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Motivated Belief Updating and Rationalization of Information

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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 update their beliefs about relative performance more optimistically as direct belief utility increases. This finding provides clean evidence for the optimistic belief updating hypothesis and supports theoretical models with direct belief utility. 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.

Keywords: Motivated beliefs, Optimistic belief updating, Direct belief utility, Bayes' rule, Ex-post rationalization

JEL Codes: C91, D83, D84

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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 implies that people's beliefs are completely unaffected by their preferences over the different states of the world. However, empirical evidence shows that people often form overconfident beliefs, resulting in 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 key question in the economics literature is how overconfidence can be sustained in the presence of objective information. In this paper, we provide clean evidence that overconfidence can persist because people derive hedonic values from holding positive beliefs and therefore process new information optimistically.

Behavioral economics explains the persistence of overconfidence with direct belief utility. 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. For instance, managers may derive direct belief utility from being overconfident about the financial returns of their projects. Direct belief utility goes beyond the standard assumption of purely instrumental belief utility, which is indirectly derived by making the best possible decision based on accurate beliefs. One behavioral prediction of models with direct belief utility is that people process information optimistically, overweighting positive feedback relative to negative feedback (Bénabou and Tirole, 2002; Möbius et al., forthcoming; Caplin and Leahy, 2019).[1] For

[1]Other important behavioral predictions include selective recall (Chew et al., 2020; Enke

instance, Möbius et al. (forthcoming) model optimistic belief updating as an optimal strategy to balance the counteracting forces of instrumental and direct 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.

In this paper, we test the optimistic belief updating hypothesis in a laboratory experiment by exogenously varying direct belief utility. To do so, we vary the ego-relevance of the underlying event in a belief updating task. Specifically, we study belief updating about relative performance in an IQ test and we manipulate subjects' beliefs about the ego-relevance of the IQ test. Overall, we show that belief updating is more optimistic when the perceived ego-relevance of the task is increased. To this end, our results provide strong evidence for the optimistic updating hypothesis.

Previous experimental literature in economics has tested the optimistic belief updating hypothesis by comparing updating behavior between ego-neutral and ego-relevant events (Buser et al., 2018; Coutts, 2019; Eil and Rao, 2011; Ertac, 2011; Möbius et al., forthcoming). The objective of this methodology is to assess the influence of ego-relevance on belief updating. Taken together, this literature 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, forthcoming, for reviews). One key challenge of the methodology used in these papers is that ego-neutral and ego-relevant events differ in the size and ambiguity of priors, making it difficult to distinguish optimistic belief updating from cognitive biases in the belief updating process such as base-rate neglect or conservatism (see Barron, 2021, for a discussion). The goal of this paper is to resolve this methodological problem by introducing exogenous variation in direct belief utility within a single event. To this end, we test the causal effect of direct belief utility on updating behavior. Specifically, we hold the distribution of prior beliefs constant across treatments and

et al., 2021; Huffman et al., 2019; Zimmermann, 2020) and information avoidance (Golman et al., 2017, 2021). 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.

manipulate only the ego-relevance of the underlying event without varying other properties of the updating task.

In our pre-registered laboratory experiments, subjects perform an IQ test and we elicit 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. Throughout this paper, we argue that this exogenous manipulation of beliefs about the ego-relevance of IQ tests results in a shift in direct belief utility. 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 explicitely inform subjects that the true state of the world will not be resolved at any point. We do this because Drobner (forthcoming) shows in a related experiment that optimistic belief updating is only activated if subjects expect no immediate resolution of uncertainty. Finally, we elicit two proxies for subjects' beliefs about the ego-relevance of the IQ test to provide a sanity check for our treatment manipulation. Taken together, our experimental methodology allows us to compare updating behavior to the normative benchmark of Bayes' rule. Most importantly, we are able to estimate the causal impact of direct belief utility on belief updating behavior, avoiding confounding differences in the size and ambiguity of priors.

Overall, this paper provides two main contributions. First, our results show 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% more optimistic than final beliefs in the *Low-Ego* treatment. In addition, we use a structural empirical framework to show that in comparison to Bayes' rule, subjects in the *High-Ego* treatment update their beliefs optimistically, while there is no such optimistic updating in the *Low-Ego* treatment. Strikingly, subjects in the *High-Ego* treatment update their beliefs almost twice as strong in response to good signals than bad signals, while there is essentially no asymmetry in the *Low-Ego* treatment.

Second, we use the noisy signal structure to show that subjects ex post alter their beliefs about the ego-relevance of the IQ test depending on the valence of the signals. Controlling for IQ test scores, 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. In an exploratory analysis, we find that this ex-post rationalization of information is predominantly driven by the minority of subjects with pessimistic updating patterns in the belief updating task about relative performance in the IQ test. To this end, we argue that pessimistic subjects find a substitute strategy to maintain strong ego utility even though they cannot explain away negative feedback through self-serving biases in information processing.

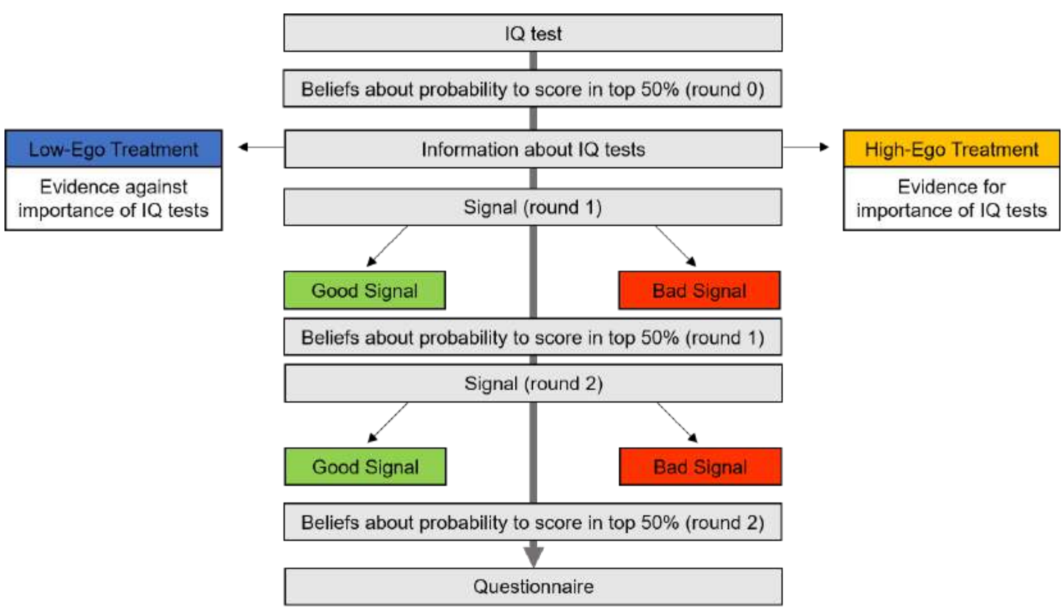
Taken together, our findings highlight two different strategies that subjects use to protect their ego despite the presence of objective information. One class of subjects processes objective information about their relative performance in the IQ test optimistically, which allows them to end up with overconfident beliefs. Another class of subjects manipulates the extent to which these beliefs enter the utility function directly by adjusting their beliefs about the ego-relevance of the IQ test depending on the valence of 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' beliefs about the 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 50% 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 50% 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.

Figure 1: Experimental design



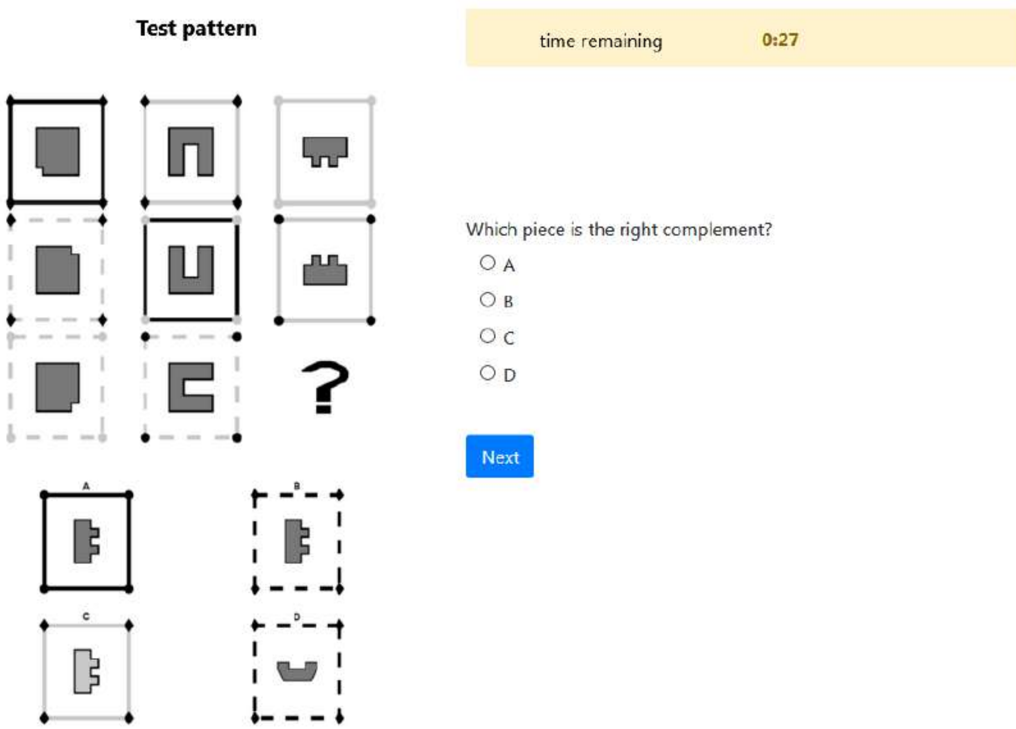
One important aspect of the experimental design is that the treatment information was randomly assigned at the individual level *after* the prior belief elicitation to rule out the possibility that other prior related errors such as *base-rate neglect* or *confirmation bias* confound treatment differences 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 (forthcoming) 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 now provide a detailed description of the different stages in the experiment.[2]

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 50% 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 receipt 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 truth-

[2]Full experimental instructions are provided in Appendix F.

Figure 2: IQ test question



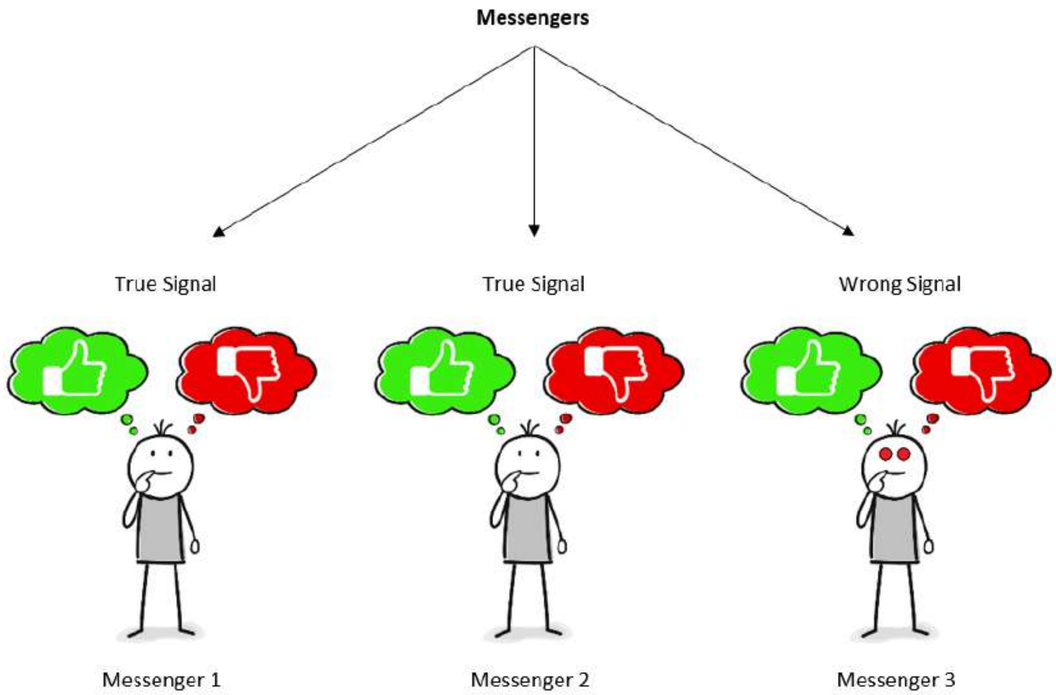
ful reporting, we implemented a variation of the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964) proposed by Grether (1981), Allen (1987), and Karni (2009). We asked subjects to state the probability x which makes them indifferent between winning a monetary prize of €2 with probability x and winning the same monetary prize if they indeed performed in the Top 50% 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. 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. 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 IQ test for their study and job success on a seven-point Likert scale. These beliefs serve as our proxy for subjects' beliefs about the 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 beliefs about the ego-relevance of the IQ

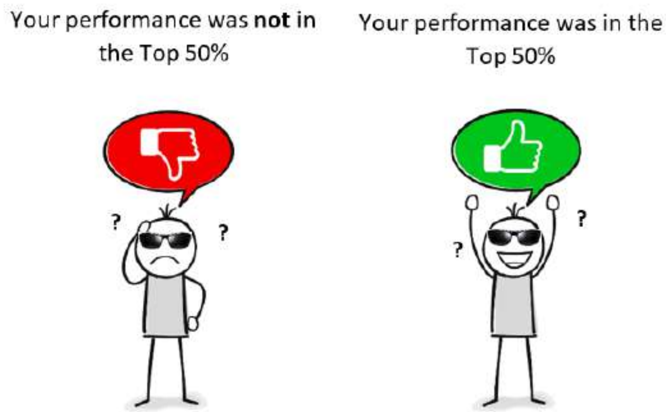
Figure 3: Signal generating process



test depending on the valence of information they received. In addition, we elicited subjects' provided effort in the IQ test 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 participants 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 (2004). A total of 419 subjects finished the experiment in 16 sessions (2 offline and 14

Figure 4: Signal realization



online).[3] 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. (2019) by modeling 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 performance distribution of an IQ test. Let p_{st} be the informativeness of the binary signal $s \in \{G, B\}$ in rounds $t \in \{1, 2\}$. Writing out Bayes' rule, the objective Bayesian belief is given by

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

[3] 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.

In our framework, subjects may form beliefs $\hat{\gamma}_{st}$ that deviate from objective Bayesian beliefs (Caplin and Leahy, 2019). Following Gervais and Odean (2001) and Coutts et al. (2020), subjects follow Bayes' rule but subconsciously choose an optimal belief distortion parameter $\hat{\mu}_{st} \in \mathbb{R}^{+}$ at the moment they process new information. Specifically, this belief distortion parameter allows subjects to overweight ($\hat{\mu}_{st} > 1$) or underweight ($\hat{\mu}_{st} < 1$) the informativeness of the signal about scoring in the top half of the performance distribution:

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

Choosing the optimal belief distortion parameter $\hat{\mu}_{st}$ emerges from an optimization problem, trading off the benefits and costs of belief distortions:

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

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 weight on direct belief utility.

Instrumental belief utility. Second, we incentivized subjects to report their beliefs $\hat{\gamma}_{st}$ using a BDM mechanism. Under the assumption of truthful reporting, the BDM mechanism implies that subjects maximize their chance of winning a monetary price M if reported beliefs $\hat{\gamma}_{st}$ coincide with objective Bayesian beliefs γ_{st} (Engelmann et al., 2019).

Cognitive costs of belief distortions. Third, any belief distortion from the objective Bayesian belief is associated with cognitive costs (Bracha and Brown, 2012; Coutts et al., 2020; Engelmann et al., 2019).

Plugging in (1) and (2) in (3), choosing the optimal belief distortion parameter $\hat{\mu}_{st}$ results in the following first-order condition:

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

If $\alpha = 0$, the belief distortion parameter is equal to 1 and subjects form beliefs according to Bayes' rule ($\hat{\mu}_{st} = 1, \hat{\gamma}_{st} = \gamma_{st}$). If $\alpha > 0$, subjects derive positive direct belief utility and the belief distortion parameter is greater than 1, resulting in inflated posterior beliefs in comparison to Bayesian beliefs ($\hat{\mu}_{st} > 1, \hat{\gamma}_{st} > \gamma_{st}$). In the context of our experimental design, we assume that subjects derive positive direct belief utility from holding confident beliefs about scoring in the top half of the performance distribution 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.*

The first-order condition (4) reveals that the belief distortion parameter $\hat{\mu}_{st}$ and the resulting subjective belief $\hat{\gamma}_{st}$ are increasing with the perceived ego-relevance α of the underlying event and decreasing with the monetary incentives M and the weight β on the cognitive costs of belief distortions. In our experiment, we exogenously manipulate subjects' perceived ego-relevance of the underlying event 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 *Compared to Bayesian updating, subjects in the High-Ego treatment update their beliefs more optimistically than subjects in the Low-Ego treatment.*

4 Results

The main objective of this paper is to evaluate how an exogenous shift of direct belief utility affects the belief updating process about relative performance in the IQ test. To this end, the results of the 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 high importance, 7-very low importance) as a proxy for subjects' beliefs about the ego-relevance of the IQ test.

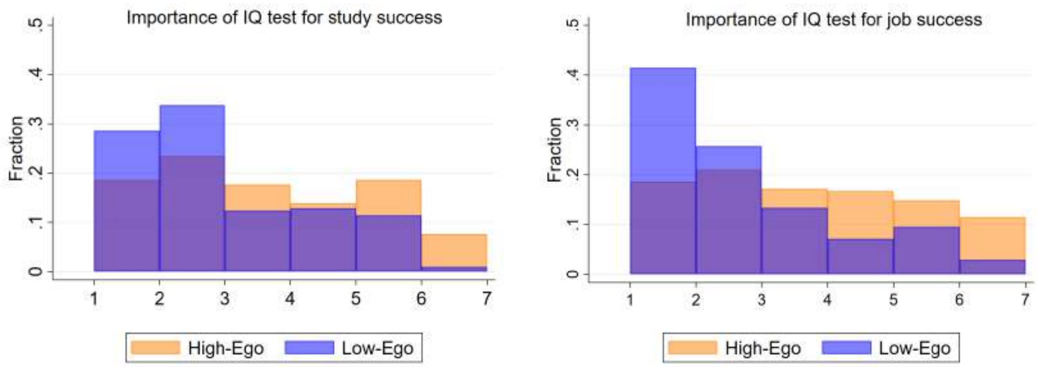
Figure 5 illustrates the distribution of stated beliefs about the ego-relevance of the IQ test separately for *High-Ego* and *Low-Ego* treatments. The different distributions between treatments shows that subjects in fact perceive the IQ test as being more ego-relevant in the *High-Ego* treatment compared to the *Low-Ego* treatment. On average, the stated importance of the IQ test for study success is 2.48 in the *Low-Ego* treatment compared to 3.14 in the *High-Ego* treatment (Wilcoxon rank sum test, $p < 0.001$). Similarly, the average stated importance of the IQ test for job success is 2.27 in the *Low-Ego* treatment compared to 3.24 in the *High-Ego* treatment (Wilcoxon rank sum test, $p < 0.001$).

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

Figure 5: Manipulation check

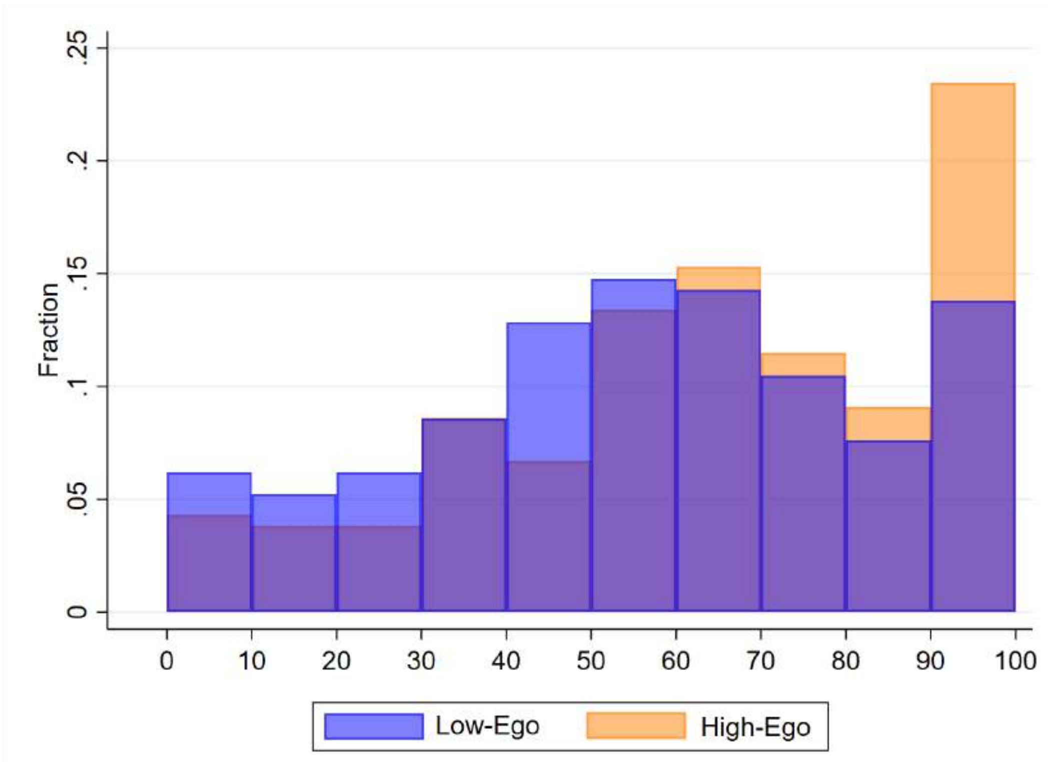


relying on a Bayesian benchmark. Prior to the receipt of the treatment information about the importance of IQ tests and the two binary signals about relative performance, *initial beliefs* are on average 55.7% and significantly above 50% (Wilcoxon signed-rank test, $p < 0.001$). This result provides evidence for overconfidence in initial beliefs at the aggregate level because only 50% of the participants score in the top half of the performance distribution.

Figure 6 shows the distribution of *final beliefs* separately for *High-Ego* and *Low-Ego* treatments after the treatment manipulation and the receipt of two binary signals. The different distribution of final beliefs between treatments provides visual evidence that subjects in the *High-Ego* treatment form more optimistic final beliefs than subjects in the *Low-Ego* treatment. This treatment difference in final beliefs is confirmed by a Wilcoxon rank-sum test ($p = 0.004$). In column 1 of Table 1, we quantify the average treatment difference in final beliefs, accounting for potentially confounding imbalances between treatments. Specifically, we regress final beliefs on a treatment dummy, controlling for initial beliefs, gender, and IQ test scores.[4] The estimated coefficient for the treatment dummy documents that final beliefs in the *High-Ego* treatment are 4.81% more optimistic than final beliefs in the *Low-Ego* treatment ($p = 0.026$).

[4]Appendix D 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.

Figure 6: Distribution of final beliefs - High-Ego versus Low-Ego treatments



Result 2 *Initial beliefs in both treatments are overconfident. Final beliefs in the High-Ego treatment are more optimistic than final beliefs in the Low-Ego treatment.*

One striking feature of Figure 6 is that the fraction of subjects holding very confident final beliefs is substantially different between treatments. Specifically, the fraction of subjects holding beliefs in the interval $[90\%, 100\%]$ is 18.76% in the *High-Ego* treatment compared to 10.95% in the *Low-Ego* treatment. In columns 2–4 of Table 1 we regress final beliefs on a treatment dummy for different distributions of signals. It shows that the treatment effect is stronger among subjects that received two positive signals, who are in return holding the most confident final beliefs in our sample.

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

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)	(8.984)
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, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

updating behavior. This conjecture would imply that we see similar treatment differences in final beliefs independent of the signal distribution. However, the heterogeneous treatment effect on final beliefs for different distribution of signals in columns 2–4 of Table 1 shows that the treatment manipulation directly affects the way how people interpret new information.

To show the robustness of the results in Table 1, Appendix A replicates the regression analysis excluding subjects with updates in the wrong direction and zero updates. Taken together, the robust treatment difference in final beliefs confirms the prediction of our framework in section 3. Specifically, it shows that an exogenous increase in direct belief utility results in a more optimistic belief updating process.

4.2 Comparison to Bayesian benchmark

In this section, we compare updating behavior to the normative benchmark of Bayes' rule using a structural empirical framework (Möbius et al., forthcoming). The reason for doing so is twofold. First, so far 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 such as 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 described by:

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

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 indicator functions for good signals $I(s = G)$ and bad signals $I(s = B)$, respectively:

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

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 more strongly upon the receipt of good signals compared to bad signals ($\beta_G > \beta_B$).

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, suggesting that subjects update their beliefs as if their priors are closer to one-half. 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, the significant difference in parameter estimates for β_G and β_B shows that subjects on average update their beliefs more strongly to good signals than bad signals ($\beta_G > \beta_B, p = 0.016$).

Result 3 *Subjects update their beliefs optimistically in comparison to Bayesian updating.*

Table 2: Belief updating

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

Dependent variable: logit belief	(1) Full Sample	(2) High-Ego	(3) 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)
P-value ($\beta_G = \beta_B$)	0.016	0.001	0.798
Observations	715	367	348
R^2	0.703	0.728	0.677
P-value [Chow test] for δ (Regressions 2 and 3)			0.355
P-value [Chow test] for β_G (Regressions 2 and 3)			0.115
P-value [Chow test] for β_B (Regressions 2 and 3)			0.158
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) Stars reflect significance in a t-test of the null hypothesis that coefficients are equal to 1 (benchmark for Bayesian updating), $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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 to good signals than bad signals ($\beta_G^{High-Ego} > \beta_B^{High-Ego}, p = 0.001$), there is no such optimistic updating in the *Low-Ego* treatment ($\beta_G^{Low-Ego} > \beta_B^{Low-Ego}, p = 0.798$). Moreover, a Chow test reveals a significant difference in the level of optimistic belief updating between treatments ($\beta_G^{High-Ego} - \beta_B^{High-Ego} > \beta_G^{Low-Ego} - \beta_B^{Low-Ego}, p = 0.025$).

Result 4 *In comparison to Bayesian updating, subjects in the High-Ego treatment update their beliefs more optimistically than subjects in the Low-Ego treatment.*

To show the robustness of belief updating patterns, appendix B.1–B.2 replicates the regression analysis using different sample selection criteria such as excluding subjects with updates in the wrong direction and zero updates. Moreover, in Appendix B.3, we interact the right-hand side variables with a dummy for being in the Top 50%. 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 a discussion). Taken together, the structural empirical framework provides robust evidence for our hypothesis that an increase in direct belief utility leads to a more optimistic belief updating process.

4.3 Ex-post rationalization

One implicit assumption of the framework in Section 3 and the analysis so far is that direct belief utility affects the way people process information but not vice versa. We now relax this assumption and allow subjects to choose how beliefs influence their utility function (i.e., they exert some control over the shape of their direct belief utility function). Based on the findings of Drobner (forthcoming), we propose that subjects who received good signals about their relative performance may be convinced that the IQ test has a strong external validity, while subjects who received bad signals may discount the external validity of the IQ test. To test this prediction, we estimate how our proxies for beliefs about the ego-relevance of the IQ test are affected by the number of bad signals received. In addition, we estimate how the number of bad signals received affects subjects' indicated effort in the IQ test. Regarding the latter, we propose that subjects rationalize bad signals about their relative performance by indicating lower levels of effort in the IQ test.

In columns 1 and 2 of Table 3, we 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, initial beliefs, and treatment status. The noisy signal structure allows us to estimate the causal effect of bad signals received on subjects' beliefs about the ego-relevance of the underlying event. Causality is established because conditional on subjects' IQ test scores, the number of bad signals received is completely random. The parameter estimates for the effect of the number of bad signals received show that subjects 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. One implication of this ex-post rationalization is that pessimistic subjects, i.e. subjects with more bad signals, decrease the subjective direct belief utility that they derive from beliefs about their relative performance in the IQ test. Moreover, in column 3, we estimate the effect of the number of bad signals received on subjects' indicated effort in the IQ test. The corresponding results show that subjects also indicate lower effort in the IQ test as the number of bad signals increases ($p = 0.036$).[5]

Table 4 replicates the regression analysis in Table 3 separately for subjects who update their beliefs pessimistically or optimistically in comparison to Bayesian updating. Specifically, we split the sample into two groups of subjects, either holding final beliefs that are more optimistic than the Bayesian counterpart or holding final beliefs that are more pessimistic than the Bayesian counterpart. Interestingly, the results in Table 4 show that ex-post rationalization is more prevalent among the minority of subjects with pessimistic 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, people may have no demand for optimistic belief updating if they find ways to explain away the ego-relevance of the task as the number of bad signals increases. To this end,

[5]The regression analysis in Table 3 represents the pooled results for both treatments. Appendix C runs the regression analysis 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 3: Ex-post rationalization of bad signals

	(1)	(2)	(3)
Dependent variable	Importance study success	Importance job success	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, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

ex-post rationalization provides a cost minimizing strategy to maintain strong direct belief utility because stated beliefs about the ego-relevance of the task are by design not affecting subjects' payoffs.

Result 5 *(Pessimistic) subjects ex-post rationalize signals about their relative performance in the IQ test by altering beliefs about the ego-relevance of the IQ test depending on the valence of information.*

5 Discussion

We have used laboratory experiments to provide causal evidence for the effect of direct belief utility on belief updating behavior. Specifically, our main result shows that subjects update their beliefs more optimistically as direct belief utility increases. This finding provides clean evidence for the optimistic

Table 4: Ex-post rationalization - pessimistic versus optimistic subjects

Dependent variable	Importance study success		Importance job success		Effort	
	(1)	(2)	(3)	(4)	(3)	(4)
	Pessimistic	Optimistic	Pessimistic	Optimistic	Pessimistic	Optimistic
Bad signals	-0.551***	-0.166	-0.483**	-0.203	-0.612***	-0.047
	(0.202)	(0.176)	(0.205)	(0.175)	(0.201)	(0.181)
IQ test score	0.177***	0.078	0.212***	0.093	0.176**	0.185***
	(0.067)	(0.058)	(0.069)	0.057)	(0.068)	(0.060)
Initial belief	0.001	0.009	-0.007	0.007	0.011	0.019***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
High-Ego	0.489*	0.792***	0.966***	1.075***	-0.210	0.056
	(0.296)	(0.256)	(0.302)	(0.260)	(0.297)	(0.256)
Observations	155	206	155	206	155	206
Pseudo R^2	0.049	0.029	0.064	0.040	0.055	0.041

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, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

belief updating hypothesis and confirms a key prediction of a broad range of theoretical models with direct belief utility. By showing a causal effect of ego-relevance on belief updating, our results are consistent with the literature, documenting a positive effect of ego-relevance on prior beliefs (Buser et al., 2018; Grossman and Owens, 2012). Moreover, we complement the findings of a contemporaneous project by Kozakiewicz (2021), who studies the effect of ego-relevance on signal interpretation. In contrast to our direct manipulation of ego-relevance, Kozakiewicz (2021) introduces exogenous variation in direct belief utility by comparing updating behavior in response to either a realized signal or potential realizations of signals. In line with our results, Kozakiewicz (2021) documents a strong effect of direct belief utility on signal interpretation.

Our second result shows that subjects ex-post rationalize bad signals, which is an alternative strategy for protecting subjects' ego. This behavior is more prevalent among subjects with pessimistic belief updating patterns. 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. Moreover, this result is consistent with self-serving attribution bias because individuals attribute good signals to ego-relevant factors such as high intelligence and explain away bad signals by indicating low effort in the IQ test (see Mezulis et al., 2004, for a review).

From a methodological perspective, our experimental manipulation of ego-relevance is well suited to study important interactions of direct belief utility with other aspects in the belief updating 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 important for researchers interested in identifying motivated beliefs. For them, limiting the possibilities of ex-post rationalization can be useful as it reduces the demand for self-serving biases in belief formation.

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Appendices

A Robustness of treatment effect

In Table 5, we replicate the findings in Table 1 using a restricted sample of subjects without wrong belief updates (column 2) and without wrong and zero belief updates (column 3).

Table 5: Robustness of treatment effect

Dependent variable: final belief	(1)	(2)	(3)
High-Ego	4.807**	5.297**	6.936**
	(2.155)	(2.290)	(2.913)
Initial belief	0.708***	0.738***	0.611***
	(0.055)	(0.054)	(0.078)
Female	-2.316	-1.706	-2.218
	(2.179)	(2.269)	(2.873)
IQ test score	1.520***	1.864***	2.427***
	(0.489)	(0.538)	(0.681)
Constant	2.554	-3.612	-2.531
	(4.726)	(5.196)	(6.707)
No wrong updates		✓	✓
No zero updates			✓
Observations (Subjects)	419	375	292
R^2	0.407	0.439	0.310

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, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

B Robustness of belief updating

B.1 Belief updating excluding wrong updates

In Table 6, we replicate the findings in Table 2 using a restricted sample of subjects who never update in the wrong direction.

Table 6: Belief updating excluding wrong updates

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

	(1)	(2)	(3)
Dependent variable: logit belief	Full Sample	High-Ego	Low-Ego
δ	0.905***	0.887***	0.913***
	(0.030)	(0.055)	(0.031)
β_G	0.756***	0.828***	0.683***
	(0.050)	(0.072)	(0.070)
β_B	0.665***	0.599***	0.715***
	(0.051)	(0.073)	(0.068)
P-value ($\beta_G = \beta_B$)	0.166	0.017	0.724
Observations	634	308	326
R^2	0.747	0.733	0.762
P-value [Chow test] for δ (Regressions 1 and 2)			0.680
P-value [Chow test] for β_G (Regressions 1 and 2)			0.148
P-value [Chow test] for β_B (Regressions 1 and 2)			0.244
P-value [Chow test] for $(\beta_G - \beta_B)$ (Regressions 1 and 2)			0.048

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.2 Belief updating excluding wrong and zero updates

In Table 7, we replicate the findings in Table 2 using a restricted sample of subjects who update their beliefs at least once and never in the wrong direction.

Table 7: Belief updating excluding wrong and zero updates

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

Dependent variable: logit belief	(1) Full Sample	(2) High-Ego	(3) Low-Ego
δ	0.909	0.891	0.921*
	(0.041)	(0.068)	(0.047)
β_G	0.949	0.995	0.899
	(0.054)	(0.074)	(0.068)
β_B	0.827***	0.761***	0.877
	(0.057)	(0.082)	(0.077)
P-value ($\beta_G = \beta_B$)	0.107	0.027	0.839
Observations	502	248	254
R^2	0.724	0.730	0.721
P-value [Chow test] for δ (Regressions 1 and 2)			0.714
P-value [Chow test] for β_G (Regressions 1 and 2)			0.382
P-value [Chow test] for β_B (Regressions 1 and 2)			0.301
P-value [Chow test] for ($\beta_G - \beta_B$) (Regressions 1 and 2)			0.163

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.3 Belief updating controlling for state

In Table 8, we replicate the findings in Table 2 interacting the right-hand side variables with a dummy for being in the Top 50% 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 because subjects in the Top 50% receive on average a different distribution of signals than subjects in the Bottom 50% (see Barron, 2021, for a discussion).

Table 8: Belief updating controlling for state

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

Dependent variable: logit belief	(1) Full Sample	(2) High-Ego	(3) Low-Ego
δ	0.828	0.767	0.851
	(0.045)	(0.091)	(0.039)
β_G	0.703	0.744	0.684
	(0.069)	(0.093)	(0.103)
β_B	0.608	0.479	0.711
	(0.066)	(0.090)	(0.090)
$Top * \delta$	0.103	0.144	0.115
	(0.061)	(0.107)	(0.074)
$Top * \beta_G$	-0.010	0.051	-0.126
	(0.097)	(0.132)	(0.138)
$Top * \beta_B$	-0.109	-0.009	-0.170
	(0.106)	(0.155)	(0.142)
P-value ($\beta_G + Top * \beta_G = \beta_B + Top * \beta_B$)	0.062	0.034	0.898
Observations	715	348	367
R^2	0.705	0.681	0.732
P-value for ($\delta + Top * \delta$) ((2) and (3))			0.397
P-value for ($\beta_G + Top * \beta_G$) ((2) and (3))			0.073
P-value for ($\beta_B + Top * \beta_B$) ((2) and (3))			0.671
P-value for ($\beta_G + Top * \beta_G - \beta_B + Top * \beta_B$) ((2) and (3))			0.006

Notes:
(i) Analysis uses OLS regressions with robust standard errors clustered at the individual level.

C Ex-post rationalization by treatment

In Table 9, we replicate the regression analysis in Table 3 separately for *High-Ego* and *Low-Ego* treatments. The results show that ex-post rationalization tends to be stronger in the *High-Ego* treatment for importance *study success* and *job success* as dependent variables, while it tends to be stronger in the *Low-Ego* treatment if we consider indicated *effort* as the dependent variable. However, Chow tests of the parameter estimates for the *number of bad signals* received provide no evidence for significant treatment differences in ex-post rationalization.

Table 9: 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, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

D Baseline Balance

Table 10 documents no statistically significant imbalances in our treatments according to initial beliefs, gender, and IQ test scores.

Table 10: Baseline Balance

Variable	High-Ego (N=209)	Low-Ego (N=210)	P-Value
Initial belief	57.44	53.91	0.150
Female	0.56	0.49	0.204
IQ test score	9.71	9.33	0.223

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 Wilcoxon rank sum test was used.

E Mapping of pre-analysis plan into the paper

Subsequently, we provide a mapping of the hypotheses in the pre-analysis plan and the results in the paper. The pre-analysis plan is available in the AEA RCT Registry (AEARCTR-0005121).

Table 11: Mapping of hypotheses and results

Hypotheses	**Results in the paper**
Hypothesis 1: Subjects hold overconfident prior beliefs.	Result 2 on page 14
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 13
Hypothesis 3: Subjects update their beliefs optimistically compared to Bayes' rule.	Result 3 on page 18
Hypothesis 4: Subjects in the *High-Ego* treatment update their beliefs more optimistically than subjects in the *Low-Ego* treatment.	Result 2 on page 14 and result 4 on page 20
Hypothesis 5: Subjects ex-post rationalize negative feedback about their relative performance in the IQ test.	Result 5 on page 22

F 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.

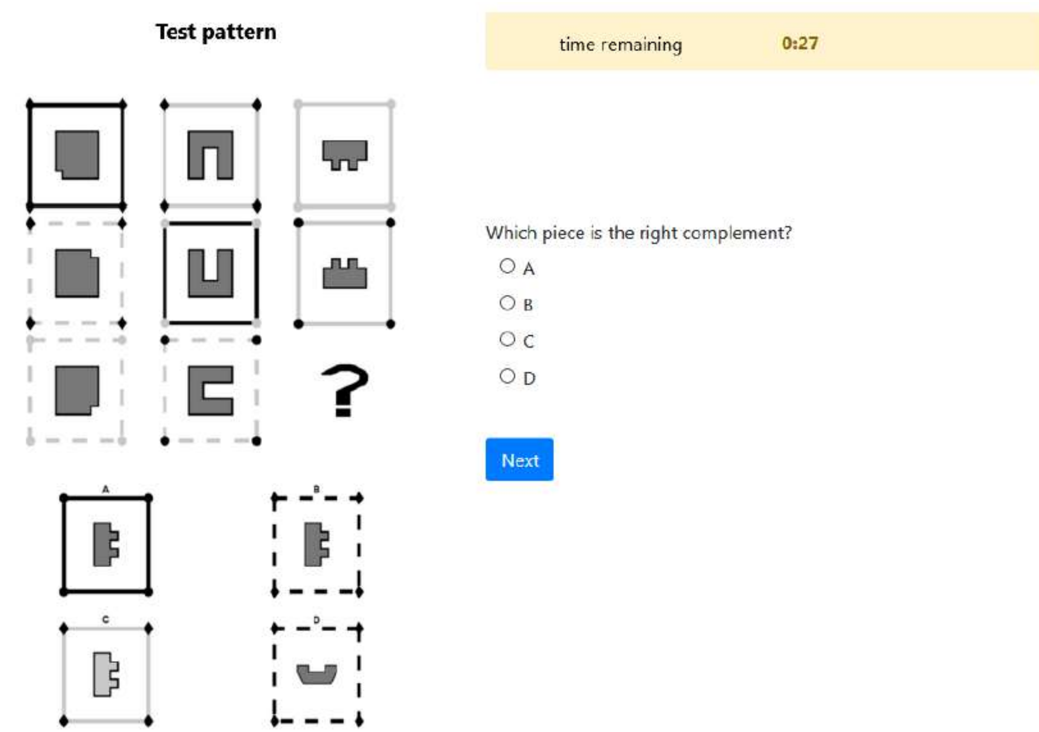
- What probability should you indicate such that you have the highest chance of a payment of 2 euros?
- What is your chance of winning 2 euros?
- Would you have had a higher probability to win 2 euros if you had a reported 60% probability instead of 30%?
  - Yes
  - No

Quiz

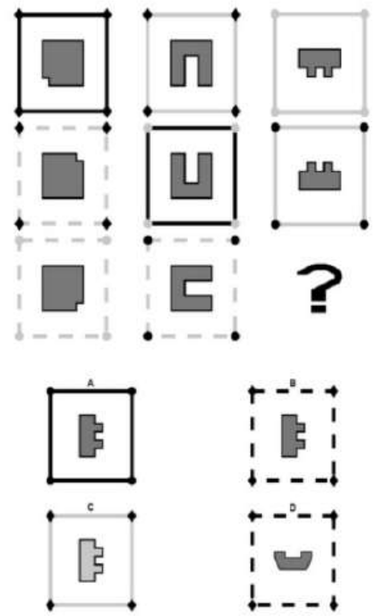
In the first part of the experiment we ask you to complete a quiz with 15 questions. You will see a pattern with one piece missing. Your task is to choose the correct piece from four suggestions and click on the Next button. You have 30 seconds to select the correct answer for each pattern and click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

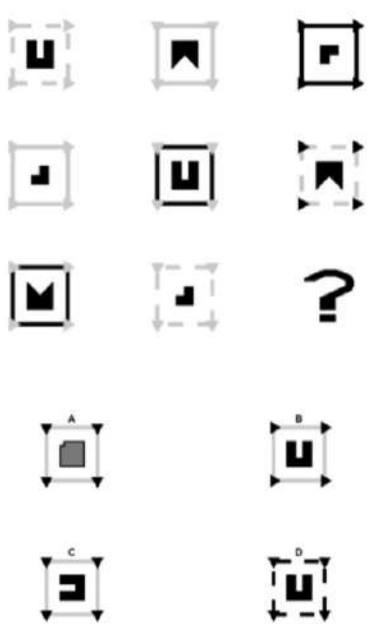
Your task is to assign the suitable section of the four possible answers to the pattern below. You have 30 seconds each to do this. **Please note that you will only get the point for a correct answer if you click the Continue button after you have selected the correct answer.**

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

Next

Pattern 1/15

time remaining 0:24



Which piece is the right complement?

- ○ A
- ○ B
- ○ C
- ○ D

Weiter

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.

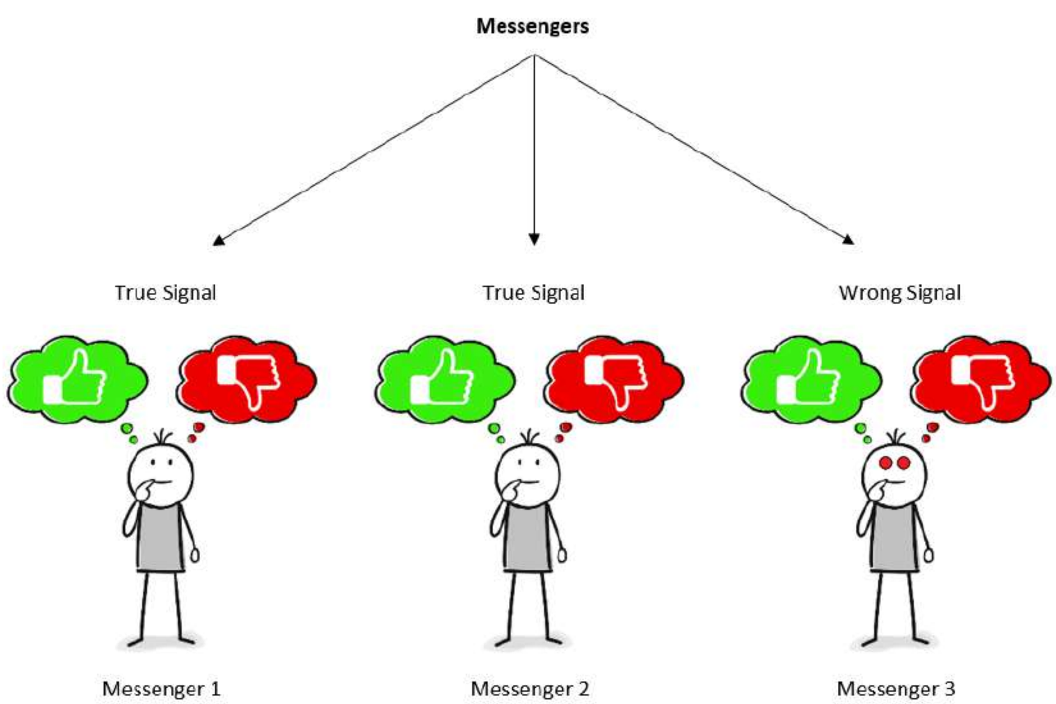
If two participants have the same number of points, the computer randomly determines which participant has the higher and the lower rank.

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

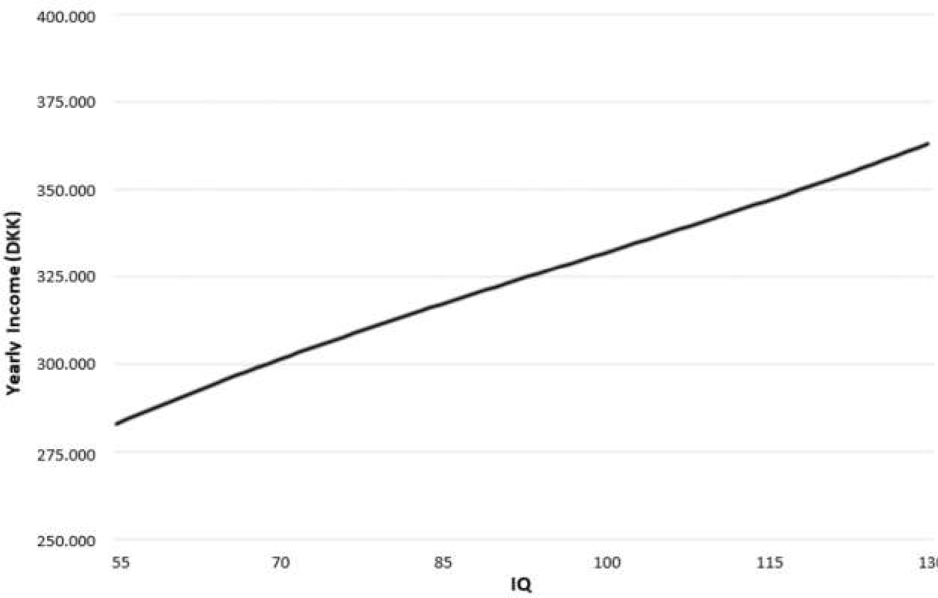
Numerous scientific studies have shown that intelligence tests have a very high significance for important areas of life (Gottfredson, 2003; Neisser et al., 1996; Strenze, 2007).

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.

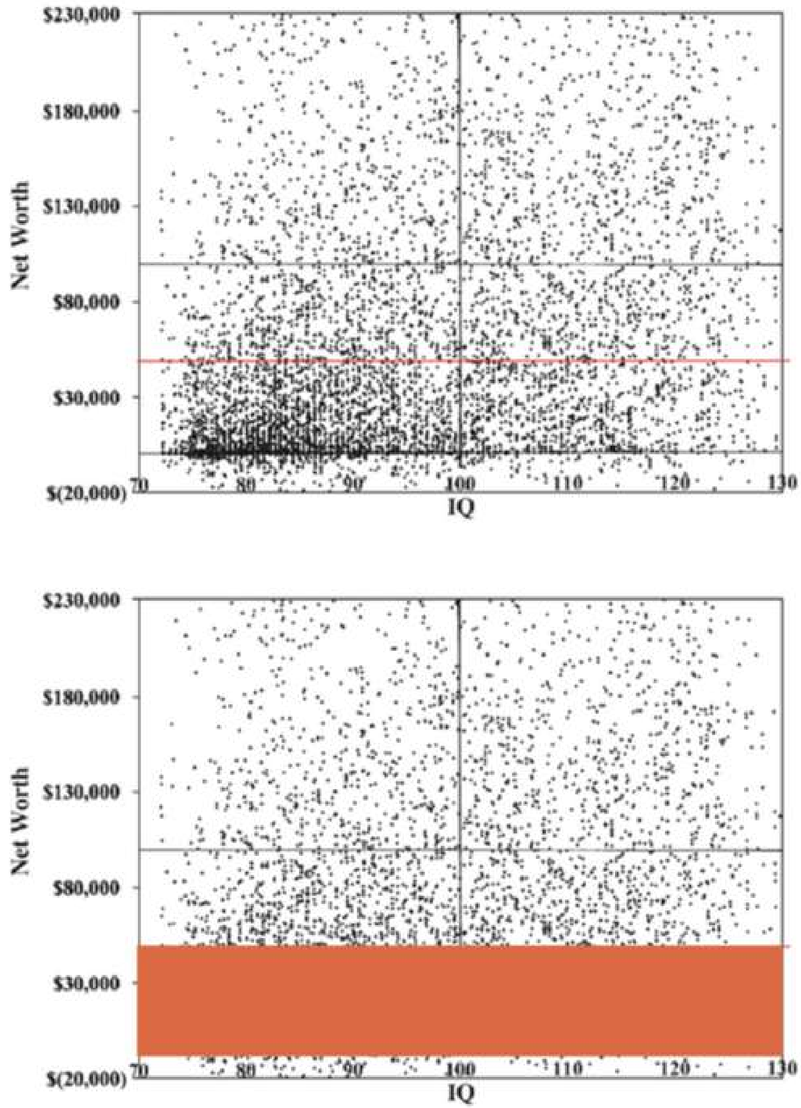
Low-Ego treatment

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 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.

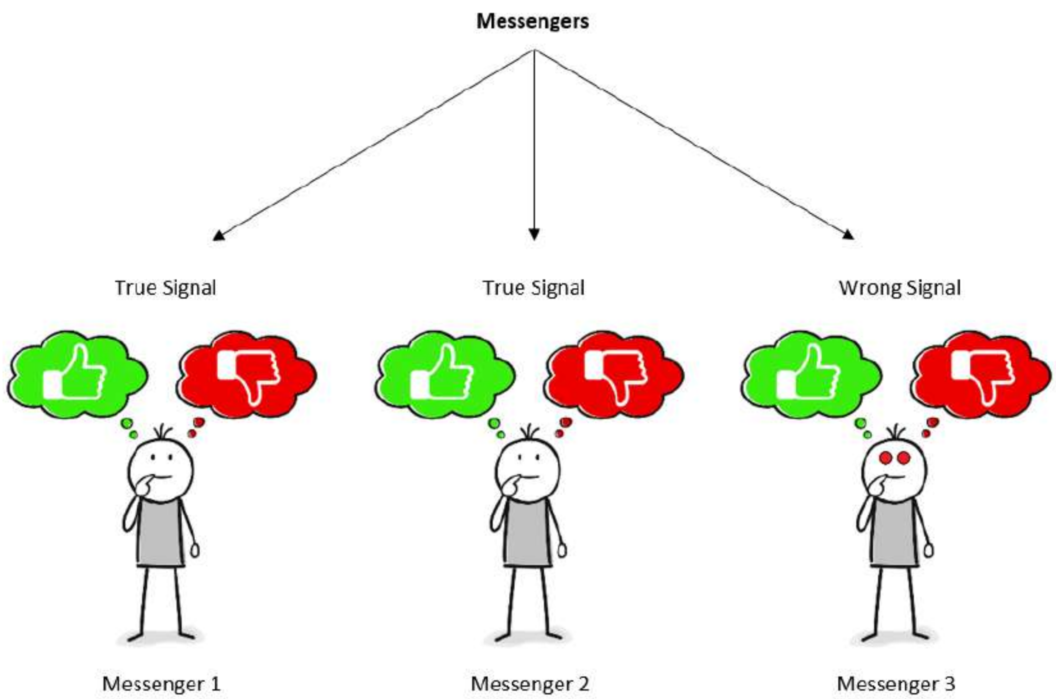
Taleb backs up his theses with plenty of probabilistic and statistical illustrative material. His data shows that the definition of intelligence used when measuring intelligence by IQ tests is too much reduced to domains that are not able to do justice to a complex phenomenon such as the human intellect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

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.

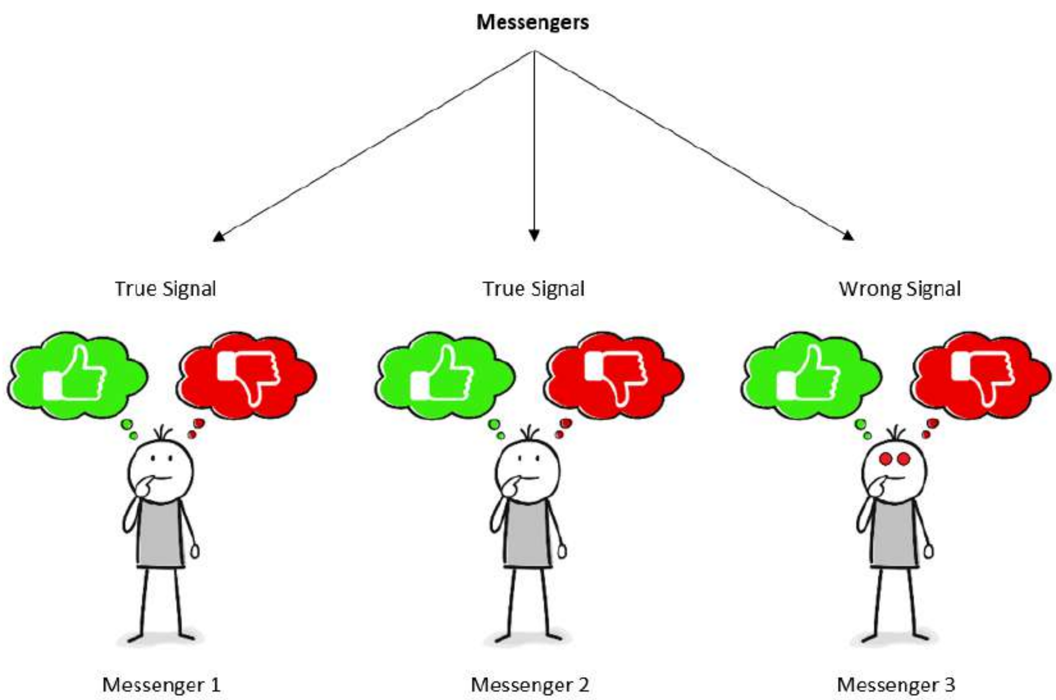
Signal realization 1

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:

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