Experimental Evidence on Misguided Learning*

Lorenz Götte† and Marta Kozakiewicz‡

May 6, 2020

Abstract

We test experimentally the theory of misguided learning formulated by Heidhues et al. (2018). The model predicts the behavior of an agent who has a biased perception of his ability and is learning about an unknown, decision-relevant parameter. We use a novel experimental design to demonstrate that the learning process of an overconfident agent differs significantly from that of an unbiased agent. In a dynamic setting, the overconfident agent repeatedly takes suboptimal actions, misinterprets the output and forms erroneous beliefs about the unknown parameter. We provide the first empirical evidence that giving a biased agent the opportunity to experiment and acquire new information is not only ineffective, but in some cases counterproductive.

Keywords: overconfidence, belief formation, learning, experiment

JEL classification: C91, D83

*We thank Ximeng Fang, Botond Kőszegi, Axel Wogrolly and Florian Zimmermann for helpful comments. Richard Franck and Zhi Hao Lim provided excellent research assistance. The authors gratefully acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (project A01).

†University of Bonn and National University of Singapore

‡Bonn Graduate School of Economics; corresponding author: martkozakiewicz@gmail.com

1 Introduction

Many economic decisions require an accurate assessment of the state of the world. Often, more than one decision-relevant aspect is unobservable, and people have to *simultaneously* form beliefs about multiple parameters. Learning in such environments is particularly challenging. Agents are not only required to take actions and keep track of changing outcomes, but also ought to disentangle the influences of various factors in order to accurately update their beliefs about specific parameters. The latter adds another layer of complexity to decision-making and constitutes a potential source of error.

In particular, if an agent holds incorrect and persistent beliefs about some parameters, he is likely to misinterpret the data and form erroneous beliefs about the state of the world. Heidhues et al. (2018) use a theoretical model to show that the learning process could go awry: the agent becomes increasingly mistaken about the state of the world with each observation. Learning is "misguided" and since it is the agent who generates the observations that lead him astray, one can describe it as "self-defeating".

An illustrative example, provided by Heidhues et al. (2018), involves a manager who knows neither the productivity of his team nor the quality of his decisions, both of which are important inputs to the production function. In every period, the manager observes the team's output and decides on the optimal level of control. If the manager is overconfident about the efficacy of his methods and reluctant to update this belief, he will attribute unsatisfactory output to the low productivity of the team. In his view, the optimal action necessitates exerting greater control over his employees. Since this action is in fact suboptimal, it results in a further drop in output. Consequently, the manager concludes that the team productivity is lower than expected and decides to adopt even stricter measures. The striking feature of the model is that taking seemingly optimal actions and observing the outcomes lead the manager to *more* biased posterior beliefs about the team.

The theory admits the possibility that this pattern of behavior arises in many settings. Examples include effective delegation of tasks in management, choice of the optimal effort level, and public policy decision making. Since the decisions are frequent and widespread, the compound loss may be substantial. However, the extent to which people engage in misguided learning remains an open question.

Studying beliefs formation in the field or with naturally occurring data proves to be an onerous task. One difficulty is that the state of the world that is unobservable to agents is typically also unobservable to the researcher. In addition, tracking beliefs in the field setting is costly and prone to systematic errors, as it requires multiple measurements using less reliable elicitation methods, while in naturally occurring data we are often unable to identify the beliefs that agents hold. For these reasons, the laboratory provides an ideal setup to study beliefs formation and learning: it allows us to precisely measure subjects' beliefs in an incentive-compatible way and ensures state observability and tight control over information available to participants.

In this paper, we provide the first clean evidence on misguided learning using data from a carefully designed laboratory experiment that directly tests the comparative statics of the model by Heidhues et al. (2018). The experiment integrates all features of the model in a simple way. Our main goal was to create an environment in which subjects learn about the state of the world by taking actions and observing the output. Importantly, the output depends both on the state of the world and an unknown parameter that is relevant to subjects' self-esteem. For this purpose, we assessed subjects' cognitive ability before the main task by measuring their relative performance in an IQ test.[1]

In the second part of the experiment, the participants completed several rounds of a learning exercise. In every round, the main task was to estimate the unknown state of the world: a randomly drawn integer between -10 and 10. Participants had 4 trials to guess the state and were remunerated based on the accuracy of their guesses. After making a guess, each participant received feedback in the form of a number displayed on

[1] We decided to use intelligence as an input to the production function for several reasons. Firstly, it is known that people care deeply about their cognitive ability, so the IQ measure seems to be a good candidate for a genuine ego-relevant parameter. Secondly, the literature provides evidence that people have biased assessments of their relative cognitive ability (see, for example, Burks et al. (2013)). Thus, we expect misguided learning to arise in this context. Last but not least, cognitive ability as a component of human capital is an actual input to many production functions.

the individual computer screen. The feedback was determined by the state of the world and one's relative performance in the IQ test. However, we did not inform participants about their test results, so they had to make decisions based on their beliefs about their relative performance. We elicited these beliefs before the learning exercise using an incentive-compatible mechanism.[2]

To help participants correctly interpret the feedback, we provided them with special tables to look up which states of the world and relative performances are consistent with the feedback they observed. We did not preclude subjects from considering different performance levels and they were free to choose any combination of the two parameters. In every trial, the optimal strategy was to enter one's best guess about the state of the world. Therefore, we could directly track participants' beliefs formation process. After the learning exercise, we again elicited subjects' beliefs about their relative performance.

We introduced two experimental conditions: treatment and control. In the treatment condition, participants received feedback after each guess, while in the control condition, the feedback was independent of subjects' actions. Therefore, in the control condition, subjects' guesses no longer affected their beliefs – the theory predicts that misguided learning would not arise in this case. By comparing the two conditions, we show that the effect is not driven by external factors, but is consistent with the mechanism outlined in Heidhues et al. (2018).

Further, we ran an additional control condition in which participants performed the learning exercise based on the performance parameter of some other, randomly selected individual who reported similar beliefs.[3] By keeping all other features of the experiment unchanged, we tested whether our results are driven by the ego-relevance of one of the parameters.

Overall, we find strong support for the predictions of the misguided learning model. When overconfident individuals can adjust their actions and learn about the state of the

[2]Our test of model's predictions is based on this independent measure of overconfidence.

[3]After eliciting beliefs about subjects' relative performance, participants were informed that they will be randomly matched to a person from one of the previous sessions, who took the same IQ test and reported the same beliefs but not necessarily obtained the same IQ test score. Before the main task, we elicited the subjects' beliefs about the relative performance of the person matched to them.

world, repeated feedback leads them to form beliefs that deviate from the true state. This learning process exhibits features that are characteristic of self-defeating learning: overconfident participants tend to attribute unsatisfactory outcome to the realized state instead of their relative performance, and they become pessimistic about the state over time. Importantly, we also find evidence for self-defeating learning when comparing the behavior of overconfident subjects in the treatment and control conditions.[4]

The effect is more pronounced for participants who are more biased about their ability. We test the model's comparative statics and show that the more overconfident the participant is, the more mistaken about the state of the world he becomes. The model also correctly predicts the learning trajectory of underconfident subjects. We do not detect those patterns in the behavior of unbiased participants. In line with the model, the unbiased subjects immediately learn the true state and take the optimal action in the following trials. The results prove that the learning process of an unbiased person is very different from that of a biased individual.

However, the effects observed in the data are not as pronounced as the theory predicts. The gap between the theoretical predictions and the observed behavior is caused by some participants learning about their relative performance during the experiment. We observe a significant difference in beliefs measured before and after the learning exercise. In our companion paper (Götte and Kozakiewicz, 2018), we further investigate the question of learning about the ego-relevant parameter over time. Notwithstanding, almost 80% of subjects who were classified as overconfident before the learning exercise remained overconfident after the task, and many of them were engaging in self-defeating learning until the end of the last round.

Using data from the additional control condition, we show that the ego-relevance of the ancillary parameter accounts for a significant part of the effect. When the feedback is based on the IQ test performance of some other, randomly selected individual, the pattern of behavior is similar to that observed in the treatment condition, albeit much

[4]We confirm that the interdependence of beliefs, actions, and feedback is a necessary condition for misguided learning to occur. We do not observe misguided learning in our control condition, in which there is no dependency between subjects' guesses and the feedback they receive.

weaker. The overconfident participants are more likely to correct their actions and are quick to learn the true value of the performance parameter. We conclude that misguided learning is more likely to arise and preserve in situations where one's ego is at stake.

Our work is partially motivated by the behavioral literature on motivated reasoning, which suggests that people may interpret feedback in a self-serving manner, especially when one of its determinants is ego-relevant (pertaining to some personal characteristic of the agent). There is a large body of evidence that people hold inaccurate beliefs with some degree of persistence, as they adopt various strategies to manipulate their beliefs to protect their egos.[5] One consequence is overconfidence, a widely-studied phenomenon among psychologists and economists, that is believed to generate great costs for both the individual and the society.[6] We contribute to the literature concerning behavioral implications of overconfidence as we document its detrimental effect on learning.

Furthermore, we build on the theoretical literature on learning with misspecified models. The unified theoretical framework for modeling agents with misspecified beliefs, Berk-Nash equilibrium, was proposed by Esponda and Pouzo (2016). What distinguishes their work from previous research, and is crucial for our purpose, is that they allow beliefs to endogenously depend on the agent's actions. This assumption enables them to study situations in which experimentation not only inhibits learning but also drives the agent's beliefs further away from the true state. Heidhues et al. (2018) analyze a similar problem, but focus on the conditions necessary for misguided learning to occur. We describe the model in detail in Section 2.

Hestermann and Yaouanq (2016) also consider two parameters that are not separately identifiable, but in their model the agent is allowed to learn about both. The authors explore the implications of different assumptions about the unknown parameter

[5] One example of such strategy is a tendency to not fully incorporate signals about ego-relevant traits into beliefs or to incorporate them in a distorted way (Buser et al., 2018; Coutts, 2019; Eil and Rao, 2011; Möbius et al., 2014). A recent study by Zimmermann (2018) adds to the literature showing that after some time people recall feedback asymmetrically, suppressing the memories of negative feedback.

[6] Negative consequences of overconfidence include excessive selection into competitive environments (Camerer and Lovallo, 1999; Niederle and Vesterlund, 2007), excessive trading (Barber and Odean, 2001), suboptimal investment decisions (Malmendier and Tate, 2005, 2008) and political polarization (Ortoleva and Snowberg, 2015).

of interest. In three distinct specifications, it is either assumed to be fixed, to be changing exogenously, or endogenously with agent's actions. It is worth mentioning that in our experiment the parameter is held fixed *within* a round, but changes exogenously *between* rounds since subjects are guessing a new, randomly drawn number in each round. However, our setup is very different from the one studied by Hestermann and Yaouanq (2016), so we cannot directly test the model's predictions.

We are not aware of any empirical work on misguided learning. The existing literature on beliefs formation and learning focuses on documenting failures of reasoning that inhibit learning but are conceptually different from the one we study. One should mention the work on selective attention in learning (the theory developed by Schwartzstein, 2014, was tested in a field experiment by Hanna et al., 2014), redundancy neglect in social learning (Eyster and Rabin, 2014, developed a theoretical framework, while the experimental evidence was provided by Enke and Zimmermann, 2017), difficulties in hypothetical thinking (Charness and Levin, 2009, Esponda and Vespa, 2014, Esponda and Vespa, 2016), overlooking selection problems (Esponda and Vespa, 2018, Enke, 2015), and misattribution of reference dependence in learning from experience (Bushong and Gagnon-Bartsch, 2016a, Bushong and Gagnon-Bartsch, 2016b). Perhaps the closest to our work, Coutts et al. (2019) test two different theories of self-attribution bias and show that, although people tend to update more favorably about themselves than about their teammates, they do not attribute the negative outcome to the other player. We contribute to the literature by providing the first empirical evidence on misguided learning and taking the first step towards unraveling the underlying mechanism.

The paper is organized as follows. In Section 2, we describe a simplified version of the model (one of the examples discussed in Heidhues et al., 2018) and its testable predictions. Section 3 outlines our experimental design and Section 4 presents the empirical results. In Section 5, we discuss the results of the additional control condition. Section 6 concludes.

2 The Model

We present the misguided learning model and its testable predictions, using a simple example with the loss-function specification that follows from Heidhues et al. (2018). For the general framework, as well as the proofs, we refer the reader to the original paper.

2.1 Preliminaries

In each period $t \in \{1, 2, 3, ...\}$, the agent produces an observable output q_t according to the following production function:

$$q_t = Q(e_t, A, \Phi) + \epsilon_t = A + \Phi - L(e_t - \Phi) + \epsilon_t,$$

where $e_t \in (\underline{e}, \bar{e})$ denotes the agent's action in period t, $A \in \mathbb{R}$ is the agent's true ability, $\Phi \in (\underline{\phi}, \bar{\phi})$ is the unknown state of the world (referred to, in the original paper, as "the external fundamental"), and $L(\cdot)$ is a symmetric loss function with $L(0) = 0$ and $|L'(x)| < k < 1$ for all x. ϵ_t is an identically, independently and continuously distributed mean-zero random variable. This functional form describes a situation in which the agent has to match his action to the state of the world. The state Φ is drawn from the continuous prior distribution $\pi_0 : (\underline{\phi}, \bar{\phi}) \to R_{>0}$, and the agent has a correct prior belief about the state, i.e. $\phi_0 = 0$.

In each period, the agent undertakes an optimal action given his belief ϕ about the state Φ. To minimize the loss function, he chooses $e^*(\phi) = \phi$. The agent follows the myopic decision rule: the undertaken action only maximizes the expected output in that period.[7] Moreover, in every period the agent aggregates enough observations so that he

[7]The assumption implies that there is no learning motive at play. The agent is neither intentionally experimenting, nor gathering data about his environment to make better choices in the future. Misguided learning is a by-product of a sequential, short-sighted optimization. This distinguishes the model from the classical learning literature, where the agent is actively exploring the environment, and in every period, he faces the decision on whether to continue learning or to stop and use the knowledge obtained so far.

is not concerned about the noise; his beliefs and the average output converge to their limits with finitely many updates.[8]

In the first period, the optimal action is equal to the agent's prior belief: $e_1^* = \phi_0 = 0$. This produces the corresponding output (normalizing $A = \Phi = 0$):

$$q_1 = Q(e_1, A, \Phi) + \epsilon_t = -L(0) = 0.$$

The agent observes the actual output q_1, relative to his expected output $\tilde{q}_1$. The extent to which the actual output differs from his expectation depends on the direction and magnitude of the agent's bias.

2.2 Overconfidence and Self-Defeating Learning

The overconfident agent believes that his ability is $\tilde{a} > A$. From taking the action $e_1^* = \phi_0 = 0$, he expects to observe the output $\tilde{q}_1$:

$$\tilde{q}_1 = Q(e_1, \tilde{a}, \phi_0) = \tilde{a} > 0.$$

The agent is not suffering from any other information-processing bias and uses Bayes' rule to update his beliefs about the state of the world. Since he does not update his beliefs about his ability, he attributes the difference in q_1 and $\tilde{q}_1$ to the state of the world and updates his beliefs accordingly. He updates his belief ϕ by solving:

$$Q(e_1, \tilde{a}, \phi) = \tilde{a} + \phi - L(0 - \phi) = 0.$$

Since the loss function is symmetric, i.e. $L(-\phi) = L(\phi)$, the new belief ϕ_1 lies at the intersection of the functions $L(\cdot)$ and $\tilde{a} + \phi$. One can depict the functions on the xy-plane, with the x-axis representing ϕ and e, and the y-axis representing a and $L(\cdot)$.

[8] For the discussion of the last assumption see Heidhues et al. (2018). As for the experiment, we specified the noise distribution such that the agent could always unambiguously identify the state of the world (regardless of the noise realization). Therefore, we circumvent the problem of providing the agent with enough observations to enable him to infer the state.

Since $\tilde{a} > 0$, the point of intersection lies in the second quadrant, implying $\phi_1 < 0$. The updated belief is *lower* than the agent's prior, thus he becomes *pessimistic* about the state of the world.

In Period 2 the agent chooses $e_2^* = \phi_1$. He observes the average output $-L(\phi_1)$, while he expected to produce $\tilde{a} > -L(\phi_1)$. Once again, he updates his belief ϕ accordingly.

$$Q(e_2, \tilde{a}, \phi_1) = \tilde{a} + \phi - L(\phi_1 - \phi) = -L(\phi_1) \iff L(\phi - \phi_1) - L(\phi_1) = \tilde{a} + \phi.$$

To derive ϕ_2, the agent looks at the intersection of $L(\cdot)$ that is shifted left by $|\phi_1|$ and down by $|L(\phi_1)|$ and $\tilde{a} + \phi$. That point lies to the left of ϕ_1, hence $\phi_2 < \phi_1$. The overconfident agent's beliefs satisfy:

$$\phi_2 < \phi_1 < \phi_0. \tag{1}$$

It is worth noting that the agent started with the correct prior, but with each passing period, his belief increasingly deviates from the true state. Under the aforementioned assumptions, the agent's belief about the state of the world converges to a unique limiting belief ϕ_∞. This limiting belief is stable in a sense that the agent has no incentive to abandon it – at this point he ends the learning process. Intuitively, a stable belief is a point belief that induces an action, which produces output that exactly matches with the agent's expectation, thereby confirming his belief. It could be found by setting the difference between the actual and the expected outputs to zero:

$$Q(e^*(\phi_\infty), A, \Phi) - Q(e^*(\phi_\infty), \tilde{a}, \phi_\infty) = 0.$$

With the loss-function specification, that condition reads:

$$(A - \tilde{a}) + (\Phi - \phi_\infty) - L(\Phi - \phi_\infty) = 0. \tag{2}$$

By rearranging the above equation one can derive a formula for the stable belief ϕ_∞. One can notice that the stable belief is a function of the agent's bias.

2.3 Underconfident and Unbiased Agents

The model also predicts the behavior of underconfident agents. The analysis is analogous, with the only difference that the agent underestimates his true ability, i.e. $\tilde{a} - A < 0$. With the normalization of $A = 0$, this implies $\tilde{a} < 0$.

In Period 1, the agent again chooses $e_1^* = \phi_0 = 0$. He observes the average output of $-L(0) = 0$, while he expected to produce $\tilde{a} < 0$. The agent does not update his beliefs about his ability, but instead he looks for ϕ that would explain the output. He looks at the intersection of $L(\cdot)$ and $\tilde{a}+\phi$. Since $\tilde{a} < 0$, this point now lies in the fourth quadrant, implying $\phi_1 > 0$. The updated belief ϕ_1 is *higher* than the agent's prior $\phi_0 = 0$, and hence he concludes that the state of the world is *better* than expected.

In Period 2, the agent chooses $e_2^* = \phi_1$. He observes the average output of $-L(\phi_1)$, while he expected to produce $Q(e_2, \tilde{a}, \phi_1) = \tilde{a} + \phi_1$. This falls short of his expectations, so he concludes that the state is *worse* than his belief. To derive ϕ_2 he looks at the intersection of $L(\cdot)$ shifted right by $|\phi_1|$ and down by $|L(\phi_1)|$, and $\tilde{a} + \phi$. The shift entails $\phi_2 < \phi_1$, so the underconfident agent chooses lower action in the following period. The adjustment runs in the right direction, bringing the agent closer to the true state. In contrast to the overconfident agent, the underconfident agent's misinference is *self-correcting*. The model predicts that the underconfident agent's beliefs satisfy:

$$\phi_1 > \phi_0 \quad \wedge \quad \phi_2 < \phi_1. \tag{3}$$

As in the case of the overconfident agent, there exists a unique stable belief described by equation (2). Note that the learning process of the underconfident agent is misdirected, as he ends up with a belief different from the true state. However, the learning trajectory of the underconfident agent is very different from that of the overconfident agent. To highlight this difference, we use the term "misguided learning" to describe the learning of a biased (over- or underconfident) agent, and we only refer to the overconfident agent's self-reinforcing misguided learning as "self-defeating learning".

The unbiased individual correctly evaluates his ability $\tilde{a} = A$. After choosing the optimal action in the first period, $e_1^* = \phi_0 = 0$, he observes exactly the output he expects: $\tilde{a} + \phi = 0 = -L(0)$. The unbiased agent has no reason to update his beliefs any further, implying:

$$\phi_2 = \phi_1 = \phi_0. \tag{4}$$

The unbiased agent never abandons his correct prior belief – it is a stable belief.

2.4 Testable Predictions

The first implication of the model concerns the characteristics of the environment that are necessary for misguided learning to occur. The role of endogenous actions is summarized in Hypothesis A1.

Hypothesis A1 (Endogenous vs Exogenous Actions)

For misguided learning to occur it is necessary that the optimal action: (i) depends on the agent's beliefs, (ii) directly affects the output, and (iii) indirectly affects beliefs in the next period. Holding everything else constant, misguided learning will not arise in an environment with exogenous actions.

The main prediction of the model is the emergence of misguided learning. The phenomenon manifests itself through the stable belief, which can be interpreted as a long-term outcome of the learning process, and through the learning process itself (the entire path of beliefs). The learning outcomes are different for the overconfident, underconfident, and unbiased agents, according to the equation (2). The stable belief is negative in the case of overconfident agent, positive for the underconfident individual, and equals the true state of the world for the unbiased agent.

Hypothesis 1 (Misguided Learning: Outcomes)

The outcome of the learning process of an overconfident agent (the stable belief) differs from the correct belief about the state of the world and from the stable belief of an underconfident agent. The outcome of the learning process of an unbiased agent is a stable belief that is identical to the true state.

The same equation enables us to perform comparative statics with respect to the magnitude of bias. The model implies that two overconfident (underconfident) agents with the same ability A, but dissimilar beliefs $\tilde{a}_1 \neq \tilde{a}_2$, will converge to different limiting beliefs. The belief of the overconfident (underconfident) agent with a larger bias will end up further from the true state relative to the belief of the less biased individual.

Hypothesis 2 (Individual Heterogeneity)

The stable belief of an overconfident (underconfident) agent with a larger bias lies further from the true state than the stable belief of a less overconfident (underconfident) agent.

The model not only predicts the learning outcomes but also characterizes the entire learning process. The path of beliefs differs significantly in the case of overconfident, underconfident and unbiased agents. The overconfident individual becomes increasingly mistaken about the state of the world with each period, whereas the underconfident agent first overshoots, but then corrects his beliefs. The learning process of the unbiased agent is immediate and the resulting belief is a stable belief.

Hypothesis 3 (Misguided Learning: Process)

The learning process of an overconfident (underconfident) agent significantly differs from that of an unbiased agent. The learning process of the unbiased individual is immediate and his belief is stable afterward. The learning process of the underconfident agent is self-correcting, in contrast with the self-defeating learning of the overconfident agent.

3 Experimental Procedures

The experiment took place in November 2017 in the Laboratory for Experimental Economics at the University of Bonn. We conducted 8 two-part sessions, each comprising 19 to 25 participants. In sum, we collected data from 171 participants, mostly students from the university. The first and second parts of the experiment lasted around 45 minutes and 90 minutes respectively. Participants earned 30 euros on average.

In the first part of the experiment, subjects completed an IQ test and filled out a questionnaire. We used the IQ test results to evaluate each subject's relative performance in the entire sample. The second part of the experiment took place one week later, after all subjects had completed the first part, and included the learning exercise as well as the elicitation of both prior and posterior beliefs.[9] Both parts of the experiment were programmed using zTree (Fischbacher, 2007) and completed by subjects on computers in private cubicles. We describe each part in detail below.

3.1 IQ Test and Belief Elicitation

In the first part of the experiment, we evaluated subjects' relative performance in the IQ test, which consisted of 29 standard logic questions. Participants were asked to solve as many of them as possible in 10 minutes. Individual score was equal to the number of correctly answered questions minus the number of incorrect answers. To incentivize effort during the test, participants were told that the individual result is important for the next part of the experiment, and their earnings will depend on their scores. After the IQ test, subjects were asked to fill out a questionnaire designed to assess their character traits and individual anxiety levels. At the end of the first session, we reminded participants about the second session one week later, and that they will not be paid unless they show up for the second session.

[9] To match subjects' data between the sessions without violating anonymity, we followed a special procedure, which included generating private codes that were used to match subjects to cubicles at the beginning of the second session.

Between the sessions, we ranked participants according to their IQ test results. For every subject, we calculated his position in the group. The individual position was defined as a number equal to the percent of participants whose test scores were lower or equal to the score obtained by the subject. We defined 20 equilength "performance intervals" ranging from 0% to 100% in steps of 5%. Every participant was assigned the performance interval that his position fell under (with $0-5\%$ denoting the lowest and $95-100\%$ the highest performance interval). We refer to the midpoint of that performance interval as the agent's *relative performance* (denoted by A).

At the beginning of the second session, we elicited subjects' prior belief about their relative position (Confidence I) using the incentive-compatible crossover method that is independent of subjects' risk attitudes (see Schlag et al., 2015). We presented participants with a choice list and asked them to indicate their preferred option in each of the 20 lines. Option A was a lottery with p chance of receiving 5 euros and $1-p$ chance of receiving 0; the winning probability increases from $p = 0.05$ to $p = 1$ in 5% steps. Option B stood for a competition with a randomly selected individual, which granted 5 euros if one's IQ test score was higher than their partner, and nothing otherwise. A rational individual would choose Option A if and only if p is larger than his perceived relative performance. Therefore, we interpret the switching probability as a measure of confidence in one's skills. We followed the same procedure in the second belief elicitation (Confidence II). During the first belief elicitation, subjects were not aware that they will be asked to state their beliefs again after the learning exercise.

3.2 The Learning Exercise

After the first belief elicitation, participants completed 6 rounds of the learning exercise. For each participant, we drew 6 numbers, with replacement, from the set $\{-10, -9, ..., -1, 0, 1, ..., 9, 10\}$.[10] We refer to this collection of 6 numbers as an "individ-

[10]The numbers were drawn from the uniform distribution that put higher weight on numbers in the interval $[-4, 4]$. Participants were not presented the exact distribution but were told that the sum of numbers drawn *is equal to zero in every round*. We explained that some participants in the lab are guessing the number 0, and among the rest half of participants is guessing a positive number, while the other half the same number with the opposite sign.

ual set" and to the set containing all feasible numbers "the feasible set". Participants were reassured that the numbers had been drawn before the experiment started.[11]

Every round, participants were asked to estimate one number taken from their individual sets without replacement.[12] For each number, participants had to make 4 guesses and enter them into the interface one at a time. After each guess, the computer program calculated a payoff according to the formula:

$$\Pi(e, A, \Phi) = 20 + 0.8 \times (28.6 \times \ A \ + \ \Phi \ - \ 0.48 \ |e - \Phi|), \tag{5}$$

where A denotes the agent's relative performance, Φ is the actual number, and e refers to his guess. The formula corresponds to the specification of the absolute value loss function. We decided to use this specification because of its simple form and straightforward interpretation. The parameters were chosen such that misguided learning could arise for moderately biased agents. We did not require subjects to adopt a myopic decision rule during the experiment. However, we expected that the task will induce short-sighted behavior to some extent.

The formula was presented to the participants in a descriptive form with an intuitive explanation of the absolute value in terms of distance on the linear scale. We drew subjects' attention to the fact that the payoff is higher the closer their guess is to the actual number (with the highest payoff for the exact match). Participants were informed that, at the end of the experiment, two out of $4 \times 6 = 24$ guesses will be randomly drawn and paid out (with the exchange rate of 0.3).

[11] We informed subjects that each individual set had been printed and placed in a sealed envelope in the participant's cabin. Participants were told not to open the envelopes until the end of the experiment. As an additional precautionary measure we placed the envelopes within the sight of the person conducting the experiment.

[12] We decided to frame the task as "guess the number" instead of "guess your ability and the number". We deliberately introduce an asymmetry in treating the two parameters, as we aim to test the theory that describes this particular type of situation. We believe that this setting is more adequate to study the implications of overconfidence. In many real-world situations learning about ability is not explicit. For instance, when an investor is trading stocks his main task is to generate profits and learn about the market, and not about his ability (even though the profits may depend on his analytical skills). For additional discussion see Section 5.

After entering a guess e, every participant received private feedback. The feedback was equal to one's payoff with an added random component and was displayed on the individual computer screen.[13] Participants were informed that they can infer the actual number they are guessing in a given round from their feedback. Knowing their relative performance A, the last guess e, and the payoff Π, they can calculate the unknown number Φ. However, it requires some arithmetical skills. Considering that computational mistakes could influence the learning behavior and obscure the results, we provided subjects with a tool to help them with the task.

3.2.1 Introducing Tables

Before the learning exercise, every participant was given a set of 21 tables (see Online Appendix A), from which they could obtain the value of Φ using the feedback they received. The tables contained payoffs for every possible combination of e, Φ, and A. The three parameters jointly determine the payoff, and hence the set of two-dimensional tables contains all feasible payoffs. There is one table for each possible guess e (indicated in the title), the rows indicate the relative performance A (performance intervals are listed in the first column), whereas the columns indicate the number Φ (its values are listed in the first row).

We provided the participants with detailed instructions to correctly utilize the tables. Firstly, we described how to find the payoff given e, Φ, and A. A user has to look for a table with his guess in the title, and then look for the intersecting cell corresponding to the row with his relative performance and the column with the number. Secondly, we explained that if someone knows the payoff Π, his last guess e and his relative performance A, he can obtain the value of Φ by reversing the last steps. After finding the right table, the subject should look at the row with his relative performance and

[13] The noise was introduced only to ensure that subjects would not be able to infer their ability by matching the feedback to a single identical number in the table. The random component was drawn from the uniform distribution over the interval $[-0.18, 0.18]$ known to the subjects. Importantly, the noise was not big enough to influence the update: in every row, there was only one number that was sufficiently close to the feedback that a subject received.

search for his payoff in this row. The column, in which the payoff lies, indicates the number.

We presented participants with multiple examples and strongly encouraged them to raise questions when in doubt. Every participant had to answer control questions that not only tested their understanding but also pointed out important aspects of the task. We reminded subjects that the payoff is displayed with an added random component drawn from the uniform distribution over the interval $[-0.18, 0.18]$. Feedback was only displayed after the first guess and participants were not given any information prior to it. Therefore, the first guess that maximizes expected payoff was $e = 0$. To avoid misunderstandings, we directly told subjects that it is in their best interest to choose zero as their first guess.

3.2.2 Experimental Conditions and Groups

We introduced two conditions: treatment (we refer to it as "multiple-feedback rounds") and control("single-feedback rounds"). The two conditions differed with respect to information provided to participants after each guess. In the multiple-feedback rounds, participants received feedback calculated according to the formula (5) after each guess.

In the single-feedback rounds, subjects received feedback calculated according to (5) only after their 1$^{\text{st}}$ guess. After the 2$^{\text{nd}}$ and the 3$^{\text{rd}}$ guess computers displayed feedback calculated using the 1$^{\text{st}}$ guess in that round. Subjects were notified that no matter what they enter as their 2$^{\text{nd}}$ or 3$^{\text{rd}}$ guess, the feedback will not reflect their choices. In spite of that, they were asked to enter their best guess two more times keeping in mind that every guess is equally important for their earnings.

Every participant completed a total of 6 rounds, alternating between the treatment and control conditions. We randomly assigned subjects to two groups (see Table 1), with the first group starting with a single-feedback round and the second group starting with a multiple-feedback round.

Table 1: Experimental Conditions and Groups

Round	Group 1	Group 2
1.	SF	MF
2.	MF	SF
3.	SF	MF
4.	MF	SF
5.	SF	MF
6.	MF	SF

SF – single-feedback round
MF – multiple-feedback round

4 Results

In this section, we present the results of our empirical analysis. We focus on self-defeating learning of overconfident agents and test the model's predictions using our independent measure of overconfidence. The description of the behavior of the underconfident and unbiased subjects, as well as the analysis based on the agents' beliefs revealed indirectly through their guesses, can be found in the appendices.

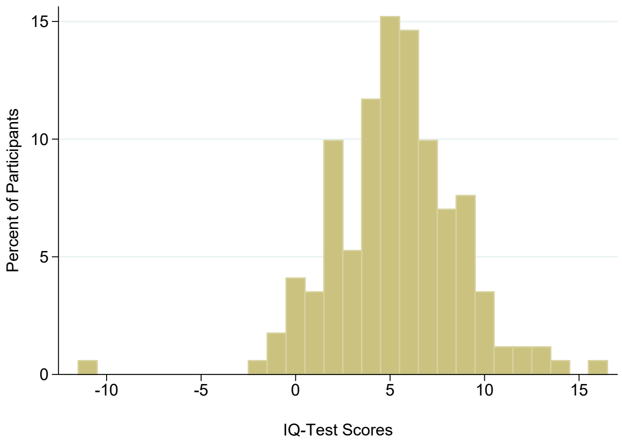
4.1 IQ Test Results and Elicited Beliefs

In Figure 1(a) we present a histogram of the IQ test results. The scores range from -11 to 16, with over 90% of participants obtaining between 0 and 10 points. The score distribution is fairly symmetrical, with a mean score of 5.29, and standard deviation of 3.38. These outcomes translate to the distribution of performance intervals depicted in Figure 1(b). Since there are groups of participants with the same test score, some intervals will be empty. Figures 1(c) and (d) show the distributions of prior and posterior beliefs about relative performance (i.e. Confidence I and Confidence II), which were elicited before and after the learning exercise respectively.

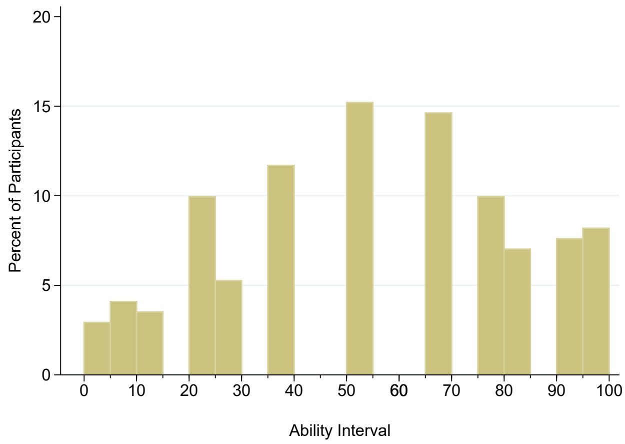
The mean prior belief about one's relative performance equals 59.46% and is significantly higher than that of the actual position, 55.25% (p-value = 0.092). The average participant is overconfident, yet the magnitude of bias in our sample is not very high.

Figure 1: Distribution of IQ test results and beliefs about relative performance.

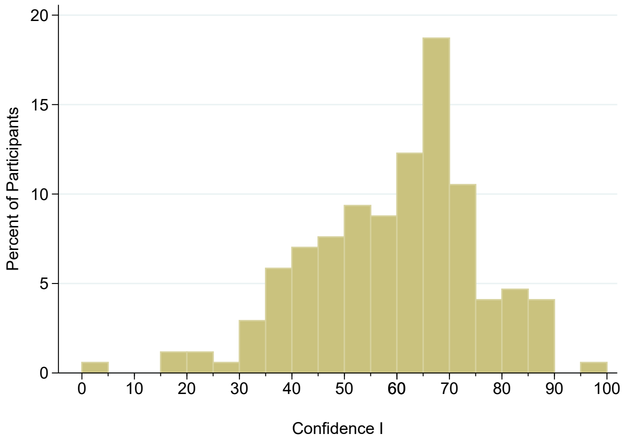
(a) Distribution of IQ test scores.



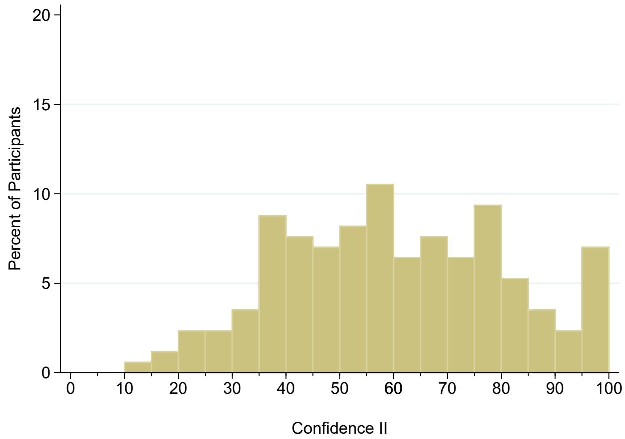
(b) Distribution of ascribed performance intervals.



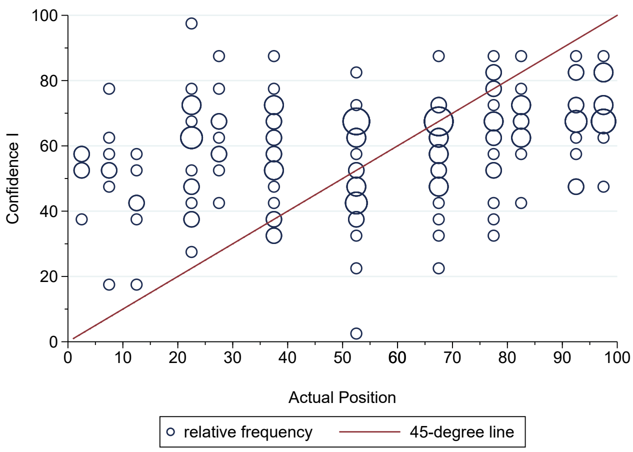
(c) Distribution of prior beliefs (Confidence I).



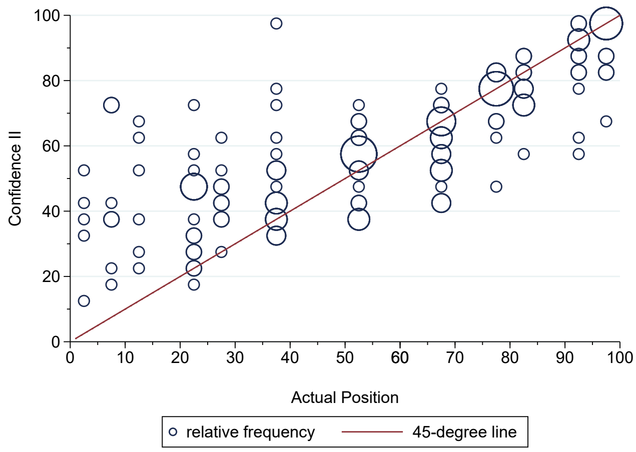
(d) Distribution of posterior beliefs (Confidence II).



(e) Prior beliefs depending on the actual performance.



(f) Posterior beliefs depending on the actual performance.



The overconfidence level remains almost unchanged after the learning exercise (the mean posterior belief equals 60.28%), but the distribution of beliefs changes (Figures 1(c) and (d)). We define an agent's bias as the difference between the agent's belief about his relative performance and his actual position (in percentiles). We classify an agent as *overconfident* (*underconfident*) if he assessed his performance to be higher (lower) than the actual, and so his bias takes on a positive (negative) sign. An unbiased participant correctly estimated his relative performance. Table 2 presents the frequencies of confidence types before and after the learning exercise.

Table 2: Frequencies of confidence types before and after the learning exercise.

		Confidence I (prior beliefs)			
		Underconfident	**Unbiased**	**Overconfident**	**Total**
Confidence II (posterior beliefs)	**Underconfident**	41	5	4	50
	Unbiased	24	4	14	42
	Overconfident	14	4	61	79
	Total	79	13	79	171

As revealed in Confidence I, there are 79 overconfident, 79 underconfident and 13 unbiased subjects in our sample. After the learning exercise, 38% of all subjects changed their type: 17% of overconfident and 30% of underconfident subjects became unbiased. Confidence II reveals that a significant portion of the sample held incorrect beliefs even after the learning exercise. At the end of the experiment, 79 subjects were overconfident (77% of them were overconfident before) and 50 subjects could be classified as underconfident.

Before the main task, the average underconfident subject held inaccurate belief that was 20.19 percentiles below his actual position. After the learning exercise, this difference decreased to 6 percentiles. The average bias of the overconfident subject was initially

29.37 percentiles and this decreased to 16.52 percentiles after the learning exercise.[14] The average actual position of overconfident subjects lies in the 32$^{\text{nd}}$ percentile, over 40 percentiles below the average position of underconfident subjects. The low-ranked participants tend to overestimate their relative performance, whereas high-ranked subjects underestimate it. The exact values are presented in Table 3. The differences in mean beliefs before and after the learning exercise are statistically significant for the overconfident and underconfident subjects (p-value = 0.000 in both cases), but not for the unbiased subjects (p-value = 0.642). The differences remain significant even if we exclude overconfident (underconfident) subjects who became underconfident (overconfident) during the experiment.

Table 3: Mean relative performance (the percentile position in the group) and beliefs elicited before the learning exercise (Confidence I) and after (Confidence II).

	Position	Confidence I	Confidence II
Underconfident			
Mean	77.50	57.31	71.42
(Std. Dev.)	(16.41)	(16.71)	(18.50)
Unbiased			
Mean	62.12	62.12	64.81
(Std. Dev.)	(13.14)	(13.14)	(15.89)
Overconfident			
Mean	31.87	61.17	48.39
(Std. Dev.)	(19.81)	(15.76)	(16.50)
All subjects			
Mean	55.25	59.46	60.28
(Std. Dev.)	(28.34)	(16.07)	(20.61)

[14] The average includes overconfident agents who became underconfident (switching from positive to negative bias), thus the average bias is underestimated. The mean bias of the overconfident (underconfident) agents who remained overconfident (underconfident) or became unbiased, equals 17.67 (-8.85).

There is a lot of heterogeneity in the sample with regard to the actual performance and participants' beliefs about their relative position within the group. Figure 1(e) depicts our subjects grouped based on (i) their relative performance, and (ii) their beliefs elicited before the main task (with circle size representing the relative frequencies). The data suggests that subjects' prior beliefs were very inaccurate (few data points lie on the 45-degree line). Subjects positioned above the red line assessed their relative performance to be higher than it was, and thus are classified as overconfident, whereas those positioned below are classified as underconfident. Figure 1(f) presents the analogous relationship between the participants' actual performance and their posterior beliefs.

4.2 Model Predictions Based on Elicited Beliefs

4.2.1 Misguided Learning

Misguided learning manifests itself partly through the end results of learning. Heidhues et al. (2018) make predictions for the limit of the belief updating process. As experimentalists, we are constrained by the number of iterations we can implement in the lab. Therefore, the best we can do is to look at the subjects' last guesses (i.e. the 4^{th} guess) in the multiple-feedback rounds and compare them to the respective numbers from the individual sets. Assuming that agents were maximizing their expected utility in every period, their guesses perfectly revealed what they had learned over time. To test Hypothesis 1, we compare the average guess with the mean value of Φ that was estimated, separately for the underconfident, overconfident and unbiased agents.[15] We reject the hypothesis that the end result of the learning process is equal to the number estimated by the underconfident and overconfident agents respectively (in both groups, p-value = 0.000), but not for the unbiased individuals (p-value = 0.228). The results confirm Hypothesis 1. Moreover, the average learning outcome is *positive* for overconfident agents and *negative* for underconfident agents, as predicted by the model.

[15] Although in every round the sum of numbers given to the participants was equal zero, we could not predict the way in which they were distributed among the overconfident, the underconfident and the unbiased agents. Thus, the average of the numbers estimated by different groups was not exactly zero.

Result 1.

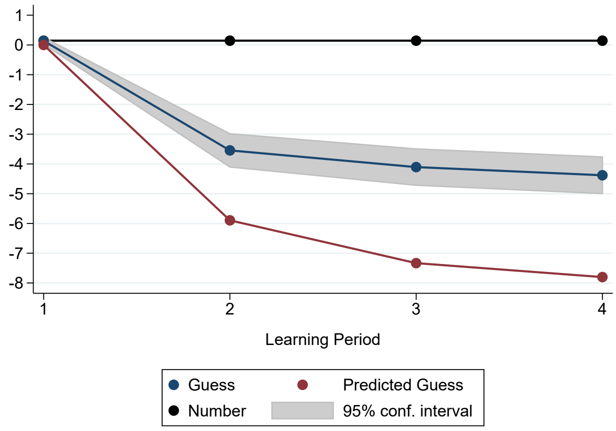
For the overconfident and underconfident agents, the belief resulting from the learning process differs from the correct belief about the state of the world. For the unbiased agents, the final belief corresponds to the true state of the world.

The specific belief paths are depicted in Figure 4. We predicted the actions for every subject, based on the number he was guessing and his bias as revealed in Confidence I. The red line connects the mean predicted guesses in the multiple-feedback rounds (the graphs on the left) and single-feedback rounds (on the right), separately for the overconfident, underconfident, and unbiased subjects. The blue line connects the means of the subjects' actual guesses, and the black points denote the mean number being guessed by participants. For both the underconfident and overconfident agents, their actual guesses (with 95% confidence intervals) are far from the ones predicted by the model. Still, the belief paths resemble the paths predicted by the model. In particular, the learning of the overconfident agent is self-defeating, with each guess diverging from the true state. We test this formally, by comparing coefficients of a simple regression explaining the difference between a guess and the number with dummy variables, one for each guess (see Online Appendix B). For the overconfident agents, the 3^{rd} guess in the multiple-feedback rounds is significantly lower than the 2^{nd} guess (one-tailed test: p-value = 0.019). Although we cannot attest the strict inequality for the 3^{rd} and the 4^{th} guess with similar confidence level, the difference between the 2^{nd} and the 4^{th} guess is highly significant (one-tailed test: p-value = 0.003). We conclude that the learning process of overconfident agents in the multiple-feedback rounds is self-defeating. Moreover, the patterns evinced by the underconfident and unbiased agents also follow the model's predictions.

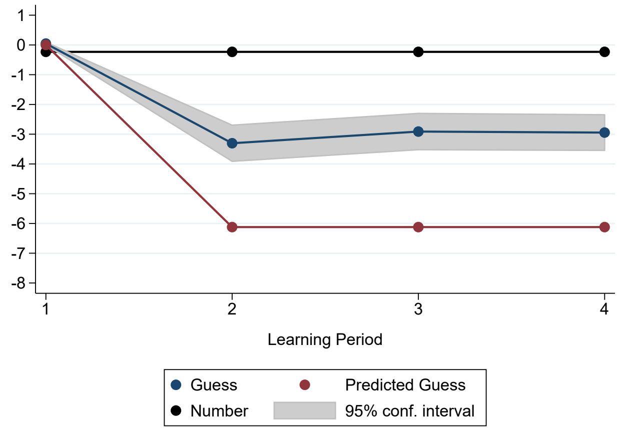
Result 2.

In line with the model's predictions, the learning process of overconfident agents is self-defeating. The learning paths of underconfident and unbiased agents also resemble the ones predicted by the model.

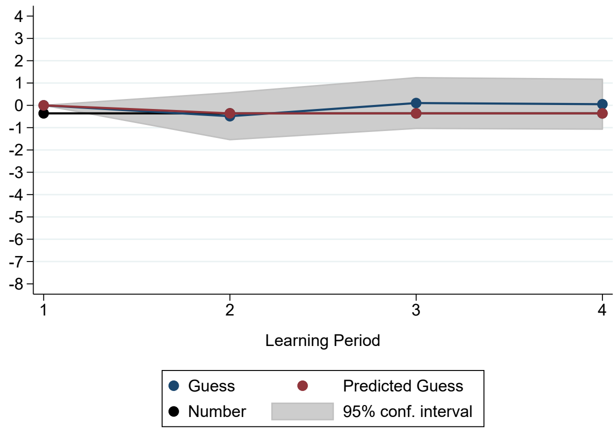
Figure 4. The mean estimated number, participants' actual and predicted guess.



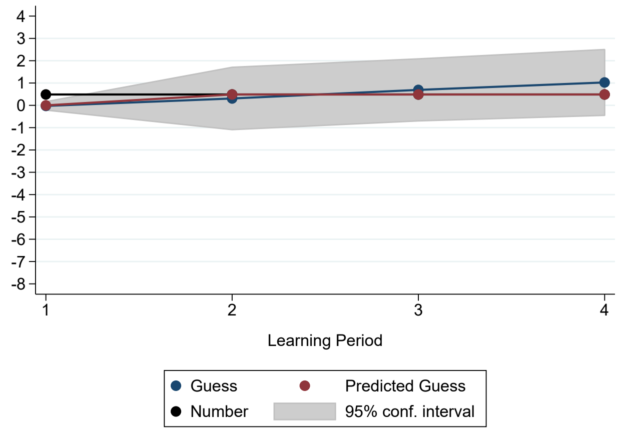
(a) Overconfident agents in MF Rounds.



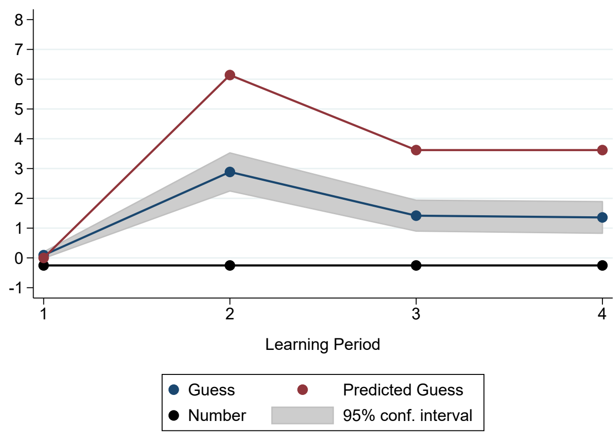
(b) Overconfident agents in SF Rounds.



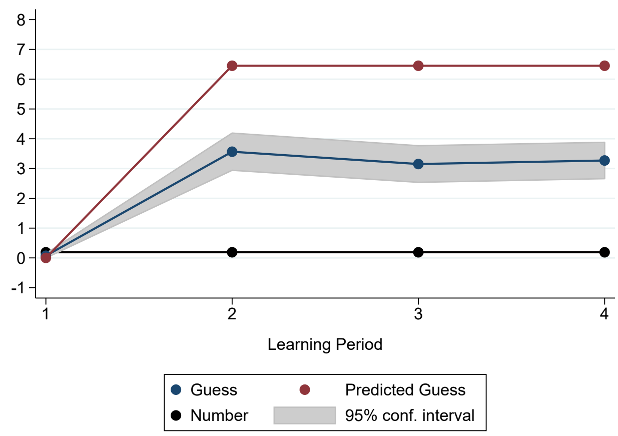
(c) Unbiased agents in MF Rounds.



(d) Unbiased agents in SF Rounds.



(e) Underconfident agents in MF Rounds.



(f) Underconfident agents in SF Rounds.

4.2.2 Misguided Learning: Endogenous Actions

In contrast to the multiple-feedback rounds, feedback received by the subjects in the single-feedback rounds was not based on agents' actions. After the 2^{nd} guess, participants were not presented with any new information, so they should not change their beliefs or actions afterward. Comparing the behavior in the treatment condition to that of the control enables us to examine the consequences of the interdependence between beliefs, actions, and feedback. Firstly, we demonstrate that there is no evidence of self-defeating learning in the single-feedback rounds. Again, we compare the coefficients of subsequent guesses in the simple regression (see Online Appendix B). The results prove that, for overconfident agents, their beliefs path in the single-feedback rounds does not exhibit the pattern characteristic of self-defeating learning: there is no downward trend in beliefs formation.

Secondly, we look at the difference between a guess and the actual number, and how it depends on the type of feedback. Here, we treat the 2^{nd}, 3^{rd}, and 4^{th} guess separately (note: we omit the 1^{st} guess, as subjects were instructed to enter 0 in that round). The estimation results in Tables 4 and 5 confirm that for overconfident agents, the difference is greater in the multiple-feedback rounds, when subjects have the opportunity to experiment and acquire new information. The coefficients of the MF Round variable are positive and highly significant for the 3^{rd} and 4^{th} guess. Providing overconfident agents with more information widens the gap between his beliefs and the true state by 1.122 in the third trial, and 1.211 in the fourth trial, relative to the single-feedback rounds. As expected, the coefficient of the MF Round variable in the second guess is not significant (subjects receive the same feedback after their initial guess in both types of rounds, so there is no effect of MF Round on the dependent variable). The results confirm Hypothesis A1.

Result 3.

The interdependence between the agents' actions, beliefs and feedback is a necessary condition for self-defeating learning to occur. Providing overconfident agents with the opportunity to experiment and learn drives their beliefs further away from the true state.

Table 4: The effect of feedback on the difference between the number and a guess.

	Overconfident (1)	Unbiased Agents (2)	Underconfident (3)
Dependent variable: the difference between the number and the 4th guess.			
MF Round	1.211***	-0.333	-1.308***
	(0.303)	(0.423)	(0.235)
Bias	0.0734***	0	-0.0282
	(0.016)	(.)	(0.021)
Const.	1.895***	0.949	2.924***
	(0.433)	(0.512)	(0.438)
Dependent variable: the difference between the number and the 3rd guess.			
MF Round	1.122***	0.0513	-1.350***
	(0.293)	(0.268)	(0.230)
Bias	0.0815***	0	-0.0387
	(0.017)	(.)	(0.021)
Const.	1.692***	0.615**	2.737***
	(0.443)	(0.197)	(0.408)
Dependent variable: the difference between the number and the 2nd guess.			
MF Round	0.236	-0.205	-0.0928
	(0.221)	(0.206)	(0.212)
Bias	0.0962***	0	-0.0307
	(0.015)	(.)	(0.023)
Const.	1.494***	0.333	3.086***
	(0.361)	(0.197)	(0.453)
N	474	78	474

MF Round is a dummy variable taking value 1 if the round is a multiple-feedback round.

The independent variable Bias stands for agent's initial bias (based on Confidence I).
It takes positive (negative) values for the overconfident (underconfident) agents.

Standard errors clustered at individual level. Their values in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: The effect of feedback on the difference between the number and a guess.

	Overconfident (1)	Unbiased Agents (2)	Underconfident (3)
Dependent variable: the difference between the number and the 4$^{\text{th}}$ guess.			
MF Round	1.839*** (0.445)	-0.333 (0.423)	-1.832*** (0.455)
Bias	0.0841*** (0.016)	0 (.)	-0.0153 (0.026)
MF Round × Bias	-0.0214 (0.016)	0 (.)	-0.0259 (0.023)
Const.	1.581*** (0.395)	0.949 (0.512)	3.186*** (0.510)
Dependent variable: the difference between the number and the 3$^{\text{rd}}$ guess.			
MF Round	1.555*** (0.445)	0.0513 (0.268)	-1.958*** (0.428)
Bias	0.0889*** (0.017)	0 (.)	-0.0237 (0.026)
MF Round × Bias	-0.0148 (0.018)	0 (.)	-0.0301 (0.022)
Const.	1.475*** (0.414)	0.615** (0.197)	3.041*** (0.489)
Dependent variable: the difference between the number and the 2$^{\text{nd}}$ guess.			
MF Round	0.557 (0.341)	-0.205 (0.206)	-0.443 (0.371)
Bias	0.102*** (0.017)	0 (.)	-0.0220 (0.024)
MF Round × Bias	-0.0109 (0.014)	0 (.)	-0.0173 (0.017)
Const.	1.334** (0.404)	0.333 (0.197)	3.261*** (0.477)
N	474	78	474

MF Round is a dummy variable taking value 1 if the round is a multiple-feedback round.

The independent variable Bias stands for agent's initial bias (based on Confidence I).
It takes positive (negative) values for the overconfident (underconfident) agents.

Standard errors clustered at individual level. Their values in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.3 Individual Heterogeneity

The regression results presented in Tables 4 and 5 enable us to assess the impact of agents' bias on learning. In the case of overconfident agents, the effect is significant and runs in the direction predicted by the model. Increasing agent's overconfidence by 10 percentiles enlarges the difference between a guess and the actual number by 0.962, 0.815, and 0.734 in the 2^{nd}, 3^{rd}, and 4^{th} guess, respectively. The effect is notable considering the scale from -10 to 10. In Table 5, we included the interaction between the MF Round variable and agents' bias to the specification. The negative sign of the coefficients indicates that the total impact of bias would be smaller in the multiple-feedback rounds, but the coefficients are not significant. For underconfident agents, the coefficients have the predicted sign, but are not significant at an acceptable level. We confirm Hypothesis 2 for the overconfident, but not for the underconfident agents.

Result 4. (Individual Heterogeneity)
The difference between the overconfident agent's beliefs and the true state increases with the agent's bias. The more biased the agent is, the further away from the correct belief he ends up.

4.2.4 Model's Performance

Up to this point, we have examined whether the model's comparative statics hold in our data set. In this section, we delve into the model's explanatory power. We test how well the model explains our data and report the results in Table 6. First, we pool the data from the multiple- and single-feedback rounds and look at early and late rounds separately. The model seems to better explain the data in the early rounds (especially in the first round) than in the later rounds. The results are in line with the observation that, during the experiment, subjects were updating their beliefs about their relative performance.[16] One would expect that in the early rounds, subjects' beliefs

[16] In Online Appendix C, we present data on subjects' *revealed* beliefs about their relative performance (with few additional assumptions we can divulge subjects' beliefs from their guesses). We also assess the model's performance comparing the predictions based on revealed beliefs to agents' guesses.

Table 6: How well the model predicts the 2^{nd}, 3^{rd} and 4^{th} guess.

	All Rounds	Early Rounds	Late Rounds	1^{st} Round
Model	0.563***	0.633***	0.493***	0.688***
	(0.030)	(0.031)	(0.036)	(0.035)
Const.	-0.119	-0.102	-0.132	-0.0213
	(0.182)	(0.185)	(0.217)	(0.213)
R^2	0.523	0.605	0.441	0.696
N	3078	1539	1539	513

	All Rounds		Early Rounds		Late Rounds	
	SF	MF	SF	MF	SF	MF
Model	0.559***	0.563***	0.609***	0.650***	0.502***	0.482***
	(0.034)	(0.032)	(0.040)	(0.033)	(0.043)	(0.042)
Const.	0.0731	-0.310	0.150	-0.340	-0.0499	-0.213
	(0.212)	(0.181)	(0.249)	(0.193)	(0.268)	(0.239)
R^2	0.516	0.522	0.567	0.634	0.458	0.422
N	1539	1539	813	726	726	813

Standard errors clustered at individual level are in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

were closer to the independent measure of beliefs (Confidence I) that we used to calculate the model's predictions. During the first three rounds, the model does a better job at explaining subjects' choices in the multiple-feedback rounds, whereas in the last three rounds it performs slightly better in the single-feedback rounds. As shown in Table 7, the choices made by unbiased agents are well-explained by the model. With R^2 of 0.85, the model explains much variation in the data. The fit is less adequate in the case of the underconfident subjects, and much worse for the overconfident subjects.

Table 7: How well the model predicts guesses of different types of agents.

	Overconfident	Unbiased Agents	Underconfident
Model	0.575***	0.969***	0.689***
	(0.068)	(0.028)	(0.035)
Const.	0.247	0.220	-1.151***
	(0.312)	(0.132)	(0.220)
R^2	0.182	0.850	0.463
N	1422	234	1422

Dependent variable: the participants' guesses.
Independent variable: guesses predicted by the model.

Standard errors clustered at individual level are in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Discussion

Channels. We hypothesize that our results are driven in part by participants' tendency to interpret feedback in a self-serving manner. An overconfident agent would rather attribute negative feedback to the state of the world instead of revising his beliefs about his performance downwards when the loss from a tarnished self-image exceeds the gains from holding accurate beliefs (assuming that agents have belief-based utility, similar to the one proposed by Kőszegi, 2006).[17] We designed an additional control condition to test this hypothesis and assess the extent to which motivated reasoning is driving our results.

Another possible explanation concerns the fact that the probabilities of possible states of the world are objectively given, whereas beliefs about one's relative performance are subjective. Participants may find it more difficult to update these subjective beliefs relative to objectively given probabilities of the states. In the additional control

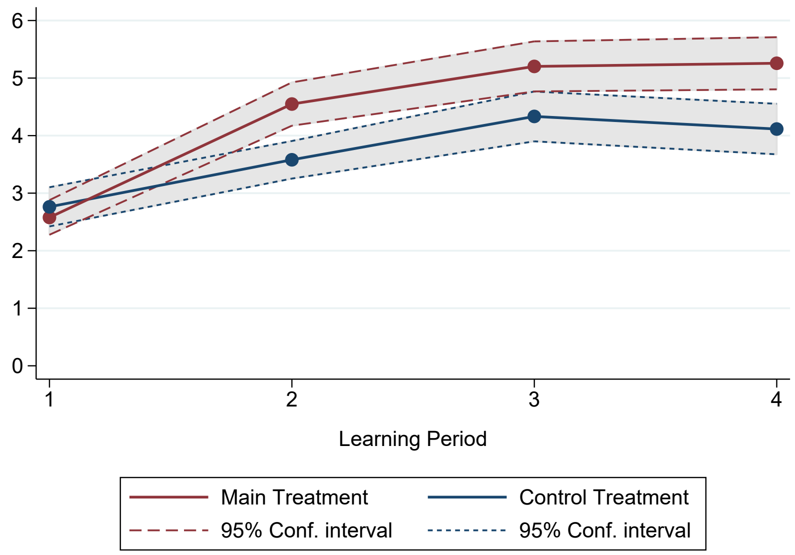
[17]However, this does not explain why the underconfident agents are reluctant to revise their beliefs upwards. Several studies found evidence of *conservatism* in updating about ego-relevant traits (Buser et al., 2018; Möbius et al., 2014). It is likely to play a role in this context.

condition, we intended to maintain the subjectivity of prior beliefs, so as to ensure comparability with the treatment condition. Lastly, it is possible that the way the subjects' attention was directed during the experiment influenced their learning process. In the treatment condition, we framed the task as "guess the number" instead of "guess your ability and the number", deliberately introducing asymmetry in the two parameters. Implicit learning about one's relative performance was one of the objectives of our experimental design, and we chose to keep this feature unchanged in the control condition to isolate the effect of motivated reasoning.

To this end, we designed a treatment in which participants were learning about two parameters that were *both* ego-neutral. We used the same experimental design, with the only difference being that in the second session, each subject performed the main task based on the performance parameter of another subject. We informed subjects that each of them will be randomly matched to another subject who completed the same IQ test and revealed similar beliefs through the elicitation procedure. We assumed that the performance of another individual is irrelevant to one's ego. Before the main task, we elicited subjects' beliefs about the relative performance of the participant matched to them and distinguished overconfident, underconfident and unbiased agents (with respect to their partner's performance). We again elicited beliefs about the relative performance of the matched partner after the learning exercise. The identical experimental design and similar instructions enabled us to control for the way subjects' attention was directed during the experiment.

We collected data from 151 participants, mostly students from University of Bonn. Figure 2 presents the mean distance between the overconfident agent's guess and the estimated number in the multiple-feedback rounds. The difference is more pronounced in the treatment condition, that is, for agents whose feedback was based on their own relative performance. Table 8 reports regression results pooling the data from the treatment and additional control conditions. For the overconfident agents, the treatment effect on the distance between the agent's guess and the actual number is large and significant. The effect persists when we control for the initial bias and is not significant for the

Figure 2: Mean absolute distance between a guess and the number in MF Rounds.



underconfident and unbiased agents, as well as in the single-feedback rounds (see additional regression tables in Online Appendix D). Our interpretation of the results is that in the control condition, overconfident agents are more willing to abandon their model of the world and admit that they were wrong about the performance of the participant matched to them. Therefore, they are more likely to correct their guesses, in contrast to overconfident agents in the treatment condition, who tend to hold on to inflated beliefs about their own performance.[18]

Welfare Comparisons. Any assessment depends on the exact form of the production function. In our specification, the overconfident agents, in comparison to the underconfident agents, end up further away from the true state if we enable them to generate additional observations and mislearn. However, changing the functional form is enough for role reversal. We would like to stress that one proposition continues to hold regardless of the functional form: the unbiased agents are always better off than the overconfident and underconfident agents.

[18]As it was pointed out to us by one of the commenters, the effect we captured with our experimental design is likely to be underestimated, as the overconfident agents may be more willing to learn more about the results of the 10-minute IQ test, than about their actual ability in more realistic set-ups.

Table 8: The treatment effect on the distance between a guess and the number in the multiple-feedback rounds.

	Overconfident (1)	Unbiased Agents (2)	Underconfident (3)
Dependent variable: the distance between the 4$^{\text{th}}$ guess and the number.			
Treatment	1.143**	-0.125	-0.344
	(0.539)	(0.570)	(0.320)
Const.	4.114***	0.741	2.530***
	(0.377)	(0.492)	(0.208)
Dependent variable: the distance between the 3$^{\text{rd}}$ guess and the number.			
Treatment	0.869*	-0.074	-0.480
	(0.520)	(0.337)	(0.303)
Const.	4.333***	0.741***	2.648***
	(0.372)	(0.221)	(0.209)
Dependent variable: the distance between the 2$^{\text{nd}}$ guess and the number.			
Treatment	0.969**	-1.020	-0.849**
	(0.404)	(0.750)	(0.403)
Const.	3.580***	1.148	4.461***
	(0.273)	(0.745)	(0.286)
N	456	66	456

Standard errors clustered at individual level. Their values in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Learning About Ability. In Online Appendix A, we describe in detail the use of tables by the overconfident, underconfident and unbiased agents. When analyzing the examples, one can notice that with more extreme noise realizations, a biased agent might not be able to find a payoff reasonably close to his feedback in the row at which he is looking (for the reason that he is looking at the wrong row). This might serve as an indirect signal, giving a hint that something is wrong with the agent's perception of his relative performance. In our companion paper (Götte and Kozakiewicz, 2018), we analyze subjects' responses to these nudges: we take a closer look at the evolution of beliefs with each round to better understand how subjects' self-esteem governs the learning process.

6 Conclusions

Successful decision-making often requires learning about unknown characteristics of the environment. At the same time, estimating the values of multiple parameters is rarely independent: the way the agent updates his beliefs about one aspect might influence his reasoning about other parameters. In particular, if the agent persistently overestimates his ability, he may repeatedly misinterpret the observed data and fail to undertake the optimal action time after time, thereby falling into a vicious circle of misguided learning. In this paper, we experimentally test subjects' propensity to engage in this kind of behavior. The results corroborate the theory formulated by Heidhues et al. (2018) and demonstrate that misguided learning is a real-world phenomenon that is likely to afflict biased agents. As long as people hold on to incorrect beliefs and cannot separately identify the underlying parameters, they continue to misread the data and form erroneous beliefs about the environment. Allowing overconfident agents to experiment and acquire new information is in these cases counterproductive. The problem is aggravated when the agents hold overconfident beliefs about the characteristics they care about: the ego-relevance of one parameter exacerbates their tendency to mislearn.

References

Barber, Brad M and Terrance Odean (2001). "Boys will be boys: Gender, overconfidence, and common stock investment". In: *Quarterly Journal of Economics* 116.1, pp. 261–292.

Burks, Stephen V, Jeffrey P Carpenter, Lorenz Goette, and Aldo Rustichini (2013). "Overconfidence and social signalling". In: *Review of Economic Studies* 80.3, pp. 949–983.

Buser, Thomas, Leonie Gerhards, and Joël Van Der Weele (2018). "Responsiveness to feedback as a personal trait". In: *Journal of Risk and Uncertainty* 56.2, pp. 165–192.

Bushong, Benjamin and Tristan Gagnon-Bartsch (2016a). "Learning with Misattribution of Reference Dependence". Working Paper.

— (2016b). "Misattribution of Reference Dependence: Evidence from Real-Effort Experiments". Working Paper.

Camerer, Colin and Dan Lovallo (1999). "Overconfidence and Excess Entry: An Experimental Approach". In: *The American Economic Review* 89.1, pp. 306–318.

Charness, Gary and Dan Levin (2009). "The origin of the winner's curse: a laboratory study". In: *American Economic Journal: Microeconomics* 1.1, pp. 207–36.

Coutts, Alexander (2019). "Good news and bad news are still news: Experimental evidence on belief updating". In: *Experimental Economics* 22.2, pp. 369–395.

Coutts, Alexander, Leonie Gerhards, and Zahra Murad (2019). "No one to blame: Self-attribution bias in updating with two-dimensional uncertainty". Working Paper.

Eil, David and Justin M. Rao (2011). "The good news-bad news effect: Asymmetric processing of objective information about yourself". In: *American Economic Journal: Microeconomics* 3.2, pp. 114–138.

Enke, Benjamin (2015). "What you see is all there is". Working Paper.

Enke, Benjamin and Florian Zimmermann (2017). "Correlation neglect in belief formation". In: *Review of Economic Studies* 86.1, pp. 313–332.

Esponda, Ignacio and Demian Pouzo (May 2016). "Berk–Nash Equilibrium: A Framework for Modeling Agents With Misspecified Models". In: *Econometrica* 84.3, pp. 1093–1130.

Esponda, Ignacio and Emanuel Vespa (2014). "Hypothetical thinking and information extraction in the laboratory". In: *American Economic Journal: Microeconomics* 6.4, pp. 180–202.

— (2016). "Contingent preferences and the sure-thing principle: Revisiting classic anomalies in the laboratory". Working Paper.

Esponda, Ignacio and Emanuel Vespa (2018). “Endogenous sample selection: A laboratory study”. In: *Quantitative Economics* 9.1, pp. 183–216.

Eyster, Erik and Matthew Rabin (2014). “Extensive imitation is irrational and harmful”. In: *Quarterly Journal of Economics* 129.4, pp. 1861–1898.

Fischbacher, Urs (2007). “z-Tree: Zurich toolbox for ready-made economic experiments”. In: *Experimental Economics* 10.2, pp. 171–178.

Götte, Lorenz and Marta Kozakiewicz (2018). “Does the world get crazier or is it just me? Learning about ability and an external parameter.” Working Paper.

Hanna, Rema, Joshua Schwartzstein, and Sendhil Mullainathan (2014). “Learning Through Noticing: Theory and Evidence From a Field Experiment”. In: *Quarterly Journal of Economics*, pp. 1311–1353.

Heidhues, Paul, Botond Kőszegi, and Philipp Strack (2018). “Unrealistic expectations and misguided learning”. In: *Econometrica* 86.4, pp. 1159–1214.

Hestermann, Nina and Yves Le Yaouanq (2016). “It’s not my fault! Ego, excuses and perseverance”. Working Paper.

Malmendier, Ulrike and Geoffrey Tate (2005). “Does overconfidence affect corporate investment? CEO overconfidence measures revisited”. In: *European Financial Management* 11.5, pp. 649–659.

— (2008). “Who makes acquisitions? CEO overconfidence and the market’s reaction”. In: *Journal of Financial Economics* 89.1, pp. 20–43.

Möbius, Markus M, Muriel Niederle, Paul Niehaus, and Tanja S Rosenblat (2014). “Managing Self-Confidence”. Working Paper.

Niederle, Muriel and Lise Vesterlund (2007). “Do women shy away from competition? Do men compete too much?” In: *Quarterly Journal of Economics* 122.3, pp. 1067–1101.

Ortoleva, Pietro and Erik Snowberg (2015). “Overconfidence in political behavior”. In: *American Economic Review* 105.2, pp. 504–35.

Schlag, Karl H, James Tremewan, and Joël J Van der Weele (2015). “A penny for your thoughts: a survey of methods for eliciting beliefs”. In: *Experimental Economics* 18.3, pp. 457–490.

Schwartzstein, Joshua (2014). “Selective attention and learning”. In: *Journal of the European Economic Association* 12.6, pp. 1423–1452.