.172)
Observations	398	395	255	284
Pseudo R^2	0.000	0.006	0.000	0.042
P-value [Chow test] for Bad Signal dummy (Regressions 1 and 2): 0.309				
P-value [Chow test] for Bad Signal dummy (Regressions 3 and 4): 0.047				

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) Analysis uses Probit regressions with clustered standard errors at the individual level in parentheses.
(iii) Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 0, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Result 4 *The propensity of wrong and zero updates is increasing for bad signals in the High-Ego treatment, while it is independent of the valence of signals in the Low-Ego treatment.*

One potential endogeneity concern of the empirical framework used in Tables 2 and 3 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 good signals and bad signals (see Barron, 2021, for an intriguing discussion). In Appendix B.5, 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. Another concern about the empirical framework used in Tables 2 and 3 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. Appendix B.6 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.

One more general discussion point on our experimental design is whether the treatments also affect subjects' instrumental belief utility. Specifically, subjects in the *High-Ego* treatment might have stronger incentives to form accurate beliefs because the IQ test has presumably a stronger signaling value for instrumentally relevant decisions outside of the experiment. For instance, holding more accurate beliefs about one's own IQ test scores potentially helps subjects to make better human capital investments. We cannot rule out this mechanism by design but the data provide no evidence that subjects overall form more accurate beliefs in the *High-Ego* treatment compared to the *Low-Ego* treatment. For instance, the regression analysis in Table 2 shows that subjects do not follow the Bayesian model more closely in the *High-Ego* treatment compared to 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). Based on the findings of Drobner (2022), we propose that subjects who by chance received good signals perceive the IQ test as being more ego-relevant than subjects who received bad signals. To test this prediction, we estimate how our proxies for ego-relevance, i.e. subjects' stated beliefs about the importance of the IQ test for study and job success, are affected by the number of bad signals received. In addition, we estimate how the number of bad signals received affects subjects' indicated effort provision in the IQ test. Regarding the latter, we propose that subjects rationalize bad signals by indicating lower effort provision.

In Table 5, we use ordered logistic regressions to regress subjects' stated beliefs about the importance of the IQ test for study and job success on the number of bad signals received. Controlling for IQ test scores, the noisy signal structure allows us to estimate the causal effect of bad signals on subjects' perceived ego-relevance. Causality is established because conditional on subjects' IQ test scores, the number of bad signals received is completely random. The results in columns 1 and 2 show that subjects in fact state lower beliefs about the importance of the IQ test for study success ($p = 0.014$) and job success ($p = 0.023$) as the number of bad signals increases. Moreover, the results in column 3 show that subjects also indicate less effort provision in the IQ test when they by chance received more bad signals ($p = 0.036$).[15] This result is consistent with self-serving attribution bias because individuals attribute apparently low IQ scores to their low effort provision in the test (see Mezulis et al., 2004, for a review).

In the following exploratory analysis we investigate whether this ex post rationalization is driven by subjects with optimistic or pessimistic belief updating patterns. This analysis allows us to test whether ex-post rationalization provides a substitute or complementary ego-protecting strategy to the opti-

[15]Table 5 shows the regression analysis for the pooled data from both treatments. In Appendix B.9 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.

Table 5: Ex-post Rationalization

Dependent Variable	(1) Importance Study Success	(2) Importance Job Success	(3) Effort
Bad 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' 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 in a t-test of the null hypothesis that coefficients are equal to 0, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

mistic belief updating patterns that we documented in section 4.2. Specifically, in Table 6 we replicate the regression analysis in Table 5 including a dummy for being pessimistic in the belief updating process, and an interaction term with the number of bad signals received. Subjects are classified as pessimistic if they hold more pessimistic final beliefs 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. This finding suggests that ex-post rationalization provides a substitute strategy for optimistic belief updating to maintain a strong ego despite the presence of objective information. Alternatively, subjects have no reason to engage in instrumentally costly optimistic belief updating if they find ways to explain away the ego-relevance of the task as the number of bad signals increases.

Result 5 *(Pessimistic) subjects ex-post rationalize bad signals about their relative performance in the IQ test.*

Table 6: Ex-post Rationalization - Pessimistic versus Optimistic Subjects

	(1)	(2)	(3)
Dependent Variable	Importance Study Success	Importance Job Success	Effort
Bad 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)
Bad 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' 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 in a t-test of the null hypothesis that coefficients are equal to 0, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

5 Conclusion

We have used laboratory experiments to provide causal evidence for the effect of ego-relevance induced direct belief utility on belief updating behavior. As opposed to a comparison of belief updating behavior in different events with varying ego-relevance, we manipulate the perceived ego-relevance in a single event and study its effect on belief updating 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. Strikingly, this ex-post rationalization is more prevalent among subjects with pessimistic belief updating patterns, suggesting that it serves as a substitute strategy to optimistic belief updating.

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. For instance, research on motivated memory can use this exogenous manipulation of ego-relevance to study its impact on memory biases in belief formation. Our findings on ex-post rationalization are of more general relevance to researchers interested in identifying motivated beliefs. For them, it is important to limit the possibilities of ex post rationalization to ensure that subjects have a motive for self-serving biases in belief formation.

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Appendices

A Mapping of pre-analysis plan into paper

Table 7 provides a mapping of the hypotheses in the pre-analysis plan and the results in the paper. The pre-analysis plan is available at the AEA RCT Registry (AEARCTR-0005121).

Table 7: Mapping of hypotheses and results

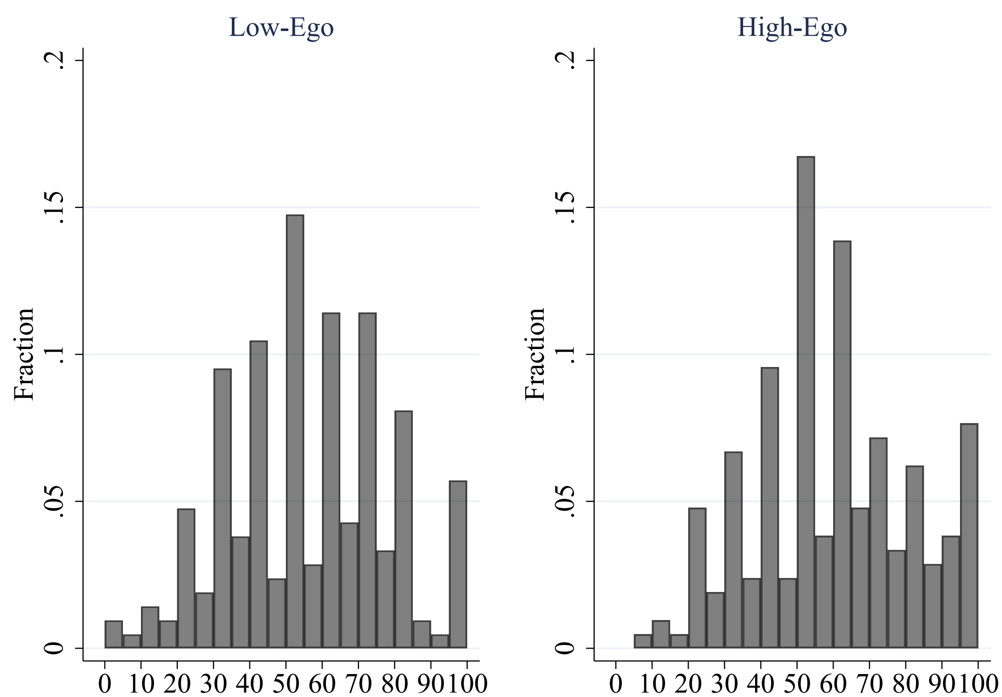
Hypotheses	**Results in the paper**
Hypothesis 1: Subjects hold overconfident prior beliefs.	Result 2 on page 17
Hypothesis 2: Subjects' reported relevance of the IQ test for study success and job success is higher in the *High-Ego* treatment compared to the *Low-Ego* treatment.	Result 1 on page 14
Hypothesis 3: Subjects update their beliefs optimistically compared to Bayes' rule.	Result 3 on page 20
Hypothesis 4: Subjects in the *High-Ego* treatment update their beliefs more optimistically than subjects in the *Low-Ego* treatment.	Result 2 on page 17 and result 3 on page 20
Hypothesis 5: Subjects ex-post rationalize negative feedback about their relative performance in the IQ test.	Result 5 on page 26

B Additional Results

B.1 Distributions of Initial Beliefs

Figure 7 shows the distributions of initial beliefs separately for *High Ego* and *Low Ego* treatments. The distributions are not significantly different between High Ego and Low Ego treatments (Kolmogrov-Smirnov test, $p = 0.647$).

Figure 7: Distributions of Initial Beliefs



B.2 Baseline Balance

Table 8 shows the means of initial beliefs, gender, and IQ test scores separately for *High Ego* and *Low Ego* treatments and documents no statistically significant imbalances in our treatments.

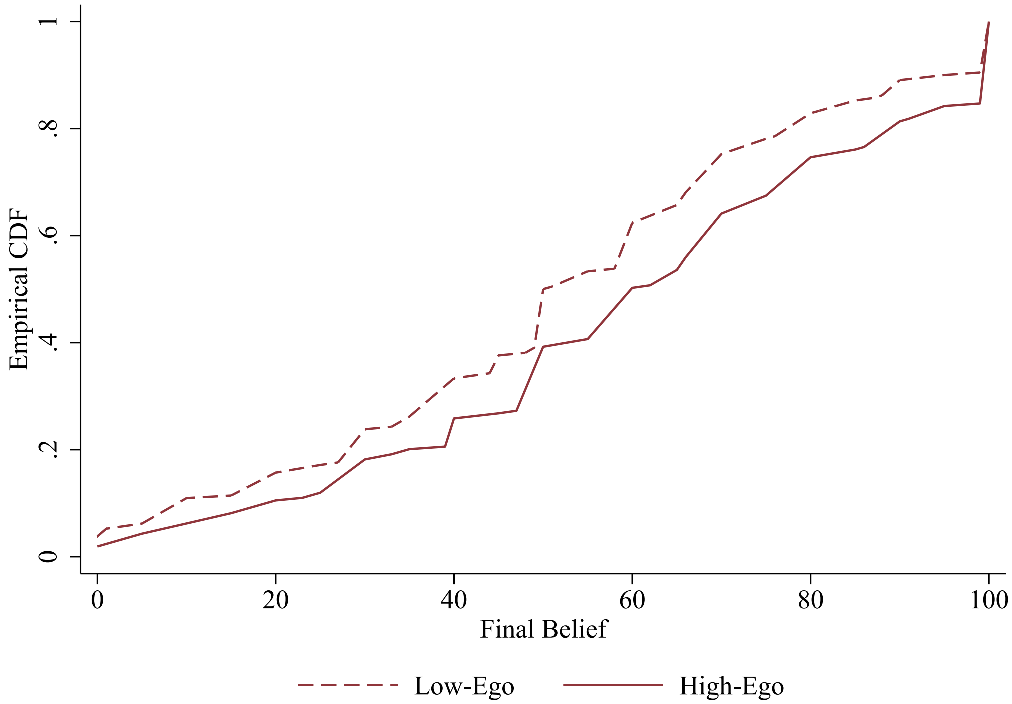
Table 8: Baseline Balance

Variable	High-Ego (N=209)	Low-Ego (N=210)	P-Value
Initial belief	57.44	53.91	0.647
Female	0.56	0.49	0.204
IQ test score	9.71	9.33	0.708

Notes:
For the comparison of gender (a dummy variable equal to 1 for a female participant) the p-value is based on Fischer's exact test, for all other comparisons a Kolmogrov-Smirnov test was used.

B.3 Cumulative Distribution Functions of Final Beliefs

Figure 8: Cumulative Distribution Functions of Final Beliefs



B.4 Gender Differences in Beliefs

We replicate the findings of previous literature by documenting a gender gap in confidence (Barber and Odean, 2001; Niederle and Vesterlund, 2007; Möbius et al., forthcoming). Initial beliefs of men are on average 58.34% and significantly higher than initial beliefs of women, which are on average 53.23% (Wilcoxon rank sum test, $p = 0.023$). This gender difference in initial beliefs is not driven by differences in IQ test scores, which are essentially equal across men and women (Wilcoxon rank sum test, $p = 0.978$).

Final beliefs of men are on average 60.58% and significantly higher than final beliefs of women, which are on average 54.94% (Wilcoxon rank sum test, $p = 0.019$). Consequently, the presence of objective information does not reduce the gender gap in confidence in our experiment. This finding is in line with recent work of Coffman et al. (2022) who demonstrate that gender differences in confidence persist over time despite the presence of objective feedback.

B.5 Belief Updating - Controlling for State

In Table 9, we replicate the regression analysis in Table 2 of Section 4.2 by interacting the right-hand side variables with a dummy for being in the top half of the IQ test performance distribution within the session. This analysis controls for the potential endogeneity issue if updating systematically differs between subjects in the two different states of the world (see Barron, 2021, for an intriguing discussion).

Table 9: Belief Updating - Controlling for State

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

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_G	0.789	0.948	0.622
	(0.137)	(0.176)	(0.189)
$Top * \beta_G$	-0.084	-0.170	0.021
	(0.146)	(0.191)	(0.202)
β_B	0.654	0.550	0.695
	(0.163)	(0.290)	(0.164)
$Top * \beta_B$	-0.112	-0.101	-0.087
	(0.172)	(0.298)	(0.180)
Observations	715	348	367
R^2	0.704	0.684	0.728
$(\beta_G + Top * \beta_G) - (\beta_B + Top * \beta_B)$	0.163	0.329	0.035
P-value $(\beta_G + Top * \beta_G = \beta_B + Top * \beta_B)$	0.019	0.001	0.729
P-value for $((\beta_G + Top * \beta_G) - (\beta_B + Top * \beta_B))$ (2 and 3)			0.033

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 in a t-test of the null hypothesis that the interaction terms $Top*\delta$, $Top*\beta_G$, and $Top*\beta_B$ are different from zero, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

B.6 Belief Updating - Including Boundary Priors

In Table 10, we replicate the regression analysis in Table 2 of Section 4.2 by replacing boundary beliefs 0 and 1 with 0.01 and 0.99, respectively. This analysis includes observations that are truncated in the main regressions in Table 2 of Section 4.2 because the logit is not defined for boundary beliefs 0 or 1.

Table 10: Belief Updating - Including Boundary Priors

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

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

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

B.7 Belief Updating - Sequence of Signals

In Table 11, we replicate the regression analysis in Table 2 of Section 4.2 for different sequences of signals and interacting the right-hand side variables with a dummy for being in the *High-Ego* treatment.

Table 11: Belief Updating - Sequence of Signals

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

Dependent Variable: Logit Belief	(1) Two Good	(2) 1st. Good, 2nd. Bad	(3) 1st. Bad, 2nd. Good	(4) Two Bad
δ	1.006	0.819	0.814	0.882
	(0.123)	(0.091)	(0.065)	(0.035)
$High\text{-}Ego * \delta$	-0.094	-0.301	-0.038	0.036
	(0.144)	(0.280)	(0.103)	(0.082)
β_G	0.497	0.690	0.745	
	(0.098)	(0.158)	(0.106)	
$High\text{-}Ego * \beta_G$	0.304**	-0.059	0.169	
	(0.142)	(0.208)	(0.173)	
β_B		0.586	0.267	0.780
		(0.148)	(0.110)	(0.104)
$High\text{-}Ego * \beta_B$		-0.344*	0.005	-0.242*
		(0.197)	(0.199)	(0.142)
Observations	181	154	187	193
R^2	0.754	0.485	0.745	0.752

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 in a t-test of the null hypothesis that the interaction terms $High\text{-}Ego * \delta$, $High\text{-}Ego * \beta_G$, and $High\text{-}Ego * \beta_B$ are different from zero, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Column 1 shows that subjects in the *High-Ego* treatment update their beliefs more strongly in response to good signals than subjects in the *Low-Ego* treatment when they received a sequence of two good signals. Column 2 shows that subjects in the *High-Ego* treatment update their beliefs less strongly in response to bad signals than subjects in the *Low-Ego* treatment when they first received a good signal and then a bad signal. Column 3 shows the updating patterns for subjects who first received a bad signal and then a good signal, and documents no significant difference in coefficients between *High-Ego* and *Low-Ego* treatments. Column 4 shows that subjects in the *High-Ego* treatment update their beliefs less strongly in response to bad signals than subjects in the *Low-Ego* treatment when they received a sequence of two bad signals. Overall, the qualitative direction of all coefficients is consistent with our hypothesis that subjects update signals more optimistically when they are in the *High-Ego* treatment compared to the *Low-Ego* treatment. Consistent with the results in Table 1 of Section 4.1, we find the strongest treatment difference in updating patterns for subjects who received a sequence of two good signals.

B.8 Belief Updating - Round 1 versus Round 2

In Table 11, 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 results show that the qualitative results are similar in both rounds but we observe a stronger treatment effect in the first round.

Table 12: 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 in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

B.9 Ex-post Rationalization - High Ego versus Low Ego

In Table 13, we replicate the regression analysis in Table 5 separately for *High-Ego* and *Low-Ego* treatments. 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 bad signals, provide no evidence for significant treatment differences in ex-post rationalization.

Table 13: Ex-post Rationalization by Treatment

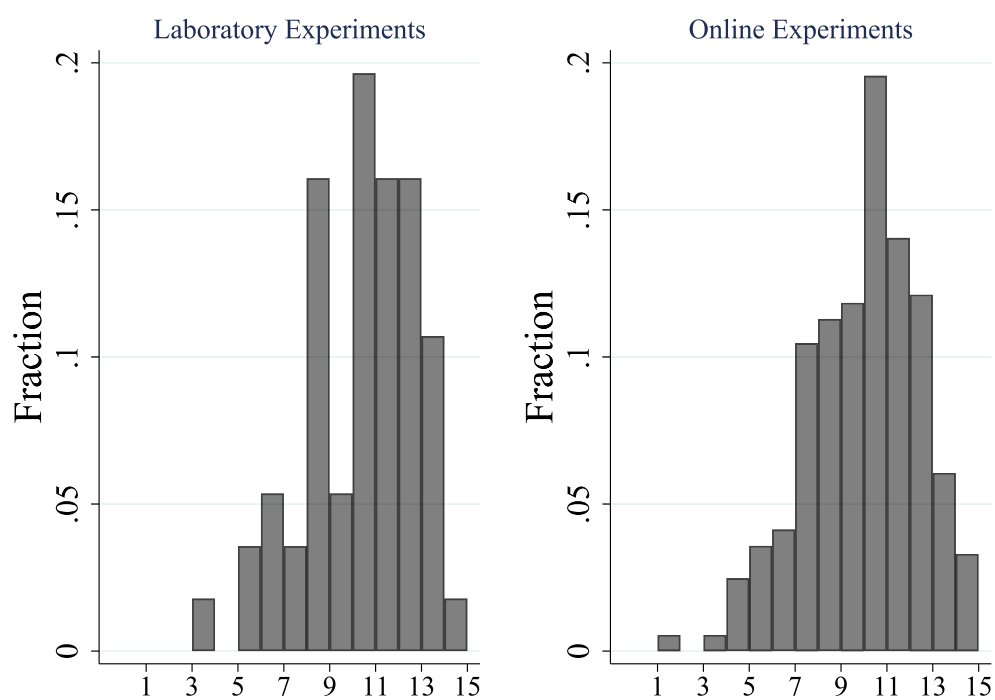
Dependent variable	Importance study success		Importance job success		Effort	
	(1)	(2)	(3)	(4)	(5)	(6)
	High-Ego	Low-Ego	High-Ego	Low-Ego	High-Ego	Low-Ego
Bad signals	-0.335**	-0.271	-0.413**	-0.164	-0.236	-0.303*
	(0.170)	(0.184)	(0.174)	(0.186)	(0.179)	(0.182)
IQ test score	0.072	0.107*	0.073	0.128**	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 in a t-test of the null hypothesis that coefficients are equal to 0, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

B.10 Laboratory Sessions versus Online Sessions

We provide several pieces of evidence that the conditions in the online sessions were similar to those in the laboratory, although the sample size in our two laboratory sessions is too small to draw definite conclusions for our main results ($n = 56$). First, we present the distributions of IQ test scores between laboratory and online sessions in Figure 9. A Kolmogorov-Smirnoff test shows that the distributions of IQ test scores are not significantly different between the two conditions ($p = 0.807$). This result suggests that subjects exerted the same effort in the laboratory and online sessions.

Figure 9: Distributions of Quiz Scores - Laboratory and Online Experiments



Second, we compare the fraction of subjects who memorized the authors cited in the articles about the importance of IQ tests. The fraction of correct answers in laboratory sessions is 89.3% compared to 91.7% in online sessions. This difference is not statistically significant (Fisher's exact test, $p = 0.606$), suggesting that subjects read the treatment information with a similar level of attention.

Third, Table 14 replicates the main regression analysis in Table 2 of Section 4.2 separately for laboratory and online sessions. The results of the online sessions in columns 4-6 provide evidence that subjects in the *High-Ego* treatment update their beliefs more strongly upon the receipt of good signals ($\beta_G^{High-Ego} > \beta_B^{High-Ego}, p < 0.001$), while there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_B^{Low-Ego}, p = 0.728$). This treatment difference in the level of optimistic belief updating is confirmed by a Chow test ($\beta_G^{High-Ego} - \beta_B^{High-Ego} > \beta_G^{Low-Ego} - \beta_B^{Low-Ego}, p = 0.032$). The results of the laboratory sessions in columns 1-3 show very similar updating patterns, although the sample size is too small to confirm the results with statistical tests at any conventional level.

Table 14: Belief Updating - Laboratory and Online Experiments

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

Dependent	Laboratory			Online		
Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Logit Belief	Pooled	High-Ego	Low-Ego	Pooled	High-Ego	Low-Ego
δ	0.997	1.080	0.935	0.860***	0.802***	0.896***
	(0.074)	(0.108)	(0.082)	(0.033)	(0.059)	(0.035)
β_G	0.789	0.948	0.622*	0.705***	0.778***	0.643***
	(0.139)	(0.183)	(0.195)	(0.051)	(0.075)	(0.072)
β_B	0.654**	0.550	0.695*	0.542***	0.448***	0.608***
	(0.166)	(0.302)	(0.169)	(0.052)	(0.067)	(0.075)
Observations	87	40	47	628	308	320
R^2	0.712	0.715	0.728	0.703	0.677	0.728
$\beta_G - \beta_B$	0.135	0.398	-0.073	0.163	0.329	0.035
P-value ($\beta_G = \beta_B$)	0.517	0.274	0.758	0.019	0.000	0.728
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 2 and 3)						0.270
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 5 and 6)						0.032

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 in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

C 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.

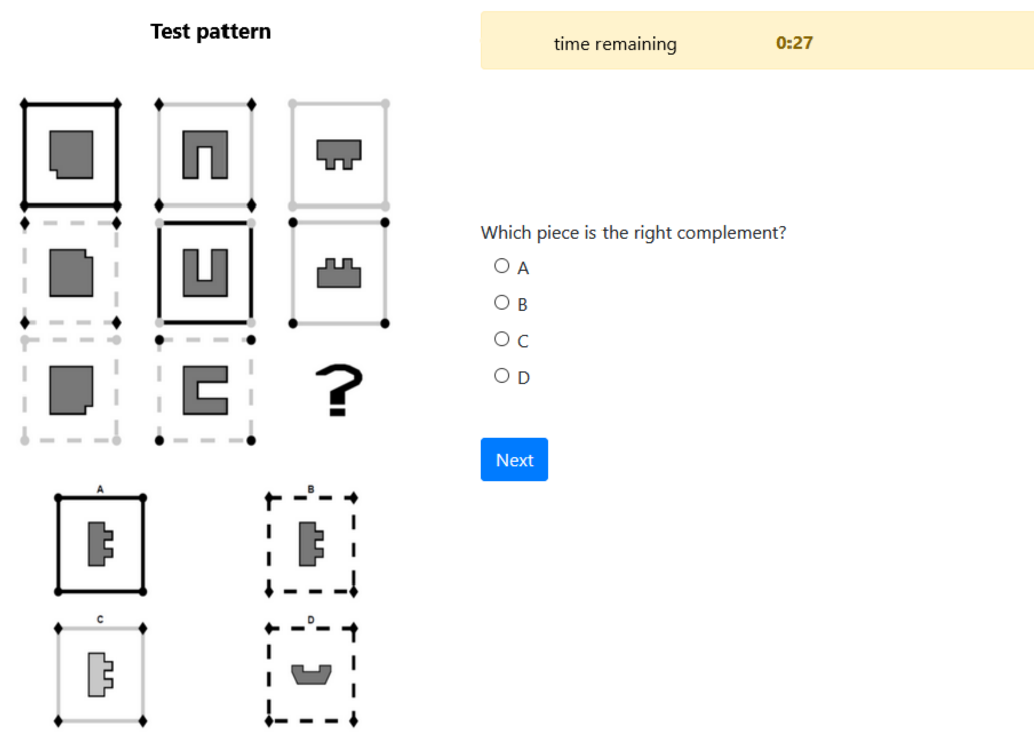
- What probability should you indicate such that you have the highest chance of a payment of 2 euros?
- What is your chance of winning 2 euros?
- Would you have had a higher probability to win 2 euros if you had a reported 60% probability instead of 30%?
    - Yes
    - No

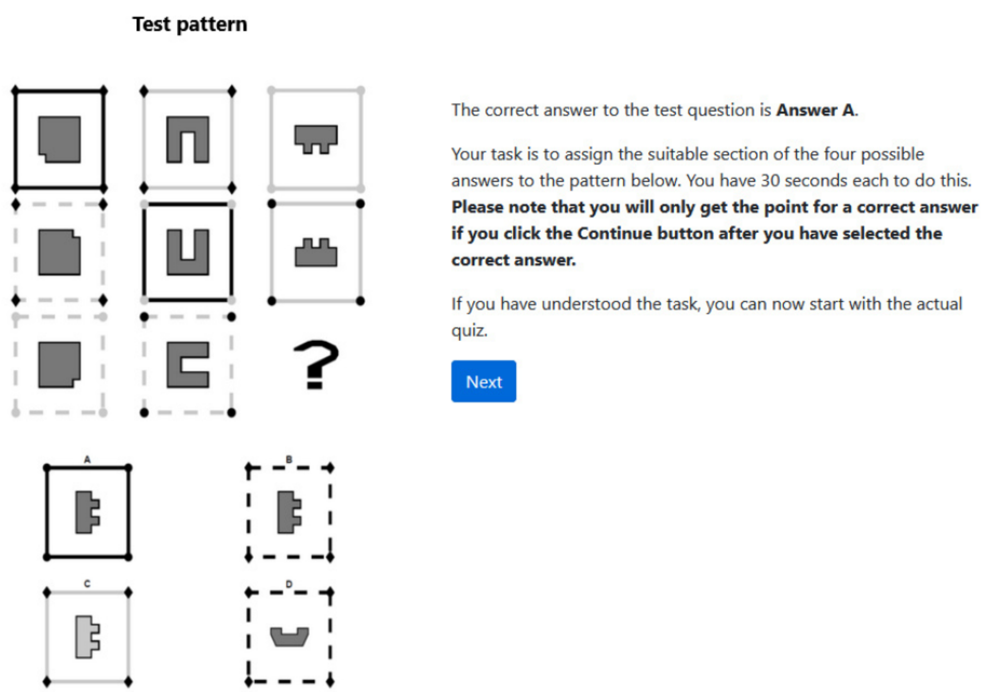
Quiz

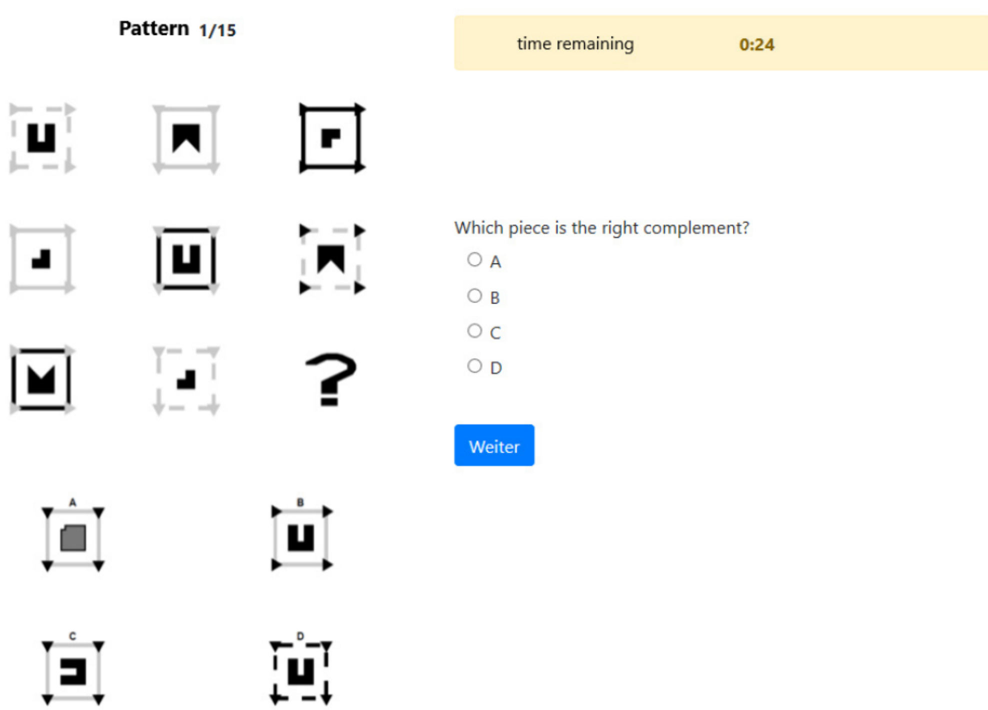
In the first part of the experiment we ask you to complete a quiz with 15 questions. You will see a pattern with one piece missing. Your task is to choose the correct piece from four suggestions and click on the Next button. You have 30 seconds to select the correct answer for each pattern and click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


Pattern 1/15
time remaining 0:24
Which piece is the right complement?
A
B
C
D
Weiter
A
B
C
D

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.

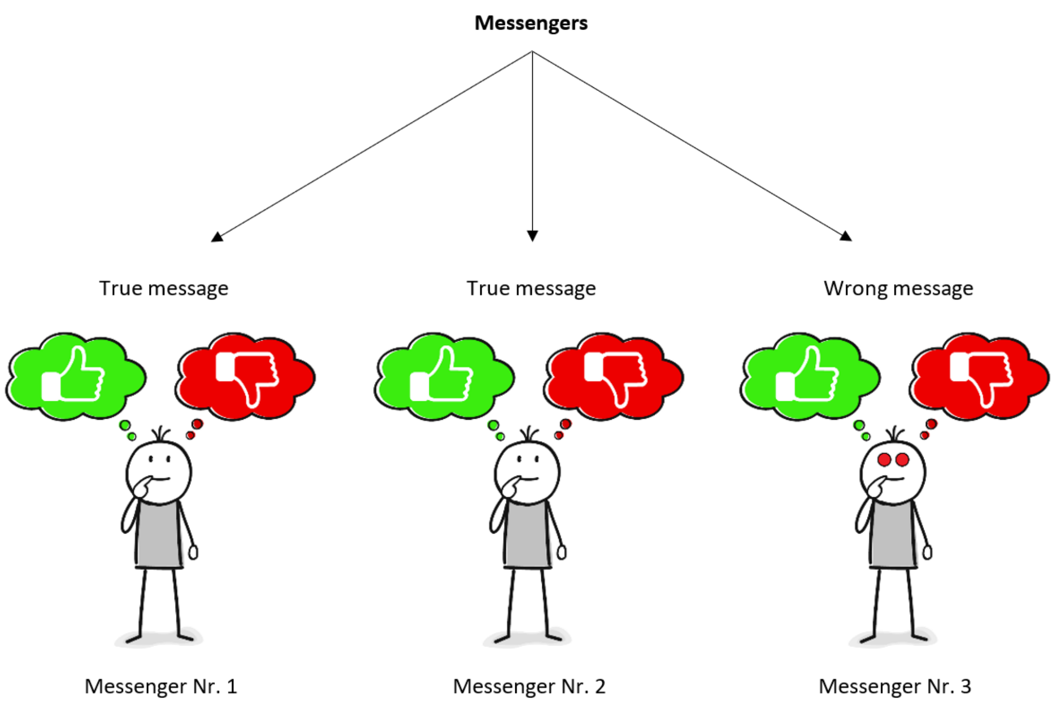
If two participants have the same number of points, the computer randomly determines which participant has the higher and the lower rank.

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

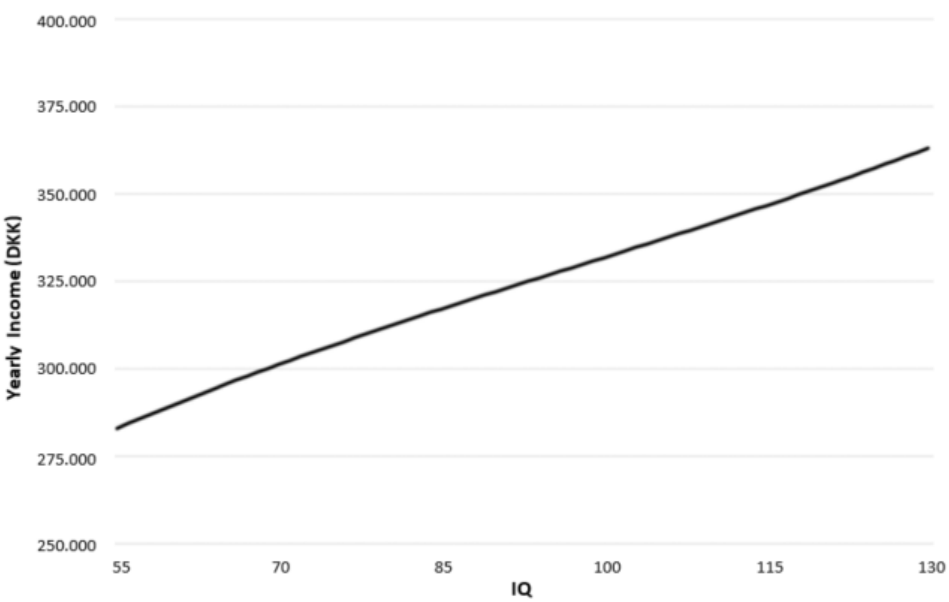
Numerous scientific studies have shown that intelligence tests have a very high significance for important areas of life (Gottfredson, 2003; Neisser et al., 1996; Strenze, 2007).

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

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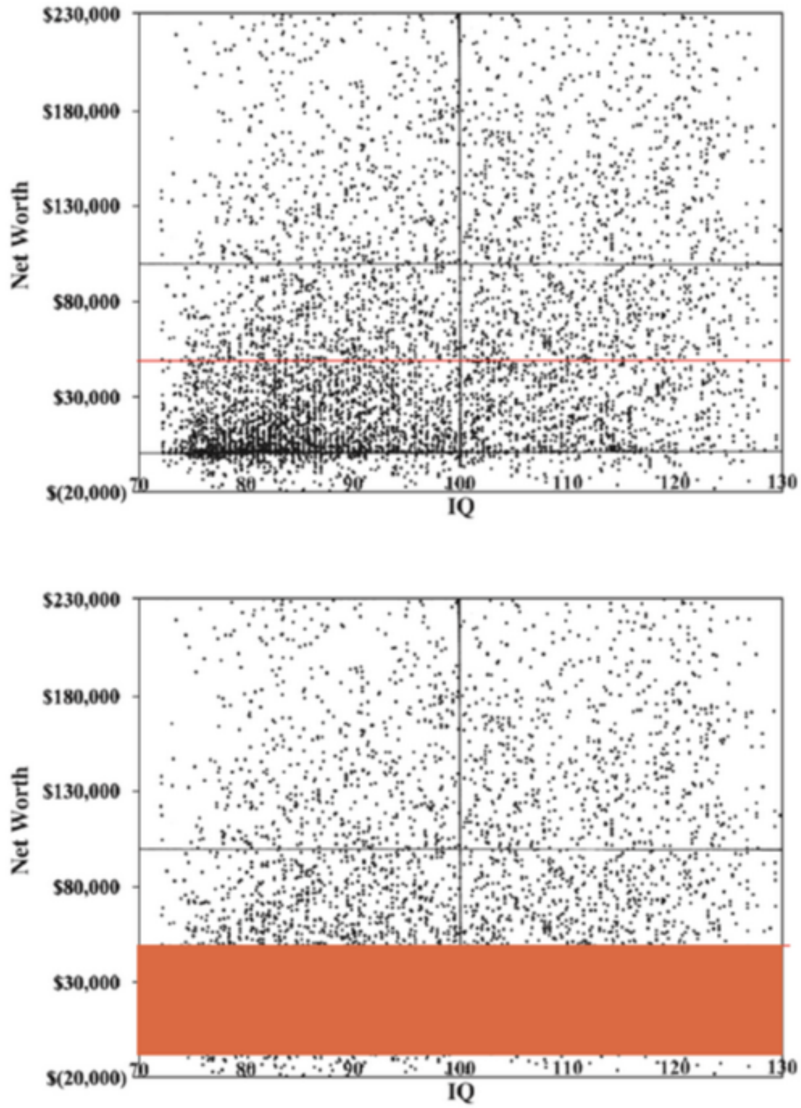
Low-Ego treatment

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 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.

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



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

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.

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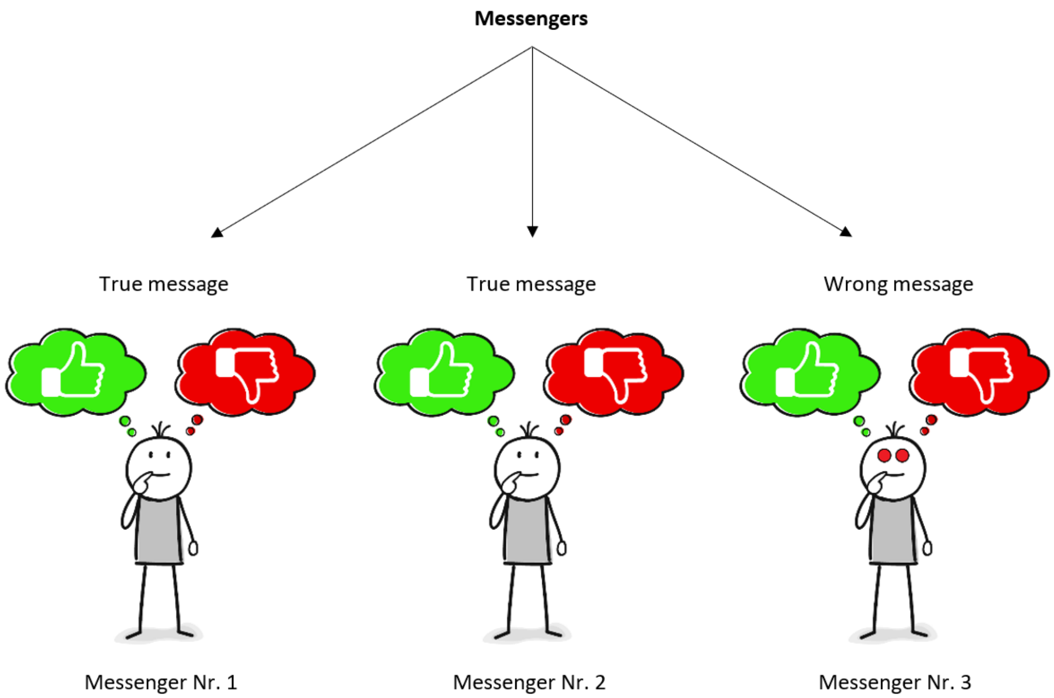
Signal explanation 1

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.

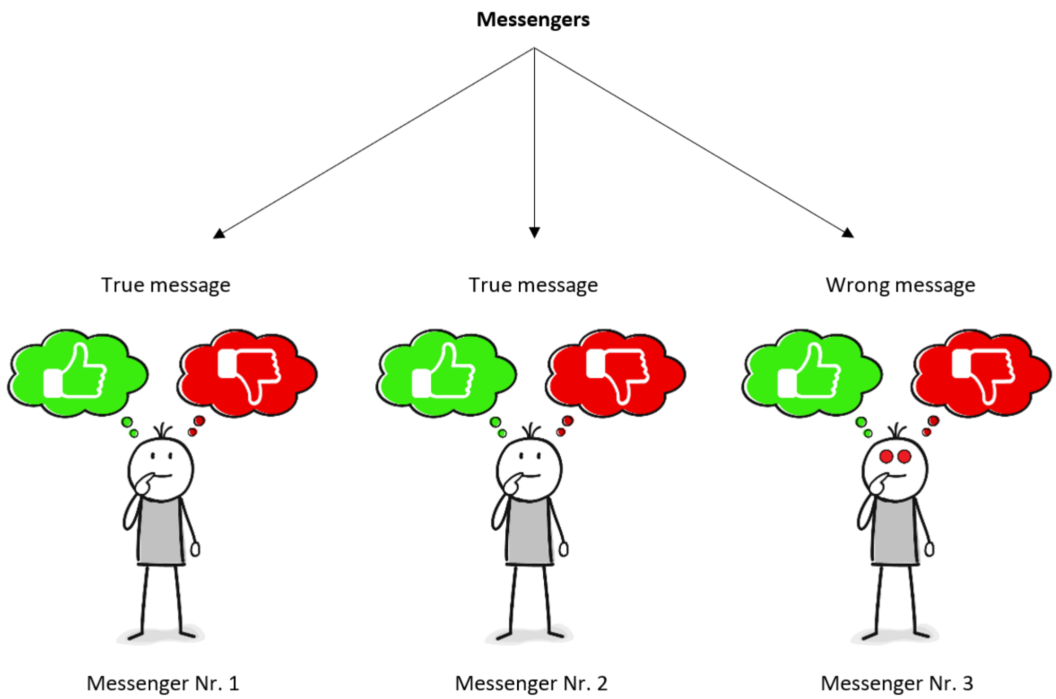
Signal realization 1

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: