To Buy Or Not To Buy:
Why do People Buy too Much Information?[*]

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Abstract

Previous studies have shown that individuals exhibit a tendency to acquire an excessive amount of private information if information can only be communicated through a small and discrete action space. In this experiment we investigate demand for information when the action space is continuous. Participants sequentially assess their subjective probability which one out of two apriori equally likely states occurred at the beginning of a game. They observe the probability assessment of their predecessor and can acquire additional private information at a fixed price. Participants interact with either human or computer simulated players. We find that individuals in general acquire too many signals and that behavior does not depend on the rationality of their counterparts. A random utility model is able to explain most of the observed behavior.

JEL C25, C9, D8

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Consider yourself acting in a market where the true value of a good depends only on the probability of a single event. Examples of such markets are widespread, think, e.g. of a stock, whose value depends on the success of a patent or the value of a bond, which strongly depends on the fact if the company issuing the bond will declare bankruptcy or not. Other examples include the labor market where you only have some idea about the success probability of a job applicant.

These markets typically have in common that one can observe the behavior of other agents and that one has the opportunity to acquire additional private information. Behavior of other agents includes observing their buying and selling decisions, their bids and asks, etc. In the following, we will call this information public information. To come up with an optimal strategy in this market environment, one has to decide how much private information to acquire and subsequently how to combine private and public information. The goal of our research is to understand what a market participant should do and to contrast this with what she is actually doing. The potential difference between rational and actual behavior will help us to better understand markets.

Investigating and understanding behavior of subjects in markets is a difficult and under some circumstances even impossible task. Being able to compare rational and actual behavior of subjects in an experimental study requires the possibility to derive an optimal strategy in every situation, subjects might be in. Generally, markets do not meet this requirement. In markets, the optimal strategy is influenced by strategic interaction of market participants and concepts of information efficiency as well as the underlying market form. All these factors aggravate and often impede the calculation of an optimal strategy. Furthermore participants' wide variety of possible actions (buying or selling, timing, volume, etc.) complicates the identification of possible reasons for their behavior.

It is therefore meaningful to define a simple market-like aggregation process where an optimal strategy can be calculated. Situations investigated in the information cascade literature (Bikhchandani, Hirshleifer and Welch 1992, Anderson and Holt 1997) share important features of aggregation processes also found in market situations, which we try to understand: Subjects have to sequentially assess the true value of a random variable based on the observation of their predecessor's guesses and their own private information. But other than in market scenarios, the simple aggregation process enables a calculation of when subjects should buy private information and how private and public information should be aggregated.

Using laboratory experiments, Kraemer, Nöth and Weber (2001) found that subjects buy too much private information, a result which has been independently replicated by Kübler and Weizsäcker (2001). There is no easy explanation for this result. Kraemer, Nöth and Weber (2001) found that neither risk aversion nor taking into account predecessors‘ errors nor other rational factors were able to explain the observed buying behavior.

In this paper we use a different aggregation process based on features of cascade experiments. The resulting design better resembles real world situations, in which continuous measures serve to aggregate information, and enables us to identify why subjects exhibit a tendency to buy too much information. In particular, we try to answer the following questions:

- How do changes in cost and quality of information affect subjects' demand for information?
- How do people decide whether to acquire additional information and how do they aggregate different pieces of information?
- Do subjects take into account irrationalities by other subjects and to what extent does that influence their behavior?

Our data suggests that behavioral variables play an important role in the answers to these questions. Overconfidence (Svenson 1981) and conservatism (Edwards 1968) have long been known by psychologists to influence probability judgments resulting from Bayesian updating. Those Bayesian concepts have recently become quite prominent in the economic literature. E.g. overconfidence is a prominent behavioral variable in models explaining trading behavior (Daniel, Hirshleifer, Subrahmanyam 1998; Gervais and Odean 2001). Combining overconfidence, i.e. overweighing ones own signal, with a random utility approach, we are able to explain subject's excessive information acquisition. Furthermore we show that subjects tend not to consider errors committed by other subjects. However, a (new) puzzle remains: subjects buying behavior given a certain piece of public information depends on their position within the experiment, i.e. apart from the implications, the weight of the given information seems to influence subjects' behavior, too.

We will proceed as follows. The next section will first motivate our experimental design and discuss the result of previous studies in more detail. Subsequently, the design is presented. The results are given in the second section. The paper ends with a short discussion of the results and an outlook for future research.

I. Experimental Design and Procedures

Methodological issues

As already stated above a complex market is not suitable to answer our research questions because neither an optimal strategy can be derived in any situation nor is it possible to identify why subjects behaved the way they did because subjects have too many ways to act. Therefore our design uses features of the aggregation processes found in cascade experiments (Anderson and Holt 1997, Nöth and Weber 2001). They simplify the aggregation process but still share important features of aggregation processes in market environments. Features taken from cascade experiments are the following: There are only two possible states of nature A and B, which are a priori equally likely. The two different states could represent e.g. the events "the stock market goes up" and "the stock market goes down". Information is represented by signals which are determined based on the state of nature which actually occurs. The signals can either be of good or bad quality and the aggregation process is simplified by determining exogenously in which order subjects have to act.

Other than in the cascade experiments, the aggregation of information is not obtained by letting subjects predict which state they think is more likely and making these predictions publicly available. Instead information is aggregated by asking subjects for their subjective probability that either one of the states occurred based on all available information and then passing this probability judgment to the next subject in the sequence. Why do we use probability judgments to aggregate the information? First, we try to closer match the notion of real markets in which prices summarize the private information held by subjects who have already taken actions. Second, a single probability is easier to interpret than actions taken by different individuals. And third, information cascades can no longer occur in this environment (Lee 1993), so that all available information is aggregated.

The situation represented by our design can be viewed as a situation we often face in real life. One has to reach a judgment concerning the probability of a certain event (e.g. that the stock market goes up). To do this, one can first observe decisions or judgments made by others, which provides one with an initial assessment (e.g. by reading a research report). Then one has to decide whether to gather additional information or not and then to reach a final judgment by aggregating the different pieces of observations. The resulting judgment or actions can then be observed by other individuals and so on (e.g. by publishing recommendations). In the end, information about the event is aggregated in the actions taken by the subjects.

Previous studies have tried to answer similar questions by using a related but different approach (Kraemer, Nöth and Weber 2001; Kübler and Weizsäcker 2001). Instead of passing probability judgments from subject to subject they made the actions taken by the subjects publicly observable as a free source of information. The studies found that subjects tend to acquire an excessive amount of private information. Kraemer, Nöth and Weber (2001) identified biased information weighing as the most likely reason for the observed behavior, whereas Kübler and Weizsäcker (2001) identified errors committed by other subjects as an explanation. The design used in these experiments has two major drawbacks. First, in order to evaluate the free information participants had to aggregate all predictions of their predecessors and the information about the preceding signal acquisitions, which could be a difficult task. Second, since only the acquisition behavior and the prediction of the state of nature could be observed, subjects' beliefs about the state of nature were only elicited as a dichotomous variable. Therefore it was impossible to precisely measure how much weight subjects assigned to the different sources of information, which is necessary to prove that a biased information weighing is responsible for the excessive signal acquisitions.

Design

The following section outlines the experimental design. In each session 6 players play several rounds of the following game. Explanations concerning specific design features follow the extensive form representation.

- At the beginning of each game nature draws one out of two equally likely states, denoted by A and B ($p_A = p_B = 0.5$).
- 6 Players have the task to sequentially assess their subjective probability that either state A or state B occurred. The ordering is given exogenously and is determined randomly for each round. **One human subject plays with 5 perfectly rational computer simulated players.** The rationality of the computer players is public knowledge since it is announced in the instructions (see Appendix A).
- At position i ($i = 1, \ldots, 6$) the ith player has the following information:
  - The design including all probabilities and payment procedures is public knowledge since it is explained as part of the instructions (see Appendix A).
  - The player at position i observes the probability assessment p_{i-1} of the player at position $i - 1$, for $i > 1$.
  - The <u>option</u> to acquire a private signal s_i at the fixed price of 35 currency units (cu) in the LC ("low cost") treatment and 45 cu in the HC ("high cost") treatment. The

private signal s_i can be one out of four possible signals $s_i \in \{a_S, a_W, b_S, b_W\}$, generated randomly and independently for each player in each round in a two step procedure depending on the realized state:

1. The signal's strength is either weak or strong with probability $p_W = p_S = 0.5$. Note that the signal's strength does not depend on the realized state.
2. If the signal is strong, the information is drawn from an urn containing 2 wrong and 8 correct signals, i.e. $p(a_S|A) = p(b_S|B) = 0.8$. A weak signal is drawn from the "weak" urn. In the LQ ("low quality") treatment the "weak" urn contains 4 wrong and 6 correct signals ($p(a_W|A) = p(b_W|B) = 0.6$) and in the HQ ("high quality") treatment the "weak" urn contains 3 wrong and 7 correct signals ($p(a_W|A) = p(b_W|B) = 0.7$).

- After having observed all available information the player at position i forms her own belief about the probability p_i that state A occurred and communicates this probability judgment to the player at position $i + 1$. All other players cannot observe the probability judgment of the player at position i. The only information they get is the number of players who have already passed a probability assessment to their successor. E.g. a player who has not yet submitted a subjective probability only receives information that the first player, the second player, the third player and so on have already decided but cannot observe any further information unless it's her turn. When it's her turn she first receives her predecessor's probability and then decides upon the signal acquisition.
- The probability is submitted using a sliding bar mechanism, which enables the player to quote her probability in steps of 1% ranging from 0% (p_i = 0.0) to 100% (p_i = 1.0) for state A (see figure 3).[1]
- The players get paid according to a quadratic scoring rule. If a subject submitted probability p_i for state A, she receives $1000 \cdot (2p_i - p_i^2)$ if state A was drawn at the beginning of the game. If state B was drawn at the beginning of the game she receives $1000 \cdot (1 - p_i^2)$ cu.
- After all six players submitted their probability assessments the true state is revealed and a new round begins.

[1] Since probabilities can only be expressed in steps of 1% we basically have only a discrete action space. But since the action space is large compared to the number of possible states of nature, we consider the action space to be continuous.

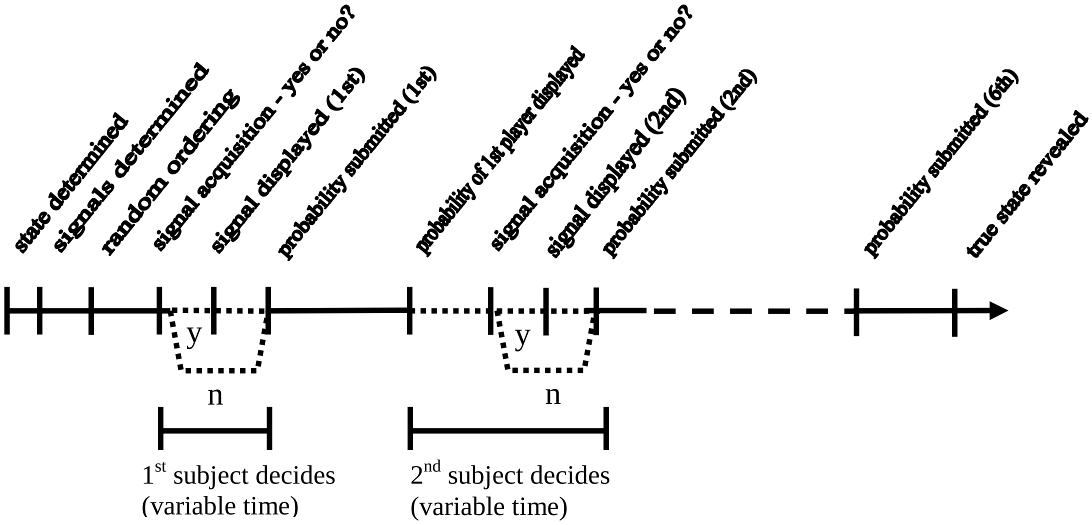


Figure 1: Course of a round

The decision sequence is illustrated in this figure. Each round begins with the determination of the state, the signals and the ordering of the six players. Except for the first acting subject each acting player privately receives the probability assessment of her predecessor prior to her own signal acquisition decision. Then she either receives a private signal followed by her own probability assessment or she has to submit a probability without additional information. There is no time limit for the actions.

In this game the probability assessments, which are communicated to subsequent individuals serve as a means for the aggregation of the information which is acquired by the individuals. Subjects decide to acquire private information if the perceived benefit from acquiring an additional signal outweighs its cost. They communicate their new piece of information through their probability assessment to subsequent decision makers, who can in turn use this probability assessment to form their own beliefs about the occurred state. In order to ensure that subjects have an incentive to honestly communicate their subjective probabilities a proper scoring rule was used to determine the payments.[2] Scoring rules reward or penalize the assessor based on her stated probability and on the event which actually occurs, so that she has an incentive to state a probability which corresponds with her judgments. Assuming risk neutrality the quadratic scoring rule used in this experiment is incentive compatible since a revelation of the true subjective probability is the ex ante expected payoff maximizing strategy.[3] For a formal argument refer to Appendix C. Since subjects are paid only according to their probability assessments the payoffs from the scoring rule also determine the signal's value in each situation.[4]

[2] See Winkler (1967) and Winkler and Murphy (1968) for a general discussion on scoring rules.

[3] Risk aversion biases the revealed probabilities towards 0.5. But Sonnemans and Offerman (2000) have shown that risk aversion has almost no influence on behavior if a quadratic scoring rule is used, especially if payments are small as in this experiment.

[4] The computer based design helps subjects to understand the quadratic scoring rule and its implications for the signal value. See the Procedures chapter for further information on the scoring rule.

Using Bayes' law and taking into account that all computer simulated predecessors act fully rationally the signal values for the different treatments depending on the predecessors probability assessment can be calculated. Figure 2 illustrates the result.

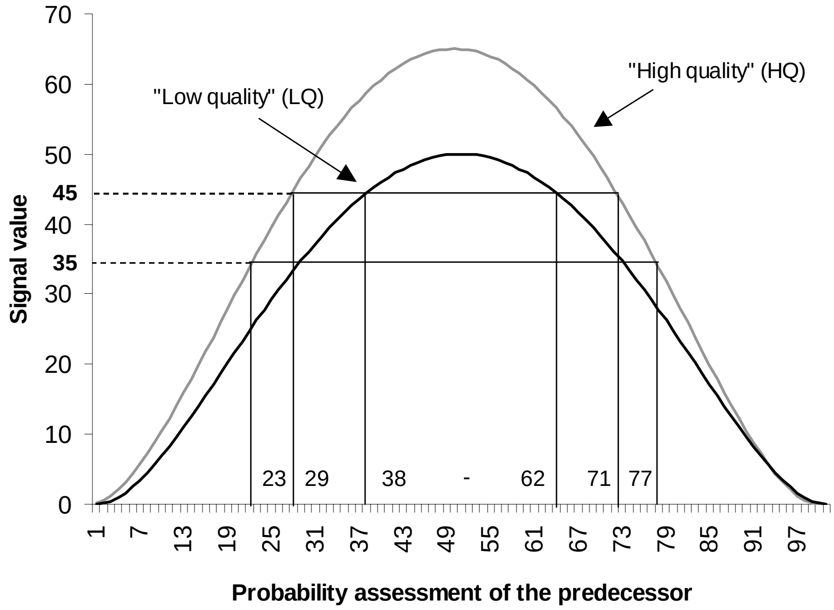


Figure 2: Bayesian signal values

One can see that the signal value drops below its cost, whenever the predecessor's probability p_{i-1} is outside of a symmetric range around 0.5. Note that because of the equal priors ($p(A) = p(B) = 0.5$), a probability for state A of p equals a probability for state B of $(1-p)$. This means that if a predecessor assesses a probability larger than a certain upper bound to either one of the two states, then a rational subject would resign to acquire additional private information and just follow the probability assessment of her predecessor. Hence, we should observe a signal acquisition in 100% cases if the predecessors probability assessment is within the "rational" range and in 0% cases if it is outside that range.

Procedures

The experiments were conducted computer based. Figure 3 exhibits a sample screen, which is displayed, when a subject at position 4 is asked to submit her probability assessment.

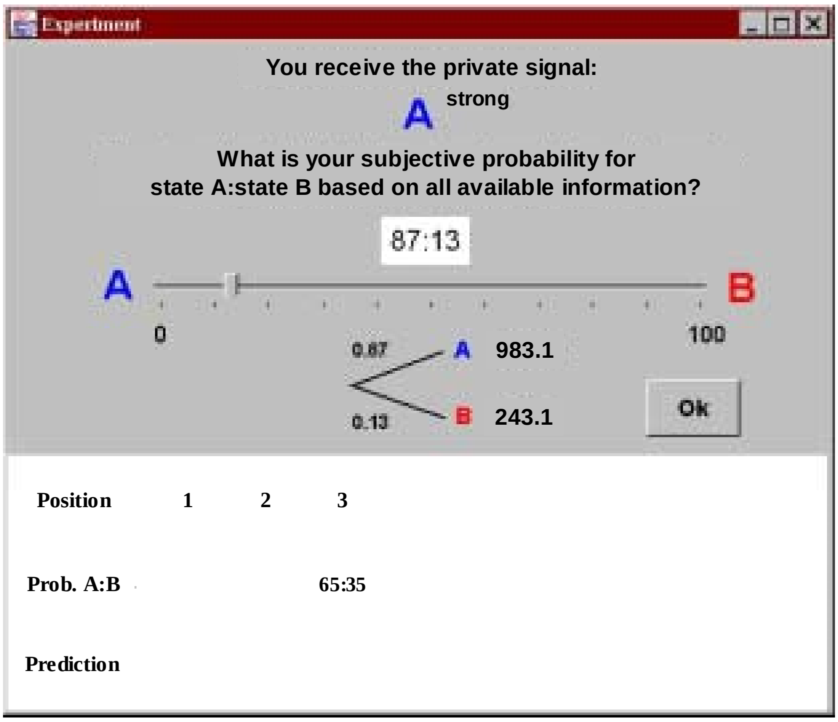


Figure 3: Sample program window

In the first line of the lower part of the window participants can observe the number of predecessors who have already acted and in the second line they can see the probability assessment of their immediate predecessor. The third line does not contain any information and is only intended for future extensions of the design. Note that participants only observe the probability assessment of their immediate predecessor once it's their turn to submit a probability judgment.

In this example the player decided to purchase a private signal, which is revealed at the top of the window. In the upper part of the window one can see the sliding bar used to input the probability judgment. The payoffs for either state A or state B are displayed below the sliding bar and are updated according to the quadratic scoring rule with every alternation of the slider. The interactive design gives subjects the opportunity to observe the payments associated with different probability judgments. This helps them to understand that their probability judgment can be considered a gradual bet on the more likely state. Instead of betting on one of the states (like in the experiments by Kraemer, Nöth and Weber 2001), subjects can express their degree of confidence in both states. The greater their confidence in one of the two states, the more they earn if their guess is correct but the less they earn if they are wrong. The quadratic formula for the division of payments between the two states is one way to ensure that the payment method provides an incentive to honestly communicate the true beliefs. Since subjects can observe the change in payments with every change of the slider, they can furthermore get a feeling in which range the change in payments is most sensible. This helps them to understand in which cases they should acquire additional information and in which cases they should not.

88 subjects participated in the experiment at the University of Mannheim in January 2001. The participants, all of whom studied business administration at that time, were split between the different cost (LC and HC) treatments. In total 42 subjects participated in the LC treatment and 46 in the HC treatment. The quality (LQ and HQ) was varied within subjects. To avoid ordering effects, 20 of the 42 participants in the LC treatment played the LQ treatment in the first half of the rounds and the HQ treatment in the second half. The other 22 subjects first played the HQ treatment and then the LQ treatment. In the HC treatment 22 subjects started with the LQ treatment followed by the HQ treatment, whereas 24 subjects first played the HQ treatment followed by the LQ treatment.[5] All experiments consisted of 50 rounds and lasted about one hour.

		Signal cost (across subjects)	
		35 cu (LC)	45 cu (HC)
Signal quality (within subjects)	60%/80% (LQ)	**LCLQ** (20 subjects in the first 25 rounds; 22 subjects in the last 25 rounds)	**HCLQ** (22 subjects in the first 25 rounds; 24 subjects in the last 25 rounds)
	70%/80% (HQ)	**LCHQ** (22 subjects in the first 25 rounds; 20 subjects in the last 25 rounds)	**HCHQ** (24 subjects in the first 25 rounds; 22 subjects in the last 25 rounds)

Table 1: Treatments.

The earned currency units were converted to Deutsche Mark (DM) at the end of each experiment such that subjects receive an expected payment of DM 16.00 per hour, which was about US$ 8.00 then. Participants knew in advance, that their expected earnings would be 16 DM per hour and they knew the approximate time for the experiment, but they did not know the exact conversion formula from currency units to DM nor the number of rounds to be played. Nevertheless they knew that the conversion formula would convert the currency units to DM at a fixed rate, which meant that their payoff did not depend on the performance of the other subjects and that maximizing the amount of earned currency units was equal to maximizing their payoff at the end of the experiment. Subjects earned on average DM 15.6 for one hour, ranging from DM 11 to DM 19.

5 We looked at possible ordering effects, but couldn't find any. Therefore we pooled the data of those subjects who participated in a specific quality treatment in the first 25 rounds and those who participated in this treatment in the last 25 rounds whenever we looked at specific treatment variable combinations, for example LCLQ.

Prior to the start of the experiment participants had the opportunity to get to know the experiment in three unpaid test rounds. During the test rounds subjects could ask questions regarding the experimental design and procedures.

II. Results

In the following chapter we will first present some general results followed by an analysis of the effects of a variation in the signal's cost, the signal's quality and the decision position. Thereafter we will look at the updating behavior of subjects. This leads to a model, which explains the observed acquisition behavior by considering subjects' information weighing and random errors. Subsequently, we look if subjects behave differently when they face human players rather than computer players. Finally, the effect of the observed behavior on welfare and on the aggregation of information is investigated.

General results

The 88 subjects submitted a total of 4400 (= 88 subjects * 50 rounds) signal acquisition decisions and probability assessments. In accordance with the findings in Kraemer/Nöth/Weber (2001) and Kübler/Weizsäcker(2001), we found that participants on average overestimate the signal value and acquire more signals than a rational Bayesian individual. Even though subjects know that their counterparts are fully rational, they acquired almost twice as many signals (2606 instead of 1388 rational signal acquisitions). Subjects purchased a signal in 1364 cases even though the signal's value was lower than its cost and only refused to buy a signal in 146 cases, in which a signal purchase would have been rational. On average they acquired 0.592 signals per round. A rational individual would have acquired only 0.316 signals per round.[6]

Looking at the average signal acquisition frequencies depending on the predecessor's probability assessment p_{i-1}, reveals subjects' demand for signals given gratuitous information of different quality. The individual signal acquisition ratio for a given subject equals the subject's relative frequency of a signal purchase when p_{i-1} was in the given interval. Figure 4 illustrates the result for the LCLQ ("**L**ow **C**ost, **L**ow **Q**uality") treatment. We only present the graph for this specific treatment here, since the qualitive features of subjects' acquisition behavior are equal across all treatments. This can be verified by looking at figures 5 and 6, which contain the signal acquisition frequencies in the other treatments.

[6] These findings contradict the explanation for the non-rational signal acquisitions provided by Kübler and Weizsäcker (2001).

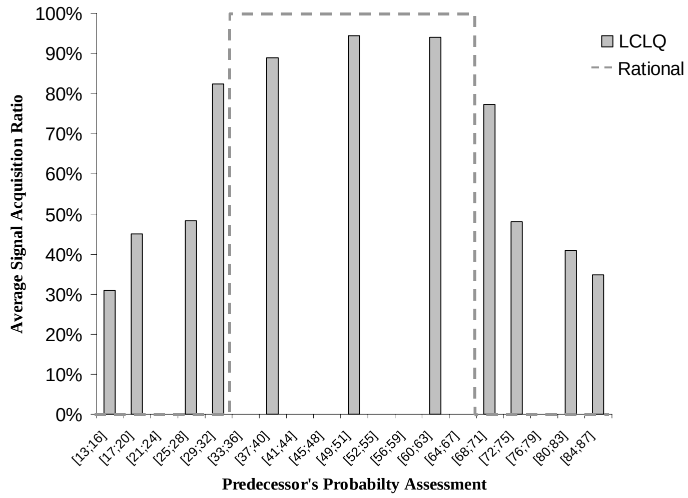


Figure 4: Distribution of signal acquisitions

Figure 4 indicates, that demand for information decreases gradually when the probability p_{i-1} approaches 0% or 100%. Remember, a rational individual would have acquired a signal whenever the predecessor's probability p_{i-1} was within the range *[29%;71%]*, further labeled the "rational" range, and none outside of that range, which is depicted by the dotted line in the graph. Even though a signal acquisition is not rational when $p_{i-1} \notin [29\%;71\%]$ the demand for information is strictly greater than 0 in those cases. Inside the "rational" interval *[29%;71%]* the signal acquisition frequency also decreases when the probability approaches the edges of the interval, thereby contradicting the rational prediction. Looking at the first and last third of the rounds reveals, that the acquisition behavior is constant over. There seems to be no significant learning effect.

These first results embody "good" and "bad" news. The "good" news is that behavior seems to be sensitive to different base rates, represented by the predecessor's probability assessment. The "bad" news is that subjects do not stop to acquire private signals when the value of such information drops below its cost, as would have been rational. Instead the likelihood of an information acquisition decreases gradually as the private signal becomes less valuable. Since the predecessors are rationally simulated by the computer, the probabilistic demand for information can only be explained if errors at the individual level are considered. Errors of predecessors cannot explain the observed behavior. Risk aversion can also not explain the observed behavior since risk aversion reduces the signal value, and therefore would lead to less and not more signal acquisitions than in the case of rational and risk-neutral individuals.[7]

[7] We ran sample calculations showing that both, constant absolute and constant relative risk aversion, reduce the signal value.

Influence of cost and quality

Now we want to take a look at how individual's behavior is influenced by a variation in the treatment variables cost and quality. First, we analyze whether an increase in the information‘s cost reduces demand for information. In order to do so, we compared the average signal acquisition ratios of the LCLQ and HCLQ treatments as well as the average signal acquisition ratios of the LCHQ and HCHQ treatments. Figure 5 illustrates the results.

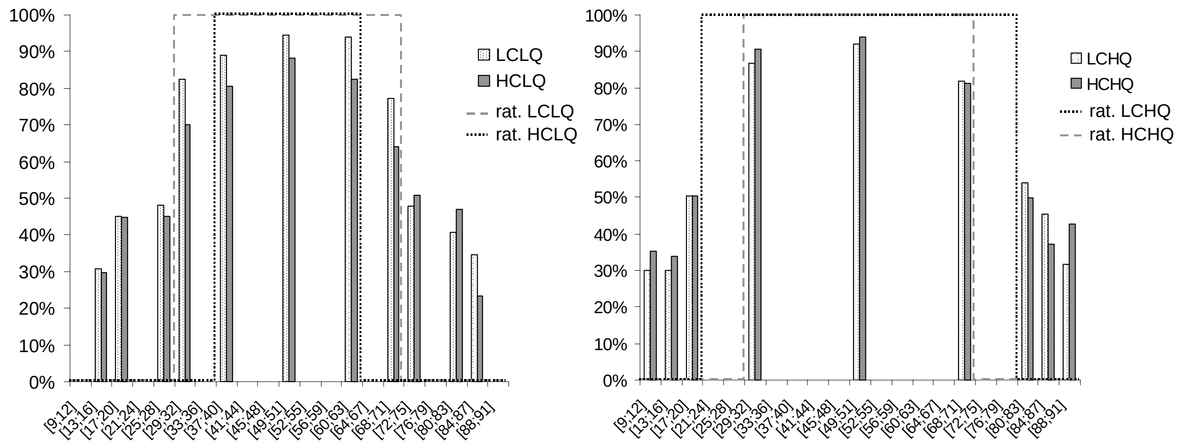
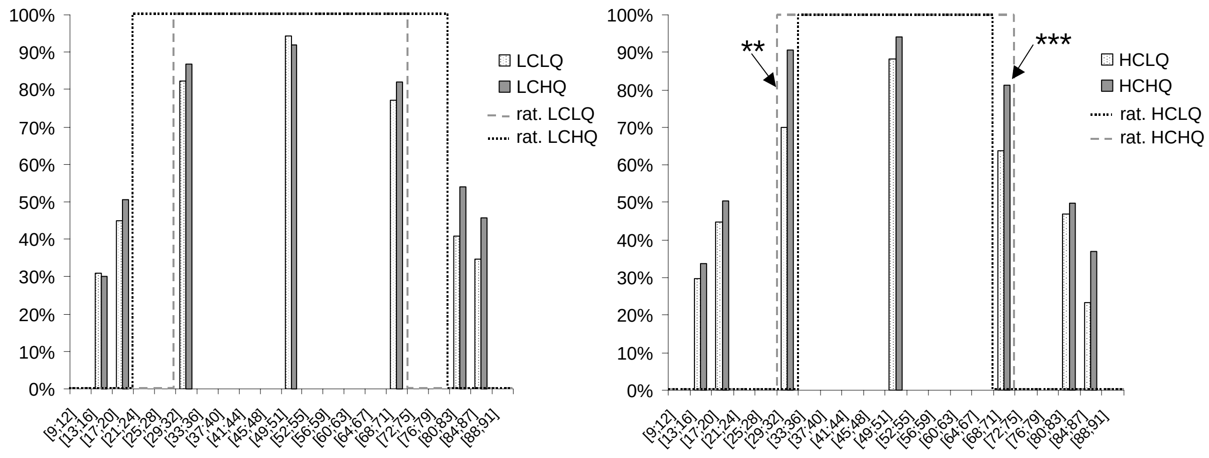


Figure 5: Influence of an increase in the cost of information

In the LQ treatment average demand for information is lower in 9 of 11 intervals if the information is of high cost. Based on a binomial test demand for information is therefore significantly smaller if its cost is higher ($p = 0.0325$). On the other hand, an increase in the signal's cost in the HQ treatment seems to have no significant influence on the demand for information as can be seen in the right graph of figure 5. This rather surprising result may be attributed to the fact, that even though the cost of the information was varied by more then 30%, this variation may not have been enough to cause significant changes in behavior. Especially since the information was of high quality and therefore subjects may not have viewed the signal as overpriced due to its high quality. Another view is that the increased cost might not have influenced the acquisition behavior in general but only in certain cases. For example, acquisition might have been influenced in those intervals, in which the variation in the signal's cost led to different rational predictions. In the LQ treatment this was the case, e.g. in the interval *[29%;32%]*, and in the HQ treatment, e.g. in the interval *[21%;24%]*. In the HQ treatment we didn't observe any signal acquisition decisions within these intervals, because all computer simulated predecessors acted fully rationally and no signal combination led to a preceding probability within this range. Hence, a potential change in behavior in these cases could not be observed. Nevertheless in the LQ treatment we have observations in the intervals *[29%;32%]* and *[68%;71%]* but the differences observed there are not statistically significant according to a T-Test.

The influences of a variation in the signal's quality can be observed in figure 6.



**: Difference significant at a 5% level according to T-test
***: Difference significant at a 1% level according to T-test

Figure 6: Influence of a variaration in signal's quality

In the LC treatment the average signal acquisition frequency is higher in 5 of the 7 intervals if the quality of the weak signal is better, which is not statistically significant according to a binomial test. The same argument as above might explain why we didn't observe any significant differences. Either subjects viewed signals of low and of high quality as equally attractive due to the low cost or behavior was only influenced in situation in which the rational prediction differs but no observations could be made in these cases.

Other than in LC treatments, the right graph in figure 6 illustrates that in the HC treatments the average demand for information is higher in all intervals if the information is of high quality. This means, demand for information is significantly higher if the information is better according to a binomial test on a 1% level (p = 0.008). In addition, demand for information is significantly higher in the intervals, in which the increased quality also leads to a shift in the rational prediction (*[29%;32%]* and *[68%;71%]*). Hence, demand for information seems to be sensitive to changes in the signal's quality especially when the information is more expensive.

In conclusion we can say that behavior seems to be influenced by a variation in the treatment variables, even though not always significantly. Significant changes in behavior can be observed if the signal is either expensive (HC) or of low quality (LQ). In the other cases the parameter, which is held constant might compensate for the variation in the other parameter. This means, reducing the quality from high to low in the "**L**ow **C**ost"-treatment might not induce a shift in behavior because the signal is considered "cheap" in both cases.

Equivalently, making the signal more expensive in the "**H**igh **Q**uality"-treatment might not influence behavior since the quality of the signal is high in both cases.

The position puzzle

Looking at the information acquisition behavior at different decision positions in the sequence reveals a puzzling finding. Figure 7 shows that demand for information decreases with the decision position in cases in which a signal acquisition is not rational. In cases in which the signal's value was higher than its cost, the decision position seemed to have no influence on the acquisition behavior. From a rational point of view it makes no difference if a subject faces a fixed probability p at position 2 or position 6. If all information is aggregated using Bayes' law, then the probability p is just as informative at position 2 as it is at position 6. Nevertheless, as the figure indicates, subjects seem to attribute different degrees of informativeness to probabilities within the non-rational range and hence different needs for additional information if they decide at different positions in the sequence.

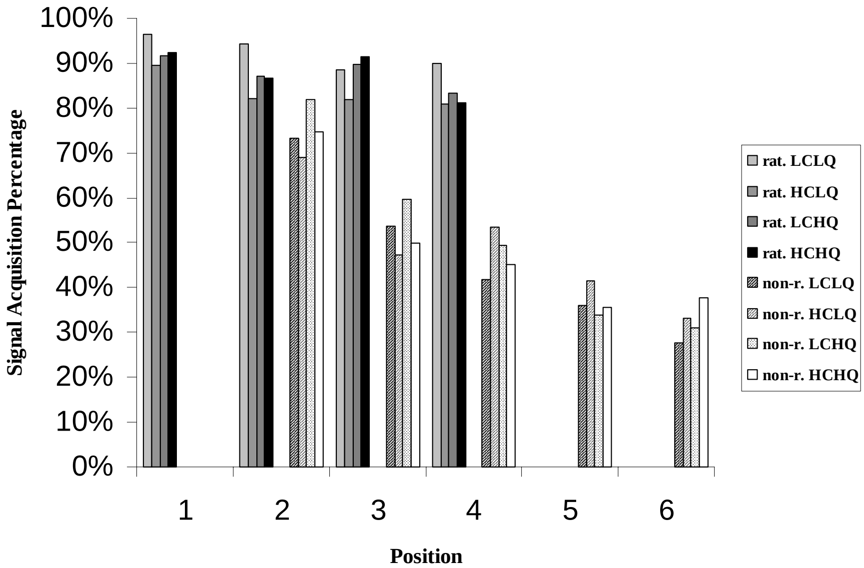


Figure 7: Demand for information depending on the decision position

A signal acquisition at positions 5 and 6 was never rational, because the preceding rational information aggregation process always led to a probability outside the "rational" acquisition range. Therefore we cannot compute signal acquisition percentages there. At position 1 a signal acquisition was always rational, so that we do not observe any acquisition decisions in the "non-rational" acquisition range.

One might argue that the observed decrease in demand for information in the "non-rational" range can be explained as follows. If the predecessor's probability assessment is within the "non-rational" range, then it is more likely to be close to the extreme values 0 or 1 if observed later in the sequence. This is due to the fact that the aggregation process leads to a convergence of the probability towards the drawn state of nature, making it more likely to observe extreme values later in the sequence. Together with the continuously decreasing likelihood of a signal acquisition when the predecessor's probability approaches 0 or 1, as shown in figure 4, this would lead to a decreasing average demand for signals within the "non-rational" range. But if we look at the average signal acquisition ratio across different positions when the predecessor's probability was exactly 80% for one of the two states, one can see that this is not the explanation for the position puzzle.[8] By looking at the acquisition behavior based on a specific predecessor's probability assessment, identical situations in terms of rational signal value at different positions in the sequence are compared. Note that a signal acquisition is never rational in this case across all treatments. Figure 8 displays the results. We pooled the observations from the different cost and quality treatments, because acquisition frequencies at different positions were almost identical in this case.

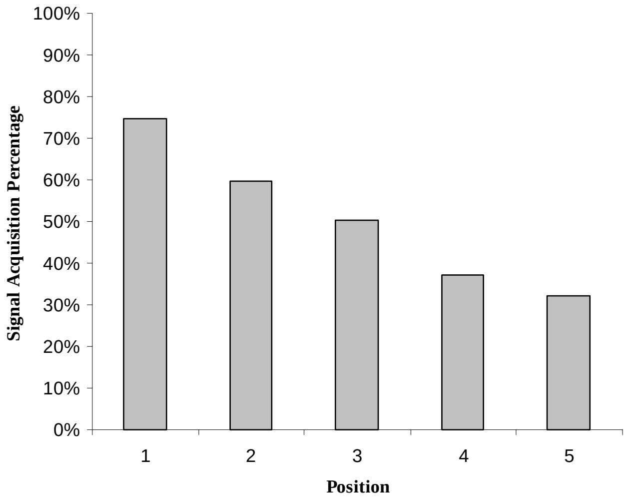


Figure 8: Demand for information if predecessor's probability is 20% or 80% for state A.

The graph clearly indicates that demand for information decreases as the position increases, indicating that subjects indeed behave differently if they face the same probability assessment earlier rather than later in the sequence.

An explanation might be that subjects interpret a probability differently if they are at different positions. Participants might view a probability observed at a later position as a "better" in terms of more informative probability due to the fact that more predecessor's were involved in forming the probability statement. They assume that the latter in the sequence they are, the more signals were purchased by their predecessors. And from their point of view

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8 We chose 80% for two reasons. First, a signal acquisition is not rational in this case, so that these observations are in the "non-rational" range. Second, whenever the computer simulated player at position 1 gets a strong signal a predecessor's probability of 80% for one of the two states is observed at all subsequent positions. Since the probability of getting a strong signal is 0.5 this situation occurred frequently in the experiment.

more signal means a more informative probability judgment. Hence, the weight and not only the implications of the information, as would have been rational, influences their behavior.[9]

An alternative explanation for the puzzle if subject had faced other human players[10] might be that subjects sacrifice individual utility in order to invest in a public good, so that successors can take advantage of the improved information level. This can be rational in the supergame, because subjects take into account that due to the random ordering, they will probably be acting late in the sequence in later rounds, too. In this case they would also benefit from predecessors who invested in the public good. Since subjects know that the later they are in the sequence the less players will follow, their willingness to overinvest in information diminishes if they act at positions more towards the end of the round. But this explanation is not applicable here, because the human player knows that the rational computer simulated predecessor will not overinvest in information.

Subjects' updating behavior

We now take a look at subjects' updating behavior to see whether their way to process information can explain some of the non-rational acquisition behavior we observed. If subjects updating is biased their calculation of the signal's value might as well be biased if the calculation is based on the same non-rational information processing. In order to calculate the subjective information value subjects have to anticipate their way of dealing with a possibly purchased piece of information. If the anticipated updating behavior contains a bias then the subjective signal value is biased, too.

Kraemer, Nöth and Weber (2001) argued that conservatism regarding the information received from predecessors can explain the excessive signal purchases observed in their experiment. Generalizing, one could say that their explanation for the non-rational signal acquisitions is an overweighing of the private information relative to the free information received from predecessors. In order to measure the weights that subjects put on different sources of information we regressed the weights using a model first proposed in Edwards (1968). We modified the model so that it accounts for different weights put on the different sources of information. Let s_i denote the private signal of the individual at position i and let p_{i-1} denote the probability of state A submitted by her immediate predecessor. Then the a posterior odds of state A in favor of state B after observing the predecessor's probability assessment and the signal are given as:

[9] See Keynes (1921) for this interpretation of ambiguity.

[10] And indeed, we found the same position effect when we ran the experiment with 6 human players. See chapter "Human vs. computer simulated counterparts".

$$\frac{p(A \mid p_{i-1}, s_i)}{p(B \mid p_{i-1}, s_i)} = \left(\frac{p_{i-1}(A)}{p_{i-1}(B)}\right)^c \cdot \left(\frac{p(s_i \mid A)}{p(s_i \mid B)}\right)^d \qquad \text{with } s_i \in \{a_W, a_S, b_W, b_S\} \qquad (2\text{-}1)$$

The odds depend on the different sources of information. c represents the weight that subjects put on the probability assessment of their predecessor, whereas d represents the weight that participants assign to their costly signal. Setting c = 1 and d = 1 leads to the rational Bayesian' odds. c < 1 or d < 1 means that subjects underweight the specific source of information and c > 1 or d > 1 represents an overweighing of the information. Taking logs on both sides of (2-1) and generalizing leads to:

$$ln\left(\frac{p_i(A \mid p_{i-1}, s_i)}{p_i(B \mid p_{i-1}, s_i)}\right) = a + c \cdot ln\left(\frac{p_{i-1}(A)}{p_{i-1}(B)}\right) + d \cdot ln\left(\frac{p(s_i \mid A)}{p(s_i \mid B)}\right) + u_i \qquad (2\text{-}2)$$

Since we can observe the subjective log odds $ln\left(\frac{p_i(A \mid p_{i-1}, s_i)}{p_i(B \mid p_{i-1}, s_i)}\right)$, the predecessor's subjective log odds $ln\left(\frac{p_{i-1}(A)}{p_{i-1}(B)}\right)$ and the signal's log odds $ln\left(\frac{p(s_i \mid A)}{p(s_i \mid B)}\right)$ we can estimate the model by OLS regression for each subject. We assume that u_i is normally distributed.

As a result we get an average c of 0.77 and an average d of 1.17. The difference between c and d is statistically significant (*T-Test; T = -6.204; p < 0.001*) as well as both values are significantly different from 1 (*c: T = -5.057; p < 0.001; d: T = 3.106; p = 0.003*). Hence, the regression provides evidence, that subjects exhibit a tendency to overweight their private signal and underweight the free information, conforming to the explanation provided in Kraemer, Nöth and Weber (2001).

A random utility model

Even though we found evidence that subjects overweigh their private signals relative to the gratuitous information, this finding cannot explain why subjects do not follow the rational deterministic behavior, which predicts a signal acquisition whenever the free information is within a specific range and no signal acquisition if it's outside of that interval. Instead, as we have shown above, demand decreases gradually as the quality of the free information increases, i.e. demand for information is probabilistic. The idea of probabilistic demand can be captured if we model subjects behavior using logistic response functions to determine the choice probabilities. By doing so, we incorporate random errors into subjects' behavior, assuming these errors are logistically distributed. The resulting model is an application of the quantal response models introduced by McKelvey and Palfrey (1995 and 1998) to the given individual decision problem. We will first estimate a model incorporating solely random errors as a reason for deviations from rational behavior. Later we will return to the idea that biased information weighing affects subjects' behavior and try to unite both, random errors and private information overweighing, in one model.

Our model is based on two assumptions. First, we assume that subjects consider all predecessor as being fully rational. This assumption is reasonable, because subjects know that the computer acts rationally. Second, we have to assume that people are perfectly Bayesian whenever they acquire a private signal and update the free information based on this signal. We will relax this assumption later.

These assumptions lead to the following choice function, describing the probability of a signal purchase as a logit model with the two options Acquisition and No-Acquisition and the error parameter μ:

$$p(\,Acquisition \mid p_{i-1}\,) = \frac{e^{\mu \cdot \pi_{Acq}(\,p_{i-1}, s_i\,)}}{e^{\mu \cdot \pi_{Acq}(\,p_{i-1}, s_i\,)} + e^{\mu \cdot \pi_{No-Acq}(\,p_{i-1}\,)}} \tag{2-3}$$

$\pi_{Acq}(p_{i-1},s_i)$ denotes the expected value of a decision based on a private signal s_i and the predecessor's probability assessment p_{i-1}. Analogously, $\pi_{No\text{-}Acq}(p_{i-1})$ denotes the expected value of a decision based solely on the free information p_{i-1}. The error parameter μ determines the amount of random errors committed by the subjects. The larger μ, the lesser subjects' behavior is affected by random errors, i.e. behavior becomes more rational. As μ approaches infinity, the choice probabilities approach the perfect Bayesian choice probabilities. On the other hand, when μ approaches 0 the probability of buying a signal approaches 0.5, i.e. behavior becomes random.

Simple transformation of the choice function leads to:

$$p(\,Acquisition \mid p_{i-1}\,) = \frac{1}{1+e^{-\mu\cdot(\pi_{Acq}(\,p_{i-1},s_i\,)-\pi_{No-Acq}(\,p_{i-1}\,))}} \qquad \text{(2-4)}$$

A maximum likelihood estimation of μ led to the following results:

Treatment	μ	% of observations explained by random utility model	% of observations explained by rational model
LCLQ	0.0670019	83.9%	70.19%
HCLQ	0.0174185	83.74%	63.04%
LCHQ	0.055786	89.52%	64.48%
HCHQ	0.0301699	89.3%	65.3%

Table 2: Logit-regression results.

The total number of signal purchases given a predecessor's probability assessment predicted by the two models is the total number of observations multiplied by the probability of a signal purchase provided by the model. Then, the number of observations not predicted by the model is calculated as the absolute difference between the number of observed and predicted signal acquisitions. The sum of all differences for all possible predecessor's probabilities results in the total number of observations not explained by the model.

Figure 9 illustrates the observed relative frequencies of a signal purchase depending on the probability assessment of the predecessor and the random utility probability of a signal acquisition based on the estimated μ in the LCLQ treatment.[11]

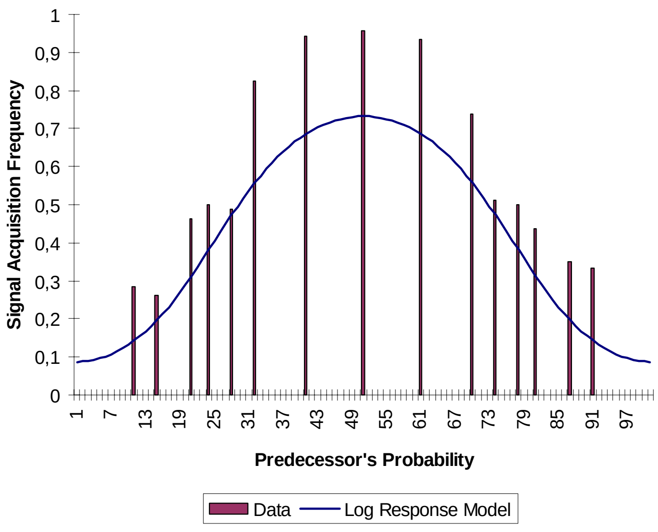

Figure 9: Observed signal acquisitions and random utility model probabilities (basic model, LCLQ treatment).

[11] Analogous graphs for the other treatments are provided in Appendix D.

Figure 9 shows that opposed to the rational model the random utility model is indeed able to explain the gradual decrease in demand for information as the quality of the free information increases. What can also be seen from the figure is that the random utility model underestimates the relative acquisition frequencies. This is also true for the other treatments.

A joined model of random utility and overconfidence

The analysis of the subjects' updating behavior revealed that participants have a tendency to underweight the predecessor's probability and overweight their own private signal. It seems reasonable to assume that this also affected subjects' demand for information since a relative overweighing of private information induces higher subjective information values. The model we will present now assumes that subjects commit random errors when deciding whether to acquire additional private information and are overconfident when updating the free information according to a possibly purchased signal. The following figure illustrates the two stage nature of the decision problem and the assumed biases in each step.

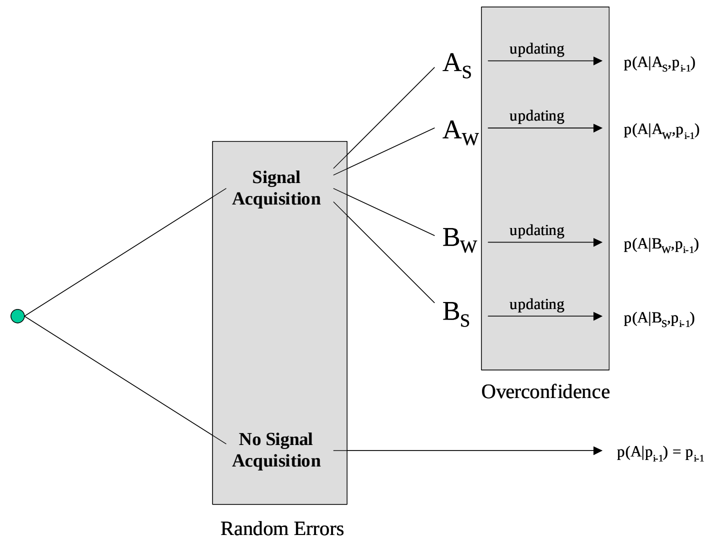

Figure 10: Two-stage decision problem

We try to incorporate overconfidence into the above presented model of random utility by assuming that a subject's judgment about the probability of the state indicated by their private signal is equal to the rational a posterior probability of the signal state plus a constant Δ:

$$p_{biased} = p_{rational} + \Delta \tag{2-5}$$

Note that $p_{rational}$ always represents the probability of the state indicated by the private signal, so that adding a constant means that subjects consider the signal's state to be more likely than rational. This would be the result of an overweighing of the private signal.

From our point of view the additive term formalizes the idea of overweighing of private information and improves the model's accuracy by incorporating a systematic bias at the updating level rather than just assuming random errors there as well. We hypothesize that a systematic bias in the updating process captures the errors committed by people in these kinds of decision problems much better than just assuming people commit random errors.

Using the biased a posterior probabilities, the biased subjective benefit from acquiring additional private information can be calculated. The added Δ increases the value of a decision based on an additional private signal and therefore increases the difference in expected value between a decision with and without a costly signal. Let $\pi_{Acq}*(p_{i-1},s_i)$ be the subjective expected value of a decision based on a private signal s_i and the predecessor's probability assessment p_{i-1}, which incorporates an overweighing of the signal measured in terms of Δ as defined above. Then some algebra leads to:

$$\pi_{Acq}*(p_{i-1},s_i) - \pi_{No\text{-}Acq}(p_{i-1}) = \pi_{Acq}(p_{i-1},s_i) + \Delta\cdot(4+0.1\cdot\Delta) - \pi_{No\text{-}Acq}(p_{i-1}) \qquad (2\text{-}6)$$

Substituting $\pi_{Acq}(p_{i-1},s_i) - \pi_{No\text{-}Acq}(p_{i-1})$ by $\pi_{Acq}*(p_{i-1},s_i) - \pi_{No\text{-}Acq}(p_{i-1})$ in the simple random utility model leads to:

$$p(\,Acquisition \mid p_{i-1}\,) = \frac{1}{1+e^{-\mu\cdot(\pi_{Acq}(\,p_{i-1},s_i\,)+\Delta\cdot(\,4+0.1\cdot\Delta\,)-\pi_{No-Acq}(\,p_{i-1}\,))}} \qquad (2\text{-}7)$$

A maximum likelihood estimation of the joined model of random utility and overconfidence yields the following results:

Treatment	μ	Δ	% of observations explained by joined random utility model	% of observations explained by simple random utility model	likelihood ratio test
LCLQ	0.0983815	2.371930755	95.33%	83.9%	<0.001
HCLQ	0.076047	4.233971259	96.35%	83.74%	<0.001
LCHQ	0.0624972	1.978375022	96.29%	89.52%	<0.001
HCHQ	0.0660138	3.889389777	95.48%	89.3%	<0.001

Table 3: Regression of joined model.

Table 3 indicates that by incorporating overconfidence the joined model is able to explain the data much better than the simple model. The additional parameter significantly increases the fit of the model as indicated by the likelihood ratio test. Figure 11 illustrates the observed relative frequencies of a signal acquisition and the probabilities of a signal purchase provided by the joined model in the LCLQ treatment.[12]

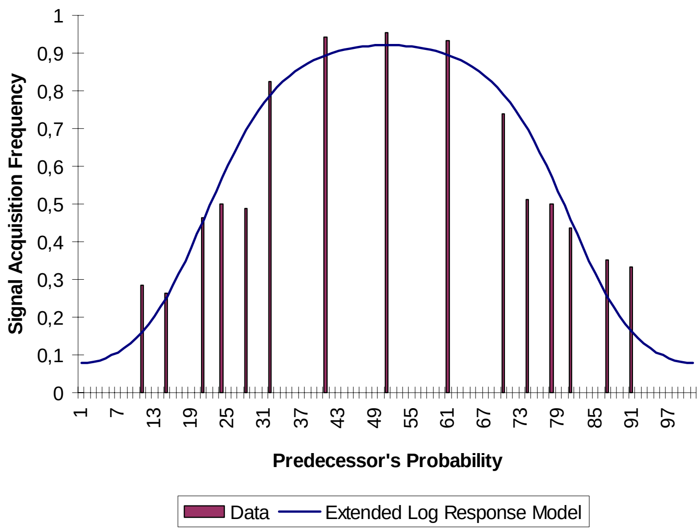

Figure 11: Observed signal acquisitions and random utility model probabilities (extended model, LCLQ treatment).

In conclusion we can say that the joined model, which captures both the idea of overweighing of private information and random errors in the signal purchase decision explains most of the decisions we observed in the experiment.

Human vs. computer simulated opponents

At this point one might argue that subjects would have acted completely differently if they had faced 5 other human players instead of 5 computer simulated players. Other human players can commit errors which in turn might influence the behavior of subsequent individuals.[13] To verify this assumption we ran a HO ("human opponents") treatment, in which 6 human players played the game described above. In doing so, we tried to investigate the influences of possible non-rational behavior of counterparts on the acquisition and updating decisions. Since we were only interested in the implications of potential irrationalities by other players we did not vary the cost and quality of the signals in the HO treatment but only used the low cost and low quality combination (LCLQHO: "**L**ow **C**ost, **L**ow **Q**uality, **H**uman **O**pponents"), so that behavior can be directly compared to the

[12] Analogous graphs for the other treatments are provided in Appendix E.

[13] This is an assumption made when estimating quantal response models in cascade experiments which incorporate quantal choice probabilities from predecessors to determine ones own choice probability. See Anderson and Holt (1997) and Kübler and Weizsäcker (2001) as an example.

LCLQCO ("**L**ow **C**ost, **L**ow **Q**uality, **C**omputer **O**pponents") treatment described above.[14] We ran 10 sessions of the LCLQHO treatment, leading to a total of 60 participants. Each session of the LCLQHO consisted of at least 22 and not more than 35 paid rounds and lasted about two hours. Participants earned on average DM 31.3 for two hours, varying between DM 21 and DM 40.

Table 4 illustrates the acquisition behavior in the LCLQCO and LCLQHO treatments.

		LCLQHO n = 1656	LCLQCO n = 1050
Rational	# rational signal acquisitions	799	379
	Rational signal acquisitions per round and subject	0.483	0.361
Observed	# non-rational signal acquistions	360	285
	# refused rational signal acquisitions	73	28
	# signal acquisitions	1086	636
	Signal acquisitions per round and subject	0.656	0.606

Table 4: Signal acquisition behavior in LCLQHO and LCLQCO treatments.

The average number of signals acquired per round and subject are almost identical in both treatments. Nevertheless the percentage of non-rational signal acquisitions is higher (40%) in the CO treatment than in the HO treatment (26%), even though counterparts are known to be fully rational. The higher number of rational signal acquisitions per round and subject in the HO treatment can be attributed to the fact, that in the HO treatment non-rational behavior of predecessors, which drove the probability back within the "rational" range led to an increased number of rational signal acquisitions.

Figure 12 illustrates the average individual signal acquisition ratio depending on the predecessor's probability assessment for state A p_{i-1} in the LCLQHO and LCLQCO treatments and the rational signal acquisition frequencies.

[14] The only difference between the CO and the HO treatment was a slightly different scoring rule used to determine the payments. Nevertheless both scoring rules lead to identical signal values, and therefore should not have influenced subjects behavior. All other parameters were identical.

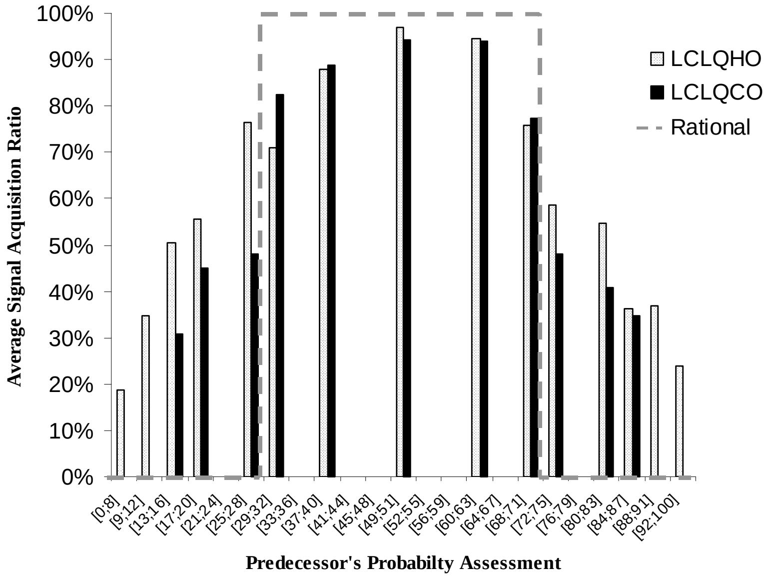

Figure 12: Distribution of signal acquisitions

In LCLQCO treatment we have no observation in the intervals [0%;8%], [9%;12%], [88%;91%] and [92%;100%] because rational behavior of the predecessors never led to a probability within these intervals.

In total, the average signal acquisition ratio in the HO treatment is higher than that in the CO treatment in 8 of 11 intervals, which is not statistically significant according to a binomial test. Demand for information outside the "rational" interval *[29%;71%]* is higher if subjects face human counterparts, than if they interact with perfectly rational computer players (p = 0.0155; Binomial test). Nevertheless the differences in signal purchase frequencies are small and mostly insignificant.

In conclusion we can say, that influences from potential irrationalities of other players are rather small. The percentage of non-rational signal acquisitions is even greater when subjects face computer players (See table 4). Looking at the signal acquisitions given different predecessor's probability assessments reveals that behavior is only affected in situation, in which a signal acquisition is not rational. Nevertheless these influences are also small. Even if subjects face perfectly rational counterparts, demand for information in the "non-rational" range is substantially greater than zero. The tendency of a decreasing demand for information as the quality of the free information increases is present in both, the CO and the HO treatments, as well. Redoing all the other analysis for the HO treatment reveals, that the numbers are almost equal. E.g., the average weights that subjects address to the different sources of information in the HO treatment are c = 0.77 and d = 1.2, which is almost the same as in the CO treatments (c = 0.77; d = 1.17). This means, subjects do not weigh probability assessments of predecessors differently when predecessors are human, and hence only boundly rational, than if they are perfectly rational.

This result might seem rather surprising in the first place. But we argue, that it is mainly driven by the features of the sequential aggregation process found in cascade experiments. In these types of aggregation processes subjects are presented with information, which is a result of the actions of their predecessors. At that point subjects can take into account non-rational behavior by others, but they don't have to. This is different from most games. In games ones own payoff depends on the actions taken by others, so that it is necessary to think about what others think, about what others think one thinks, etc. In sequential aggregation processes found in cascade experiments, ones own payoff does NOT depend on the actions taken by others. Actions of others only affect the information provided free of charge, thereby only indirectly affecting ones own actions. Since actions are only affected indirectly, thinking about limited rationality of others is optional rather than mandatory.

Welfare and Information aggregation

Finally, we want to take a look at the implications of the observed behavior on welfare and the aggregation of information.

Treatment	# Currency units earned	# CU earned if rational	# Signal acquisitions	# Signal acquisitions if rational
HO	2,144,321	2,137,628	1086	799
CO	3,646,874	3,712,887	2606	1388

Table 5: Welfare results.

Table 5 indicates that the total payment deviated only slightly from what would have been paid if all subjects had acted rationally. Nevertheless in both treatments participants purchased much more private information. This raises the question whether the excessive signal acquisitions led to an increase in the information level and to a better revelation of the occurred state, thereby compensating the increased information costs. In order to analyze the aggregation of information, we take a look at the convergence of the probability assessment towards the occurred state. Therefore we took the probability submitted at position 6 in each round and transformed this probability to a probability for the state that actually occurred. Then we calculated the difference of this probability and 100%. The observed differences are then compared to the differences if all participants had acted rationally (denoted by “Rational” in figure 13) and to those if all participants had acquired a private signal and acted rationally upon this information (denoted by “Signal” in figure 13). To be able to directly compare the aggregation of information if only 1 human player (CO treatments) was involved to that when

6 human players participated in the experiment, we only looked at the convergence in the LCLQCO and LCLQHO treatments.[15] The hypothetical results from the “rational” and “signal” strategies were derived from observations in the LCLQCO treatment, because the outcomes derived from the LCLQHO treatment are alike.[16] Figure 13 illustrates the result.

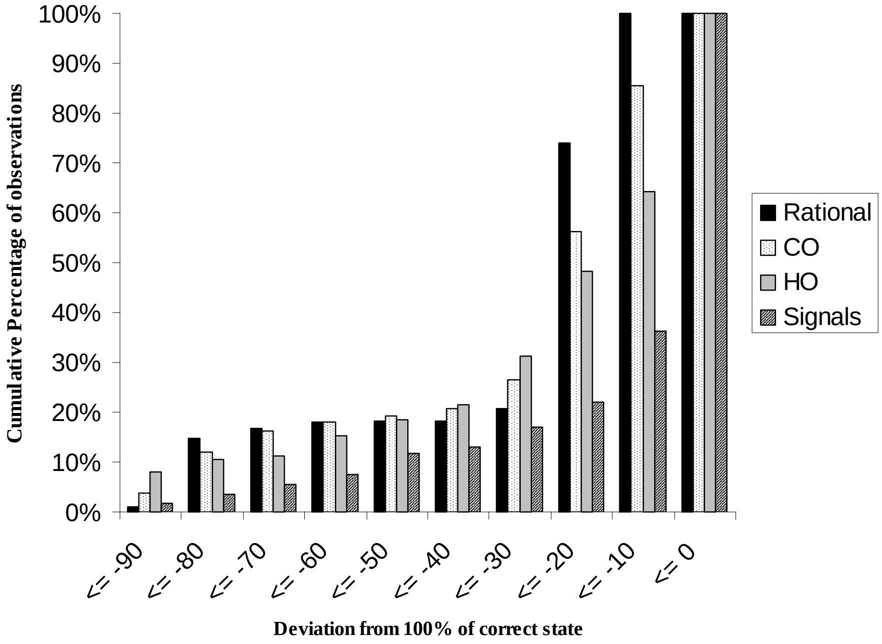

Figure 12: Convergence against the occurred state.

The cumulative distribution illustrates that the convergence in the HO and in the CO treatment was better than if all participants had acted rationally. In most cases the probability converges to the true state of nature, but on some occasions we observe a convergence to the wrong state, which is represented by the left hand side of the distribution in figure 13. Furthermore, there seems to be a close relationship between the amount of signals bought per round and the convergence towards the true state of nature. In the LCLQCO treatment there was one out of 6 players who on average acquired more signals than a rational Bayesian individual. This already led to a better convergence compared to the rational benchmark, as can be seen in figure 13. In the LCLQHO treatment all six participants on average exhibited a tendency to acquire an excess amount of information which resulted in an even better convergence than in the LCLQCO treatment. Finally, the “signal” strategy, where all players acquire a private signal in all cases, would have resulted in the best possible convergence

[15] The convergence observed in the other CO treatments was very similar to the one observed in the LCLQCO treatment.

[16] This is because the information structure and information cost is identical in the LCLQCO and LCLQHO treatments as well as the rational strategies are identical. Therefore the outcomes of both strategies are similar in both treatments.

given the information subjects would have received. The following table compares the average convergence for the different cases.

Treatment	Rational; average deviation	Observed; average deviation	Signal; average deviation	Difference Rat vs. Obs	Difference Sig vs. Obs
LCLQHO	30.09%	24.71%	14.87%	T = 2.947 (p=0.003)	T = 6.405 (p<0.001)
LCLQCO	29.87%	27.93%	17.07%	T = -3.623 (p<0.001)	T = -19.149 (p<0.001)
Difference LCLQHO vs. LCLQCO		T = 1.705 (p=0.089)			

Table 6: Convergence to the occurred state.

The numbers support what we have stated above. The average convergence was better in both treatments than if all participants had acted rationally but worse than if all had always purchased a private signal and updated their information using Bayes' law. Besides, the convergence was better if all participants in the experiment were human than if just one was human. Hence, the more players are willing to overinvest in information the better the information level and in turn the better the convergence.

III. Conclusions

We investigated an aggregation process with a continuous action space and two possible states of nature. We found that participants acquire significantly more signals than predicted by theory. Furthermore they seem to believe that the information communicated by their predecessor is more informative when they decide later in the sequence. Subjects do not realize that a signal purchase is not rational anymore when the quality of the predecessors information exceeds a certain threshold. Instead the demand for information gradually decreases as the quality of the predecessor's information increases, not reaching zero demand even if the computer simulated predecessor communicated almost perfect information.

The investigation of subjects' updating behavior provides evidence that subjects on average underweight the information submitted by their predecessor and overweight their own signal. Since deterministic theories fail to explain the probabilistic nature of demand observed in this experiment, we estimated a random utility model which describes the probability of a signal acquisition as a log response function. The results indicate that the random utility model fits the data much better than the rational Bayesian model and is able to explain the excess demand for information even when free information is of high quality. A model which takes into account both, random utility and biased information weighing is able to explain more than 90% of the acquisition behavior observed in the experiment.

Surprisingly, subjects' behavior seems to be influenced only slightly by the degree of rationality of their counterparts. Behavior is almost identical when subjects interact with rational computer simulated players than if they interact with other human players. Neither the acquisition behavior nor the updating of information provides evidence that errors committed by others play an important role.

In terms of information aggregation we can say that the excess signal acquisitions led to a better convergence to the occurred state than if all had been Bayesian individuals. Hence, the excessive demand for information on average had a positive influence on the information level.

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Appendix A: Instructions in the CO treatments

Sequential Information Processing Experiment Instructions

Thank you for your participation in this experiment of economic decision making. The money for your payment has been provided by the Deutsche Forschungsgemeinschaft. This session will probably last about one hour. Please follow the instructions very carefully, in order to earn as much money as possible. You can always ask questions until the end of the test rounds.

Information structure and course of a round

In this experiment you will participate in several rounds of a game.

The course of the experiment is as follows. At the beginning of each round a state of nature is determined. Two state, named A and B, can occur. Which one of the two states occurs is determined by a coin toss at the beginning of each round, i.e. both states are equally likely. You cannot observe which state actually occurred as well as all other players cannot do so.

Your task is to assess your subjective probability that state A or state B, respectively, occurred at the beginning of the round.

6 subjects participate in each round of the game and sequentially submit their probability assessments. You are the only human player. The other 5 players are simulated by the **computer**. **All** computer simulated players (this means **all** your counterparts) act perfectly rationally under the assumption of risk neutrality. This means, the computer simulated players do the same tasks as you do and act like a perfectly rational and risk neutral individual.

The ordering, in which participants submit their probability assessments is determined randomly in each round.

Information

One source of information for your probability assessment is the probability assessment of your immediate predecessor. This means, that once it’s your turn to assess the probability of the two states of nature, the computer first displays the probability assessment which your immediate predecessor submitted. Has your predecessor, e.g. stated a probability of 80% for state A, then she thinks that state A occurred with a probability of 80%. Note that this information is only displayed to you when it is your turn to submit your subjective probability. You receive this information **free of charge**.

In addition to that costless information you have the opportunity to acquire a costly private signal, which only you can see. Apart from the probability assessment of your predecessor this private signal gives you a hint which state occurred. Therefore the computer asks you if you want to acquire such a signal, **after** you have observed the probability assessment of your predecessor. Once the computer asks you whether you want to acquire a signal or not, the computer also displays the two different qualities the signal might possess and the cost of the signal. The signal can have two different qualities, either **weak** or **strong**. Weak signals are determined by a draw from the "weak" urn whereas strong signals are drawn from the "strong" urn. Under "quality" the computer displays the composition of the "weak" and the "strong" urn. The "weak" urn contains either 60% or 70% correct signals. The "strong" urn always contains 80% strong signals. The private signal will be determined depending on the occurred state and independently for each subject as follows:

- First, a fair coin toss ($p = \frac{1}{2}$) determines if the signal is **weak** or **strong**.
- The signal is now being determined, dependant on its strength, by a draw from an urn with 10 signals:
    - The "weak" urn contains either 6 signals (quality display: 60%/80%) or 7 signals (quality display: 70%/80%) indicating the occurred state and 4 resp. 3 signals indicating the opposite state. That means, the weak signal indicates the occurred state with a probability of *p = 60%* (resp. *70%*) and the opposite state with a probability of *p = 40%* (resp. *30%*).
    - The "strong" urn contains 8 signals indicating the occurred state and 2 signals indicating the opposite state. That means, the strong signal indicates the occurred state with a probability of *p = 80%* and the opposite state with a probability of *p = 20%*.

E.g. the computer asks you if you would like to buy a signal with the possible qualities 60%/80% for 35 currency units (cu). If you decide to do so then the at first a fair coin toss decides if you get a weak or a strong signal (you don't know which type of signal you will get once you decide upon the signal acquisition). If it should be a strong signal then the computer draws from an urn containing 8 correct and 2 false signals. Should the signal be of weak quality then the computer draws from an urn containing 6 correct and 4 wrong signals.

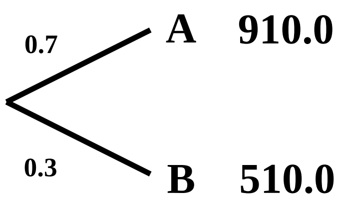
Take into account that the signal is not free of charge!

If you have decided to acquire a signal the computer displays the signal, as well as the accompanying strength of the signal. Afterwards you will be asked to submit your subjective probability for state A resp. state B based on all your information.

If you have decided not to acquire a signal then you have to submit your subjective probability for state A resp. state B immediately based on all your information.

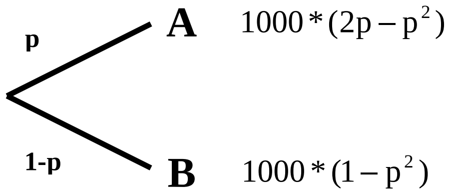
Take into account that the computer simulated players also acquire private information if it is rational to do so and that they rationally incorporate these signals into their probability assessments.

In order to submit your subjective probability you have to adjust the sliding bar according to your subjective probability and press the Ok-button. Underneath the sliding bar you can see the two possible payments corresponding to the probability adjusted on the sliding bar. You receive the payment in currency units (cu) indicated behind the upper branch if state A occurred at the beginning of the round and you receive the payment indicated behind the lower branch if state B occurred at the beginning of the round. If you acquired a signal then the signal cost will be subtracted from the amounts displayed. Example:



In this example the subject assessed a subjective probability of state A of 0.7. If state A in fact occurred then she receives 1910 cu. If state B occurred then she receives only 510 cu. If she bought a signal prior to her decision, 35 cu are subtracted from the amount displayed. Then she only receives 875 cu (910 cu – 35 cu) if state A occurred and 475 cu (510 cu – 35 cu) if state B occurred.

The displayed payments changes with every alternation of the sliding bar. The probabilities displayed at the branches equal the probability adjusted on the sliding bar. The payments for the two possible states of nature vary with the adjusted probability. The payments are determined such that you maximize your ex ante expected payoff if your subjective probability equals the adjusted probability. This means, that it makes no sense always submitting a probability of 0 or 1, depending on which state you think is more likely, but instead a truthful disclosure of your true subjective probability is the expected payoff maximizing strategy. The exact formulas for the payoffs are as follows:



A signal costs 35 cu. In the lower part of the program window you can observe how many Participants have already submitted their probability assessment. Your own decision position is indicated in red. As soon as all six participants have submitted their subjective probabilities, the occurred state will be announced and a further round (with new information) begins.

Test rounds

Before you can start earning money with your predictions, you will get to know the course of the experiment in three unpaid test rounds. During these test rounds you can always ask question about the information structure and the course of the experiment.

Payment

Your payment depends only on your own probability assessments and signal acquisitions. The behavior of the other subjects has no direct influence on your payment as well as your behavior has no direct influence on the payment of others. At the end of the experiment your total payoff will be converted in Deutsche Mark (DM) according to the expected hourly earnings of 16 DM.

Appendix B: Instructions in the HO treatment

Sequential Information Processing Experiment

Instructions

Thank you for your participation in this experiment of economic decision making. The money for your payment has been provided by the Deutsche Forschungsgemeinschaft. This session will probably last about two hours. Please follow the instructions very carefully, in order to earn as much money as possible. You can always ask questions until the end of the test rounds.

Information structure and course of a round

In this experiment you shall assess your subjective probability for a state of nature in each round based on your given information.

The course of the experiment is as follows. Two states, named A and B, can occur. Which one of the two states occurs is determined by a coin toss at the beginning of each round, i.e. both states are equally likely.

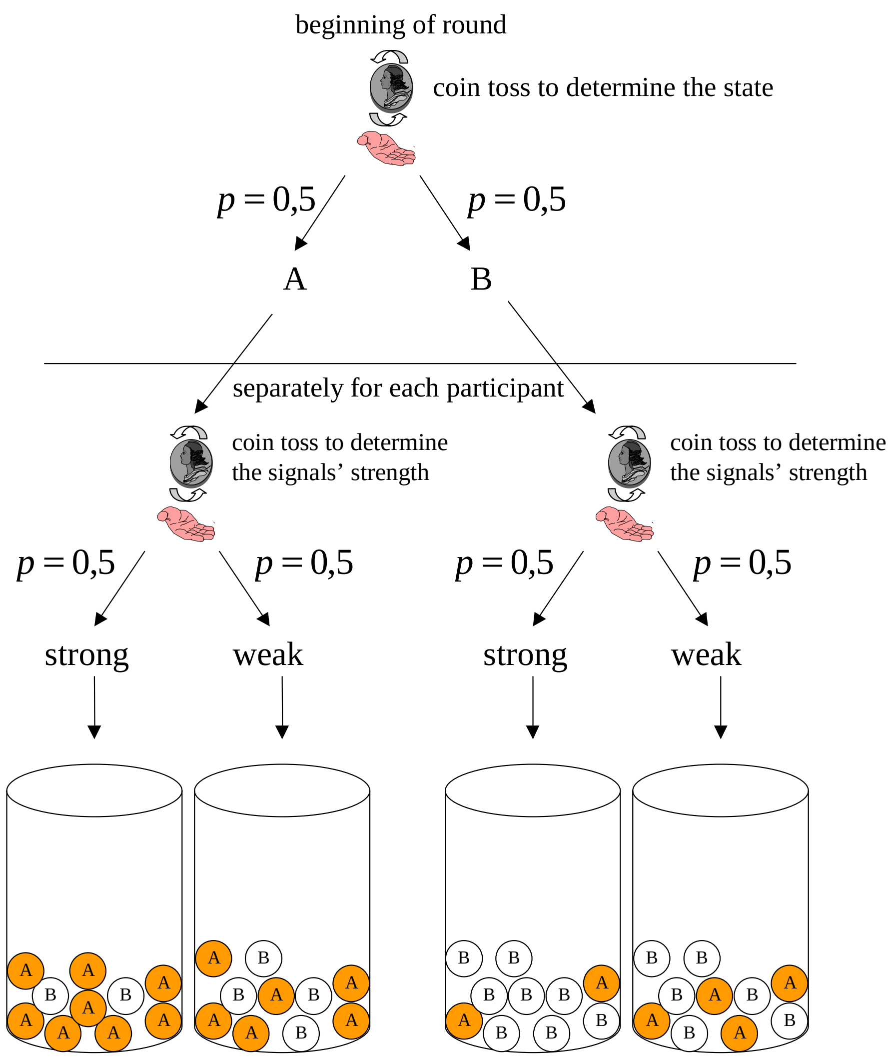
The occurred state is not publicly observable. Your task is to assess your subjective probability that state A or state B, respectively, occurred at the beginning of the round. The ordering of the six participants is determined randomly in each round.

One source of information for your probability assessment is the probability assessment of your immediate predecessor. Note that this information is only displayed to you when it is your turn to state your subjective probability. The information can be observed in the upper and lower part of the program window. You receive this information free of charge.

In addition to that costless information you have the opportunity to acquire a private signal for 35 cu, which only you can see. This private signal gives you an indication which state could have occurred. The private signal will be determined depending on the true state as follows:

- First, a fair coin toss ($p = \frac{1}{2}$) determines if the signal is either strong or weak.
- The signal is now being determined, dependant on its strength, by a draw from an urn with 10 signals:
  - The "strong" urn contains 8 signals indicating the occurred state and 2 signals indicating the opposite state. That means, the strong signal indicates the occurred state with a probability of $p = 0.8$ and the opposite state with a probability of $p = 0.2$.
  - The "weak" urn contains 6 signals indicating the occurred state and 4 signals indicating the opposite state. That means, the weak signal indicates the occurred state with a probability of $p = 0.6$ and the opposite state with a probability of $p = 0.4$.

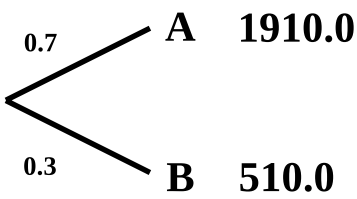
The following figure illustrates the determination of the signal.



If you have decided to acquire a signal the computer displays the signal, as well as the accompanying strength of the signal. Afterwards you will be asked to submit your subjective probability. In order to do so you have to adjust the sliding bar according to your subjective probability and press the Ok-button.

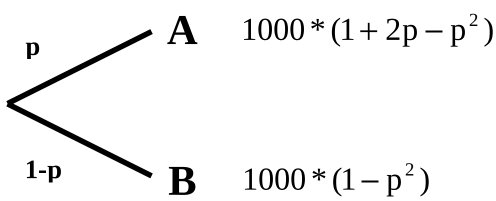
If you refuse to buy a signal you have to submit your subjective probability immediately. Take into account that you have to spend 35 cu to buy a signal.

Underneath the sliding bar a lottery is displayed, which you play as soon as you press the Ok-button and which determines your payment. You receive the payment in currency units (cu) indicated behind the upper branch if state A occurred at the beginning of the round and you receive the payment indicated behind the lower branch if state B occurred at the beginning of the round. If you acquired a signal then 35 cu will be subtracted from the amounts displayed. Example:

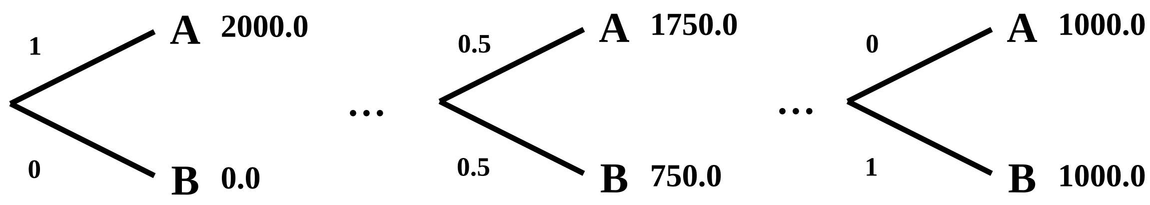


In this example the subject assessed a subjective probability of state A of 0.7. If state A in fact occurred then she receives 1910 cu. If state B occurred then she receives only 510 cu. If she bought a signal prior to her decision, 35 cu are subtracted from the amount displayed.

The displayed lottery changes with every alternation of the sliding bar. The probabilities displayed at the branches of the lottery equal the probability adjusted on the sliding bar. The payments for the two possible states of nature vary with the adjusted probability. The payments are determined such that the displayed lottery is the optimal lottery for you if your subjective probability equals the adjusted probability. Therefore you maximize your expected payoff when you submit the probability which equals your subjective probability. The exact formulas for the payoffs are as follows:



The lotteries vary between the following extreme values:



The rest of the participants can observe the number of probability assessments already submitted in the lower part of the program window. However, they cannot see neither the underlying signal nor the accompanying signal's strength nor the submitted probability assessment. The identification of the participant is not possible either. Your position within a round is displayed as a red number.

Attention: An additional information cannot be inferred from the reaction time of the acting participant since the computer enforces a random delay of at least 2 and not more than 5 seconds before asking for the subjective probability even if the participant decides not to buy a signal.

As soon as all six participants have submitted their subjective probabilities, the occurred state will be announced and a further round (with new information) begins.

Test rounds

Before you can start earning money with your predictions, you will get to know the course of the experiment in three unpaid test rounds. During these test rounds you can always ask question about the information structure and the course of the experiment.

Payment

You will participate in at least 20 rounds, in which you will be paid according to the probabilities you submit. The behavior of the other subjects has no direct influence on your payment as well as your behavior has no direct influence on the payment of others. At the end of the experiment your total payoff will be converted in Deutsche Mark (DM) according to the expected hourly earnings of 16 DM.

Appendix C: Incentive compatibility of the quadratic scoring rule

Let $p_{subjetive}$ denote the player's true subjective probability after having observed all available information and let p_{submit} denote the submitted probability using the sliding bar mechanism. Then the expected payoff in the CO treatment can be calculated as follows:

$$EV(p_{subjective}, p_{submit}) = 1000 \cdot (2 \cdot p_{submit} - p^2_{submitt}) \cdot p_{subjective} + 1000 \cdot (1 - p^2_{submitt}) \cdot (1 - p_{subjective})$$

Deriving for p_{submit} leads to:

$$\frac{\partial}{\partial p_{submit}} EV(p_{subjective}, p_{submit}) = 2000 \cdot p_{subjective} - 2000 \cdot p_{submit}$$

Setting this equal to 0 leads to:

$$p_{submit} = p_{subjective}$$

Since

$$\frac{\partial^2}{(\partial p_{submit})^2} EV(p_{subjective}, p_{submit}) = -2000 < 0$$

setting p_{submit} equal to $p_{subjective}$ is ex ante payoff maximizing. An analogous proof applies to the HO treatment where we used an asymmetric scoring rule.

Appendix D: Basic model probabilities and observed data

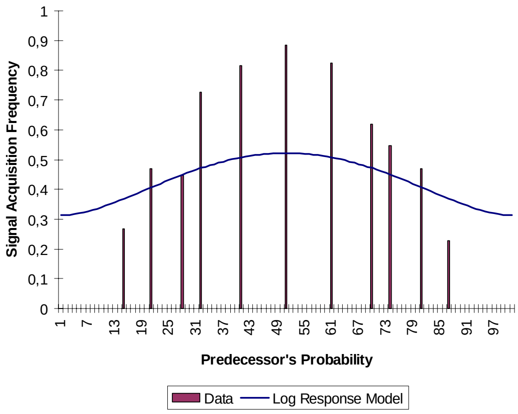


Figure D-1: Observed signal acquisitions and random utility model probabilities (basic model, HCLQ treatment).

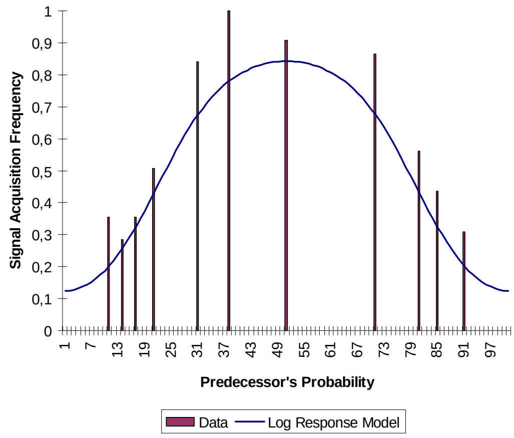


Figure D-2: Observed signal acquisitions and random utility model probabilities (basic model, LCHQ treatment).

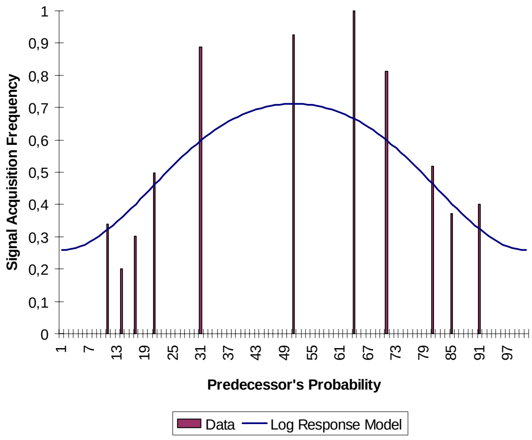


Figure D-3: Observed signal acquisitions and random utility model probabilities (basic model, HCHQ treatment).

Appendix E: Extended model probabilities and observed data

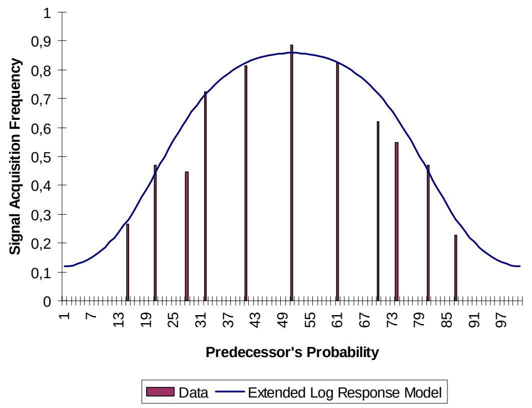


Figure E-1: Observed signal acquisitions and random utility model probabilities (extended model, HCLQ treatment).

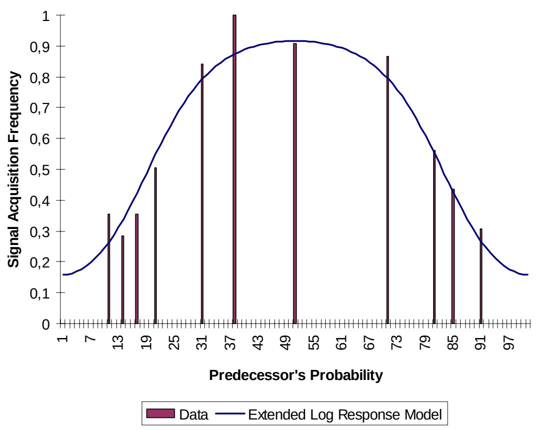


Figure E-2: Observed signal acquisitions and random utility model probabilities (extended model, LCHQ treatment).

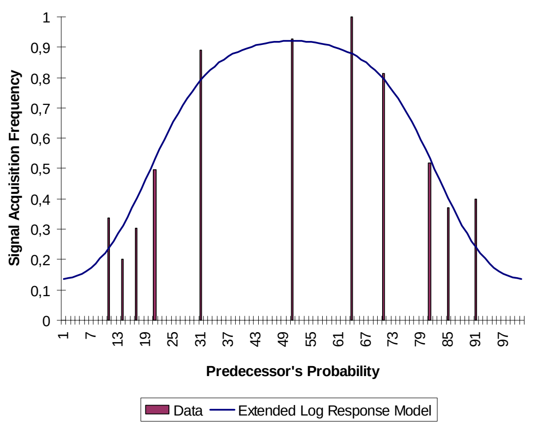


Figure E-3: Observed signal acquisitions and random utility model probabilities (extended model, HCHQ treatment).