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# Information Overload and Confirmation Bias*

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**Abstract**

We show that information overload contributes to confirmation bias. In an experiment, we vary the difficulty of information processing as subjects receive a sequence of signals of an unknown state. In the treatment condition, the preceding signal disappears as the next signal appears. In the control condition, the preceding signal remains visible. We find stronger confirmation bias among subjects in the treatment condition. Our results provide empirical support for models that emphasize the role of limited information processing in confirmation bias (Wilson (2014), Leung (2018), Jehiel and Steiner (2018)).

**Keywords:** information overload, belief formation, confirmation bias
**JEL codes:** D83, D91

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# 1 Introduction

Confirmation bias refers to the tendency to seek or interpret evidence in ways that affirm one's existing beliefs, expectations, or a hypothesis in hand (Nickerson (1998)). The bias has been well-documented in different contexts, including medical diagnoses (Croskerry (2003), Pang et al. (2017)), judicial decisions (Roach (2010)), financial markets (Farmer (1999)), political polarization (Iyengar and Hahn (2009), Flaxman et al. (2016)) and many others. Understanding its underlying mechanism and driving force is important for improving decision-making and enhancing social welfare.

Many existing explanations for confirmation bias proposed in the economics literature are preference-related. For instance, Akerlof and Dickens (1982), Kőszegi (2003) and Brunnermeier and Parker (2005) show that anticipatory utility or belief-dependent utility leads to the confirmation bias; Carrillo and Mariotti (2000) and Bénabou and Tirole (2002) demonstrate that confirmation bias is a remedy for time inconsistent preferences; Crémer (1995) and Aghion and Tirole (1997) explain it with interpersonal strategic concerns. However, we are not aware of direct experimental tests showing that these mechanisms lead to belief formation that exhibits confirmation bias.

In this paper, we follow a nascent literature that emphasizes the role of cognitive constraints in giving rise to confirmation bias. A small, but growing theoretical literature analyzes how limited ability/information overload can explain a number of behavioral biases, including confirmation bias and wishful processing (Compte and Postlewaite (2012), Wilson (2014), Leung (2018) and Jehiel and Steiner (2018)).

We draw our hypotheses based on Leung (2018), who formalizes the intuition that limited information processing ability can lead to confirmation bias. To understand the intuition behind the mechanism, consider an individual who has to form a belief about an unknown binary state. Suppose the individual receives two sequential signals, which can either be belief-confirming or belief-challenging (but of equal strength). However, the individual can only process one of the two signals due to cognitive constraints. If the first signal were belief-confirming, processing it would yield a posterior that would be difficult to alter by the subsequent signal. Conversely, if the first signal were believe-challenging, the individual's posterior would be closer to 50-50, in the sense that there is more uncertainty. In this case, being able to process the second signal would yield a large benefit. Given that the decision-maker can only process one signal, processing belief-confirming information in the first signal has a lower opportunity cost of passing on the second signal than for belief-challenging information. Therefore, limited capacity to process signals leads individuals to (optimally) adopt a processing strategy that is belief confirming.

In our experiment, subjects receive a sequence of numbers, which are drawn from either a "low" or "high" distribution. The "low" distribution is more likely to generate small numbers while the "high" distribution is more likely to generate large numbers. Subjects have to navigate through the sequence within 30 seconds and then report their beliefs of the underlying distribution that generated the numbers they have seen. In each round of the experiment, two subjects are matched and are assigned to either the treatment or control condition. To isolate the effect of information overload on belief updating, we hold constant the available signals for the matched subjects in the treatment and control conditions but vary the difficulty of belief-updating. Thus, a Bayesian subject will form the same belief in both conditions. In the treatment condition, subjects navigate through the sequence by clicking the "next" button and they only see one signal at a time; while in the control condition, they advance through the sequence only when their matched subject in the treatment condition have clicked the "next" button. The important distinction is that as the control subjects advance through the sequence, the preceding numbers remain visible and they observe multiple numbers at the same time.

This experimental design allows us to compare how two individuals, who observe the same signals at the same time, update their beliefs differently when exposed to different magnitudes of information overload. We define information overload according to Speier et al. (1999)[1], which is not on the absolute amount of the information, but on the amount of the information relative to processing capacity of the individuals. As belief updating is less cognitively taxing in the control condition (i.e., subjects do not have to remember the numbers they have seen, and as they see multiple numbers at the same time, it is easier to develop an idea about the aggregate information conveyed by the numbers), it imposes weaker information overload on the subjects than the treatment condition.

Building on the theoretical insights, we define confirmation bias as an asymmetric belief updating behavior. We say that a stronger information overload drives a stronger confirmation bias if subjects update more with belief-confirming information and less with belief-challenging information in the treatment condition than in the control condition. Indeed, we find that upon receiving belief-challenging information, subjects in the treatment condition update less compared to the subjects in the control condition. On the other hand, upon receiving a belief-confirming signal, subjects' belief updating behaviors do not differ significantly across the two conditions. Thus, holding the available signals constant, stronger information overload (empirically) leads to more biased processing behavior. The stronger bias is driven by a stronger under-reaction to belief-challenging information, but not the updating behavior with belief-confirming information. As a result, subjects in the treatment condition are also less likely to switch between guessing "high" and "low" than in the control condition, even when they receive strong belief-challenging signals.

[1] Speier et al. (1999) stated that "Information overload occurs when the amount of input to a system exceeds its processing capacity.". For example, grading thirty assignments within one hour is much more demanding than grading thirty assignments within a week.

Our findings constitute the first direct evidence linking a particular mechanism to confirmatory bias, and have novel implications. Our findings that information overload makes individuals more prone to confirmation bias suggests that besides preferences, informational environment also contributes to the bias. This novel channel leads to different policy implications from that of the utility-based mechanisms. Much like in the experiment reported here, our results imply that one way to weaken confirmation bias is to make information easier to process. Lastly, our findings are particularly pertinent to different social issues in this information age, with the leading example being ideological polarization (Gentzkow and Shapiro (2011), Flaxman et al. (2016)).

Our paper also contributes to the experimental literature on how individuals update their beliefs. Eil and Rao (2011), Ertac (2011), Grossman and Owens (2012) and Möbius et al. (2014) study how subjects' beliefs about their task performances, IQ or beauty scores evolve with information, and find evidence supporting the phenomenon of overconfidence. Enke and Zimmermann (forthcoming) finds that large proportion of their subjects neglect correlation between signals when they form their beliefs. Liang (2019) shows that subjects substantially discount the signals when the quality of information source is ambiguous.

The remainder of this paper is organized as follows. In the next section, we present a simple theoretical model to motivate our hypotheses. In section 3, we outline the experimental design. In section 4, we present descriptive statistics for our sample, as well as our analysis strategy and hypotheses. In section 5, we present the results. Section 6 offers some concluding remarks.

## 2 Model and Intuition

To motivate the intuition that information overload could give rise to confirmation bias, we present an (toy model) example of Leung (2018). While the example does not perfectly match our experimental design, it comprises all the key feature of our experimental design and illustrates the theoretical foundation of our hypotheses. Consider a subject who has to guess whether the "high" distribution or "low" distribution was randomly chosen in each round to generate the numbers he observes as signals. If he makes the correct guess, he gets 1 util; otherwise, he gets 0. His prior belief is denoted by $(p_H, 1 - p_H)$ where $p_H$ is the prior probability assigned to the "high" distribution. Without loss of generality, we assume $p_H > 0.5$.

Before he makes a guess, he receives two signals, denoted by $s_1$ and $s_2$. Each signal is either a high or low number, denoted by $h$ and $l$ respectively. The "high" distribution is more likely to generate a high number while the "low" distribution is more likely to generate a low number. Formally, $s_i = h$ with probability $f$ when the "high" distribution is true and correspondingly, with probability $1 - f$ when the "low" distribution is true, where[2] $f > p_H > 0.5$.

We first analyze the Bayesian benchmark where there is no information overload and the subject can update his belief perfectly with both $s_1$ and $s_2$. His posterior belief, denoted by $\tilde{p}_H^B$, is given by the following Bayesian formula:

$$\tilde{p}_H^B = \begin{cases} \dfrac{p_H f^2}{p_H f^2 + (1-p_H)(1-f)^2} & \text{if } s_1 = s_2 = h, \\ \dfrac{p_H f(1-f)}{p_H f(1-f) + (1-p_H) f(1-f)} & \text{if } s_1 \neq s_2, \\ \dfrac{p_H (1-f)^2}{p_H (1-f)^2 + (1-p_H) f^2} & \text{if } s_1 = s_2 = l. \end{cases} \tag{1}$$

It could also be rearranged to the following "odds ratio" form:

$$\frac{\tilde{p}_H^B}{1-\tilde{p}_H^B} = \begin{cases} \dfrac{p_H}{1-p_H} \times \dfrac{f^2}{(1-f)^2} & \text{if } s_1 = s_2 = h, \\ \dfrac{p_H}{1-p_H} \times 1 & \text{if } s_1 \neq s_2, \\ \dfrac{p_H}{1-p_H} \times \dfrac{(1-f)^2}{f^2} & \text{if } s_1 = s_2 = l. \end{cases} \tag{2}$$

That is, the posterior relative likelihood of the "high" instead of the "low" distribution being chosen equals the prior relative likelihood times the relative probability of receiving the two signals with the "high" instead of the "low" distribution.

Next, we turn to a setting with information overload, where the subject has limited ability to process and update his belief. More specifically, we assume that the subject can process and update his belief with only one of the two numbers. After seeing the first number $s_1$, he decides whether to process or to ignore the number. If he chooses to process it, he updates his belief with $s_1$, at the cost of forgoing $s_2$. If he chooses to ignore $s_1$, he proceeds to process the next signal $s_2$. After processing either signal $s_1$ or $s_2$, he makes an optimal guess given his posterior belief $\tilde{p}_H^{IO}$. For simplicity, we assume that he "naively"[3] neglects the information conveyed by his processing strategy, thus the posterior under information overload $\tilde{p}_H^{IO}$ follows:

$$\frac{\tilde{p}_H^{IO}}{1-\tilde{p}_H^{IO}} = \begin{cases} \dfrac{p_H}{1-p_H} \times \dfrac{f}{(1-f)} & \text{if he processes } h, \\ \dfrac{p_H}{1-p_H} \times \dfrac{(1-f)}{f} & \text{if he processes } l. \end{cases} \tag{3}$$

**Proposition 1.** *With information overload, the subject processes (ignores) $s_1$ if it is belief-confirming (belief-challenging) information, i.e. his processing strategy exhibits confirmation bias.*

[2] $f > p_H$ ensures the signals are convincing enough such that the subject switches to guessing "low" after he updates his belief with a low number.

[3] The result holds when we extend this assumption so that the DM rationally infer information from his processing strategy.

*Proof.* Note that if the subject is Bayesian, he will guess "low" if and only if $s_1 = s_2 = l$. In all other cases, he will guess "high". In the following, we refer to the Bayesian choice as the optimal choice as it maximizes the expected utility given $s_1$ and $s_2$. On the other hand, in this setting with information overload, he will guess "high" if he processes $h$ and will guess "low" if he processes $l$.

If the subject sees $s_1 = h$, he knows that his optimal guess is to guess "high" no matter what the second number is. However, if he ignores the first high number and sees $s_2 = l$, his future self will guess "low" (as he discarded the high number) which is sub-optimal. Hence, he processes the high number, which is belief-confirming, in order to prevent himself from switching sub-optimally.

On the other hand, if the subject sees $s_1 = l$, he knows that his future self will guess "low" if he processes it. However, if he ignores it, he will guess "high" if $s_2 = h$ and guess "low" if $s_2 = l$, which is the same as the optimal choice. Thus he ignores $l$, which is belief-challenging. $\square$

Note that this result of confirmation bias holds qualitatively in more general settings, for example when the belief-challenging information is (slightly) more convincing than the belief-confirming information, or with a more general information structure (see Leung (2018)).

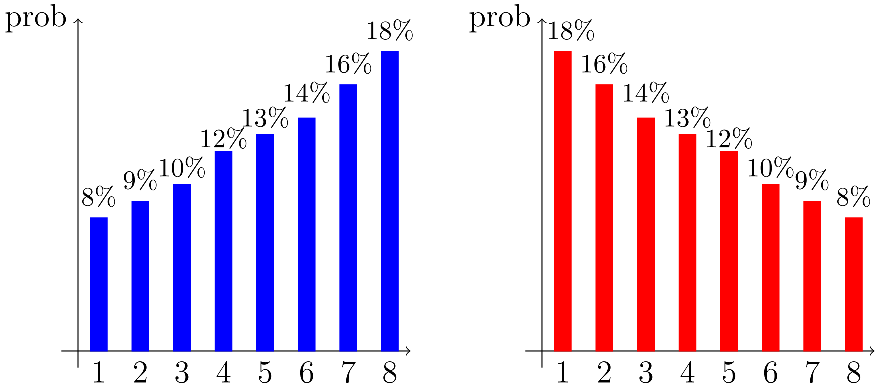
To understand the intuition of the result, note that the decision-maker (DM) trades off between allocating his processing capacity to the current signal $s_1$ and the future signal $s_2$. Roughly speaking, he compares the value of the current and future information. When $s_1$ confirms his belief, he becomes more confident that the "high" distribution was drawn. As a result, the value of the future signal $s_2$ decreases (to 0 in this simple example). In contrast, when $s_1$ is belief-challenging, the DM's belief moves towards $(\frac{1}{2}, \frac{1}{2})$. This increases the value of the future information $s_2$ as he becomes more uncertain about the state. This asymmetry in the value of future information drives confirmation bias, as the subject tends to update his belief with a belief-confirming signal and stop looking for future information, but ignore a belief-challenging signal and save his cognitive resources for future information. The result suggests that information overload leads to biased processing behavior (also see Wilson (2014), Jehiel and Steiner (2018)).

# 3 Experimental Design

In the experiment, subjects have to complete 12 rounds of a guessing task, which involves belief-updating with multiple signals.

## 3.1 States and Information of The Guessing Task

The guessing task is designed to investigate how subjects update their beliefs in the face of information overload. In each round of the guessing task, subjects receive two sequences of numbers which are drawn independently from either a "high" or "low" distribution. The set of numbers are integers from 1 to 8, inclusive. The probability distribution of a drawn number given a "high" or "low distribution is shown in figure 1.




(a) The "high" distribution. (b) The "low" distribution.

Figure 1: The two distributions shown in bar charts.

As shown in figure 1, the "high" distribution is more likely to generate larger numbers, while the "low" distribution is more likely to generate smaller numbers. Therefore, subjects can infer which distribution generates the numbers they observe in a particular round. The reasoning behind the parameters of two distributions is explained in detail in Appendix A.1. Briefly speaking, the two distributions are designed to be sufficiently informative so that subjects could easily make inferences, while not to being too informative to ensure that the probability of receiving belief-challenging information is significant for the analysis. Lastly, the informativeness of a signal should increase steadily as it goes towards the two extremes (number 1 and 8).

To make the task more accessible to subjects, we call the distributions that generate the numbers "computers" where the "high" ("low") computer is more likely to generate high (low) numbers.

## 3.2 The procedure of the guessing task

**Pairing and assignment of treatment and control.** All subjects play 12 rounds of the guessing task and are assigned to the treatment and control condition alternately. In the beginning of each round, each treatment subject is randomly matched with a control subject to form a pair, and two pairs are randomly matched

| super-pair | pair | subject | condition | underlying distribution | numbers |
|---|---|---|---|---|---|
| super-pair 1 | pair 1 | subject 1 | Treatment | "Low" | $2, 3, 1, 4, 5, 3, 6, 1, \cdots$ |
| | | subject 4 | Control | "Low" | $2, 3, 1, 4, 5, 3, 6, 1, \cdots$ |
| | pair 2 | subject 2 | Treatment | "High" | $7, 6, 8, 5, 4, 6, 3, 8, \cdots$ |
| | | subject 3 | Control | "High" | $7, 6, 8, 5, 4, 6, 3, 8, \cdots$ |

Table 1: An example of the underlying distributions and numbers for subjects in two pairs which belong to the same super-pair.

to form a super-pair[4]. During the respective round, the two matched subjects in a pair observe the same sequence of numbers drawn from the same underlying distribution, which is either the "high" or "low" distribution with equal probability. This is illustrated in table 1 as subject 1 and 4 (or 2 and 3), who belong to the same pair, see the same numbers drawn from the same underlying distribution. As mentioned in the introduction, it allows us to single out the effect of information overload, by keeping the two subjects' available information constant.

On the other hand, the two matched pairs in a super-pair see numbers drawn from different underlying distributions, and the numbers received by the two pairs are symmetric around $4\frac{1}{2}$ (and add up to 9). Given the symmetry of the two distributions[5], the numbers they receive are of the same strength but support different underlying distributions. This is illustrated in table 1. The numbers seen by pairs 1 and 2, which belong to the same super-pair, are symmetric around $4\frac{1}{2}$ and drawn from different distribution. First, by comparing the beliefs of subjects in the two matched pairs, it allows us to test whether there is any intrinsic bias towards either of the two distributions. Second, if there is no bias towards either of the two distributions, the subjects in the two matched pairs should have exactly opposite beliefs, i.e., if subject 1 believes the "low" distribution has been chosen with probability $x$ after seeing a sequence of numbers, subject 2 should believe the"high" distribution has been chosen with probability $x$. Thus, with careful normalization, it allows us to leverage on the symmetry of the two distributions to increase our statistical power, as it essentially doubles the observations of belief-updating with the same sequence of numbers.

The timeline of a round of the guessing task is illustrated in figure 2 and we explain in detail below.

**First belief elicitation and belief elicitation mechanism.** Before the subjects have seen any numbers, we conduct the first belief elicitation at the beginning of

[4]The numbers of subjects of every sessions are restricted to even numbers, but not to multiple of 4.

[5]The probability of seeing a number $x$ with the "low" distribution is equal to the probability of seeing a number $9 - x$ with the "high" distribution.

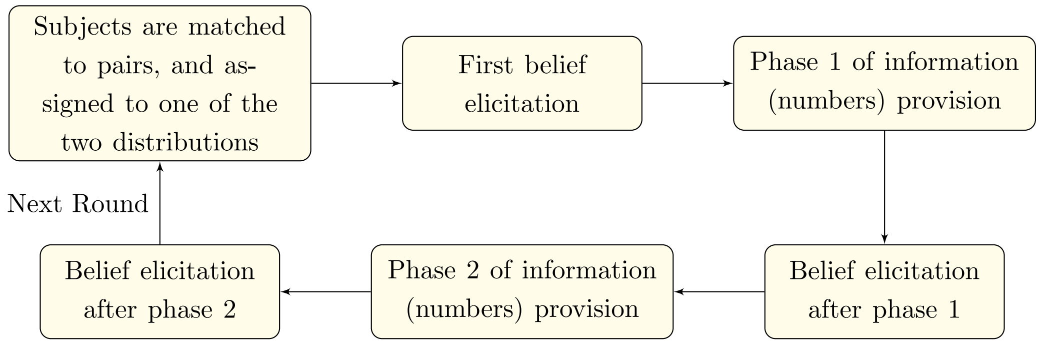



Figure 2: Sequence of a round.

each round. We use a variant of the Becker-DeGroot-Marschak method (Becker et al. (1964)), which is shown in figure 3. First, subjects have to guess whether the "high" or "low" distribution has been selected. Second, they have to choose between the following two options: earn 8€ if their chosen distribution is selected, or earn 8€ with probability $x\%$, where $x$ starts at 50% and increases in 5% increments per row. The mechanism is incentive compatible. As an example, if a subject believes the "high" distribution has been chosen with 66%, he should choose "high" for the first question and for the second question switch from option 1 to option 2 when $x = 70$ as shown in the figure.

This first belief elicitation is used to ensure that subjects hold the 50-50 belief before seeing any numbers (and that they understand they are at the beginning of a new round). There is a soft time limit of 30 seconds[6] for the belief elicitation. Afterwards, subjects see two sequences of numbers drawn by the selected distribution in two phases, with a second belief elicitation in between the two phases and a third belief elicitation after the second phase.

**Phase 1 of information (numbers) provision.** In the first phase, all subjects see 5 numbers displayed on the screen for 30 seconds (figure 4). The two matched subjects from treatment and control condition see the same 5 numbers. After 30 seconds, the subjects are redirected to the page of the second belief elicitation.

**Belief elicitation after phase 1.** After phase 1, we elicit subjects' beliefs using the same table shown in figure 3. Their choices in the first belief elicitation is shown as a default. The first phase, which shows 5 numbers to the subjects, naturally induces heterogeneous beliefs across all the subjects. Thus, it allows us to define belief confirming and belief challenging information and studies how belief updating is different with the two types of information.

**Phase 2 of information (numbers) provision.** In the second phase, subjects can see up to 7 numbers with a strict time limit of 30 seconds. Paired subjects in the

[6] If a subject has spent more than 30 seconds, he is shown a warning message which reminds him that time is up. However, subjects are not automatically redirected to the next page.

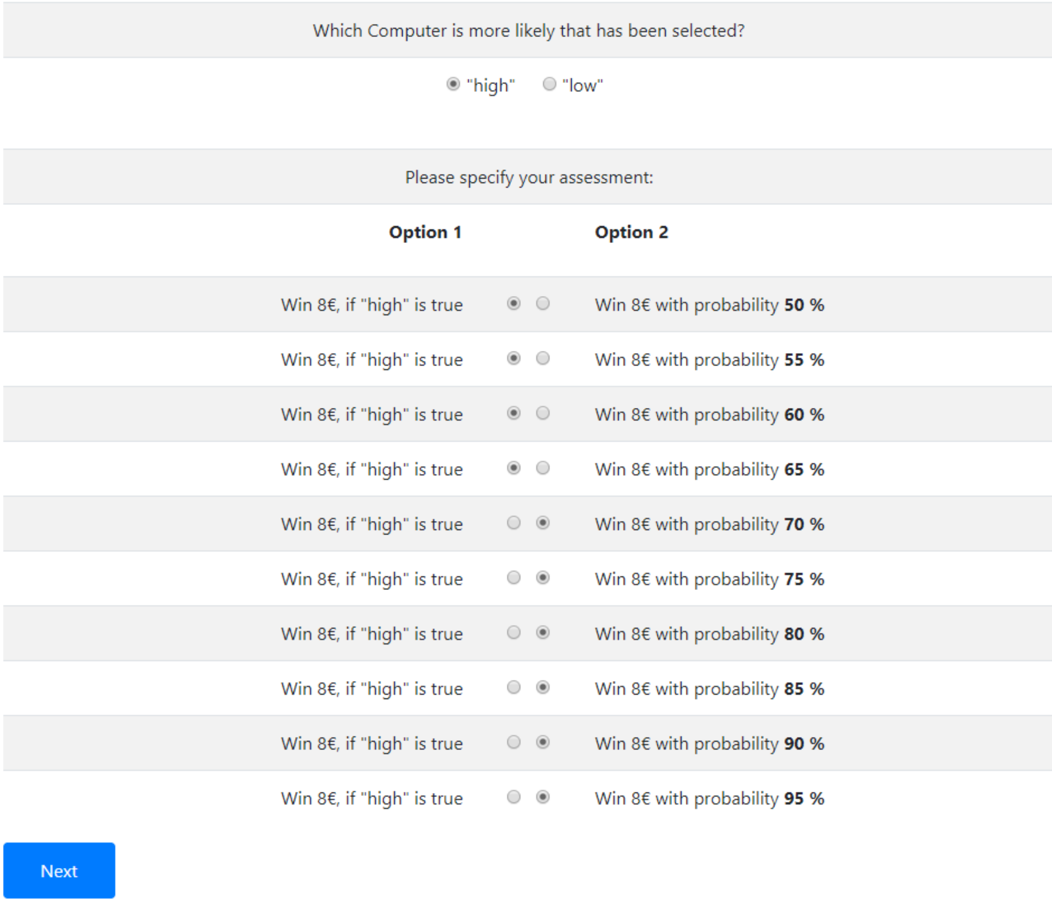



Figure 3: The belief elicitation screen.

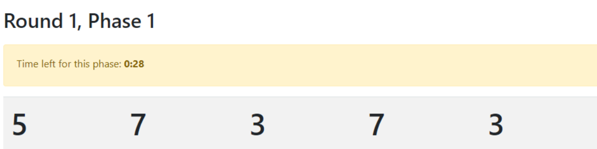



Figure 4: A screen shot of Phase 1.

treatment and control conditions see the same numbers but with a different screen layout.

**The treatment condition** The layout and flow of the treatment condition is illustrated in figure 5. The subjects see one number at a time. They can decide when to advance the sequence by clicking the blue "Next" button. Upon clicking "Next", the next number in the sequence is revealed and the preceding number disappears. Moreover, the subject is unable to return to the preceding numbers. Subjects in the treatment condition face a trade-off between spending more time on the current number and saving time for the next numbers.


Figure 5: A screen shot of phase 2 in the treatment condition.

**The control condition** In contrast, subjects in the control condition cannot influence when the next number appears, while the preceding numbers do not disappear when additional numbers are displayed (figure 6). They start with one number on their screen and as they advance through the sequence, they see two, three, four (etc.) numbers on the screen at the same time. To ensure the information they receive and the timing of information provision are the same as their counterpart in the treatment condition, the control subjects advance in the sequence at the same time as their matched treatment subject click "Next". The treatment subjects, however, are not aware that they can control the other's advancement in the sequence, nor do the control subjects know that their advancement is controlled by others.

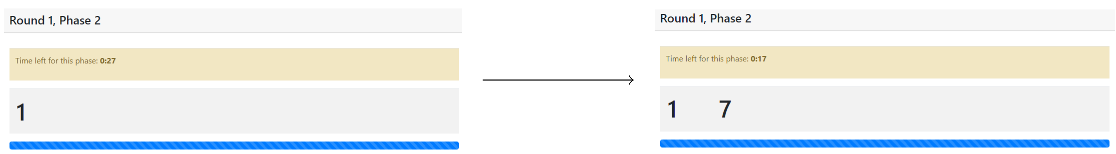



Figure 6: A screen shot of phase 2 in the control condition.

The main difference between the treatment and control conditions is that it is easier for the control subjects to update their beliefs with all the signals being visible at the same time. In other words, subjects in the treatment condition are exposed to stronger information overload than those in the control condition, despite the fact that they essentially receive the same information.

**Belief elicitation after phase 2.** After 30 seconds of phase 2, subjects are redirected to the page of the third belief elicitation. Their choices of the second belief elicitation are shown as default. By comparing how subjects update their beliefs in the treatment and control condition with belief confirming and belief challenging information, we draw insights on how information overload gives rise to confirmation bias.

**New round.** Following the belief elicitation after phase 2, a new round begins where subjects are randomly re-matched and assigned to either the "high" or "low" distribution with equal probability. Subjects are re-directed to a screen that reminds them that a new round has started.

### 3.3 Procedural Details

We conducted 12 sessions of the experiment, involving 260 subjects in the BonnEconLab at the University of Bonn. The participants were university students and were recruited through the online recruitment system h-root (Bock et al. (2014)). The experiment was coded and run in o-Tree (Chen et al. (2016)). Each sessions took about 2h 15min. The subjects were paid according to a randomly drawn decision in the first, second and third belief elicitation (figure 3) from three different randomly chosen rounds. For example, if the first belief elicitation of round 2 is chosen, we randomly choose one of the binary choices in the corresponding belief elicitation table to determine the payment: if the binary choice for the first question "Which Computer is more likely that has been selected?" is chosen, we pay the subject 8€ if the answer is correct; if the binary choice of one of the "option 1 v.s. option 2" decision is chosen, we pay according to the option chosen by the subject. We then repeat the same process for the second and third belief elicitation of two other randomly chosen rounds. The maximum earning is thus 24€. The average earnings were 18.12€ per subject, plus a participation fee of 7€ .

## 4 Analysis

In this section, we begin by presenting the descriptive statistics for our sample, before constructing and introducing the main variables of interest. Thereafter, we explain our analysis strategy and hypotheses.

### 4.1 Data

Across all 12 sessions, 260 subjects each played 12 rounds of the guessing task. The average age of the subjects was 23, while the maximum age was 30. 109 subjects were male and 151 subjects were female. 50% of the subjects stated that they have taken economics or statistics courses.

### 4.1.1 Observations

Every subject in each round gives us one observation for the guessing task. Each of the 260 subjects played 12 rounds of the guessing task, which contributed 3120 observations in total. In the first four sessions, unfortunately there was a technical glitch with the computer system recording how many numbers a subject saw in phase 2. More specifically, with some small probability, the recorded number was one fewer than it should be, e.g., the computer system may have recorded 6 while the subject has seen 7 numbers in phase 2. Thus, we dropped the observations in the first four sessions if the recorded numbers of signals seen in phase 2 were less than 7, which amounts to 264 of 1008 observations[7]. The technical glitch was fixed in later sessions. After dropping the observations as mentioned above, we have 2856 observations in total.

Furthermore, in the analysis, we only use the observations where choices in the first belief elicitation are compatible with the belief that the underlying distribution is "high" or "low" with equal probability, i.e., they chose option 2 in all rows in the table shown in figure 3, except possibly in the first row. This is a test to ensure that subjects understood the belief elicitation mechanism, and that they were at the beginning of a new round and a new distribution has been drawn with equal probability. In 615 of the 2856 observations (i.e., 21.53%), subjects' choices in the first belief elicitation fail the test[8].

For example, in 84 observations, subjects' choices in the first belief elicitation indicate that they are at least 95% confident about the underlying distribution (that they chose option 1 in all rows in the table shown in figure 3). This might be due to misunderstanding of the belief elicitation mechanism. However, in most cases subjects realized in later rounds that they were filling out the belief elicitation table incorrectly and would not make the same mistake over all 12 rounds. In fact, only 6 subjects chose option 1 for all rows in the first belief elicitation in more than 6 rounds. After excluding observations in which the first elicited belief is not $(50\%, 50\%)$, we have 2241 final observations. Unless otherwise stated, all the analyses are based on these observations.

[7]As shown in table 2 in almost all (97%) of the observations, subjects have seen all 7 numbers in phase 2. We therefore are confident that dropping the data does not affect systematically our results.

[8]Among the subjects who have never taken any statistics or economics courses, 26.70% of the observations exhibit choices in the first belief elicitation that are not compatible with belief of equal probability on the two distribution, while the proportion is 16.27% for the subjects which have taken statistics or economics courses.

| Number of signals seen in phase 2 | All Sessions | | All sessions, with only observations where first elicited belief equals $(50\%, 50\%)$ | | Sessions 5 - 12, with only observations where first elicited belief equals $(50\%, 50\%)$ | |
|---|---|---|---|---|---|---|
| | Frequency | Percentage | Frequency | Percentage | Frequency | Percentage |
| 4 | 2 | 0.07% | 2 | 0.09% | 2 | 0.12% |
| 5 | 12 | 0.42% | 9 | 0.40% | 9 | 0.55% |
| 6 | 49 | 1.72% | 34 | 1.52% | 34 | 2.07% |
| 7 | 2793 | 97.79% | 2196 | 97.99% | 1691 | 97.27% |

Table 2: Frequencies and proportion of observations where 4, 5, 6 and 7 numbers have been seen in phase 2. Note that in this table we do not include observations in sessions 1 to 4 where the number of signals seen in phase 2 is less than 7, but have included the observations with non-$(50\%, 50\%)$ first elicited belief .

#### 4.1.2 Numbers of Signals Seen in Phase 2

Table 2 shows the descriptive statistics of the number of signals subjects have seen in phase 2. We see that only a small fraction of subjects have seen less than 7 numbers in phase 2. For instance, in sessions 5 to 12, where the technical glitch mentioned in previous section was fixed, less than 3% of the subjects saw less than 7 numbers, i.e., almost all subjects manage to reveal all 7 numbers in the 30 seconds time limit. Thus, we are confident that the results presented in this paper is not artificially created by the fact that we have dropped the observations in the first four sessions where the number of signals seen is less than 7.

#### 4.1.3 Randomization of High and Low States

Among all 2241 final observations, 48.77% are assigned to the "high" distribution while 51.23% are assigned to the "low" distribution. The composition is not exactly half-half because we have dropped some observations as mentioned before.

#### 4.1.4 Treatment and Control Condition

Each subject was alternately assigned to the treatment and control conditions in the 12 rounds of the guessing task. Among the final 2241 observations, 1124 observations are from the control condition and 1117 observations are from the treatment condition. Again, the composition is not exactly half-half because we have dropped some observations as mentioned before.

### 4.2 Variables of Interest

#### 4.2.1 Elicited Beliefs

The first elicited belief is denoted by $p_0$, while the elicited belief after phase 1 and phase 2 are denoted by $p_1$ and $p_2$ respectively. All elicited beliefs are normalized such that $p_0$, $p_1$ and $p_2$ represent the (subjective) probability of the "high" distribution being chosen. Note that $p_0 = 0.5$ in all observations used in the analysis, as we exclude those whose first elicited belief does not equal to 0.5. On the other hand, $p_1$ and $p_2$ are pinned down by the point subjects switch from option 1 to option 2 in the belief elicitation table. As an example, if in the belief elicitation after phase 1, subjects guess "high" for the first question as shown in figure 3, and switch from option 1 to option 2 when the winning probability of the random lottery is 70%, we define $p_1 = 0.675$, i.e., the average belief compatible with those choices. In the analysis, $p_1$, is treated as the prior belief of the subjects, and we investigate how subjects update their beliefs upon receiving the belief-confirming or belief-challenging signals in phase 2 differently in the control and treatment condition.

### 4.2.2 Bayesian Beliefs

The Bayesian counterpart of the first elicited belief is denoted by $p_0^B$ and correspondingly, the Bayesian counterparts of the elicited belief after phase 1 and phase 2 are denoted by $p_1^B$ and $p_2^B$ respectively.

$p_0^B$ is always equal to 0.5 as the distribution is drawn with equal probability. The Bayesian belief after phase 1, $p_1^B$, is constructed using the first elicited belief $p_0$.

$$\frac{p_1^B}{1-p_1^B} = \prod_{s_i \in \mathscr{S}_1} \frac{f_H(s_i)}{f_L(s_i)} \times \frac{p_0}{1-p_0}, \tag{4}$$

where $\mathscr{S}_1$ denotes the set of the 5 numbers in phase 1, and $f_H(s_i)$ is the probability that the "high" distribution generates number $s_i$ while $f_L(s_i)$ is the probability that the number is drawn from the "low" distribution. Since we only include observations where $p_0 = 0.5$, this equals to

$$\frac{p_1^B}{1-p_1^B} = \prod_{s_i \in \mathscr{S}_1} \frac{f_H(s_i)}{f_L(s_i)} \times \underbrace{\frac{0.5}{1-0.5}}_{=1}.$$

Similarly, the Bayesian belief after phase 2, $p_2^B$, is constructed using the elicited belief after phase 1, $p_1$:

$$\frac{p_2^B}{1-p_2^B} = \prod_{s_i \in \mathscr{S}_2} \frac{f_H(s_i)}{f_L(s_i)} \times \frac{p_1}{1-p_1}, \tag{5}$$

where $\mathscr{S}_2$ is the set of numbers seen in phase 2. In other words, $p_2^B$ is equal to the belief of a Bayesian individual if he takes his prior belief $p_1$ as given and updates his belief with $\mathscr{S}_2$ in a statistically optimal way.

### 4.2.3 Treatment and control condition

For each observation $i$, the condition imposed on the subject is denoted by the dummy variable $T_i$, which takes on the value of 1 if the subject is assigned to the treatment condition, and 0 otherwise.

## 4.3 Empirical Strategy and Hypothesis

To examine how information overload plays a role in confirmation bias, we analyze two indicators of confirmation bias, namely switching behavior and changes in belief.

### 4.3.1 Switching Behavior

The first indicator we analyze pertains to the switching decisions of the subjects. A switch is defined as the scenario where a subject guessed "high" after phase 1 but guessed "low" after phase 2, or vice versa. Moreover, we say that a subject has made a switching mistake when his switching decision is different from that of a Bayesian individual. We analyze two different switching mistakes. The first mistake is the case where the subjects should switch if they were Bayesian but they ended up not switching; the second mistake is the case where the subjects should not switch if they were Bayesian but they ended up switching.

If information overload induces a stronger confirmation bias, subjects in the treatment condition should update (weakly) more to belief-confirming information and conversely, update (weakly) less to belief-challenging information relative to their counterpart in the control condition. Thus, they should be less likely to switch their decisions, which leads us to the following hypotheses:

**Hypothesis 1W.** *Subjects in the treatment condition are **weakly** less likely to switch decisions when they should, than their counterparts in the control condition.*

**Hypothesis 2W.** *Subjects in the treatment condition are **weakly** less likely to switch decisions when they should not, than their counterparts in the control condition.*

The strong form of hypotheses 1W and 2W are as follows:

**Hypothesis 1S.** *Subjects in the treatment condition are **strictly** less likely to switch decisions when they should, than their counterparts in the control condition.*

**Hypothesis 2S.** *Subjects in the treatment condition are **strictly** less likely to switch decisions when they should not, than their counterparts in the control condition.*

Given the theoretical insights from Leung (2018), we expect both hypotheses 1W and 2W to hold and at least one of the two strong hypotheses 1S and 2S to hold[9].

[9]Note that if both hypotheses 1W and 2W hold, while both strong hypotheses 1S and 2S do not hold, subjects' switching decisions do not differ significantly in treatment and control condition.

It is worth noting that a subject should switch when he receives belief-challenging signals of sufficient strength, while he should not switch when he receives belief-confirming signals or weak belief-challenging signals. Thus hypothesis 1W/1S and hypothesis 2W/2S corresponds to different scenarios: the former examines the subjects' belief updating behavior with strong belief-challenging signals while the latter analyzes the subjects' belief updating behavior with belief-confirming or weak belief-challenging signals.

Next, we present the regression specifications for our analysis. The notation is as follows: $i$ denotes the observation while $m(i)$ denotes the pair that observation $i$ belongs to. As mentioned before, $T_i$ indicates whether observation $i$ is assigned to the treatment or control condition. $\alpha_{m(i)}$ is the fixed effect for pair $m(i)$ that observation $i$ belongs to, so as to account for the numbers seen by each pair in phases 1 and 2. Furthermore, as we have multiple observations per subject since they play 12 rounds of the guessing task, we cluster standard errors at the subject level. Lastly, we denote $\text{Switch}_i = 1$ if the subject switched decisions in observation $i$, and $\text{Switch}_i = 0$ otherwise. For hypothesis 1W/1S, we estimate the following regression for all observations $i$ where a theoretical Bayesian subject should switch, i.e., where $(p_2^B - 0.5)(p_1 - 0.5) < 0$:

$$1 - \text{Switch}_i = \beta_0 + \beta_1 T_i + \alpha_{m(i)} + \epsilon_i. \tag{6}$$

$\beta_1$ measures the treatment effect on switching mistake (not switching when the subject should switch), and hypothesis 1W (1S) translates to $\beta_1 \geq (>)0$. Similarly, for hypothesis 2W/2S, we estimate the follow regression for all observations $i$ where a theoretical Bayesian subject should not switch:

$$\text{Switch}_i = \beta_0 + \beta_1 T_i + \alpha_{m(i)} + \epsilon_i, \tag{7}$$

and similarly hypothesis 2W (2S) translates to $\beta_1 \leq (<)0$.

### 4.3.2 Quantifying Bias

For the second indicator, we quantify subjects' biases in belief formation. We proceed by drawing an analogy between the evolution of the elicited belief to the Bayesian formula.

Consider a subject whose elicited belief after phase 1 is equal by $p_1$. After he has seen $n$ numbers in phase 2, in which the set is denoted as $\mathscr{S}_2$, his Bayesian belief after phase 2, $p_2^B$, is given by:

$$\frac{p_2^B}{1 - p_2^B} = \prod_{s_i \in \mathscr{S}_2} \frac{f_H(s_i)}{f_L(s_i)} \times \frac{p_1}{1 - p_1}, \tag{8}$$

where $f_H(s_i)$ and $f_L(s_i)$ are the probabilities of seeing number $s_i$ when the "high" and "low" distribution is chosen respectively. The product of the odds ratios $\prod_{s_i \in \mathscr{S}_2} \frac{f_H(s_i)}{f_L(s_i)}$ measures the relative likelihood of seeing the numbers in $\mathscr{S}_2$ with the "high" distribution over that with the "low" distribution. For the simplicity of notation, we denote $\prod_{s_i \in \mathscr{S}_2} \frac{f_H(s_i)}{f_L(s_i)}$ by $y_{obj}$, or as the "objective odds ratio". Note that the objective odds ratio is a sufficient statistic for a Bayesian individual to update his belief.

We now use the elicited beliefs after phase 1 ($p_1$) and the elicited beliefs after phase 2 ($p_2$) to characterize the subjective counterpart of the objective odds ratio, which is denoted as $y_{sub}$:

$$\begin{aligned} \frac{p_2}{1-p_2} &= y_{sub} \times \frac{p_1}{1-p_1} \\ y_{sub} &= \frac{p_1}{1-p_1} \times \frac{1-p_2}{p_2}. \end{aligned} \tag{9}$$

$y_{sub}$ measures the subject's perceived relative likelihood of seeing the numbers in $\mathscr{S}_2$ with the "high" distribution over that with the "low" distribution. When $y_{sub} > y_{obj}$, the perception of the subject is biased towards the "high" distribution; when $y_{sub} < y_{obj}$, the perception of the subject is biased towards the "low" distribution.

As mentioned before, if the treatment condition induces a stronger confirmation bias, the treatment subjects update (weakly) more to belief-confirming information but update (weakly) less to belief-challenging information than subjects in the control condition. We denote the subjective odds ratio of the subjects in the treatment and control condition by $y_{sub}^T$ and $y_{sub}^C$ respectively, such that $y_{sub}^T > y_{sub}^C$ implies that subjects are more biased towards the "high" distribution in the treatment condition than in the control condition. We have the following hypotheses:

**Hypothesis 3W.** *Suppose the numbers seen by the subjects in phase 2 are in aggregate belief-challenging, i.e.,* $(p_1 - 0.5)(y_{obj} - 1) < 0$. *The subjective odds ratio of the subject in the treatment condition is* ***weakly*** *more biased towards his prior belief than that of his matched subject in the control condition, i.e.,* $(p_1 - 0.5)(y_{sub}^T - y_{sub}^C) \geq 0$.

**Hypothesis 4W.** *Suppose the numbers seen by the subjects in phase 2 are in aggregate belief-confirming, i.e.,* $(p_1 - 0.5)(y_{obj} - 1) > 0$. *The subjective odds ratio of the subject in the treatment condition is* ***weakly*** *more biased towards his prior belief than that of his matched subject in the control condition, i.e.,* $(p_1 - 0.5)(y_{sub}^T - y_{sub}^C) \geq 0$.

The strong form of the hypotheses 3W and 4W are as follows:

**Hypothesis 3S.** *Suppose the numbers seen by the subjects in phase 2 are in aggregate belief-challenging, i.e.,* $(p_1 - 0.5)(y_{obj} - 1) < 0$. *The subjective odds ratio of the subject in the treatment condition is* ***strictly*** *more biased towards his prior belief than that of his matched subject in the control condition, i.e.,* $(p_1 - 0.5)(y_{sub}^T - y_{sub}^C) > 0$.

**Hypothesis 4S.** *Suppose the numbers seen by the subjects in phase 2 are in aggregate belief-confirming, i.e., $(p_1 - 0.5)(y_{obj} - 1) > 0$. The subjective odds ratio of the subject in the treatment condition is* ***strictly*** *more biased towards his prior belief than that of his matched subject in the control condition, i.e., $(p_1 - 0.5)(y^T_{sub} - y^C_{sub}) > 0$.*

Similar to the analysis on switching mistakes, we expect both hypotheses 3W and 4W to hold and at least one of the two strong hypotheses 3S and 4S to hold. For the analysis, we assume a multiplicative relationship between $y_{sub}$ and $y_{obj}$ such that their logarithmic forms follow an additive relationship[10]. Put differently, we estimate the treatment effect on $\frac{y_{sub}}{y_{obj})}$. Note that with a multiplicative instead of an additive model that would otherwise estimate the treatment effect on $y_{sub} - y_{obj}$, we can interpret the multiplicative constant as an attention weight on the objective odds ratio (See Jehiel and Steiner (2018) for the theory). Moreover, the estimated $y_{sub}$ is always larger than 0.

Our notation is the same as in the analysis for switching behavior: $i$ denotes the observation and $m(i)$ denotes the pair that observation $i$ belongs to. $y_{i,sub}$ and $y_{i,obj}$ denote the subjective and objective odds ratio of observation $i$ respectively. Again, we include pairwise fixed effects $\alpha_{m(i)}$ and cluster standard errors on subject-level. We estimate the following regression for all observations.

$$\log(y_{i,sub}) - \log(y_{i,obj}) = \beta_0 + \beta_1 T_i + \alpha_{m(i)} + \epsilon_i. \tag{10}$$

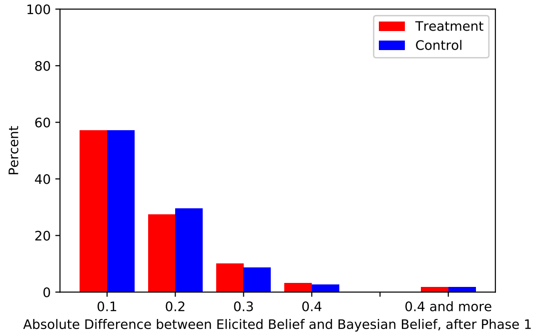
Thus, the treatment effect $\beta_1$ is interpreted as follows: as the regression is run in logarithmic form, the subject's subjective odds ratio in the treatment condition is $\exp(\beta_1)$ times that of his matched subject in the control condition, i.e., $y^T_{sub} = \exp(\beta_1) \times y^C_{sub}$. When $\beta_1 > 0$, we have $\exp(\beta_1) > 1$ which means the treatment subject's subjective odds ratio is larger than that of the his matched control subject, and the treatment subject is biased towards the "high" distribution. In other words, $(p_1 - 0.5)(y^T_{sub} - y^C_{sub}) \geq 0$ if and only if $\beta_1(p_1 - 0.5) \geq 0$, and the testing of the hypotheses collapses to a testing of the sign of $\beta_1$.

# 5 Results

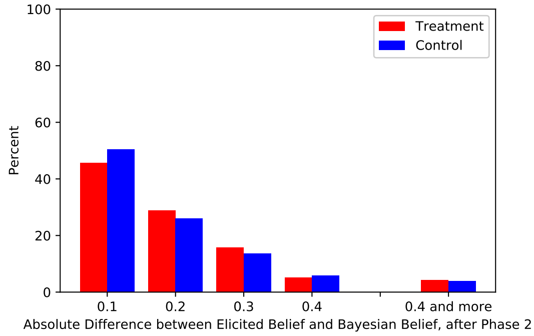
## 5.1 Preliminaries

Before we present the main results for our two indicators of confirmation bias, we first analyze the relationship between elicited belief and Bayesian belief. While it is not the main focus of this paper, the results in this subsection give us a rough idea of how "Bayesian" subjects behave. More importantly, we can ascertain whether subjects

[10] $y_{sub} = \lambda y_{obj}$ implies that $\log(y_{i,sub}) = \log\lambda + \log(y_{i,obj})$.




(a) Beliefs after Phase 1, treatment versus control.




(b) Beliefs after Phase 2, treatment versus control.

Figure 7: Distribution of the absolute difference between elicited and Bayesian belief.

understand the experiment well and whether our belief-elicitation mechanism works well in eliciting "normal" behavior of belief-updating.

Figure 7a shows the histograms of the absolute difference between elicited and Bayesian belief (the updating mistakes) after phase 1 in the treatment and control conditions, while figure 7b shows the corresponding histograms for beliefs after phase 2. The two graphs show that most of the mistakes ($40\% - 60\%$) are less than 10%. Moreover, the frequencies of the mistakes decrease with the magnitude. For example, for belief formation in phase 1 in both treatment and control condition, almost 60% of the elicited beliefs are within 10% difference of the Bayesian beliefs, while only around 10% of the mistakes are as big as 20%.

On the other hand, by comparing the difference between elicited belief and Bayesian belief in the treatment condition after Phase 1 to the ones after phase 2 (and control condition after Phase 1 and Phase 2 respectively), we can see that the mistakes in belief formation in phase 2 are in general bigger than the mistakes in phase 1 because of the stronger information overload, i.e., there are more numbers to be processed in the same period of time. For similar reasons, when looking at figure 7b, the mistakes in the belief formation in phase 2 in the treatment condition are in general bigger than in the control condition, i.e., in the control condition, the share of small mistakes is higher than in the treatment condition, while the share of big mistakes is smaller.

Lastly, as we can see in figure 7a, being in the treatment or control condition has no effect on the mistakes made in phase 1, as there are no differences in the settings in phase 1. This is also confirmed by the second and the third column of table 3, which shows that there is no treatment effect on the relationship between elicited and Bayesian belief in phase 1 and thus, no inherent difference between treatment and control condition.

Figures 8a and 8b show the scatter plots and simple regression lines of elicited beliefs against Bayesian beliefs, after phase 1 and phase 2 respectively. From both

| | (1) elicited belief after phase 1 | (2) elicited belief after phase 1 | (3) abs. distance elicited and bayesian belief after phase 1 |
|---|---|---|---|
| Bayesian Belief after phase 1 | 0.752*** | 0.752*** | |
| | (0.016) | (0.016) | |
| Treatment | | -0.00241 | 0.00153 |
| | | (0.006) | (0.004) |
| Constant | 0.152*** | 0.153*** | 0.109*** |
| | (0.009) | (0.009) | (0.003) |
| R-squared | 0.701 | 0.701 | 0.0000546 |
| Observations | 2241 | 2241 | 2856 |
| Subjects | 235 | 235 | 260 |

Clustered standard errors on subject-level in parentheses

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

Table 3: Analysis of the (absence) of treatment effects after Phase 1, OLS.

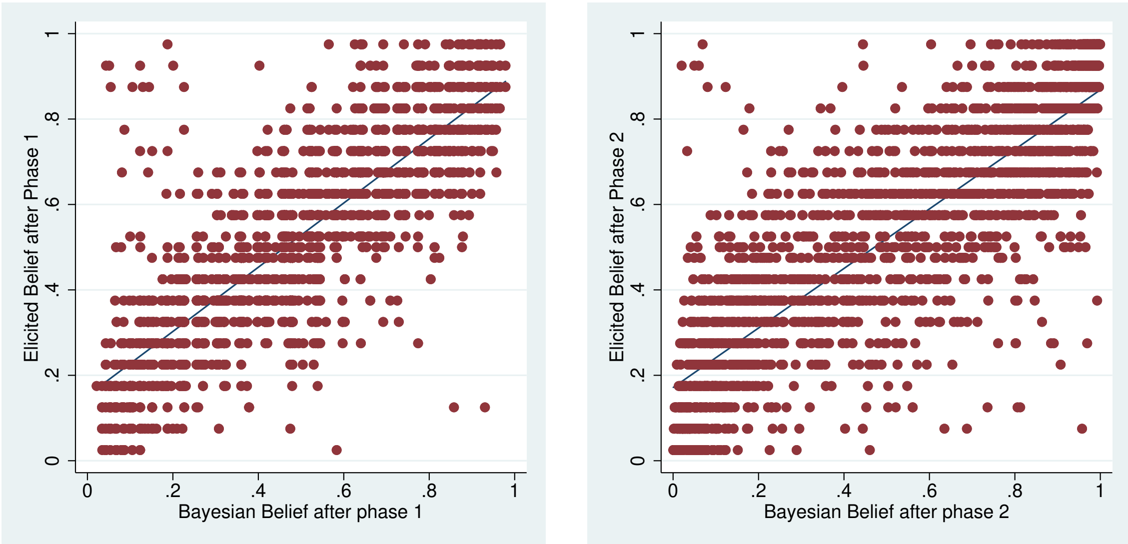
figures, we can see that there is a significant and positive correlation between elicited and Bayesian belief, which means that subjects understand the essence of the information structure, i.e., higher numbers serve as stronger evidence that the "high" distribution was chosen in the respective round. On the other hand, the slope of the regression line is smaller than 1. Taken together, both findings suggest that on average, subjects believe more in the "high" ("low") distribution when they receive higher (lower) numbers, but they tend to under-react to signals compared to the Bayesian benchmark. This result coheres with the findings presented in Eil and Rao (2011) and Liang (2019).

## 5.2 Switching Behavior

In this subsection, we analyze the switching behavior of the subjects. Table 4 shows the proportion of observations in which the subject has made a switching mistake, in treatment and control condition. Note that in the table, we include only complete pairs, i.e., where both subjects in the pair have an first elicited belief equals to 0.5; furthermore, we only include pairs which have the same Bayesian switching choice (e.g., both of them guess "high" after phase 1 and should switch to "low" after phase 2). In total, there are 701 complete pairs with the same Bayesian switching choice.

The first column of the table shows the case where the subjects should switch if they were Bayesian but they ended up not switching. We see that around 36.8% of subjects in the treatment condition did not switch even if they should, while only 27.6% of subjects made such a mistake in the control condition[11]. On the other hand, the second column shows the case where the subjects should not switch

[11]The numbers are 38.1% v.s. 32.6% if we also include incomplete pairs.




(a) Beliefs after Phase 1. (b) Beliefs after Phase 2.

Figure 8: Scatter plot and regression line with Bayesian belief on x-axis and Elicited belief on y-axis.

| | Should switch but DID NOT | Should NOT switch but did |
|---|---|---|
| Treatment | 56/152 $\approx 36.8\%$ | 30/549 $\approx 5.5\%$ |
| Control | 42/152 $\approx 27.6\%$ | 32/549 $\approx 5.8\%$ |

Table 4: Proportion of observations in which subjects have made a switching mistake. Only complete pairs with the same Bayesian switching choice are included.

but ended up switching. In the treatment condition, subjects are (marginally) less likely to switch when they should not than in the control condition[12]. However, the difference is much smaller compared to the first column, i.e., the difference is 0.4% in the case where the subjects should not switch, while it is 9.2% in the case where the subjects should switch. In both cases, subjects are less likely to switch when exposed to a stronger information overload.

To explore further, we run an OLS regression with pairwise fixed effects, using clustered standard errors at the subject level. As shown in the first column of table 5, the treatment effect is positive and highly significant ($p < 0.01$) in the scenario where the subject should switch but did not, which confirms hypothesis 1S. When there is strong enough belief-challenging information so that the subjects should switch, subjects in the treatment condition are 9.21% less likely to do so than subjects in the control condition.

| | (1)<br>should switch<br>but didn't | (2)<br>shouldn't switch<br>but did |
|---|---|---|
| Treatment | 0.0921*** | -0.00364 |
| | (0.033) | (0.008) |
| Constant | 0.305*** | 0.0612*** |
| | (0.019) | (0.005) |
| R-squared | 0.0280 | 0.0002 |
| Observations | 592 | 1649 |
| Subjects | 207 | 233 |

Clustered standard errors on subject-level in parentheses
Pairwise fixed effects
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 5: OLS of Switching Decisions after Phase 2.

On the other hand, in the scenario where the subject should not switch but ended up switching, the treatment effect is not significant, which confirms hypothesis 2W, but not hypothesis 2S. In the case where there are no strong enough belief-challenging information such that subjects should stick to their prior belief, the magnitude of information overload has no effect on switching behavior.

Combining the two findings, we can see that information overload has an asymmetric effect on individuals' switching decision when they receive different types of information. More specifically, the effect is significant only when the subjects receive strong belief-challenging information. Subjects react less to belief-challenging information when they are exposed to stronger information overload, while their reaction to belief-confirming information is unaffected by information overload. This finding

[12]If we include the incomplete pairs, the numbers are 5.6% in the treatment and 6.5% in the control.

suggests that a stronger information overload inhibits switching through individuals' under-reaction to strong belief-challenging information.

The asymmetric effect also speaks against another possible hypothesis that subjects switch less under stronger information overload only because they under-react to every signal they receive instead of being more biased. First note that the scenarios where they should not switch is predominately composed of cases where they receive belief-confirming information. Suppose in contrast the subjects under-react more to both belief-confirming and belief-challenging information in the treatment condition, they will be more reluctant to update their beliefs towards the extreme when they receive belief-confirming information. It implies that there should be a higher probability of switching in the treatment condition, and this is clearly rejected by the second column of table 5. The results above are also consistent with the analysis of quantifying bias as will be shown in the following subsection.

## 5.3 Quantifying Bias

To further illustrate the asymmetric effect of information overload on belief updating, we now present the regression analysis of the quantified bias. The quantified bias is represented by $\log(y_{i,sub}) - \log(y_{i,obj})$ as shown in equation (10). It measures the direction and magnitude of the discrepancy between the subjective belief updating of the subjects and the Bayesian benchmark.

We first look into the scenario where the numbers seen in phase 2 are in aggregate belief-challenging, i.e., $(p_1 - 0.5)(y_{sub} - 1) < 0$. The results are presented in table 6. The first and second column shows the case where subjects guessed "high" and "low" after phase 1 respectively. In the third column, we pool the two cases by taking advantage of the symmetry of the information structure[13], and this allows us to increase statistical power.

We observe that the treatment effects are significant in all three cases when subjects receive in aggregate belief-challenging information in phase 2. For example in the first column, we see that $\beta_1 = 0.17 > 0$ ($p < 0.05$) such that the subjective odds ratio is $\exp(0.17) = 1.19$ times higher in the treatment condition than in the control condition. This implies that a subject with a "high" prior under-reacts more to belief-challenging information when facing a stronger information overload. Similar conclusions can be drawn from the second and third column. For subjects with "low" priors, we find $\beta_1 = -0.155$ which is also significant ($p < 0.05$), such that the subjective odds ratio is $\exp(-0.155) = 0.856$ times lower in the treatment condition than in the control condition. For the pooled sample, we find $\beta_1 = 0.164$ ($p < 0.01$) such that the subjective odds ratio is $\exp(0.164) = 1.178$ times higher

[13] We pool the two cases as follows: in the case where subject guessed "low" after phase 1, we normalize the belief as the probability that the "low" distribution is drawn. Odds ratios are also normalized accordingly. Thus a larger belief implies that the subject is more confident about his guess, while a larger odds ratio implies that the signals are "more" belief-confirming.

| | (1) high prior, should update downwards | (2) low prior, should update upwards | (3) pooled, challenging info |
|---|---|---|---|
| Treatment | 0.170** | -0.155** | 0.164*** |
| | (0.068) | (0.073) | (0.050) |
| Constant | 0.378*** | -0.211*** | 0.305*** |
| | (0.041) | (0.045) | (0.032) |
| R-squared | 0.0174 | 0.0161 | 0.0169 |
| Observations | 516 | 398 | 914 |
| Subjects | 205 | 188 | 225 |

Clustered standard errors on subject-level in parentheses
Pairwise fixed effects
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: OLS on quantified bias when numbers seen in phase 2 are in aggregate belief-challenging.

| | (1) high prior, should update upwards | (2) low prior, should update downwards | (3) pooled, confirming info |
|---|---|---|---|
| Treatment | -0.0278 | 0.0552 | -0.0411 |
| | (0.057) | (0.052) | (0.037) |
| Constant | -0.774*** | 0.863*** | -0.816*** |
| | (0.035) | (0.032) | (0.024) |
| R-squared | 0.0005 | 0.0025 | 0.0012 |
| Observations | 703 | 624 | 1327 |
| Subjects | 214 | 211 | 230 |

Clustered standard errors on subject-level in parentheses
Pairwise fixed effects
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: OLS on quantified bias when numbers seen in phase 2 are in aggregate belief-confirming.

in the treatment condition than in the control condition. These results all shows that subjects react less to belief-challenging information when they are imposed with stronger information overload. Thus, we conclude that the results confirm hypothesis 3S.

The results for the second scenario, where numbers seen in phase 2 are in aggregate belief-confirming, are shown in table 7. In contrast with the results for belief-challenging information, we can see that the treatment effects are not significant in all three cases, even when we pool the subjects with "high" and "low" priors and take advantage of the larger sample size. Thus, the results confirm hypothesis 4W, but not hypothesis 4S.

Combining the results in both tables, we conclude that stronger information overload in the treatment condition induces a stronger confirmation bias which is similar to the analysis of switching behavior: subjects under-react more to belief-challenging information in the treatment condition than in the control condition, while the updating behavior with belief-confirming information is not affected by the magnitude of information overload. The stronger confirmation bias is driven via the under-reaction to belief-challenging information, but not via the updating behavior with belief-confirming information. Similar to the analysis of switching behavior, this asymmetry is in contrast with the hypothesis that stronger information overload would induce more under-reaction to both belief-confirming and belief-challenging information.

# 6 Conclusion

In this study, we investigate the role of information overload in giving rise to confirmation bias. We show that when subjects are exposed to stronger information overload, their belief updating behavior exhibits a stronger confirmation bias, holding constant the signals they receive. The effect is driven by the increased under-reaction to belief-challenging information while the updating behavior concerning belief-confirming information is unaffected. In addition to the popular view that confirmation bias is driven by intrinsic preferences for belief-confirming information, our findings demonstrate that the bias also strongly depends on the informational environment. This lends credence to the growing theoretical literature which details that limited attention and ability could explain a number of behavioral anomalies.

This additional channel of confirmation bias has important implications. First, it sheds light on the debate of whether the Internet strengthens biased behavior and promotes ideological polarization. Our results suggest that information overload, as driven by the Internet, could pose substantial problems by driving individuals to ignore belief-challenging information. Thus the Internet could promote polarization even though it provides more and on average, better information to the public. Simply providing more information might not be a good way to mitigate confirmation bias and the extent of polarization. In particular, this paper suggests that a better solution could be to make it less cognitively demanding to process information.

On the other hand, the results imply that research and policy evaluations have to take into account that confirmation bias or more generally, how information processing behavior interacts with the informational environment. This effect is absent if one assumes that confirmation bias is solely driven by intrinsic preferences. For example, a mandate for firms to provide more information to consumers may seem welfare-improving. However, such a policy intervention could lead to information overload and exacerbates confirmation bias, which in turn reduces market competition. Ignoring this indirect effect might yield dramatically different results.

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## A.1 The distribution in the Guessing Task

We present the reasoning behind the parameters of the distribution. In particular, they are chosen to satisfy the following criteria:

1. The logarithmic odds ratios are monotonic and approximately linear, as shown in figure A1. That is, higher numbers are stronger evidence that the "high" distribution is true and the differences in the strengths of adjacent signals are approximately constant;

2. After seeing the first sequence of numbers, there are enough subjects with confident belief, i.e., they believe that the state is high (low) with probability 75% or above. Table A.2 shows that more than 40% of the subjects are "confident" after seeing 5 signals. This is to ensure that there exists a significant amount of confident individuals such that confirmation bias could take effect;

3. After seeing the first sequence of numbers, there should not be many subjects with too confident belief, e.g., believe that the state is high(low) with probability 95% or above. Table A.3 shows that less than 2% of the subjects are extremely confident after seeing 5 signals. This is because the belief elicitation is restricted to increments of 5%. When a subject believes that the state is high with 95% certainty, even if he receives several "number 8"s, the change in his belief is bounded by +5% and is not measurable. Moreover, it ensures that there are sufficient number of observations where a switching occurs, as shown in table A.1.

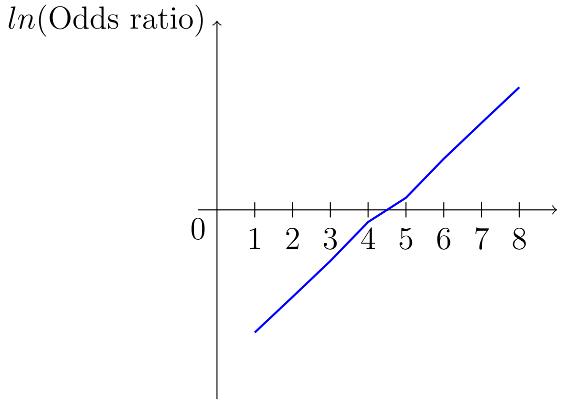



Figure A1: Logarithmic Odds ratios of the numbers 1-8

| min | mean | max |
|---|---|---|
| 18.5% | 24.2% | 29.5% |

Table A.1: Simulated proportion of observations where subjects should switch from believing "High" after phase 1 to believing "Low" after phase 2, or from believing "Low" to believing "High", with 10000 simulations of 2000 observations

| | | Belief | | | | |
|---|---|---|---|---|---|---|
| | | = 0.5 | > 0.6 or < 0.4 | > 0.65 or < 0.35 | > 0.7 or < 0.3 | > 0.75 or < 0.25 |
| 5 draws | Average proportion of subjects | 0 | 76.1% | 64.7% | 52.5% | 41.7% |
| 12 draws | Average proportion of subjects | 0% | 94.4% | 88.8% | 76.0% | 68.9% |

Table A.2: Distribution of Bayesian beliefs given 5 and 12 draws, with 10000 simulations of 2000 observations.

| | | Belief | | | |
|---|---|---|---|---|---|
| | | > 0.8 or < 0.2 | > 0.85 or < 0.15 | > 0.9 or < 0.1 | > 0.95 or < 0.05 |
| 5 draws | Average proportion of subjects | 32.2% | 19.2% | 10.1% | 1.65% |
| 12 draws | Average proportion of subjects | 60.9% | 51.35% | 40.05% | 24.35% |

Table A.3: Distribution of Bayesian beliefs given 5 and 12 draws, with 10000 simulations of 2000 observations.

# Instructions for the first part of the experiment[1]

In this part of the experiment you will go through 12 rounds of a task which will be explained to you in the following. Each round will take about 2 - 3 minutes. In this part of the experiment you can win up to 24 €.

## 1 What is the experiment about?

This part of the experiment consists of 12 rounds of a task which will be described in the following. There are two computers, a "high" computer and a "low" computer: One of these computers, the "high" computer, generates high numbers more frequently, while the "low" computer generates low numbers more frequently. At the beginning of each round, one of the two computers (high or low) is randomly selected, but you do not know which one. The probability for each computer is equal, i.e. 50% for each computer. In each round, you will see numbers which have been generated by the selected computer. We will ask you to indicate your guess which one of the two computers has been selected in this round using the numbers you have seen as indicators for the selected computer.
As you can see in figure 5, we will ask you three times per round to indicate your guess.

- The first time, we will ask you at the beginning of a round, before you have seen any numbers, without any additional information.
- The second time, after you have seen 5 numbers in phase 1, which have been generated by the selected computer of this round.
- The third time, after you have seen additional numbers in phase 2, which have been generated by the selected computer of this round.

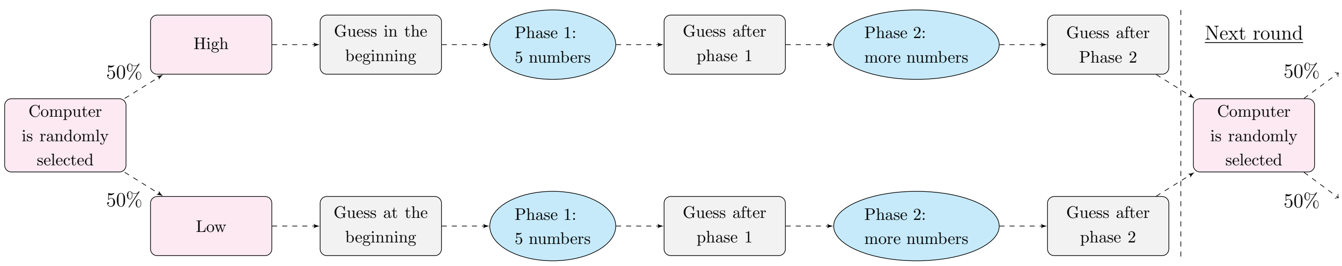



Figure 1: Sequence of a round

[1]These instructens were originally in German and have been translated to English. The original German version is available o request.

# 2 How to make a guess?

In the following, we explain how you can use numbers as indicators for the computer which has been selected at the beginning of a round and how we will retrieve your guess on the monitor.

## 2.1 The high and the low Computer

Both computer can only generate numbers between 1 and 8. Table 1 shows the probabilities with which the computers produce the numbers 1 to 8. For example, the probability that the “high” computer generates the number 8 is 18%, this means that it happens in 18 out of 100 cases on average. The “high” computer generates smaller numbers less likely. For example, the probability that the computer generates the number 1 is only 8%, in other words, in 8 out of 100 cases.
The “low” computer generates numbers with the probabilities shown in table 2 and can be seen as a mirror image of the “high” computer. For example, the probability with which the “low” computer generates the number 8 is only 8%, on other words, in 8 out of 100 cases. A number 1 is generated by the “low” computer with a probability of 18%, in other words, in 18 out of 100 cases.

| generated number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| probability of the number | 8% | 9% | 10% | 12% | 13% | 14% | 16% | 18% |

Table 1: The “High” Computer

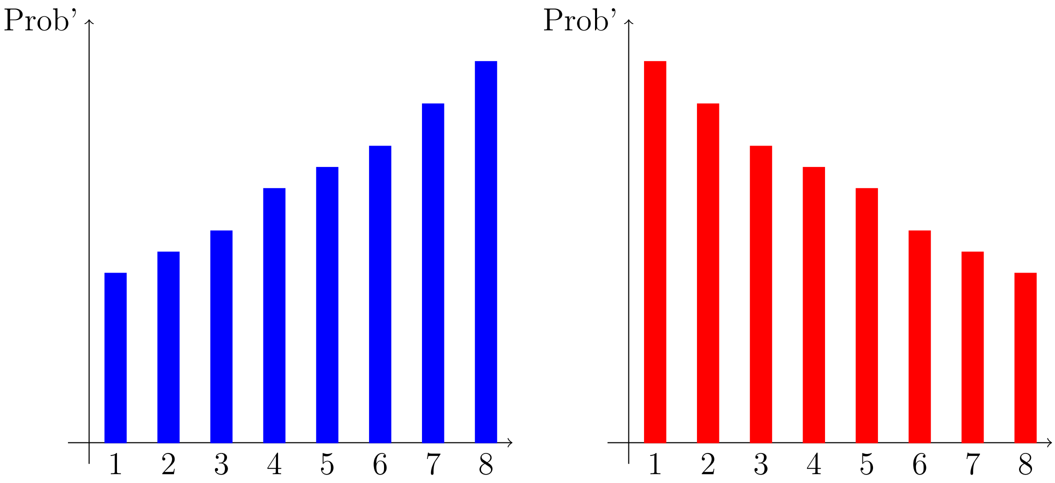
| generated number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| probability of the number | 18% | 16% | 14% | 13% | 12% | 10% | 9% | 8% |

Table 2: The “Low” Computer

As described in the beginning, it is your task to guess whether the “high” or the “low” computer is generating the numbers of the current round.
At the beginning of each round, one of the two computers is selected with equal probability. Each one of the computers has the probability 50%. The computers are selected independently over the rounds, this means that the probability that the “high” or the “low” computer is selected in a round, is always 50%. The selection of the computers is independent from which computer has been selected in the previous round.

## 2.2 Shown numbers as indicators of the computer

You can use the shown numbers as indicator of which computer has been selected in the respective round. For example, the number 1 is an indicator that the “low‘” computer has been selected in this round and is generating the numbers - however, this is not certain. As shown in table 1 and table 2, the probability that the “low”




(a) The "High" Computer    (b) The "Low" Computer

Figure 2: Graphical illustration of the probabilities with which the "high" and the "low" computer generate the numbers 1 to 8.

computer generates a number 1 is 18%, while the probability that the "high" computer generates a number 1 is only 8%.
On the contrary, when you see a number 8, it is an indicator that the "high" computer has been selected in this round and is generating the numbers. The probability that the "high" computer generates a number 8 is 18%, while the probability that the "low" computer generates a number 8 is only 8%.

In general, high numbers are an indicator that the "high" computer has been selected while low numbers are an indicator of the "low" computer having been selected. For example, the number 5 is an indicator that the "high" computer has been selected. Higher numbers, for example 6 or 7, are a stronger indicator that the "high" computer has been selected. Likewise, a number 4 is an indicator that the "low" computer has been selected, but a less strong indicator than a lower number as for example a 3 or a 2.

## 2.3 How we measure your guess

We will ask you for your guess which computer is generating all the numbers you see in a round. To make your guess as specific as possible, you should consider **all** numbers you see in a round; those of the first phase and those of the second phase.

Each of your guesses will have the form below:

### 1. Which computer is more likely?

In the first step you will be asked, which computer is generating the numbers in the current round in your opinion. This is shown in figures 3a and 3b. To answer this first question, you can click on one of the two pictured buttons and state, which computer has been selected with a higher probability in your opinion in the respective round.

**2. Your exact assessment:**

In the second step, we want to know your precise assessment, i.e. how certain you feel about your guess in the first step. The tables shown in figures 3a and 3b provide some assistance. In each row you can decide between two options:

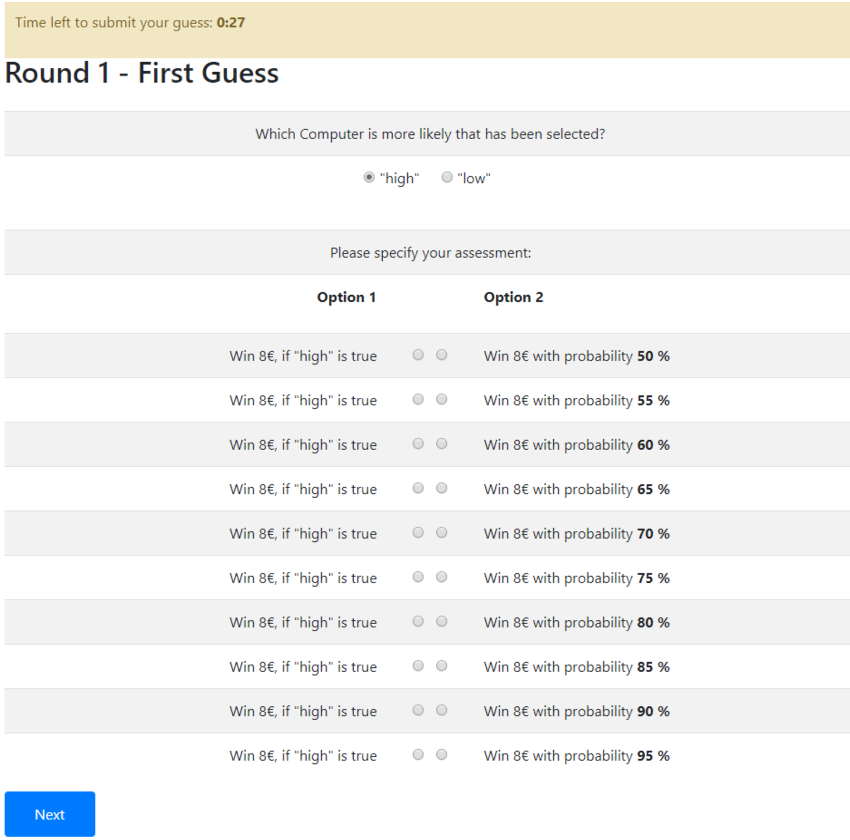
- Win 8 € if you have guessed the right computer
- Win 8 € with some probability which starts at 50% in the first row and increases by 5% per row.

One of the rows will be randomly selected for your payment. However, your choice in a row **CANNOT** influence, **which** one of the rows will be selected. Therefore, think about your choice between option 1 and option 2 very carefully in each row since every row could be selected for your payment.

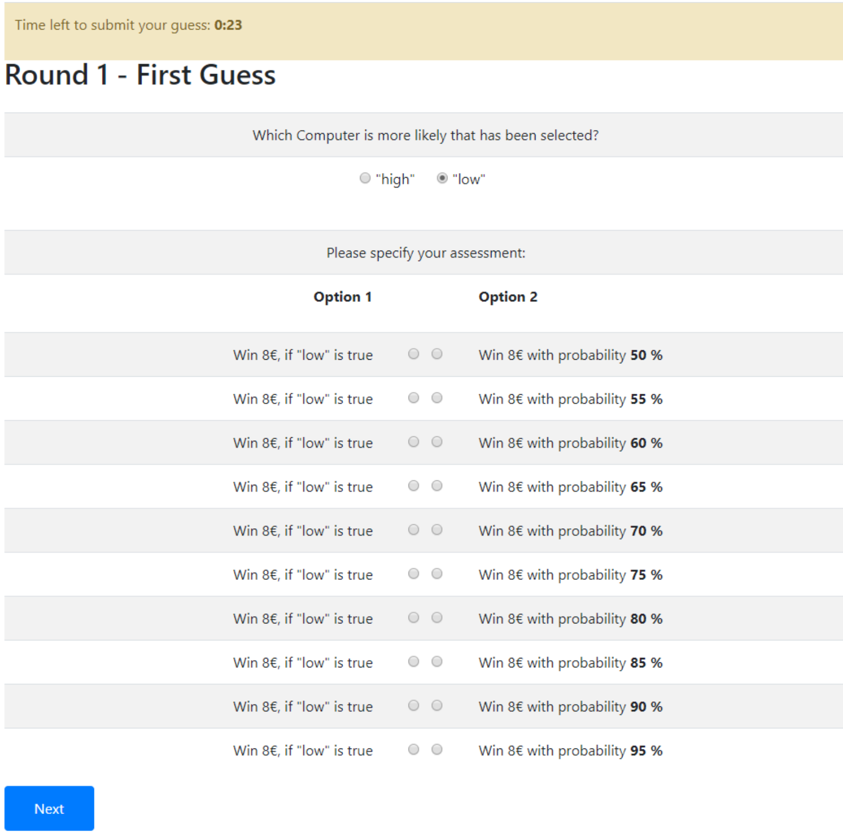
**An example**

Assume you make the following assessment: You believe that the high computer has been selected and is generating the numbers in the respective round with a probability of 66%.
So, in the first step, for the question "Which of the two computers is more likely?" you click on the button "high".
Now, in the second step, for the question "Please specify your exact assessment", you have two options to choose from to specify your assessment:

- In the first row, you have the options "Win 8 € if "high" is right" and "Win 8 € with probability 50%". Since you believe that "high" is right with probability 66%, you should choose option 1 since this way, you win 8 € with probability 66% (instead of 50% as it would be the case with option 2).
- In the second row you have the options "Win 8 € if "high" is right" and "Win 8 € with probability 55%". Since you believe that "high" is right with probability 66%, you should choose option 1, since this way, you win 8 € with probability 66% (instead of 55% as it would be the case with option 2).
- Accordingly, you should choose option 2 in the rows where the probability of winning 8 € is 70% or higher, it is, equal or higher to the probability with which you believe that the computer you think has been choosen is right.




(a) The monitor after you clicked "High"




(b) The monitor after you clicked "Low"

Figure 3: The assessment monitor of the first guess in the beginning of a round, after you have clicked "high" or "low"

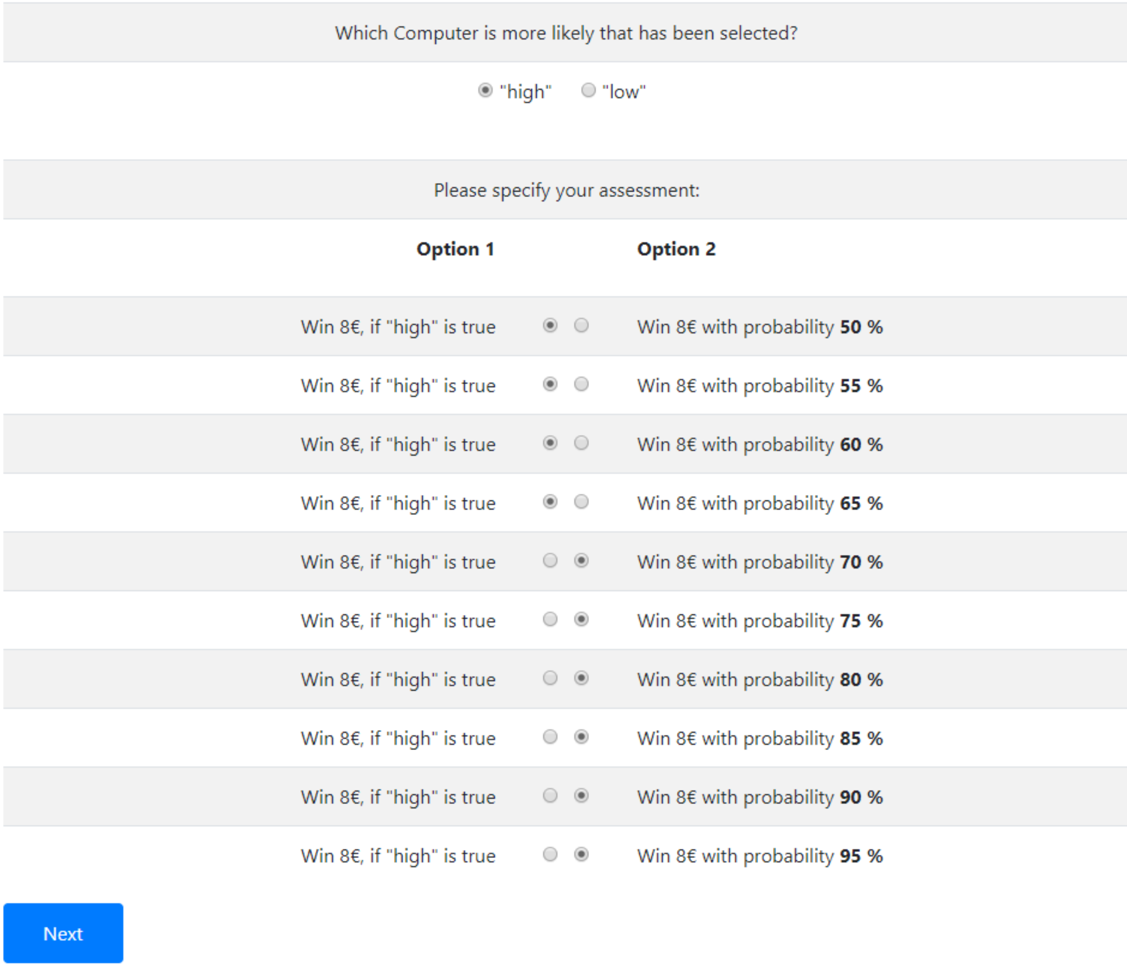



Figure 4: The guessing screen from the example with a guessed probability of 66% for the “high” computer. The button for “High” and the button of option 2 with winning probability 70% has been clicked.

So, as soon as the probability of winning in option 2 is higher than your certainty of your guess (whether the high/low computer has been selected), you should choose option 2. This is illustrated in figure 4.

Please notice the fill-in assistance: The fill-in assistance will automatically choose option 2 in all the following choices under option 2 with a higher winning probability than the one you have choosen (it is, all the rows under the row where you have choosen option 2 for the first time), since the winning probabilites are increasing by 5% per row.

After you have chosen option 2 with a winning probability of 70%, all following rows with a higher probability than 70% in option 2 will be automatically chosen for you.

On the other hand, when you think that it is more likely that the numbers in the respective round are generated by the "low" computer, you click on the button "low" in the first step. For the second step, you proceed as described above and compare for each row, whether you prefer option 1 or option 2. You can indicate your exact assessment as described above. The only difference lies in option 1, as illustrated in figure 3b: You win 8 € if the "low" computer has been selected.

**Reminder:**

- In the first step you indicate which computer you think is more likely
- In the second step, you make a more exact assessment:
  - Therefore, you should read the table row by row and compare option 1 to option 2 in each row to decide which option you prefer in the respective row.
  - This is very important, since every one of your decisions is relevant for your payment and determines, how much you will earn in this experiment. Therefore, please think about your choices very carefully.
- As soon as the winning probability in the second step under option 2 is higher then your certainty of your guess (whether the high or low computer has been selected), you should choose option 2
- The fill-in assistance will automatically choose option 2 for you in all the following choices with a higher winning probability in option 2 then the one where you have chosen option 2 for the first time.

# 3 The sequence of each round

In the following we explain the procedure of the experiment to you by guiding you through the sequence of a round. In this part of the experiments, 12 rounds will be played. Each round consists of a number of guesses and phases. In the phases of a round, you see numbers which you can use as indication for which computer has been selected in the respective round. The sequence of a round is illustrated in figure 5.

## 3.1 A computer is randomly selected

At the beginning of each round, one of the two computers (it is, the "high" or the "low" computer) is randomly selected. Each of the computers (high or low) has the same chance to be selected. Thus, the probability for the "high" or the "low" computer is 50% in each case at the beginning of a round. You will see a screen which points out that a new round has started and once again one of the two computers ("high" or "low") has been randomly selected.

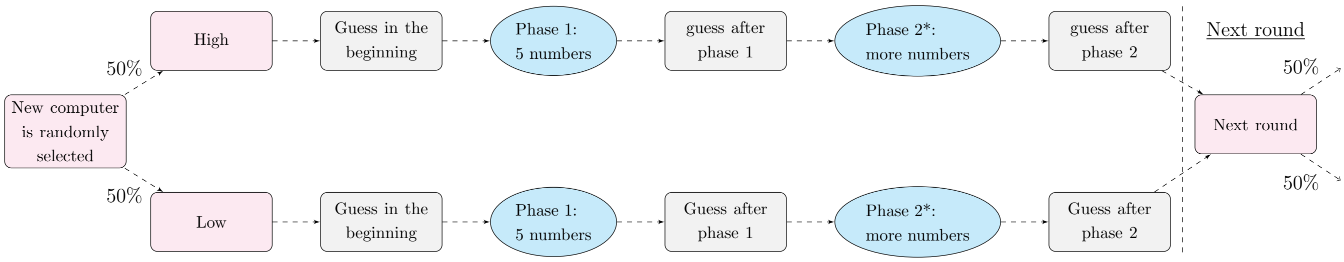



Figure 5: Sequence of a round
(* Phase 2 can occur in 2 versions)

## 3.2 Guess at the beginning of a round

In each round, at the beginning of the round, the "high" or the "low" computer will be randomly selected with a probability of 50% each. This happens randomly at the beginning or each round.
At the beginning of a round, before you see any numbers, we will ask you for your guess which computer has been randomly selected. We do this to make sure that you know you are at the **beginning** of a round. You have 30 seconds to make your guess.

**Reminder:** If you do not feel confident how to fill out the assessment screen or do not know when to choose option 1 or option 2 in a row, please read section 2.3 "How we measure your guess" again.

## 3.3 Phase 1

In phase 1 you will see 5 numbers, as illustrated in figure 6. Those numbers are generated by the computer which has been randomly selected at the beginning of the current round; for example "5 7 3 2 2" or "7 7 6 4 2". You have 30 seconds time to look at the numbers and to form your assessment. After 30 seconds, the numbers will disappear and you will be directed to the next screen. On the next screen, you will be asked to indicate your guess as described above.

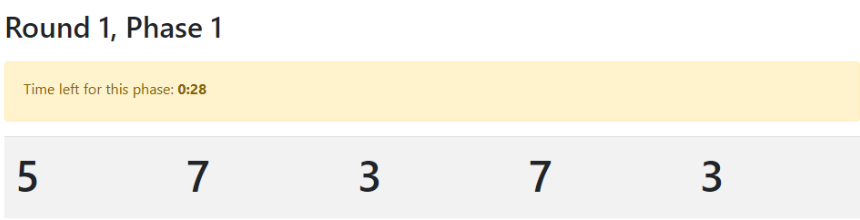



Figure 6: Screenshot of Phase 1

## 3.4 Guess after phase 1

After phase 1, we will ask you again to make a guess which computer has been selected at the beginning of the round and is now generating the numbers. You can use the numbers from phase 1 as indication of the randomly selected computer. Again, you will indicate your guess in the table from figures 3a and 3b, at this, you will see your assessment from the first guess as default setting. However, you can change this assessment as you like. You have 30 seconds time to make indicate your guess and to make it more precise.

**Reminder:** If you do not feel confident how to fill out the assessment screen or do not know when to choose option 1 or option 2 in a row, please read section 2.3 "How we measure your guess" again.

## 3.5 Phase 2

In phase 2, you will see up to 7 additional numbers. These numbers are generated by the computer which has been randomly selected at the beginning of the current round. There are two versions of phase 2 which can switch randomly from round to round.

## Phase 2, Version 1

In version 1 of phase 2, you can reveal up to 7 additional numbers. Again, those numbers are generated by the computer which has been randomly selected at the beginning of the current round and has already generated the 5 numbers from phase 1 of the current round. You can only see one number at a time: When you uncover the next number, the number shown until then will disappear. You have no possibility to go back to this number.
The first number appears as soon as phase 2 starts. When you want to see the next number in this version of phase, you can click "Next". You will be redirected to a screen as in figure 7.

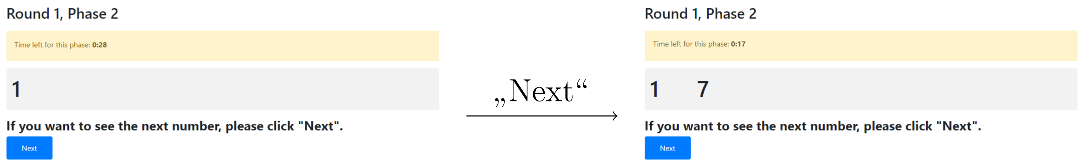



Figure 7: Screen of phase 2, version 1

Please notice: As soon as you click "next", the currently displayed number will disappear. You have **no** possibility to go back to the previous screen to see this number again.
After 30 seconds in phase 2 and no matter whether you have seen all 7 numbers, you will be redirected to the screen for the guess after phase 2. You will have 30 seconds in phase 2 in total and cannot proceed earlier. Thus, consider carefully how you want to allocate your time between the 7 numbers that you can uncover in total.

### Phase 2, Version 2

In version 2 of phase 2 you will be shown up to 7 additional numbers. Again, those numbers are generated by the computer which has been randomly selected at the beginning of the current round and has already generated the 5 numbers from phase 1 of the current round.
The additional numbers appear one after another on your monitor. In this version of phase 2, you **cannot** control the display of the next numbers. Instead, the numbers will be shown automatically. Differently to version 1, the shown numbers will not disappear again: The previous numbers will be still visible. An example is shown in figure 8.

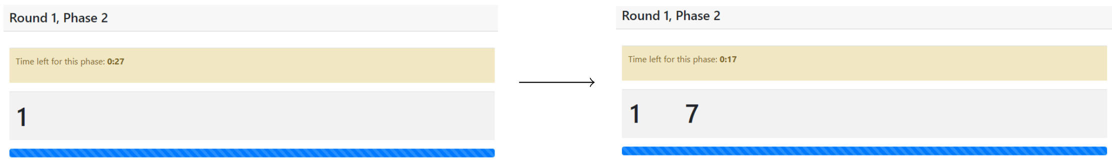



Figure 8: Screen of phase 2, version 2

After 30 seconds have passed, you will be redirected to the next screen to make your guess after phase 2. Note that you have 30 seconds time but it can happen that you see less than 7 numbers in these 30 seconds.

## 3.6 Guess after phase 2

After phase 2, we will ask you again to make a guess which computer has been selected at the beginning of the round. You can use the numbers from phase 1 and phase 2 as indication of the randomly selected computer. Again, you will indicate your guess in the table from figures 3a and 3b, at this, you will see your assessment from the first guess as default setting. However, you can change this assessment as you like. You have 30 seconds time to indicate your guess and to make it more precise.

**Reminder:** If you do not feel confident how to fill out the assessment screen or do not know when to choose option 1 or option 2 in a row, please read section 2.3 "How we measure your guess" again.

## 3.7 Next round

After your guess after phase 2, a new round will start and a new computer (the "high" or the "low" one) will be randomly selected and will be generating the numbers in the new round.

# 4 How you will get paid

For this part of the experiment, you play 12 rounds with 3 guesses each per round. From these guesses, we will randomly select 3 of your guesses:

One guess at the beginning of a round, one guess after you have seen 5 numbers in phase 1, and one guess at the end of a round after you have seen up to 7 numbers in phase 2. Each of these randomly selected guesses will come from a different round. Subsequently, from each of these guesses, a row will be randomly selected in the corresponding decision table. Your choice in this row will determine your payment:

1. if you chose option 1, you will win 8 € if you guessed correctly whether it was a "high" or "low" computer generating the numbers of the round;
2. if you chose option 2, you will win 8 € with the probability specified in the row we randomly selected.

# 5 Control Questions

1. In the first guess of a round (before you have seen the numbers of phase 1), what is the probability that the "high" computer has been selected?

   **Answer:** The probability is ____________ percent.

2. In the first guess of a round (before you have seen the numbers of phase 1), what is the probability that the "low" computer has been selected?

   **Answer:** The probability is ____________ percent.

3. Suppose that in the previous round, you have seen the numbers

   $$1, 2, 2, 3, 3, 1, 4, 7.$$

   Now, in the first guess of the next round (before you have seen the numbers of phase 1), what is the probability that the "high" computer was selected for this round? Why?

   **Answer:** The probability is ____________ percent.

   **Please explain:** ________________________________________

4. What do you choose in the table when you believe that the “low” computer is right with a probability of 72%? Please draw your choice in the table below.

Which Computer is more likely that has been selected?

○ "high" ◉ "low"

Please specify your assessment:

| Option 1 | | | Option 2 |
|---|---|---|---|
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **50 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **55 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **60 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **65 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **70 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **75 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **80 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **85 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **90 %** |
| Win 8€, if "low" is true | ○ | ○ | Win 8€ with probability **95 %** |

Next

5. Assume that you think at the beginning of a round, that the probability for the “high” computer is 50%. Please draw in the table below, how the screen should look like before you would click “next”.

Which Computer is more likely that has been selected?

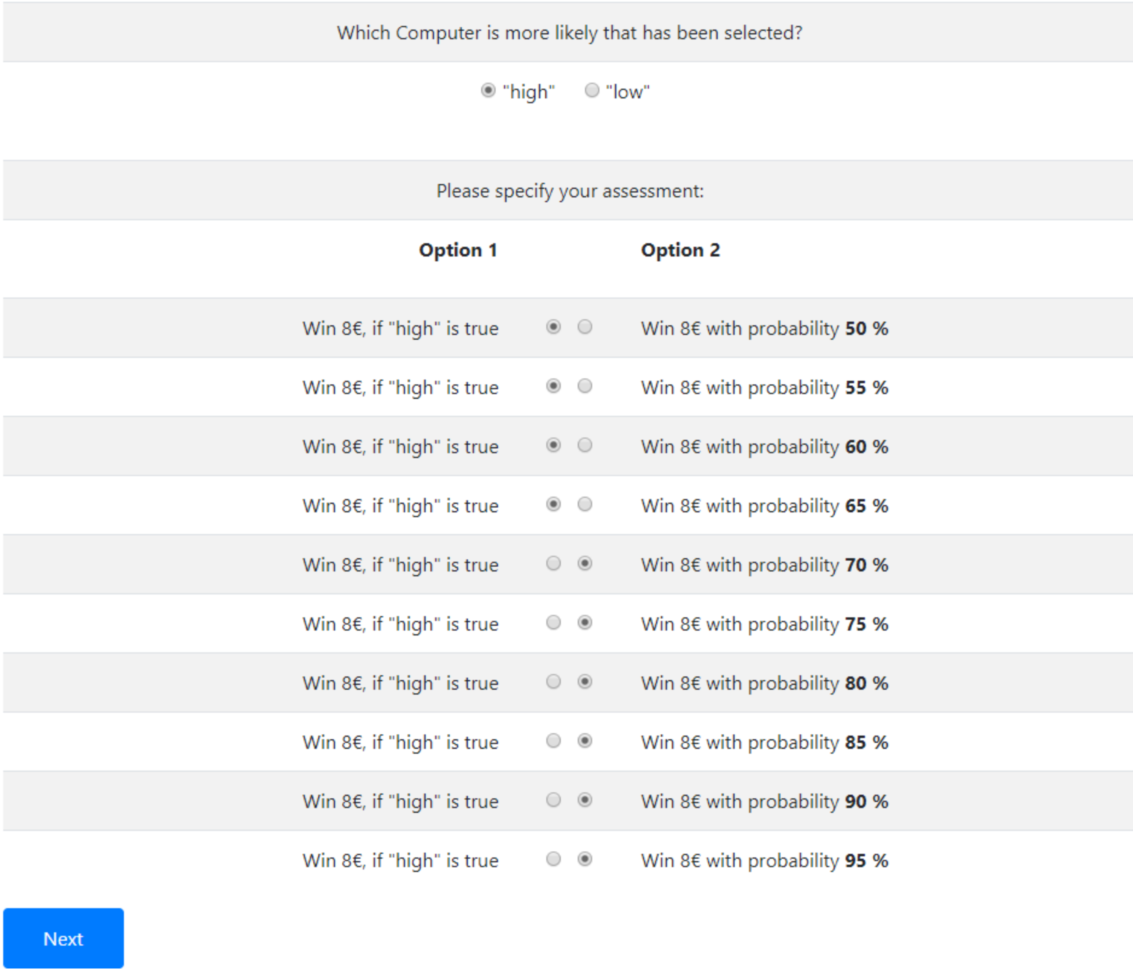
"high" "low"

Please specify your assessment:

| Option 1 | Option 2 |
|---|---|
| Win 8€, if "____" is true | Win 8€ with probability **50 %** |
| Win 8€, if "____" is true | Win 8€ with probability **55 %** |
| Win 8€, if "____" is true | Win 8€ with probability **60 %** |
| Win 8€, if "____" is true | Win 8€ with probability **65 %** |
| Win 8€, if "____" is true | Win 8€ with probability **70 %** |
| Win 8€, if "____" is true | Win 8€ with probability **75 %** |
| Win 8€, if "____" is true | Win 8€ with probability **80 %** |
| Win 8€, if "____" is true | Win 8€ with probability **85 %** |
| Win 8€, if "____" is true | Win 8€ with probability **90 %** |
| Win 8€, if "____" is true | Win 8€ with probability **95 %** |

Next

6. Take a look at the following example: After you have seen the numbers, you belive that the “high” computer has been selected with a probability of 85%. What has not been filled in correctly in the following screen?



Which Computer is more likely that has been selected?

◉ "high" ○ "low"

Please specify your assessment:

| Option 1 | | | Option 2 |
|---|---|---|---|
| Win 8€, if "high" is true | ◉ | ○ | Win 8€ with probability **50 %** |
| Win 8€, if "high" is true | ◉ | ○ | Win 8€ with probability **55 %** |
| Win 8€, if "high" is true | ◉ | ○ | Win 8€ with probability **60 %** |
| Win 8€, if "high" is true | ◉ | ○ | Win 8€ with probability **65 %** |
| Win 8€, if "high" is true | ○ | ◉ | Win 8€ with probability **70 %** |
| Win 8€, if "high" is true | ○ | ◉ | Win 8€ with probability **75 %** |
| Win 8€, if "high" is true | ○ | ◉ | Win 8€ with probability **80 %** |
| Win 8€, if "high" is true | ○ | ◉ | Win 8€ with probability **85 %** |
| Win 8€, if "high" is true | ○ | ◉ | Win 8€ with probability **90 %** |
| Win 8€, if "high" is true | ○ | ◉ | Win 8€ with probability **95 %** |

Next

**Answer:** ____________________________________________