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Information Aggregation with Random Ordering: Cascades and Overconfidence*

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Abstract

In economic models, it is usually assumed that agents aggregate their private and all available public information correctly and completely. In this experiment, we identify subjects' updating procedures and analyze the consequences for the aggregation process. Decisions can be based on private information with known quality and observed decisions of other participants. In this setting with random ordering, information cascades are observable and agents' overconfidence has a positive effect on avoiding a non-revealing aggregation process. However, overconfidence reduces welfare in general.

JEL: C92, D8

Keywords: aggregation, Bayes' rule, cascades, experiment, overconfidence

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In most economic models, it is assumed that agents apply rules of conditional probability (Bayes' rule) to make decisions based on private and public information. Sequential decision making without a pricing mechanism leads to the development of information cascades if Bayesian updating is used. In an information cascade, an agent takes an identical action for all possible private signals because no private signal can overrule the available public information. Information cascades were studied theoretically by Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992, 1998), and Welch (1992). Cascades can be stable after as few as two consecutive identical decisions especially if the information quality for all agents is identical and if all agents act rationally. Even if a distribution of information qualities exists, the results will not change in the limit as long as the information is positively correlated with the true value (Lee 1993). Clustering of decisions or herding can also occur because of endogenous timing decisions and waiting costs as in Gul and Lundholm (1995) and in Zhang (1997), or because of exogenous incentives (Scharfstein and Stein 1990).

Informational cascades and herding models are typically used to explain clustering of decisions. However, the question of how systematic biases and random irrational behaviour influences the aggregation process is usually not addressed. With our experiment we want to evaluate the structure of agents' updating behavior. The experimental method is chosen mainly because it is possible to control all major parameters, to vary the available information, and to repeat identical situations to account for potential learning effects. Furthermore, no restrictions are imposed on how participants use private and public information. As a result, theoretical predictions and actual behavior can be compared to evaluate and to explain observed differences. More specifically, it is possible to distinguish between rational herd behavior and non-Bayesian behavior. Our experimental setting will also demonstrate why huge swings in opinions or asset prices might be observed although no new information seems to be available. Individual overconfidence within cascades is identified to be the most likely reason since we can eliminate other explanations that are not consistent with the observed decisions.

To keep our experimental design as simple as possible we focus on sequential decisions with random ordering of the agents who decide once in every round. At the end of each round, uncertainty about the true value is resolved to allow for controlled learning. Our design is an extension of the experiment of Anderson and Holt (1997) which is based on the binary example of Bikhchandani, Hirshleifer, and Welch (1992).[1] We introduce two instead of one signal qualities because a simple counting heuristic leads to the same observed behavior as using Bayes' rule in a design with a uniform signal quality.[2] The signal quality is part of the private information and known with certainty. This modification increases the complexity of the decision problem sufficiently to eliminate the success of simple heuristics. In addition, it reflects economic situations more appropriately because agents usually do not receive identical signal qualities. Different information qualities on the one hand increase the information content of observed decisions

[1] Hung and Plott (1999) replicated and extended Anderson and Holt (1997) to investigate the effect of different reward mechanisms on the evolution of cascades.

[2] About one third of the participants used the counting heuristic in a modified asymmetric design when Bayesian updating would lead to the alternative prediction (Anderson and Holt 1997).

but on the other hand introduce uncertainty about others' information.[3] Thus, there is enough room for identifiable non-Bayesian updating behavior. Finally, two signal qualities reduce the likelihood that agents have to randomize their decision because of inconclusive private and public information.[4]

Potential cascades can collapse in our design if an agent receives high quality information or if somebody believes more in her private information than justified by Bayes' rule. Note that putting more weight on the own private information might be a signal for overconfidence but it can be a (rational) reaction to others' behavior, too. Whereas we can distinguish between superior information and overconfidence since we know the signal distribution, it is rather difficult observing only others' predictions. As a result, the aggregation process can switch from a cascade to a reverse cascade and vice versa either because of superior information or because of undetected overconfidence.

Our experiment is related to the psychological research on overconfidence in probability judgment. Weinstein (1980), Lichtenstein, Fischhoff, and Phillips (1982) and many other studies demonstrate that unrealistic optimism in almost every judgment situation is a common human trait. Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999) present a more recent experiment to shed more light on the stability of overconfidence in different domains. Underweighing of likelihood information or conservatism (Edwards 1968) is an alternative explanation for the observed behavior that subjects put too much weight on their own information rather than using publicly available information adequately. In our experiment, we cannot formally distinguish between conservatism and overconfidence. However, since subjects emphasized the dependency on their own private information as well as others' mistakes in their questionnaires after the experiment we label the observed behavior as overconfidence.

Recent comprehensive overviews of psychological findings with their implications for economics in mind are provided by Camerer (1995), Odean (1998) and Hirshleifer (2001). In markets, overconfidence can cause speculation because traders are "certain" that they have superior skills or information. As a result, information mirages can develop in which the price process looks as if new information exists (Camerer and Weigelt 1991). Smith, Suchanek, and Williams (1988) and Porter and Smith (1994) investigated experiments in which huge bubbles occurred that are based mostly on overconfident speculators.[5] Overconfidence and other results from individual experiments in psychology and economics have recently been incorporated in market models. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) used individuals' overconfidence and the self-attribution bias to explain overreaction and volatility changes. Although it is legitimate to use results from individual decision making to build market models, two potential problems have to be addressed. First, individual behavior varies largely and may not be as stable as assumed in models. Second, agents might identify or anticipate others' behavior and try to act accordingly. Whether this attempt offsets or increases the effect of non-Bayesian behavior on information aggregation is an open question. The answer depends on whether others' errors are correctly identified

[3] This uncertainty together with the above mentioned uncertainty about others' behavior creates composition uncertainty as in Avery and Zemsky (1998).

[4] Anderson and Holt (1997) assume that agents follow their own signal in this situation. This assumption is justified since a small probability of incorrect updating by other participants would also lead to this prediction instead of randomizing.

[5] See Camerer (1989) for an overview of earlier research to explain bubbles and fads.

or anticipated, or not. For these two questions, we want to find some answers within our experimental setting.

The most important result is that participants do not make their predictions using Bayes' rule but they employ an identifiable heuristic, which put too much weight on private information. The heuristic is based on overconfidence. As a consequence a relatively large number of potential cascades collapse or do not develop at all. However, participants are able to increase the number of correct predictions significantly above their private information level despite their own and others' updating mistakes using specific heuristics which improve predictions especially if public and private information is not very reliable. In relative terms, more ex post incorrect (reverse) cascades collapse. But in absolute numbers, ex post correct cascades are destroyed more often than reverse cascades due to systematic mistakes. As a result, groups' welfare decreases compared to the situation in which all participants use Bayes' rule. This result seems to contradict the theoretical results derived by Bernardo and Welch (2000) who emphasized the welfare benefits of entrepreneurs' overconfidence in their model. A certain level of overconfidence could also have a positive welfare effect in our experiment if we had more than six subjects in an experimental session. The avoidance of reverse cascades would then have a positive effect for more subsequent predictions whereas destroyed cascades would develop nevertheless due to the information structure.

We proceed with the experimental design and procedures. In section 2, we will present the information aggregation theory for this experiment. Section 3 contains the main results and an analysis of observed cascades and their survival. In the final section 4, we summarize the results and present some ideas about design extensions.

1 Design and Procedures

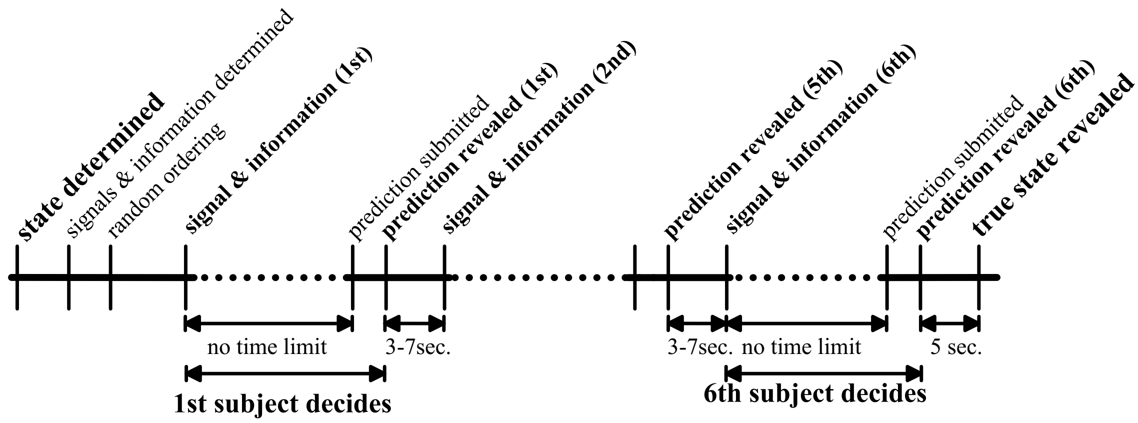
As mentioned, we extend the experimental design of Anderson and Holt (1997) in two respects: We introduce two different information qualities and use computers to increase the number of repetitions per experimental session to analyze whether individuals or the whole group learn within a session. Based on private and public information each of the six participants in a session has to predict in every round whether state A or state B occurs.

Before we describe the design in more detail we introduce some notation. States and predictions are denoted in capital letters (A, B) - private signals in small letters (a, b). Probabilities are always expressed with respect to state A. The general position index is denoted by $y \in \{1, 2, ...6\}$. i_X^y denotes the private information with $i \in \{a, b\}$ and signal strength $X \in \{S, W\}$ which is distributed at position y. $h^y = D_1, ..D_y$ with $D \in \{A, B\}$ are histories of predictions that can be publicly observed at position $y+1$ before making a prediction. h_{id}^y refer to identical predictions of all predecessors, i.e. $h_{idA}^y = A_1...A_y$.

Figure 1 illustrates the procedure within one round. Note that subjects face no time restrictions making their decisions and submitting their predictions. At the beginning of each round the state is determined. Both states (A, B) occur with the same probability $\left(p_A = p_B = \frac{1}{2}\right)$. Then, the ordering of all six subjects is fixed randomly for this round.

Figure 1: Procedure within one round

The decision procedure within one round is illustrated in this figure. After the state is determined, the signals' strengths and private information for each subject are drawn. In addition, the ordering is randomly fixed for the round. Then, each subject receives the private information as soon she has to submit a prediction. There is no time limit for submitting a prediction, which will become public knowledge. The next subject receives her private information after a random delay of three to seven seconds. At the end of each round, the true state is revealed.



Finally, private signals (i_X) are generated independently for each subject in a two step procedure depending on the realized state:

1. The signal strength is drawn first. It is either *weak* or *strong* with probability $p_W = p_S = \frac{1}{2}$.

2. *Strong* private information i_S is correct with probability $p(A \mid a_S) = p(B \mid b_S) = \frac{4}{5}$.

   Weak private information i_W is correct with probability $p(A \mid a_W) = p(B \mid b_W) = \frac{3}{5}$.

Thus, even *weak* signals contain some information about the realized state.[6] Public information consists of all predictions that are already made within a round. Predictions contain the predicted state as well as the position at which they have been submitted, i.e. state $A_y$orB_y has been predicted at position y.

Based on public and private information, a participant must submit her prediction for which she will receive 300 cu if the prediction is correct and 100 cu otherwise. The information structure and the experimental procedure is common knowledge because it is explained as part of the instructions (see appendix). Note that a subject cannot identify neither other participants' private information and signal strengths with certainty[7] nor the identity of these other participants since predictions were submitted anonymously and the participants' ordering was determined randomly for each round.

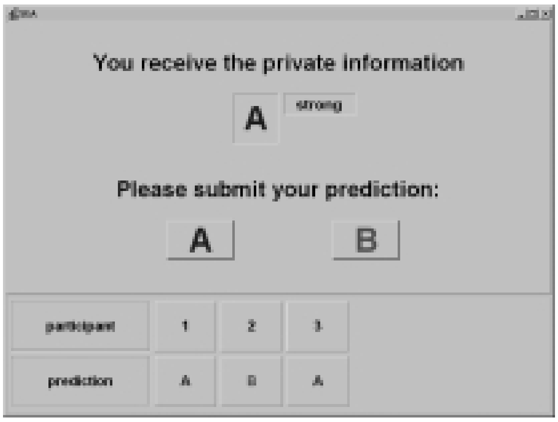
[6]The probabilities associated to strong and weak signals are selected to satisfy the following restrictions. First, the difference of information quality between *strong* and *weak* signals should be as large as possible to increase the value of public information. Second, the weak signal should be considerably more informative than having no information at all. Third, the strong signal should not contain too much information since otherwise no information aggregation task would remain. Fourth, we wanted to have on average the same information content as in Anderson and Holt (1997) who chose $p(\text{state} \mid \text{signal}) = \frac{2}{3}$. Finally, the probabilities should be some "prominent" number such that subjects understand the design easily within 20 minutes.

[7]In some situations it is possible to infer the signals' strength of the immediate predecessor assuming Bayesian updating.

The experiment was performed using software that was developed specifically for this experiment. Figure 2 shows the screen of a subject at position IV before she made her decision.

Figure 2: Screenshot at position IV

This screenshot shows all available information for the participant who has to submit her prediction at position IV. She receives the private information a_S, i.e. $p(A \mid a_s) = \frac{4}{5}$. The public information contains the observable predictions in this round: $(A_1 B_2 A_3)$.



The observable predictions (A_1, B_2, A_3) can be used to update the own private information a_S. The rational updating procedure assuming rationality for the first three participants is analyzed in section 2. Predicting the state might be easier in some situations (e.g. first three predictions: B_1, B_2, B_3; own private information at position IV: b_S) than in others (e.g. first three predictions: A_1, A_2, B_3; own private information: a_W). As a result, the time between getting the private information and predicting the state might depend on the complexity of the individual problem. Because other agents might try to learn something by evaluating the length of this time interval, the new signal is delayed randomly by a minimum of three seconds and by a maximum of seven seconds to generate a noisy "time" signal. This procedure is public information. At the end of each round, the true state is revealed.

Each session lasted about 110 minutes and consisted of at least 74 rounds (maximum: 86 rounds) of which the first three periods were part of the instructions and thus not paid. The relatively large number of rounds per session enables us to evaluate the data with respect to learning. Moreover, the questionnaire, which subjects filled out at the end of the experiment, will help to distinguish between systematic non-Bayesian behavior and random errors since participants were asked to describe their decision heuristics. 126 subjects participated in this experiment (=21 sessions). They were recruited from undergraduate and graduate business administration courses at the University of Mannheim, Germany, and had no previous experience with this experiment. Each session lasted about two hours. All earned currency units were converted to Deutsche Mark (DM) and rounded up to the next DM at the end of each session. Participants earned on average 31.79 DM with a minimum of 27.00 DM and a maximum of 36.00 DM.[8]

[8]Fixed exchange rate: 1 Euro = 1,95583 DM.

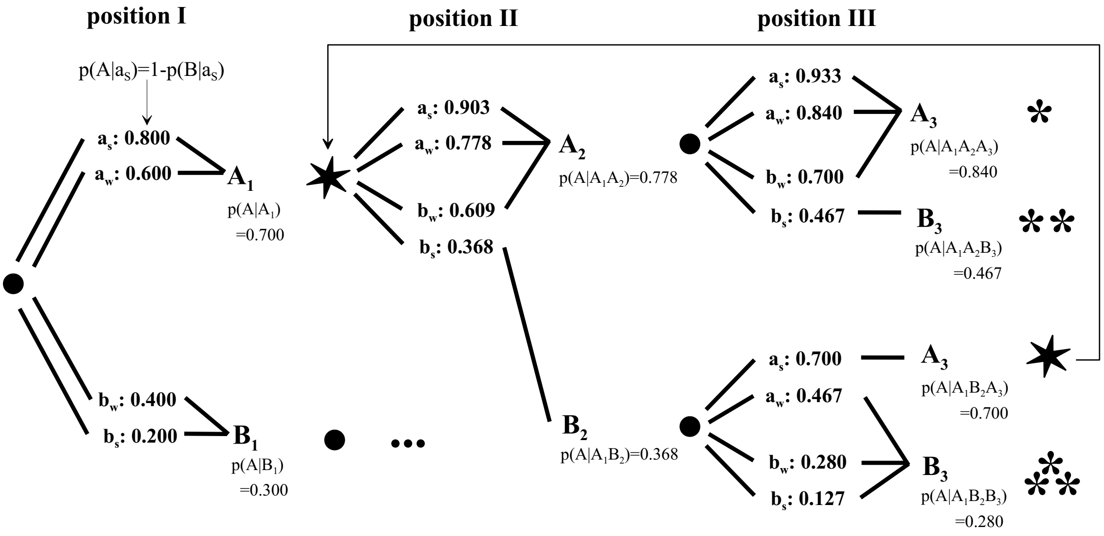
2 Rational Bayesian Strategy

The obvious benchmark to analyze the experimental data is based on Bayes' rule assuming that every participant acts accordingly in every situation. By contrast, public information is assumed to contain no information under the alternative Private Information (PI) assumption. Agents believing that PI is optimal are overconfident because they consider others' decisions as being completely useless under all circumstances.[9]

At position I, a subject should predict according to her signal, since this is always better than random guessing. Thus, the first participant should predict state A if she has received an a_X^1-signal and state B otherwise. Figure 3 shows the possible prediction paths up to position III with the respective probabilities that state A will occur assuming Bayesian updating.

Figure 3: Some prediction paths at positions I, II and III

The decision situations at positions I, II and III are shown depending on the private signal $i_X \in \{a_S, a_W, b_W, b_S\}$ and the observable decision history. Based on probabilities for state A the rational decision is shown. Moreover, the posterior probabilities for an observed decision are provided. History $h^3 = A_1 B_2 A_3$ leads to the same posterior probability (0.700) as history $h^1 = A_1$. The star symbol indicates this circle.



If the first prediction is A_1, it is obvious that this prediction should be based on private information a_S^1 or a_W^1. The second participant who observes the first prediction can infer using Bayes' rule that the predicted state will occur with probability $p(A \mid A_1) = \frac{7}{10}$. If she receives a strong signal she should predict according to her private information. Thus, in this situation Bayes' rule and PI lead to the

[9] In our experimental setting, overconfidence is equivalent to being sceptical about others' capabilities to solve the decision problem correctly. If a subject insinuates that other participants have committed an error she will make exactly this error. As a result the subject is implicitly overconfident relative to the population. In section 3 we will show that those participants who take correct decisions are *not* under-confident because even incorporating others' decision errors cannot justify deviating from the Bayesian updating case at position II.

same prediction. However, a weak signal is dominated by the first participant's prediction. The private information b_W^2 cannot lead to a prediction B_2 using Bayes' rule because the first decision is based on contradicting information, which is more informative than b_W^2.

The prediction history $h_{id(A)}^2 = A_1A_2$ with $p(A \mid A_1A_2) = \frac{\frac{7}{10}\cdot\frac{3}{5}\cdot\frac{1}{2}}{\frac{7}{10}\cdot\frac{3}{5}\cdot\frac{1}{2}+\frac{3}{10}\cdot\frac{2}{5}\cdot\frac{1}{2}} = \frac{7}{9}$ leads to the same prediction pattern at position III, i.e. only a b_S signal can prevent the development of a cascade at this stage. The other probabilities can be calculated as usual. It is important to remember that all private information signals are drawn independently.

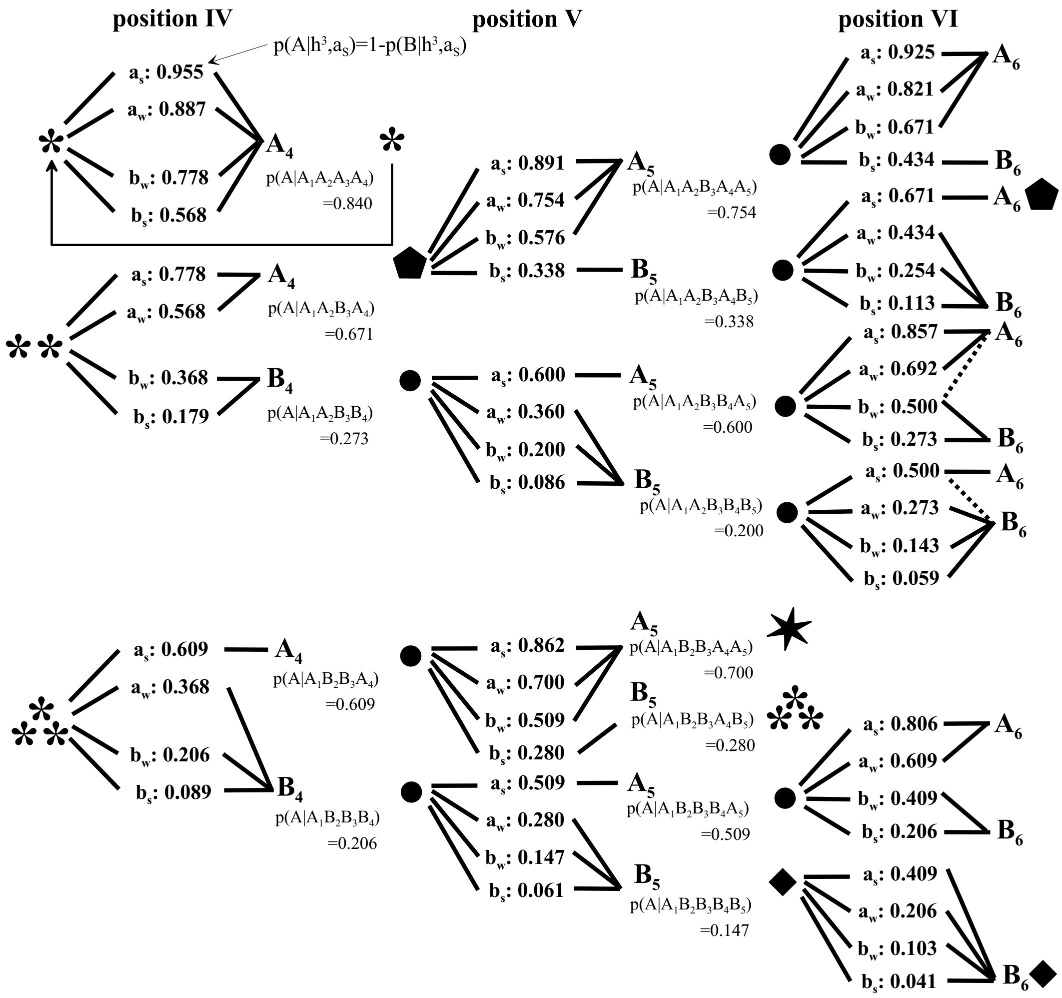
Observing the other possible history $h^2 = A_1B_2$, all remaining participants know that the second decision is based on b_S^2. As a result, only a_S^3 can lead to prediction A_3. Thus, the prediction history $h^3 = (A_1, B_2, A_3)$ implies two contradicting strong signals at positions II and III which neutralize each other. The probability for state A is the same as after position I observing a prediction A_1 $\left(p(A \mid A_1B_2A_3) = \frac{7}{10} = p(A \mid A_1)\right)$. The prediction paths displayed in figure 4 are based on histories $h_{id}^3 = A_1A_2A_3$ (*), on $h^3 = A_1A_2B_3$ (**) or on $h^3 = A_1B_2B_3$ (***).

After three identical predictions (*) one should always predict the same state regardless of the own private signal, i.e. an information cascade arises rationally. State B is predicted at position III after two A-predictions (**) only if a b_S^3 signal has been drawn. As a result, it is rational to predict the state according to the own private signal at position IV. At positions V and VI no obvious heuristic can be provided. Note that an information cascade always starts after three consecutive identical predictions. In addition, public and private information lead with two exceptions at position VI to unambiguous predictions in contrast to Anderson and Holt (1997).

A potentially interesting situation arises if the a posteriori probabilities for both states are close to 50%. If participants are just slightly uncertain whether observable predictions are reliable or whether the probability of individual mistakes is greater than zero, they will put more weight on their own private information that might lead to a collapse of an information cascade. However, the data will show that it is possible to distinguish between "rational" adjustments in the updating procedure and "irrational" overconfidence.

Figure 4: Some prediction paths at positions IV, V and VI

The decision situations at positions IV, V and VI are displayed in this figure depending on the private signal $i_X \in \{a_S, a_W, b_W, b_S\}$ and the decision histories based on histories $h^3_{id(A)} = A_1A_2A_3$ (*), on $h^3 = A_1A_2B_3$ (**) or on $h^3 = A_1B_2B_3$ (***). Based on probabilities for state A the decision is shown. Moreover, the posterior probabilities for an observed decision are provided. Situations, which occur identically at different positions, are marked with a special symbol (e.g. a star).



3 Results

Our analysis is based on the experimental data from 21 sessions with a total of 126 subjects. In 1639 rounds, subjects submitted 9834 individual predictions. 107 of the 126 participants made more correct predictions than they would have made based only on their private information. On average, subjects were able to make correct predictions in 3.78 rounds ($\bar{\sigma} = 0.47$) in which their own signal was wrong using the available public information.[10] This significant improvement (t-statistic=8.1, $\alpha < 0.001$) was achieved during the whole session.

Learning within the whole group is not observable since comparing the results of the first fifteen rounds with those of the last fifteen rounds does not reveal a significant difference. In addition, individuals' behavior was stable, i.e. systematic deviations from rationality did not disappear or worsen. Based on this result we will consider all predictions as being independent. However, we will check for session specific results.

To understand the development of cascades it is necessary to analyze the first three predictions within each round since these decisions have a crucial influence on the aggregated results of the round. Moreover, it is easier to identify plausible reasons for deviations from rational behavior. Then, we proceed with the analysis of cascades and reverse cascades. This includes the extraction of behavioral regularities and the identification of their effect on welfare. Finally, we will present and discuss results from probit regressions.

3.1 Predictions at position I

At position I within a round, a participant can base her decision only on her private information and on her knowledge about the information structure. It is obvious that she should predict the state indicated by her private information since even a weak signal has a higher probability than random guessing. Note that the risk attitude or beliefs about others' behavior do not influence the prediction at position I because only two states exist and the prediction is irreversible. Table 1 shows the aggregated predictions classified as "Bayesian" or "non-Bayesian" depending on the signal strength.

As table 1 shows, about 91% of all first predictions were made according to the first participant's private information. There are only 23 (3.0%) predictions against a strong signal, but 123 (14.2%) predictions against a weak signal. A plausible (but non-rational) explanation can be found for 14 of these 23 decisions based on a strong signal: in the previous round they had predicted the ex post wrong state although this might have been rational for them. 47 of the 123 predictions against a weak signal occurred after an ex post wrong prediction in the previous round.[11] Of the remaining 74 non-Bayesian predictions, twelve

[10] Subjects participated on average in 78 rounds. Based on the probabilities for strong and weak signals, they received 23.4 (=30%) wrong signals.

[11] Only two predictions against the own weak signal occurred in round 1. At position I, the median of predictions against the own weak signal is five for all sessions. This number varies between zero and ten except for one session, in which 18 out of 46 predictions were made against the own *weak* private information.

Table 1: First Prediction

The first predictions of each round are shown for all 1639 rounds depending on the signal strength (strong/weak). In addition, each decision is classified as "Bayesian" or "non-Bayesian". Since only the own private information is available at position I, the predicted state should be the one indicated by the private information. In this case, the prediction is classified as "Bayesian".

position I	strong		weak		$\sum$	
	obs.	in %	obs.	in %	obs.	in %
Bayesian	747	97.0	746	85.8	1493	91.1
non-Bayesian	23	3.0	123	14.2	146	8.9
all	770		869		1639	

(six) occurred within the first (last) ten rounds of an experimental session. Thus, there does not exist any indication that these predictions should be attributed to inexperience or to boredom confirming our result of no learning.[12]

However, gambler's fallacy can explain about half of the predictions against the own private information if the prediction in the previous round has been correct. These subjects believe that the probability for both states is changing based on the observed history of state realizations in previous rounds: subjects predict against their own signal more often if the private information indicates the state which occurred in the previous round(s) even though they have submitted a correct prediction. Suppose a subject receives the private information a_W^1. In addition, she has observed and has correctly predicted state A in the previous n rounds ($n \geq 1$). In this situation, 37 of the 74 predictions against the own weak private information occurred. The same happened in five of the nine similar cases with a strong signal. In addition, nobody predicted against the own private information if this person's prediction in the previous round has been correct and the private information indicates the other state for this round. The remaining 37 predictions against the own private information at position I cannot be explained since they exhibit no regularity.

3.2 Predictions at position II

The predictions at position II are based on observed predictions at position I and on own private information. Moreover, the information structure is common knowledge and can be used for updating probabilities. In table 2 the predictions are classified as "Bayesian" or "non-Bayesian" depending on both, the signal strength and the first prediction D_1.

More than 97% of all predictions at position II are made according to the own *strong* private information. Predictions against the own strong private information are resulting from random errors. If the private weak information confirms the first prediction, about 91% of the participants decide to follow

[12]The result that subjects did not learn is not too surprising given the limited information they received at the end of each round. They could only compare the prediction sequence and their own signal with the outcome but the underlying signal sequence was not revealed.

Table 2: Second prediction

In this table the second predictions within a round are displayed for all 1639 rounds depending on private information (i_X^2) and on the round's first prediction (D_1). In addition, each decision is classified as "Bayesian" or "non-Bayesian" assuming rationality of the first decider. The decision should be based only private information if the signal is strong. A weak signal implies the same decision as the first one regardless of the signal. Thus, if $D_1 \neq i_W^2$ it is rational to follow the first prediction. Results are given in percentage of column total. Rational herding, i.e. following the previous decision against the own private information, can occur only with a weak signal (*italics*). Predictions that can be caused by overconfidence are denoted in **bold**.

position II	$D_1 = i^2$		$D_1 \neq i^2$		
	strong	weak	strong	weak	$\sum$
Bayesian	97.1	90.8	97.7	*50.7*	78.3
non-Bayesian	2.9	9.2	2.3	**49.3**	21.7

the own information and thus the first prediction. The remaining 9% of the predictions are submitted against the own weak private information *and* the first prediction ($D_1 = i_W^2$). As at position I, gambler's fallacy, random errors and a reaction to the own ex post wrong prediction in the previous round explain some of these predictions. It is notable however that the number of deviations is almost three times as high as at position I with a strong signal although the probabilities are almost the same $\left(p\left(A \mid A_1 a_W^2\right) = \frac{7}{9} \text{ vs. } p\left(A \mid a_S^1\right) = \frac{4}{5}\right)$.

Although one should predict against the own weak signal that is contradicting the first prediction ($D_1 \neq i_W^2$) based on Bayes' rule, 49.3% of all decisions follow the own signal. It is obvious that such a deviation cannot be explained using the above mentioned reasons especially since the probability for the correct state is about the same as having a weak signal at position I (60.9% vs. 60.0%). The only difference is that it requires a prediction against the own private information at position II. Obviously, participants put too much weight on their private information compared to the public information, which clearly indicates the existence of overconfidence.[13] Note that gambler's fallacy would increase the proportion of "Bayesian" predictions because agents would then predict against their own private signal.

One might argue at this point that the observed deviations are the result of a more sophisticated updating procedure, i.e. taking a certain amount of mistakes at position I into account. Both random ordering and anonymous predictions prevent conditioning the decision at position II on the identity of the person predicting at position I. As a consequence, error rates include beliefs about individual error rates as well as their distribution within the group. Prediction errors attributed to decisions based on a strong signal (ϵ) and decision errors based on a weak signal (θ) must be high enough such that $p\left(A \mid \tilde{A}_1\right) \leq \frac{3}{5}$ to justify a prediction of state B based on information $\tilde{A}_1 b_W^2$.[14] Thus,

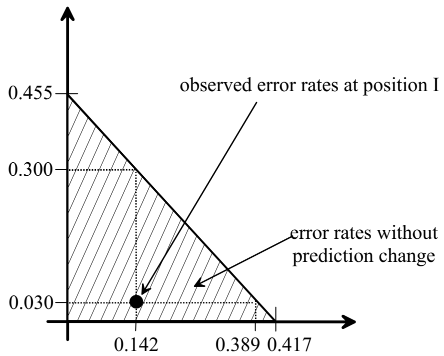
[13] Anderson and Holt (1997) report about 15% deviations in which subjects predict according to their own signal but should follow the crowd without evaluating possible reasons.

[14] $\tilde{A}_1$ denotes a prediction of state A at position I including error rates ϵ and θ.

$p\left(A \mid \tilde{A}_1\right) = \frac{\frac{1}{2}\left[\frac{1}{2}\left[(1-\epsilon)\frac{4}{5}+(1-\theta)\frac{3}{5}\right]\right]}{\frac{1}{2}\left[\frac{1}{2}\left[(1-\epsilon)\frac{4}{5}+(1-\theta)\frac{3}{5}\right]+\frac{1}{2}\left[(1+\epsilon)\frac{1}{5}+(1+\theta)\frac{2}{5}\right]\right]} \leq \frac{3}{5}$. Using some algebra leads to the conclusion: $\epsilon \geq \frac{5}{11} - \frac{12}{11}\theta$. Figure 5 shows the error rate combinations for predictions at position I which do not warrant a deviation from the Bayesian prediction without error rates. Note that an error rate of 0.5 is equivalent to assuming that *all* predictions at position I are random.

Figure 5: Error rates at position II

A subject at position II who receives a weak signal which indicates the other, not yet predicted state $\left(i_W^2 \neq D_1\right)$, should predict against her own signal as long as the anticipated error rates at position I are less than ϵ and θ after receiving a strong or weak signal, respectively. An error rate of 0.5 is equivalent to the assumption that *all* predictions with the associated strength are randomly made at position I.



The actual average error rates (see table 1) are $\epsilon = 0.03$ and $\theta = 0.142$ for strong and weak signals at position I, respectively. Error rates vary between 0 and 0.114 for ϵ and between 0 and 0.391 for θ between sessions. Only in one session, error rates were almost sufficiently high enough to justify a prediction according to the own weak signal at position II. On average, error rates could have been 2.5 times higher than the actually observed ones, before it would have been rational to deviate from predicting the state suggested by Bayesian updating.

These results are a clear indication of overconfidence because agents believe that the others made more mistakes than they actually did. An alternative explanation would be regret aversion. Regret averse people suffer an additional utility loss if they predict against their own signal and this turns out to be ex post wrong. To avoid this, agents put a higher weight on their own information than is rationally appropriate. Regret aversion and overconfidence are closely related in our experimental setting since both biases lead to overweighing of the own private information. However, only overconfidence is consistent with gambler's fallacy because the decision maker believes in her superior prediction ability even if this implies predicting against the own information. Overconfidence is also consistent with subjects' answers in the final questionnaire. Only very few subjects mentioned that they adjusted their predictions to account for others' potential errors. They simply believed in their (wrong) decision heuristics and the observed behavior is not the result of random mistakes. Other alternative explanations such as conformity and representativeness would enforce predictions according to Bayesian updating.

Summing up, potential cascades collapse relatively often at position II because subjects assign more weight to their own weak private information. Although we have collected only subjects' predictions and not their probability judgments that lead to these predictions it is possible to identify some more precise decision heuristics. In addition to the observed behavior, subjects' answers in the final questionnaire reveal that a lot of subjects followed their own signal if they had to decide at positions II without considering the first prediction. As a consequence, two contradicting predictions at the beginning of a round would contain no additional information compared to the situation without public information since the distinction between strong and weak signals at position II is lost. Moreover, this heuristic demonstrates that agents use simple heuristics which may often lead to Bayesian-like predictions but not always.

3.3 Predictions at position III

This fact has an important impact on some decisions at position III which are shown in table 3 depending on the observed history of predictions and on the private information. The classification of predictions assumes that all agents use Bayes' rule to aggregate information.

Table 3: Third prediction

In this table the third predictions of each round are displayed for all 1639 rounds depending on the signal (i^3), its strength (strong/weak) and on the first two decisions (h^2) within this round, which are either identical $\left(h^2_{id} \in \{A_1A_2, B_1B_2\}\right)$ or not $\left(h^2 \in \{A_1B_2, B_1A_2\}\right)$. In addition, each decision is classified as "Bayesian" or "non-Bayesian" assuming rationality of the first two deciders. Rational herding, i.e. following the previous decision against the own private information, can occur only with a weak signal (*italics*). Predictions, which can be caused by overconfidence, are denoted in **bold**. "Irrational" herding is marked with a star (*).

	$h^2_{id} \in \{A_1A_2, B_1B_2\}$				n=958
position III	$D_2 = i^3$		$D_2 \neq i^3$		
	strong	weak	strong	weak	$\sum$
Bayesian	98.8	95.3	85.3	*76.4*	88.5
non-Bayesian	1.2	4.7	14.7*	**23.6**	11.5
	$h^2 \in \{A_1B_2, B_1A_2\}$				n=681
	$D_2 = i^3$		$D_2 \neq i^3$		
	strong	weak	strong	weak	$\sum$
Bayesian	95.9	84.2	98.5	*26.3*	78.1
non-Bayesian	4.1	15.8	1.5	**73.7**	21.9

At position III it is rational to predict always according to the own strong private information. With a weak signal one should follow the immediate predecessor. Decisions, which are based on a strong signal, are almost always in line with Bayes' rule. The only notable exception can be observed if subjects observe h^2_{id} and $D_2 \neq i^3_S$. Then, 14.7% follow the crowd by predicting against their own private information.

This "irrational" herding is consistent with conformity and assumed errors in observed predictions. In addition, it is in line with the stated heuristics of the questionnaire because the prediction A_2 is based in this case only on signals a_W^2 and a_S^2 which overrule the information b_S^3 using Bayes' rule. However, the same reasoning as well as anticipated error rates cannot explain the substantial deviation from predictions based on a weak signal in the same situation. The only explanation for this behavior is overconfidence, i.e. assigning almost no weight to the first two predictions.

If the first two predictions disagree and the own weak information contradicts the last observed prediction ($D_2 \neq i_W^3$), about three quarters of the predictions (73.7%) follow the own signal. This evidence can be explained with the anticipation of error rates and with the stated heuristic in the questionnaire, which is based on overconfidence. A noteworthy 26.3% of Bayesian predictions indicate as in the previous situation with h_{id}^2 that public information is not completely ignored as suggested by the Private Information hypothesis.

In summary, predictions at position III are mostly consistent with overconfident agents who put too much weight on their own information. The attempt to "correct" for errors contained in the public information is an indication for overconfidence at position III because it assumes a degree of sophistication at position II that contradicts the assumption of errors at both positions I and II. Moreover, predictions at positions IV, V and VI confirm also that overconfidence is the reason for deviations from rational Bayesian updating.

3.4 Aggregate results - survival of cascades

If the first three predictions were made using Bayes' rule, 723 complete cascades and 220 complete reverse cascades would have occurred[15] because three consecutive identical predictions cannot be overruled even with strong contradicting private information. Only the assumption of position independent error rates without attempts to correct for these errors at earlier positions can change the information content of the publicly observable predictions enough to justify a prediction against the crowd based on a strong signal. If the agent at position IV believed that every predecessor decided based only on each subject's own private information, there would be even more reason to follow the crowd $\left(p = \frac{343}{451}\right)$ than under the assumption of Bayes rule $\left(p = \frac{21}{37}\right)$.

Due to non-Bayesian predictions at positions I through III, at most 503 complete cascades and 139 complete reverse cascades might be observed in this experiment. The other potentially complete (reverse) cascades are destroyed by random errors and by overconfident behavior at positions II and III. Table 4 shows how many (reverse) cascades survive until the end of the round. In addition, the private information, which is responsible for the collapsing cascade, is provided.

Of the 503 complete cascades, which should occur after position III with there identical predictions, only 318 (63.2%) are actually completed at the end of a round. About 75% of the cascades collapse due to a strong private signal that indicates the opposite state. These collapses result in a welfare loss especially if the remaining participants follow this prediction. Reverse cascades collapse relatively more often. Their

[15] A (reverse) cascade is complete if all six subjects predict the same state and this prediction is ex post correct (wrong).

Table 4: Survival of cascades and reverse cascades

In this table the number of (reverse) cascades are shown that survived until this position. In addition, the private information i_x^y with $x \in \{S, W\}$ in relation to the most recent prediction D_{y-1} is provided if the (reverse) cascade collapses.

	cascades			reverse cascades		
position y	IV	V	VI	IV	V	VI
start	503	422	372	139	91	77
$i_S^y = D_{y-1}$	2	0	2	0	0	0
$i_W^y = D_{y-1}$	4	0	8	5	0	0
$i_S^y \neq D_{y-1}$	65	40	35	38	13	16
$i_W^y \neq D_{y-1}$	10	10	9	5	1	1
end	422	372	318	91	77	59

number is reduced from a potential of 139 after position III to 59 completed reverse cascades at the end of a round. The higher rate of collapsed reverse cascades (57.6% vs. 36.8%) is not surprising due to the information structure. Since all private information depends on the realized state it is more likely that strong and weak signals indicate the correct state. As a direct consequence, the likelihood of a strong signal that contradicts the developing reverse cascade is higher than the likelihood for a contradicting strong signal within a cascade. Together with overconfidence the result is explained.

Collapsing reverse cascades increase welfare, i.e. overconfidence can be beneficial. But since the absolute number of collapsed cascades (185) is larger than that of the collapsed reverse cascades (80), the overall effect of overconfidence on information aggregation is negative. Participants were obviously scared by the prospect of encountering a reverse cascade and therefore tried to avoid it although this was costly. After they had received their payment, some participants were asked to guess how often complete cascades occurred in relation to reverse cascades. The most common answer was "close to 1:1" although the relation was more than 5:1 as the results in table 4 show.

The analysis of the prediction behavior in potential (reverse) cascades is the next step. Looking only at those cases in which an unanimous prediction history exists has one advantage: The stable Bayesian updating benchmark allows to identify hints about the updating procedure. Table 5 provides the percentage of conforming predictions within potentially complete (reverse) cascades.

As expected, differences in prediction behavior in cascades and reverse cascades do not exist since the agents do not know in which cascade situation they are. Deviation from the rational prediction is almost non-existent starting at position III if the own private signal confirms the observed previous predictions.[16] Agents with a weak contradicting signal deviate in more than 10% of all cases until position V. The increasing percentages demonstrate that subjects do not ignore public information completely but they

[16] We did not find a systematic pattern to explain why weak confirming signals led to 13% contradicting predictions at position VI. 52 out of 60 possible cascades (=87%) occurred. The remaining eight cascades collapsed in six different sessions. Therefore, individual random errors are the most likely reason.

Table 5: Confirming predictions within complete (reverse) cascades

The percentage of conforming predictions after observing an unanimous history (h^y_{id}) until position y is displayed dependent on the private information i_X and on whether a cascade (C) or a reverse cascade (RC) is developing. Following previous predictions (D_{y-1}) is rational except in those cases marked with a star (*).

	predictions (in %) after observing h^y_{id}									
position	II		III		IV		V		VI	
	C	RC	C	RC	C	RC	C	RC	C	RC
$i^y_S = D_{y-1}$	98	94	99	100	99	100	100	100	98	100
$i^y_W = D_{y-1}$	90	92	96	94	96	89	100	100	87	95
$i^y_W \neq D_{y-1}$	51	50	80	72	91	79	90	96	93	95
$i^y_S \neq D_{y-1}$	3*	2*	18*	11*	35	39	50	46	61	47

put more weight on their own information than it is rational. The same pattern can be observed looking at predictions based on strong contradicting private information. From positions IV to VI the prediction percentage increases by about ten percentage points with each confirming prediction.

As mentioned before, learning did not occur in this experiment since the prediction pattern did not change within a session. However, the decision time (excluding the random delays) decreases significantly if the first ten rounds are compared with the last ten rounds. This decrease is due to subjects' experience because there is no evidence that previous outcomes have an influence on the decision time even after experiencing a reverse cascade. Thus, we can conclude that subjects used their decision heuristics and that they did not modify them systematically during the session. In some sense this confirms the notion of overconfidence because subjects were (over-)confident predicting optimally. This result does not support the result of Gervais and Odean (2001). In their multi-period market model traders become overconfident early. After some time, they learn to reduce the degree of overconfidence. It is possible that our subjects did not have enough experience although there exists no hint why subjects should start learning after more than 60 rounds.

3.5 Welfare and updating heuristic

We have shown that agents are on average overconfident. Now, two questions still remain. First, the consequences for the information aggregation process must be quantified. Second, the performance of agents' stated heuristics will be evaluated. To answer the first questions, we compare the observed data with our two benchmarks, Bayesian Updating (BU) and Private Information (PI). Within both scenarios it is assumed that all agents use the same decision rules, i.e. under PI everybody uses only her private information and disregards publicly observable predictions in all situations completely. For the second question, we generate a third benchmark, a modified counting heuristic (MCH). This updating procedure is derived from a combination of heuristics which subjects provided after the experiment:

- Predict according to your own **strong** signal if you are at position I, II, III or IV. In addition, use it at positions V and VI if more than one deviation is observable. Otherwise, follow the majority.
- Predict according to your own **weak** signal if your are at position I or II. In addition, use the own signal only if no majority exists <u>and</u> the last two subjects have not predicted the same state. Otherwise, follow the majority.

The modified counting heuristic is consistent with the notion of overconfidence since it puts more weight on the private information than on the public information which is the major difference to BU. Therefore, the decisions reveal the basic information better or more obviously than under BU. However, the information quality decreases because the distinction between strong and weak signals is no longer possible in some situations.

We calculate $\frac{M-PI}{BU-PI}$ with $M \in \{BU, PI, MCH\}$ as a measure for efficiency. Observed predictions lead to an efficiency of 62.8% whereas using exclusively the heuristic increases efficiency significantly to 88.9%. In other words, agents would have earned more if they had used their own heuristics. This heuristic is obviously a reasonable response to others' behavior as long as everybody is not completely discarding public information. It is more robust than Bayes' rule because it is easy to use especially given the uncertainty about others' behavior. Moreover, it avoids most of the "painful" reverse cascades at an efficiency loss of about 10%. This rather small loss explains why learning does not occur. In four (of 21) sessions subjects were not able to predict better than PI, i.e. earnings would have been higher using only the own information.

The described heuristic is a combination of Bayesian Updating and using only private information. Therefore, the heuristic may be better suited to deal with deviations from Bayesian Updating than using Bayes rule. Table 6 contains predictions derived from 24 probit regressions. All observations are used regardless of whether BU and MCH imply the same decision, or not. The prediction $p(D = x \mid BU = x)$ with $x \in \{0, 1\}$ at position y is derived from probit regressions containing BU as exogenous variable. $BU = 0$ ($BU = 1$) denotes the situation if Bayesian updating leads to an ex post wrong (correct) prediction. The actually observed decision D is either ex post correct (=1) or wrong (=0).

It is obvious from the data in table 6 that using the heuristic leads to better prediction results in most situations. One exception is position I at which both the heuristic and Bayesian updating lead to the same predictions. Thus, the estimates are the same. Bayesian updating only leads to better results if the decision is ex post wrong ($D = 0$) at position II or if the decision is ex post correct ($D = 1$) at position III. In all other situations, the heuristic describes subjects' decisions better than Bayes updating.

Bayesian updating and the heuristic imply the same decisions in a considerable number of situations. If we drop all these situations we can better distinguish between the two "updating" procedures, i.e. we analyze only those situations with $BU \neq MCH$. Table 7 contains predictions derived from probit regressions if BU and MCH lead to different predictions.

All predictions derived from the probit regressions are greater than or equal to 0.500. Thus, the above described modified counting heuristic explains the observed decisions better than Bayesian updating

Table 6: Comparison of Bayesian updating and a simple heuristic

Ex post, subjects' decisions can be either correct ($D = 1$) or wrong ($D = 0$) depending on the realized state. $BU = 0$ ($BU = 1$) denotes the situation if Bayesian updating leads to an ex post wrong (correct) prediction. MCH is equal to 1 if the modified counting heuristic leads to an ex post correct prediction. The predictions are derived from probit regressions using all observations of the specified subsamples.

	all observations			
position	$p(D = 0 \mid BU = 0)$	$p(D = 0 \mid MCH = 0)$	$p(D = 1 \mid BU = 1)$	$p(D = 1 \mid MCH = 1)$
1	0.917	0.917	0.908	0.908
2	0.741	0.715	0.760	0.828
3	0.706	0.822	0.876	0.872
4	0.585	0.683	0.793	0.854
5	0.521	0.676	0.802	0.845
6	0.502	0.556	0.744	0.761

Table 7: Bayesian updating vs. modified counting heuristic

Ex post, subjects' decisions can be either correct ($D = 1$) or wrong ($D = 0$) depending on the realized state. $BU = 0$ ($BU = 1$) denotes the situation if Bayesian updating leads to an ex post wrong (correct) prediction. MCH is equal to 1 if the modified counting heuristic leads to an ex post correct prediction. The predictions are derived from probit regressions using only those observations of the specified subsamples with different predictions based on Bayesian updating and based on the modified counting heuristic.

	Bayes $\neq$ Heuristic	
position	$p(D = 0 \mid MCH = 0, BU = 1)$	$p(D = 1 \mid MCH = 1, BU = 0)$
2	0.524	0.545
3	0.627	0.654
4	0.599	0.635
5	0.620	0.691
6	0.500	0.608

in all but one situation. This result shows that simple heuristics can lead to better prediction results if public information is based on others' non-Bayesian decisions. More specifically, the experimental results indicate that a certain degree of overconfidence is a better response to others' overconfidence and non-systematic errors than Bayesian updating.

4 Conclusion

The purpose of this experiment was to study information aggregation with two different qualities of information and to identify how the individual updating process influences the aggregation process. The available information is (partially) aggregated since almost all participants predicted better than based only on their own private information. Agents' overconfidence provides the only consistent explanation for the observed deviations from Bayes' rule. Other explanations, such as advanced error correction, regret aversion and gambler's fallacy are inconsistent with the data. Overconfident prediction behavior leads to fewer than expected cascades and reverse cascades. Although this individual behavior reduces relatively more reverse cascades than correct cascades the (absolute) effect on welfare is significantly negative. Sometimes, the collapse of information cascades initiates new cascades.

Based on this experiment several extensions may provide further insights about how information is aggregated in groups. Eventually, these will then lead to market situations in which prices might provide additional information about the precision of private information. A next step to evaluate the updating procedure might be to extract probability judgments immediately before participants submit their predictions. Another modification of this baseline experiment is the choice whether participants want to buy private information for a fixed cost, or not. This will answer the question whether participants can distinguish between informative and uninformative decisions in a rather simple environment. A crucial feature of markets is the possibility to decide at which time one would like to take action. An endogenous timing decision can have two effects on the aggregation process. On the one hand it can improve aggregation especially if participants with higher quality of information have an incentive (e.g. to avoid a waiting cost) to move earlier than those with weak signals who gain more by observing public information. But on the other hand overconfidence can lead to situations in which agents move too fast based on their private information and thus create misleading public signals for the others. Finally, our simple setting can be extended by a pricing mechanism and by allowing simultaneous or repeated decisions.

Appendix

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 these instructions very carefully 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 predict the occurring state in each round based on your private signal and the existing public information. The ordering of the six participants is determined randomly in each round.

Two states, marked "A" (white ball) and "B" (black ball), can occur. The state is being determined by random draw from an urn, which contains ten "A"-balls and ten "B"-balls, i.e. both states occur with the same probability $\left(p = \frac{1}{2}\right)$.

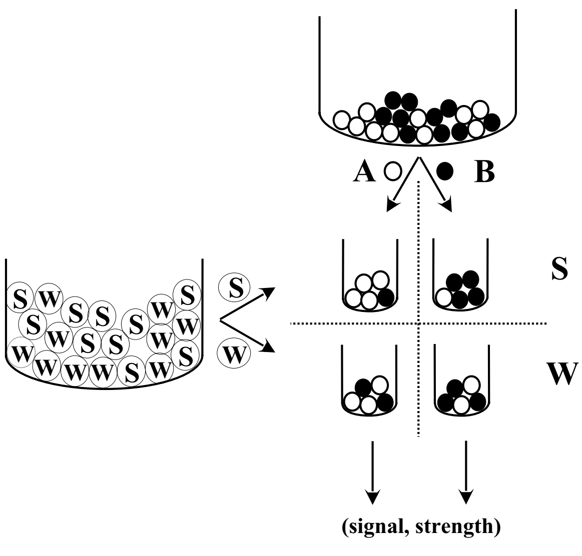
If state A occurred, the private signal will be determined for each participant as follows:

First the strength of the signal has to be determined by drawing from an urn, which contains ten "strong" and ten "weak" signals, i.e. the possibility of the signal being strong (S) or weak (W) is equal $\left(p = \frac{1}{2}\right)$ (see left big urn).

The signal is now being determined, dependant on its strength, by a draw from another urn:

- The "strong" urn contains four "A"-signals and only one "B"-signal (small urn, top-left).
  ⇒ The ratio of "A"- and "B"-signals is 4:1.
- The weak urn contains three "A"-Signals and two "B"-signals (small urn, lower-left).
  ⇒ The ratio of "A"- and "B"-signals is 3:2.

The following figure illustrates the procedure:



First of all, the computer determines the order, in which the predictions have to be submitted. When it is your turn, you first see your private signal, as well as the accompanying strength of signal. Then you are asked to submit your prediction. Submitted predictions are public information, i.e. the following participants can observe the predictions of all predecessors in addition to their own signal (at the bottom of your monitor). However, they cannot infer neither the underlying signal nor the accompanying signal's strength. The identification of the participants is not possible either. Your position within a round is display 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 three and not more than seven seconds before passing on the private signal.

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

Test Rounds

Before you will earn money with your predictions, you will become better acquainted with the procedures in three unpaid test rounds. During these test rounds you can always ask questions about the information structure and the course of the experiment.

Payment

You will participate in at least 25 and at most 100 rounds, in which you will be paid according to the correctness of your predictions. For each correct prediction you will receive 300 currency units (cu) , for each wrong prediction only 100 cu. At the end of the experiment the total payoff for all six participants will be converted in Deutsche Mark (DM) according to the expected hourly earnings of 16 DM. With the resulting exchange rate for this session your earnings will be converted in DM (and rounded up to the next DM).

Example:

- You have submitted 27 correct and 8 wrong predictions in 35 rounds: 8900 cu.
- All six participants have earned with their predictions: 43200 cu.
- The experiment (instructions and test rounds included) has lasted 2 hours.

Consequently, the exchange rate is computed as $\frac{43200cu}{16\frac{DM}{h}*6*2h} = 225\frac{cu}{DM}$.

As a result you earned 39.56 DM and you will receive 40.00 DM.

If you have any questions, now or during the test rounds, you can ask them in the next three minutes as well as during the three test rounds.

Final questionnaire

This questionnaire can help us to understand your decisions better and to generate new ideas for other experiments. The more precisely you formulate your statements, the better we can use them.

1. Which decision rule (or heuristic) have you used to make your predictions?
2. Has your behavior changed during the experiment? If so, why?

3. How strong, depending on the decision time (first position, second position, etc.), have you weighed your signal compared to the decisions that were already publicly known?
4. Would you like to decide again at the end of a period? If applicable, how often and why would you predict against your own information?
5. What would you do, if you could decide when to submit your prediction, instead of doing this in a predetermined order?
6. How would you change your behavior, if you lose money by waiting for a longer time?

References

Anderson, L. R., and C. A. Holt, 1997, "Information Cascades in the Laboratory," *American Economic Review*, 87, 847–862.

Avery, C., and P. Zemsky, 1998, "Multidimensional Uncertainty and Herd Behavior in Financial Markets," *American Economic Review*, 88, 724–748.

Banerjee, A., 1992, "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107, 797–818.

Bernardo, A., and I. Welch, 2000, "On the Evolution of Overconfidence and Entrepreneurs," UCLA, mimeo.

Bikhchandani, S., D. Hirshleifer, and I. Welch, 1992, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100, 992–1026.

Bikhchandani, S., D. Hirshleifer, and I. Welch, 1998, "Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades," *Journal of Economic Perspectives*, 12, 151–170.

Camerer, C. F., 1989, "Bubbles and Fads in Asset Prices," *Journal of Economic Surveys*, 3, 3–41.

Camerer, C. F., 1995, "Individual Decision Making," in: Kagel, J. H., and A. E. Roth (eds.), *The Handbook of Experimental Economics* , chap. 8, 587–703, Princeton University Press, Princeton, NJ, 1 edn.

Camerer, C. F., and K. Weigelt, 1991, "Information Mirages in Experimental Asset Markets," *Journal of Business*, 64, 463–493.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, "A Theory of Overconfidence, Self-Attribution, and Security Market Under- and Overreaction," *Journal of Finance*, 53, 1839–1885.

Edwards, W., 1968, "Conservatism in Human Information Processing," in: Kleinmuntz, B. (ed.), *Formal Representation of Human Judgment* , 17–52, Wiley, New York, NY, 1 edn.

Gervais, S., and T. Odean, 2001, "Learning to be Overconfident," *Review of Financial Studies*, 14, 1–27.

Gul, F., and R. Lundholm, 1995, "Endogenous Timing and the Clustering of Agents' Decisions," *Journal of Political Economy*, 103, 1039–1066.

Hirshleifer, D., 2001, "Investor Psychology and Asset Pricing," *Journal of Finance*, 56, forthcoming.

Hung, A. A., and C. R. Plott, 1999, "Information Cascades: Replication and an Extension to Majority Rule and Conformity Rewarding Institutions," forthcoming: *American Economic Review*.

Klayman, J., J. B. Soll, C. Gonzáles-Vallejo, and S. Barlas, 1999, "It Depends on How, What, and Whom You Ask," *Organizational Behavior and Human Decision Processes*, 79, 216–247.

Lee, I. H., 1993, "On the Convergence of Informational Cascades," *Journal of Economic Theory*, 61, 395–411.

Lichtenstein, S., B. Fischhoff, and L. D. Phillips, 1982, "Calibration of Probabilities: The State of the Art to 1980," in: Kahneman, D., P. Slovic, and A. Tversky (eds.), *Judgment under Uncertainty: Heuristics and Biases* , 306–334, Cambridge University Press, Cambridge, MA, 1 edn.

Odean, T., 1998, "Volume, Volatility, Price, and Profit when all Traders are above Average," *Journal of Finance*, 53, 1887–1934.

Porter, D. P., and V. L. Smith, 1994, "Stock Market Bubbles in the Laboratory," *Applied Mathematical Finance*, 1, 111–127.

Scharfstein, D. S., and J. C. Stein, 1990, "Herd Behavior and Investment," *American Economic Review*, 80, 465–479.

Smith, V. L., G. L. Suchanek, and A. W. Williams, 1988, "Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Asset Markets," *Econometrica*, 56, 1119–1151.

Weinstein, N. D., 1980, "Unrealistic Optimism About Future Life Events," *Journal of Personality and Social Psychology*, 39, 806–820.

Welch, I., 1992, "Sequential Sales, Learning and Cascades," *Journal of Finance*, 47, 695–732.

Zhang, J., 1997, "Strategic Delay and the Onset of Investment Cascades," *RAND Journal of Economics*, 28, 188–205.

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