Do individuals recognize cascade behavior of others?
— An experimental study —*

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Abstract

In a cascade experiment subjects are confronted with artificial predecessors predicting in line with the BHW model (Bikhchandani, Hirshleifer and Welch, 1992). Using the BDM mechanism we study subjects' probability assignments based on price limits for participating in the prediction game. We find increasing price limits the more coinciding predictions of predecessors are observed and regardless of whether additional information is actually revealed by predecessors' predictions. Individual price patterns of more than two thirds of the participants indicate that cascade behavior of predecessors is not recognized.

JEL Classification: C91, D81, D82

Key Words: information cascades, Bayes' rule, decisions under risk and uncertainty, experimental economics

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1. Introduction

Information cascades as modelled by Bikhchandani, Hirshleifer and Welch (1992), henceforth BHW, have become a very popular approach to explain herding behavior, especially among economists.[1] The BHW model can be used to explain central features of herding as erroneous mass behavior and can account for many examples to be found in practice. But herding can also be derived within a rational choice approach assuming agents who update information according to Bayes' rule. Last but not least, the BHW model also withstood a first experimental test by Anderson and Holt (1997), henceforth AH.[2] It shows that in a choice situation under incomplete private information it may be rational just to follow predecessors by disregarding one's own private information. Hence a cascade starts since no further information will be aggregated. Agents may follow wrong decisions of predecessors even if the aggregated private information would suggest the opposite. Individual rationality may thus lead to market inefficiencies.

The BHW model implicitly assumes that agents recognize cascade behavior of others. If not, perceived posterior probabilities increase with the length of the cascade even if no further information aggregation takes place. Boundedly rational behavior of agents thus would result in an overvaluation of public information and thereby cause economic consequences. Consumers, for instance, might misinterpret past sales of a specific product as signaling quality. They consequently may be willing to pay unreasonably high prices for best-sellers compared to competing products with similar features. Promotion instruments, that refer to number or

[1] For an online survey of theoretical and empirical studies faced with information cascades see Bikhchandy, Hirshleifer and Welch (1996) available at [http://welch.som.yale.edu/cascades/].

[2] They ran a prediction game in which the underlying information structure of BHW was reflected by urns and balls and conclusions drawn from subjects' urn predictions.

degree of already made sales as, e.g. best-seller lists, could not only be used to raise sales numbers but also to get consumers to accept price increases.[3]

Whether individuals actually recognize cascade behavior of others is the focus of this study. The answer to this question is not only of practical relevance as discussed above; it is also of theoretical interest. Following AH, most previous experimental studies investigate cascade behavior by varying the underlying information structure and selling costly private information.[4] Conclusions are usually drawn from subjects' predictions and buying decisions. It turned out that individuals, if confronted with more complex decision tasks, tend to overestimate private information and thus to deviate from the rational cascade pattern. They follow their private signal longer than predicted by BHW and buy more information than would be rational. Even in the AH experiment itself prediction errors increase up to 50 percent if simple counting does not lead to a correct urn prediction (see Huck and Oechsler, 2000). In these situations the rule 'follow your own signal' offers better predictions than Bayesian updating.

In contrast, we especially focus on individual updating behavior if confronted with a symmetric cascade design, in which even simple counting inherently leads to correct urn predictions. We conjecture that people confronted with these rather simple decision tasks predict according to theory but do not recognize cascade behavior of others and, hence, tend to overestimate public information.

Oberhammer and Stiehler (2002) already investigated whether cascade behavior in a symmetric cascade design reflects Bayesian updating. Using the BDM procedure (Becker, De Groot and Marshak, 1964) they asked participants to submit maximum prices they are willing to pay to participate in the prediction game. This enables them to use maximum prices as indicators of subjective probability perceptions and thus to test directly the explanatory power of the standard BHW model as well as of cascade models in which errors of predecessors are included in subjects' updating process.[5] The authors report on increasing prices

[3] We are aware, that in markets in which prices instantly and smoothly adjust, as e.g. in financial markets, prices would incorporate additional public information and thus rule out information cascades as shown by Avery and Zemsky (1998) and experimentally tested by Cipriani and Guarino (2001) and Drehmann at al.(2002).

[4] See e.g.Willinger and Ziegelmeyer (1998), Kraemer at al. (2000), Kraemer and Weber (2001), Nöth and Weber (2001), Kübler and Weizsäcker (2001).

[5] The examination of errors by econometric methods in so called quantal response models (McKelvey and Palfrey 1995,1998) has become increasingly popular for the analysis of cascade data, since resulting approaches inter alia can account for a significant portion of deviations from standard BHW model as reported above. For different approaches of quantal response equilibria in information cascade models see e.g. Anderson and Holt (1997), Anderson (2001), Kübler and Weizsäcker (forthcoming) or Kreamer and Noeth (2001).

up to cascade positions at which no further information is revealed by predictions of predecessors. In contrast to the standard BHW model, error models can account for the observed price increase. But the observed pattern could also be caused by subjects who do not recognize cascade behavior of others and, thus, overestimate public information. Even if the authors succeeded in designing an experiment that provides more insight into subjects' updating behavior, they were not able yet to distinguish between different explanations for the observed price setting pattern. Moreover, their data source is limited. The cascade situations in which individuals have to decide are endogenously determined, so that observing complete individual price patterns is nearly impossible.

In this experiment we use a similar design as Oberhammer and Stiehler (2002). Subjects are confronted with the same information structure and the BDM mechanism is used to extract prices as indicators of subjects' probability perceptions. In addition, artificial agents are incorporated as predecessors, who follow a simple counting rule and - by definition - never err. Using a strategy method subjects are asked to state their decisions for all possible cascade situations. Clearly such a design allows to address the central question of whether individuals recognize cascade behavior of others on the basis of complete individual price setting patterns with individual price decisions for all possible cascade positions.

The remainder of this paper is organized as follows: In section 2 the experimental design and procedures are described. In the subsequent section 3 predictions are derived for both rational behavior as assumed in the BHW model and behavior based on the assumption that subjects do not recognize cascade behavior of others. The results are presented in section 4. The paper finishes with a discussion of the results in section 5.

2. Experimental design and procedure

We incorporate artificial agents and apply the strategy method in a design similar to Oberhammer and Stiehler (2002). One of our major concerns when planning the procedure was to ensure that all design features were clearly understood by the participants. In this section each part of the design and the experimental procedure will be explained in detail and discussed in the light of our central question to be tested.

`Experimental scenario`

There are two urns, A and B, with 5 balls each (3 white balls and 2 black balls and vice versa). One urn is randomly chosen with equal probability at the beginning, and players predict repeatedly the randomly chosen urn. For a correct urn prediction they receive 100 ECU (Experimental Currency Units) and nothing else. As participant's private information a ball is drawn from the urn and its color revealed. As public information predecessors' urn predictions are publicly announced.

Participants are further asked to submit maximum prices $p_{\max}$ they are willing to pay to participate in the prediction game, i.e. to seize the chance of winning 100 ECU for a correct urn prediction. As an incentive compatible mechanism to elicit subjects' maximum willingness to pay we implemented the Becker-DeGroot-Marshak (BDM) mechanism (Becker, DeGroot and Marshak, 1964). A uniformly distributed random price p_r from the interval [0,100] is drawn and compared with the maximum prices submitted by the participants. If the random price exceeds the maximum price ($p_r > p_{\max}$) the participant earns nothing. If the random price is equal or lower than the maximum price ($p_r \leq p_{\max}$) the participant earns the money amount resulting from her urn prediction minus the random price (see also Table 2.1).

	Correct urn prediction	Wrong urn prediction
$p_r \leq p_{\max}$	100 ECU - p_r	0 ECU - p_r
$p_r > p_{\max}$	0 ECU	0 ECU

Table 2.1: Income calculation.

If participants were risk neutral and would maximize their income according to standard expected utility theory the submitted maximum prices would perfectly reflect their probability perceptions. But these assumptions are hardly satisfied as many experimental studies on decision making show.[6] We are also aware that the implementation of the BDM mechanism in a lottery-like decision task might provoke preference reversals (Safra et al., 1990).

However, for our purpose it is sufficient if prices and probabilities are positively correlated. Under the assumption of a positive correlation we are able to

[6] For surveys of experimental studies on individual decision making under risk and uncertainty see e.g. Camerer (1995) or Hey (1991).

compare resulting price patterns with the probability pattern according to BHW. To test this necessary assumption participants are additionally asked to state subjective probabilities for the correctness of their urn predictions. For 38 out of 39 participants (97.4 %) we observe highly significant positive correlations between maximum prices and subjective probabilities and thus consider this assumption as fulfilled.

Implementation of artificial agents

In this cascade experiment a subject's predecessors are artificial agents, whose predictions are clearly defined by simple counting, e.g. agents predict according to the majority of (public and private) signals in favor of Urn A or B. Consequently, errors of predecessors are excluded by definition. Note that in the applied symmetrical information structure simple counting leads to the same urn predictions as Bayesian updating (see Anderson and Holt, 1997). Thus urn predictions of predecessors are in line with BHW. In case of a tie-break, i.e. an equal number of signals in favor of urn A and B, artificial agents decide according to their private signal. This tie-breaking rule, that was also assumed by AH to analyze data of the symmetric design, rather simplifies the updating process compared to a randomization between urn A and B, as assumed by BHW.

One may object that we influenced participants' decisions by incorporating artificial agents who followed a simple counting heuristic. That might be true since we, admittedly, teach participants to predict according to the BHW model. But note that we are interested in price setting behavior rather than in urn predictions. If maximum prices were also influenced, this would strengthen the evidence against the hypothesis, that subjects do not recognize cascade behavior of others. We, however, find this hypothesis supported by the data as will be reported in section 4.

Use of the strategy method

Participants are asked to state their decisions for all resulting situations up to position 6 (and thus are confronted with up to 5 artificial agents as predecessors). Depending on

- participants' own positions (1 to 6),

- the color of the privately drawn ball (black or white) and
- the history regarding predecessors' predictions

there are overall 74 cascade situations (summarized in Appendix C) for which participants have to submit their urn predictions and their maximum prices. One situation was randomly chosen at the end of the session to be paid out according to each participant's respective decisions and the outcome of the random processes.

The choice of the payment-relevant situation works as follows:

1. One urn (A or B) is randomly chosen.
2. Subjects' position (1 to 6) is determined.
3. For each artificial agent a ball is drawn from the actually chosen urn and its predictions with respect to the defined decision rules determined and publicly announced.
4. At (real) participants' position a ball is drawn and the color announced.

Then one situation (out of 74) is chosen to become payoff-relevant. Further, the actually chosen urn is revealed and the random price is drawn from all integers between 0 and 100. Now the incomes from the experiment can be calculated according to the rules summarized in Table 2.1.

The implementation of the strategy method has two major advantages: First it enables us to observe complete individual price patterns as discussed in the previous section. Secondly, the strategy method, as investigated so far causes rather 'cold', i.e. less emotional responses than spontaneous play and thus helps us to focus on participants ability to recognize cascade behavior of others.[7]

`Procedure`

At the start of a session participants were provided with formal instructions (see Appendix A) as well as with a supplementary sheet on the working of the BDM mechanism demonstrating that strategic behavior does not pay (see Appendix B). Upcoming questions were answered privately during the whole experiment.

[7] For experimental studies on presentation effects see e.g. Brandts and Charness (2000) or Schotter, Weigelt and Wilson (1994).

After reading the instructions it was demonstrated how the payment-relevant situation would be chosen. While all decisions had to be submitted via the computer, the choice of the payment-relevant situation and the draw of the random price were done by hand using real urns (opaque blue bags), balls (table tennis balls), dice and chips with numbers from 1 to 100. Participants themselves were asked to execute the random processes.

Before starting the experiment participants were confronted with a pre-experimental control questionnaire, in which they were systematically asked about decision rules of artificial predecessors and the work of the price mechanism (see Appendix D). We provided an additional payment of € 5 for subjects who answered all questions correctly in the first go. Moreover, participants were not allowed to proceed before all questions were answered correctly.

In the experiment participants submitted their decisions for all 74 situations which were – in random order – displayed on the computer screen. After the decisions were taken the payment relevant situation (out of 74) was chosen and subjects paid according to their respective decisions and the outcomes of the random processes.

By using of real urns and balls and the execution of random choices by participants themselves, by demonstrating the choice of the payment-relevant situation before a session started and by using a pre-experimental control questionnaire we ensured that the structure of the experiment, the decision rules of artificial agents as well as the working of BDM were understood by the participants. In addition, our findings are controlled for a possible bias resulting from lack of understanding of the artificial agents' decision rules (see section 4).

The computerized experiment (using the software toolkit z-Tree, Fischbacher, 1999), was conducted at Humboldt-University in Berlin. We ran 4 sessions with 9, 12, 7 and 11 participants. The 39 subjects, mainly students of the economics faculty, were randomly recruited from a pool of potential participants. In order to avoid losses a show-up fee of 100 ECU was paid. The experiment lasted about 80 minutes. 100 ECU corresponded to € 10. Average earnings amounted to approximately € 17 on average.

3. Hypotheses

In a symmetric cascade structure in which predecessors update information in line with Bayes' rule and predict in case of a 50% chance according to their private signal posterior probabilities just depend on the number of signals in favor of urn A and B. For the applied design they can be calculated as follows (see Anderson and Holt,1997 p.850).

Let $n(m)$ be the number of signals in favor of urn A (B). Then:

$$\Pr(A|n,m) = \frac{\Pr(n,m|A)\Pr(A)}{\Pr(n,m|A)\Pr(A)+\Pr(n,m|B)\Pr(B)} \tag{3.1}$$

$$= \frac{\left(\frac{3}{5}\right)^n\left(\frac{2}{5}\right)^m\left(\frac{1}{2}\right)}{\left(\frac{3}{5}\right)^n\left(\frac{2}{5}\right)^m\left(\frac{1}{2}\right)+\left(\frac{2}{5}\right)^n\left(\frac{3}{5}\right)^m\left(\frac{1}{2}\right)} \tag{3.2}$$

It can, furthermore, be shown that under the described assumptions only the difference between A-and B-signals $d = n - m$ is relevant as illustrated in the following equation 3.3. If n is substituted by $m + d$ then:

$$\Pr(A|d) = \frac{3^{m+d} * 2^m}{3^{m+d} * 2^m + 2^{m+d} * 2^m} = \frac{1}{1+\left(\frac{2}{3}\right)^d} \tag{3.3}$$

Posterior probabilities thus increase with an increasing difference in favor of the respective urn. However, rational subjects as assumed in the BHW model would recognize that a cascade starts once a difference of $d = 2(-2)$ is reached. From this point on subsequent players would always predict according to the ongoing cascade even if their private signal was in opposite, diminishing the difference to $d = 1(-1)$. Therefore, no further information can be inferred from their predictions. Posterior probabilities for all further situations remain stable at $Pr(A|d = 3) = 0.77$ if confronted with a signal in accordance with the ongoing cascade or at $Pr(A|d = 1) = 0.60$ if confronted with an opposed signal.

For the remaining part of the paper we refer to private signals in accordance or in opposition to the ongoing cascade as *pro*, resp. *contra* signals. We further refer to a player's position at which a cascade starts as cascade positions 0. We respectively refer to former positions as cascade positions -1, -2 and -3[8] and later positions within the cascade as cascade positions 1, 2 and 3.

[8] Cascade position -3 reflects a tie-breaking situation, i.e. the posterior probability is 0.5. It could also be defined as cascade position -1 after seeing a contra signal; see also appendix C.

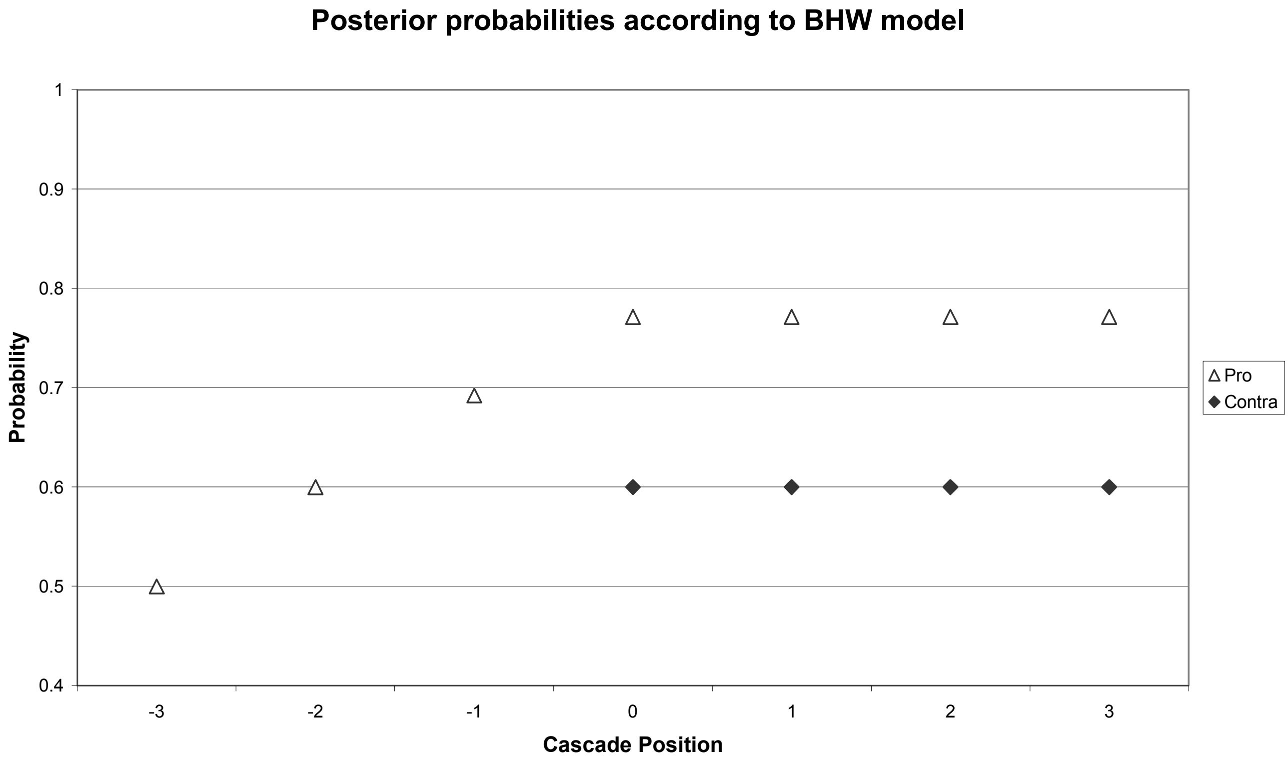


Figure 3.1: Resulting probability pattern according to the standard BHW model (assuming that subjects realize cascade behavior of others).

Figure 3.1 shows a graphical representation of posterior probabilities for all cascade positions given pro or contra signals according to the BHW model. Posterior probabilities increase up to cascade position 0 if confronted with pro signals but are constant after a cascade has started given pro, resp. contra signals. Assuming that prices are positively correlated with probabilities allows us to make predictions regarding the resulting price pattern with respect to the BHW model.

Predictions according to the BHW model: Individuals update information according to Bayes' rule and take cascade behavior of others into account.

a) *Prices* $p_{\max}$ *increase from cascade position -3 to 0 if confronted with pro signals.*

b) *Prices* $p_{\max}$ *are constant from cascade position 0 to 3 if confronted with pro signals.*

c) *Prices* $p_{\max}$ *are constant from cascade positions 0 to 3 if confronted with contra signals.*

There are many studies showing that individuals' depths of reasoning are limited.[9] In the context of information cascades Kübler and Weizsäcker (forthcoming) already ran a limited-depth-of-reasoning analysis by estimating a quantal response model based on subjects' urn predictions and the purchase of costly information. According to their results individuals take into account errors of predecessors but "they do not reason far enough to realize that other subjects also sometimes rely on third players decisions" (Kübler and Weizsäcker, forthcoming; p. 8). We deliberately excluded errors of predecessors but conjecture that even in this simple decision task individuals do not recognize cascade behavior of others. According to equation 3.3 probabilities would increase the longer a cascade continues due to the increasing difference between A- and B-signals, as illustrated in Figure 3.2.

Predictions regarding individual price setting behavior in line with our behavioral hypothesis can be summarized as follows.

Predictions according to the behavioral Hypothesis: Individuals update information according to Bayes' rule, but do not recognize cascade behavior of others.

a) *Prices* $p_{\max}$ *increase from cascade position -3 to 0 if confronted with pro signals.*

b) *Prices* $p_{\max}$ *increase from cascade position 0 to 3 if confronted with pro signals.*

c) *Prices* $p_{\max}$ *increase from cascade position 0 to 3 when confronted with contra signals.*

Both hypotheses have in common that subjects generally infer additional information revealed by predecessors' urn predictions and thus predict increasing price limits from cascade position 0 to cascade position 3 if confronted with pro signals. But the hypotheses clearly differ in terms of the predicted price pattern from cascade position 3 to 6 as can be inferred from Table 3.1. The analysis of price setting data allows to test both separating hypothesis and to distinguish subjects who recognize a cascade formation from subjects who ignore cascade behavior of predecessors.

[9]For depth of reasoning analyses in normal form games see e.g. Ho, Camerer, and Weigelt, 1998) or Nagel (1995).

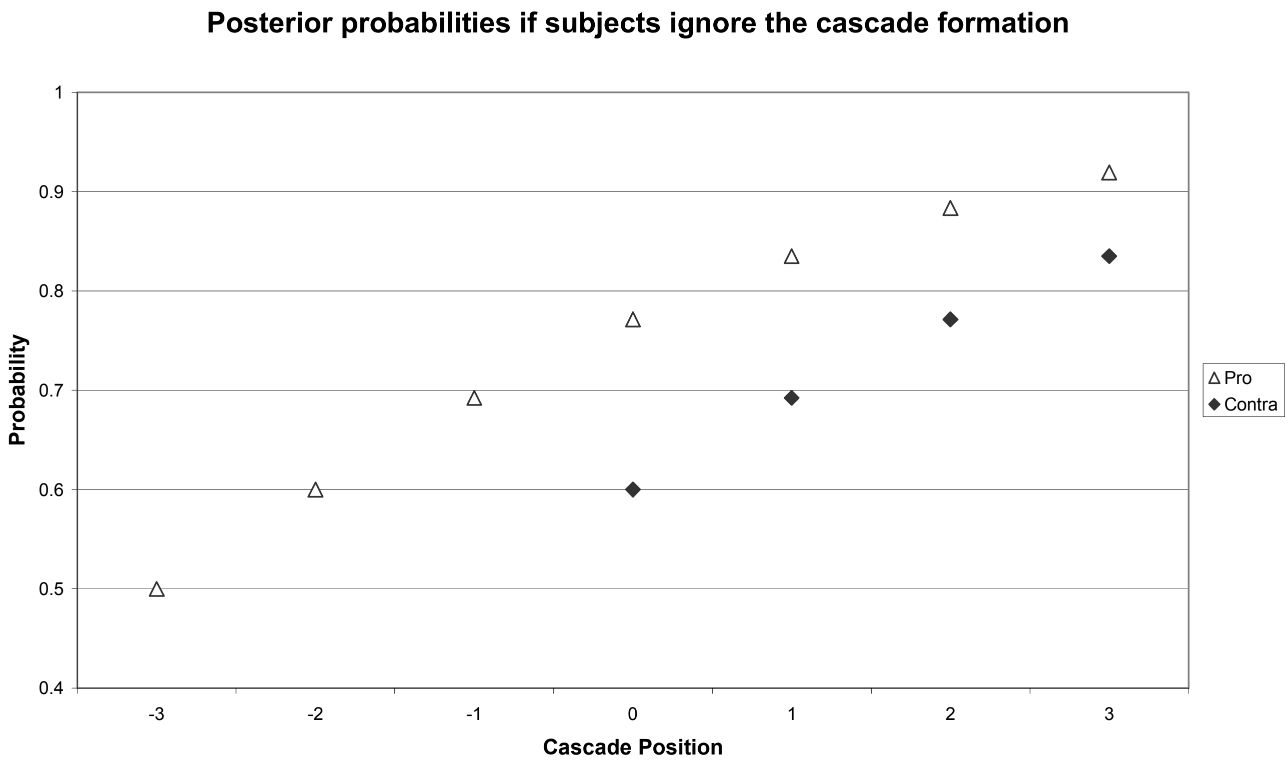


Figure 3.2: Resulting probability pattern if subjects do not realize cascade behavior of others (behavioral hypothesis).

Do individuals recognize cascade behavior of others?	Standard BHW model: *Yes*	Behavioral hypothesis: *No*
a) $p_{\max}$ from casc. pos. -3 to 0pro	$p_{\max}^{-3pro} < p_{\max}^{-2pro} < p_{\max}^{-1pro} < p_{\max}^{0pro}$	
b) $p_{\max}$ from casc. pos. 0pro to 3pro	$p_{\max}^{0pro} = p_{\max}^{1pro} = p_{\max}^{2pro} = p_{\max}^{3pro}$	$p_{\max}^{0pro} < p_{\max}^{1pro} < p_{\max}^{2pro} < p_{\max}^{3pro}$
c) $p_{\max}$ from casc. pos. 0con to 3con	$p_{\max}^{0con} = p_{\max}^{1con} = p_{\max}^{2con} = p_{\max}^{3con}$	$p_{\max}^{0con} < p_{\max}^{1con} < p_{\max}^{2con} < p_{\max}^{3con}$

Table 3.1: Expected price patterns.

4. Results

4.1. Prediction behavior

We will first shed some light on prediction behavior. The 39 participants were independently asked to make decisions for 74 situations. The data file thus consists of $39 * 74 = 2886$ urn predictions, prices and subjective probabilities. For the analysis of urn predictions we excluded observations at cascade position -3, i.e. from situations with a posterior probability of 0.5, since in these cases any prediction can be supported by the BHW model. Of the remaining 2340 urn predictions 2268 (96.9%) are in line with BHW. 15 subjects (38.5 %) predicted always in line with the theory. The rate of seemingly rational predictors sharply increases up to 82.1 % (32 out of 39), if we consider subjects who predicted in more than 95% of relevant the situations in line with the BHW model, i.e. those who erred only randomly.

The high rate of predictions in line with rational Bayesian updating may not astonish, given that we by incorporation of artificial agents indirectly influenced subjects to predict in line with BHW as already discussed in section 2. However, in 23.1 % of all tie-breaking situations (with posterior probabilities of 50%), at which artificial agents always predict according to their private signal participants predicted against it.

From cascade position 0 on rational agents are supposed to follow their predecessors even if they are confronted with a contra signal. As already observed in previous experiments the error rate in such situations is essentially higher (6.9%) than in cases in which the signal coincides with the ongoing cascade (1.7%). In order to get more insights into the structure of prediction errors, we compared error rates at different cascade positions if subjects were confronted with contra signals and summarized the results in Table 4.1. The error rate at cascade position 0 if confronted with contra signals is clearly higher (13.2%) than at later cascade positions, even if no further information aggregation by predecessors' predictions takes place and errors of predecessors are excluded. It seems that a substantial fraction of participants rather overvalues its private information at early cascade positions but assigns more weight to predecessors predictions the longer the cascade continues.

Cascade situation	Number of cases	Number of errors	Error rate (%)
0 contra	234	31	13.2
1 contra	234	11	4.7
2 contra	78	0	0.0
3 contra	78	1	1.3
Total	626	43	6.9

Table 4.1: Prediction errors at different cascade positions if confronted with contra signals.

4.2. Price setting behavior

The question remains whether subjects who actually predict in line with the BHW model also recognize that a cascade formation takes place. To check this we examined submitted maximum prices that belong to predictions in line with BHW. In order to account for the different number of individual observations at different cascade positions, we averaged submitted maximum prices for each participant at each cascade position given pro, resp. contra signals. The data file to be analyzed thus consists of 418 individual average prices, i.e. average prices for 38 subjects[10] at 11 different cascade situations[11]. For a first overview individual average prices are summarized for each cascade position in Table 4.2 and the resulting aggregated price pattern is graphically illustrated in Figure 4.1. In addition, the same aggregated measures are calculated for stated subjective probabilities and summarized in Table 4.2.

As predicted by both, the BHW model as well as our behavioral hypothesis price limits increase from cascade position -3 to 0 if confronted with pro signals. Average maximum prices further increase – in line with the behavioral hypothesis – from cascade position 0 to 3 for pro as well as for contra signals.

A similar pattern can be observed considering stated subjective probabilities. But in comparison with submitted maximum prices stated subjective probabilities are for each cascade situation 6 to 10 units higher, indicating that risk neutral utility maximizers would be willing to pay even more for the chance to take part in the prediction game. Stated subjective probabilities at cascade position -3 (after

[10] For the analysis of price setting behavior we excluded observations of the one subject, whose submitted maximum prices do not significantly correlate with the stated subjective probability (see section 2). However, it would not change our main findings at all, if we included this observations.

[11] For the assignment of possible cases to cascade situations see also appendix C.

Private signal	Cascade position	Individual avg. prices Mean	Median	Std. Dev.	Subj. probabilities Mean	Median	Std.Dev
	-3	32.90	35.61	18.58	42.62	47.14	12.62
	-2	39.67	39.15	17.30	48.81	51.18	11.19
	-1	53.08	53.87	17.91	59.55	61.64	11.08
	0	59.45	60.41	20.16	65.24	66.67	12.15
pro	1	67.84	76.67	22.24	73.58	77.5	13.88
	2	73.13	80.00	20.68	80.73	85.00	13.58
	3	73.93	81.25	23.86	81.23	87.00	16.88
	0	39.71	41.04	16.67	46.90	50.33	14.17
contra	1	50.83	50.83	20.53	58.15	61.00	15.50
	2	55.46	58.25	23.59	63.32	65.50	16.88
	3	63.76	70.25	25.91	72.87	75.00	18.69

Table 4.2: Descriptive statistics of price setting behavior and subjective probability statements.

observing a pro signal) show that the probability concept in the pure statistical sense is misunderstood by many participants. In these situations the majority of participants stated probabilities of less than 50 %. They seem to (mis)interpret probabilities rather qualitatively as degree of certainty or uncertainty when confronted with risky choices. Following this reasoning, subjects at the first cascade positions rather distrust the information aggregation, but they become more convinced by the correctness of their urn prediction the longer a cascade continues. Overall, at the very last cascade positions both, submitted price limits and subjective probabilities are for the majority of participants clearly higher than predicted by the BHW model.

In order to test the hypotheses derived in the previous section we ran the nonparametric Friedman-test which is appropriate to test whether $n > 2$ related samples are from the same distribution. Based on individual average prices we additionally calculated Spearman rank correlations between maximum prices and the respective cascade positions at the considered cascade situations. The results are presented in Table 4.3.

Both statistical measures confirm that subjects generally infer information from predecessors' urn predictions (see line a), the H_0-hypothesis that prices are constant from cascade position -3 to 0 if confronted with pro signals is significantly rejected. Instead, we observe a significantly positive relation (Spearman's

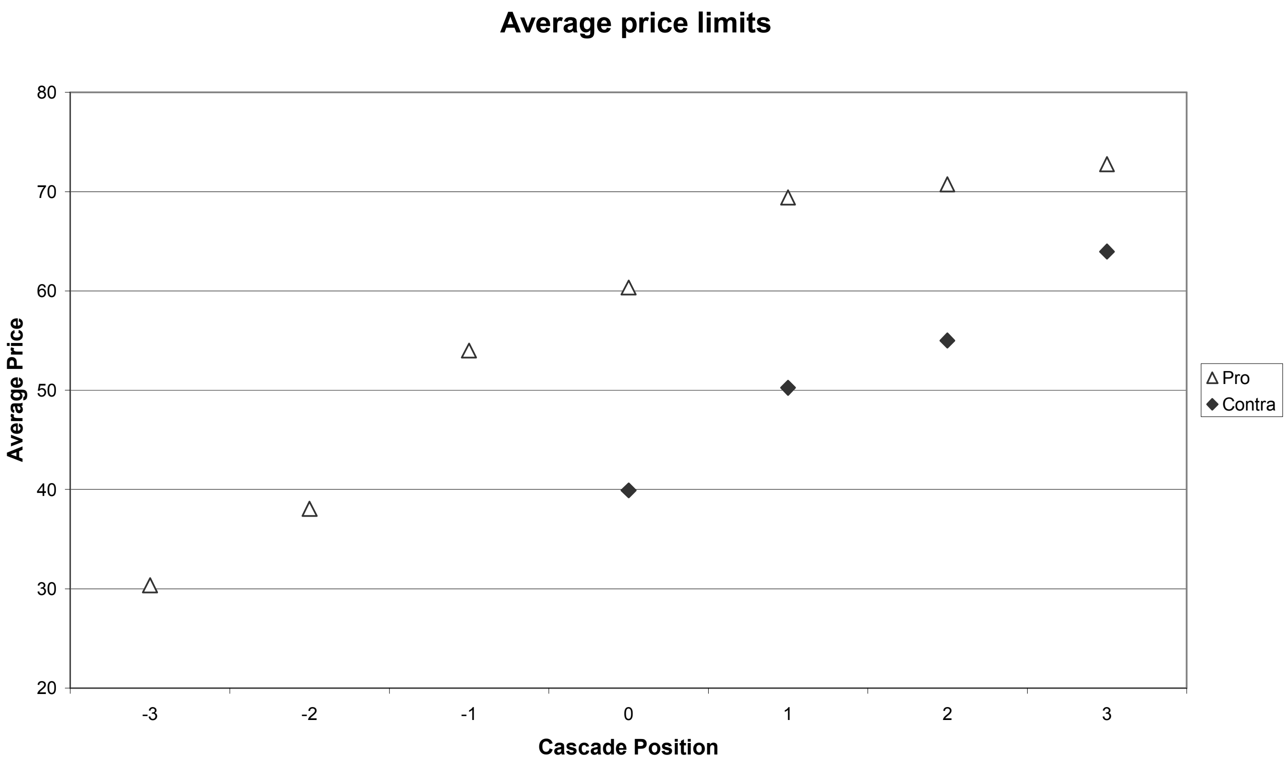


Figure 4.1: Mean of individual average prices at different cascade situations (characterized by cascade position and private signal).

	Friedman-test Hypothesis (H_0)	χ^2 (sign.)	Spearman rank corr. ρ (sign. 2-tailed)
a)	$p_{\max}^{-3pro} = p_{\max}^{-2pro} = p_{\max}^{-1pro} = p_{\max}^{0pro}$	91.016 (.000)	.467 (.000)
b)	$p_{\max}^{0pro} = p_{\max}^{1pro} = p_{\max}^{2pro} = p_{\max}^{3pro}$	42.858 (.000)	.257 (.001)
c)	$p_{\max}^{0con} = p_{\max}^{1con} = p_{\max}^{2con} = p_{\max}^{3con}$	64.445 (.000)	.367 (.000)

Table 4.3: Friedman-test and Spearman rank correlations price limits and cascade positions at different cascade situations.

$\rho > 0$ with $p < 0.01$) between submitted price limits and the respective cascade positions, i.e price limit increase with increasing cascade positions. This finding is in line with Bayesian updating. But, apart from the price increase up to cascade position 0 pro, all other characteristics in line with the standard BHW model are significantly rejected (see line b and c). In contrast, we observe – in line with the alternative (behavioral) hypothesis – significantly positive correlation coefficients at cascade positions 0 to 3 if confronted with pro, resp. contra signals.

Observations I Aggregate price pattern

a) *Prices $p_{\max}$ significantly increase from cascade position -3 to 0 if confronted with pro signals as predicted by both, BHW model and the derived behavioral hypothesis.*

b) *Prices $p_{\max}$ significantly increase from cascade position 0 to 3 if confronted with pro signals as predicted by the behavioral hypothesis, whereas the hypothesis claiming constant price limits after a cascade has started (as predicted by BHW) has to be rejected.*

c) *Prices $p_{\max}$ significantly increase from cascade position 0 to 3 if confronted with contra signals as predicted by the behavioral hypothesis, whereas the hypothesis claiming constant price limits after a cascade has started (as predicted by BHW) has to be rejected.*

One may object that the observed aggregated price setting pattern might be biased for two reasons:

1. Subjects systematically deviate from the cascade pattern, since only submitted prices for predictions in line with BHW are included.

2. Subjects did not completely understand predictions of artificial predecessors.

Therefore we applied the same analysis for the subsample of subjects who:

1. showed more than 95% of their urn predictions in accordance with BHW and

2. answered all questions about artificial predecessors correctly at the first time[12].

Our findings, however, turn out to be robust. Supported by the statistical analysis (see Appendix E.1) we find a similar pattern for the considered subsample as for all subjects. Moreover, the resulting price pattern as stated above strongly coincides with the observed probability pattern, derived from stated subjective probabilities. A statistical analysis of the probability pattern (see Appendix E.2) brings up the same conclusions, i.e. the hypothesis according to BHW has to be rejected in favor of our behavioral hypothesis. We thus conclude that subjects in general show a Bayesian like updating: They infer informations from predecessors in their updating process, but they do not recognize cascade behavior of others.

The use of the strategy method, furthermore, allows to observe complete individual price setting patterns (see Figures 4.2 and 4.3) and to calculate Spearman rank correlations between submitted maximum prices and the respective cascade positions for each single participant. As before we calculated 3 correlation coefficients regarding:

a) price limits at cascade positions -3 to 0 if confronted with pro signals,

b) price limits at cascade positions 0 to 3 if confronted with pro signals and

c) price limits at cascade positions 0 to 3 if confronted with contra signals.

Using the correlation coefficients and their significance at the 5% level we are now in the position to distinguish 4 different groups of participants:

- **BHW subjects**: Those who show a significant positive correlation between cascade positions and price limits at cascade positions -3 to 0 if confronted with pro signals, but no significant correlation coefficients from cascade position 0 to 3 if confronted with pro, resp. contra signals.

- **Subjects completely in line with the behavioral hypothesis:** Those who show significant positive correlation coefficients at cascade position -3 to 0 if confronted with pro signals as well as at cascade positions 0 to 3 for both, pro and contra signals.

[12] Note, that we confronted our subjects in two questions even with situations at which artificial predecessors showed cascade behavior, i.e. predicted against their private signal.

- **Subjects partly in line with the behavioral hypothesis**: Those who show significant positive correlation coefficients at cascade positions -3 to 0 if confronted with pro signals as well as at cascade positions 0 to 3 either for pro or for contra signals.

- **Others:** Those who do not show a significant positive correlation at cascade position -3 to 0 if confronted with pro signals and thus showing price setting behavior in contrast to the predictions according to BHW model as well as behavioral hypothesis.

Identified groups	Id. patterns*			Total	(%)	Subject- Ids
	a)	b)	c)	number		(see Figure 4.2 and 4.3)
BHW subjects	+	-	-	7	17.95	2;22;26;27;29;30;32
Subj. completely ignoring	+	+	+	18	46.15	1;4;6;8;9;12;13;14;17;18
the cascade formation						20;24;25;33;34;35;38;39
Subj. partly ignoring	+	+	-	10	25.64	5;7;10;19
the cascade formation	+	-	+			16;21;28;31;36;37
Others:	-	+	+	4	10.27	23
	-	-	+			15
	-	-	-			3;11
Total				39	100	

*Identified price patterns according to predictions on price limits from cascade position -3 to 0 if confronted with pro signals (column a) and from cascade position 0 to 3 if confronted with pro (column b), resp. contra signals (column c). Significant positive correlations ($p<0.05$, 2-tailed) are indicated with (+) and correlations that are not significantly different from zero with (-).

Table 4.4: Individual price patterns.

The results are summarized in Table 4.4. Overall, we did not detect any significantly negative correlation coefficient. Moreover, only 4 subjects out of 39 show no significant positive correlation considering submitted maximum prices at cascade position -3 to 0 if confronted with pro signals. Two of them did not vary their prices at all, indicating that they used heuristics which result in stable subjective probabilities throughout the cascade as simple counting or overconfidence. Interestingly these two subjects also show an error rate which is widely above average with 8.3 %, resp. 10 %. However, only 7 subjects out of 39 (17.95%)

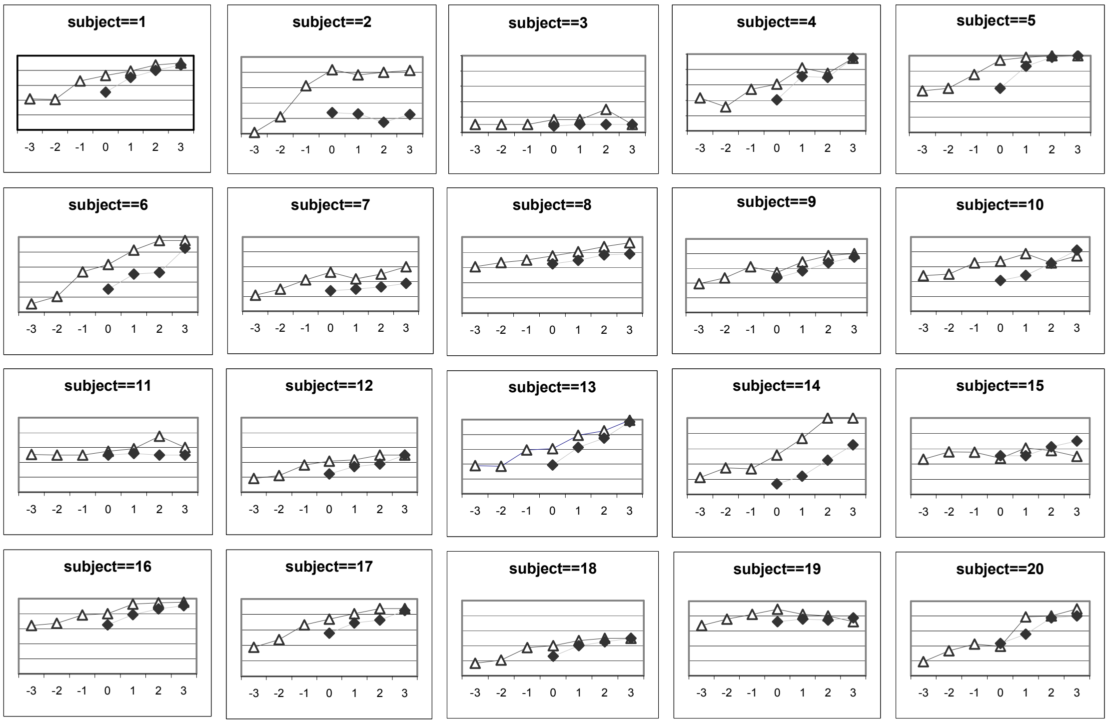


Figure 4.2: Individual price patterns for subjects 1 to 20. (Note: Cascade Positions are assigned to the x-axis and average maximum prices to the y-axis with gridlines from 0 to 100 in steps of 20; white triangles indicate prices for pro signals and black quads prices for contra signals).

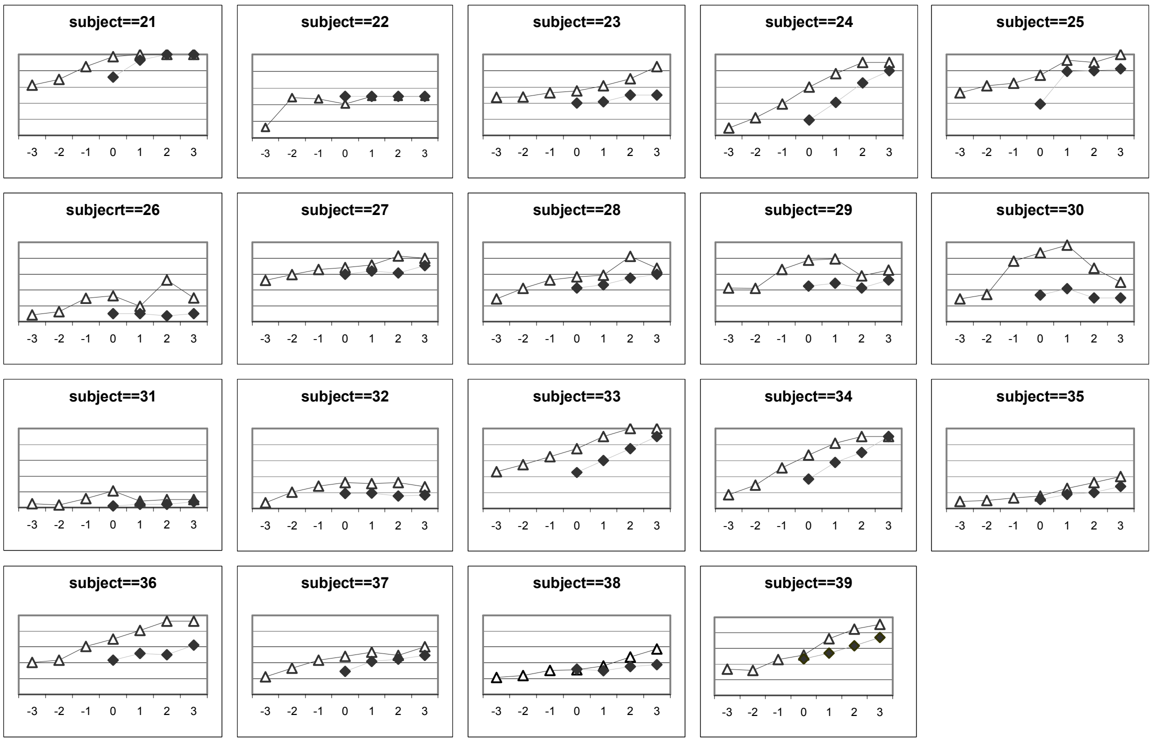


Figure 4.3: Individual price patterns for subjects 21 to 39. (Note: Cascade Positions are assigned to the x-axis and average maximum prices to the y-axis with gridlines from 0 to 100 in steps of 20; white triangles indicate prices for pro signals and black quads prices for contra signals).

show all three correlation coefficients in line with the standard BHW model, i.e. showing a significant positive correlation at cascade positions -3 to 0 if confronted with pro signals, but no significant correlation coefficients at cascade positions 0 to 3.

In contrast, for almost half of the subjects (46,15%) all three considered correlation coefficients are significantly positive, i.e. completely in line with the behavioral hypothesis. Further 25.64% of subjects show a significant positive correlation coefficient at cascade positions 0 to 3 either for pro or for contra signals, indicating that cascade behavior of predecessors is not recognized. Altogether, price setting behavior of more than two thirds of participants indicates that the cascade formation is not recognized whereas less than 20% of the participants show price setting patterns in line with the standard BHW model.

Observations II: Individual price setting patterns

i) *Considering cascade positions -3 to 0 if confronted with pro signals almost 90% of participants show a significant positive rank correlation between submitted maximum prices and the respective cascade positions, indicating that public information revealed by predecessors urn predictions is incorporated.*

ii) *Less than 20% of subjects show a price setting pattern in line with the standard BHW model, i.e. showed significantly positive correlation at cascade positions -3 to 0 but no significant correlation coefficients at later cascade positions.*

iii) *For almost half of the participants price setting patterns are completely in line with the behavioral hypothesis, i.e. all 3 considered correlation coefficients are significantly positive. For more than two thirds of the subjects price setting behavior is at least partly in line with the alternative hypothesis, i.e. at least one of the 2 correlation coefficients at cascade positions 0 to 3 is significantly positive.*

5. Discussion

We designed an experiment to test, whether individuals recognize cascade behavior of others. Our findings clearly support the alternative (behavioral) hypothesis, that they do not. Price limits increase the longer a cascade continues. More than two thirds of the participants obviously ignored cascade behavior of predecessors. They are at maximum willing to pay more than they would do if they recognized the cascade formation. In contrast, less than 20 percent of participants showed price setting patterns in line with the BHW model.

Participants in our experiment have clear beliefs about decision rules used by predecessors and, by definition, errors by predecessors are excluded. We are aware that in practice decision errors occur and there exists uncertainty concerning the heuristics that predecessors apply. This, hence, may also influence cascade behavior. But if individuals do not recognize cascade behavior of others in our setting, then it is hard to believe that they include predecessors' prediction errors into their updating process as it is assumed by cascade models based on quantal response equilibria.

To sum up, our results have shown that boundedly rational behavior of participants influences individual updating when confronted with information cascades. Normative models, which are based on rationality and adjusted by the inclusion of prediction errors in subjects' updating processes may explain cascade data quite well. But they do not sufficiently explain individual updating behavior and thus are not able to completely account for the phaenomenon of information cascades and its consequences. For a full understanding of the cascade pheanomenon more data are needed. The latter should be attained by experiments which truly investigate the influence of decision errors as well as of subjects' beliefs about the decision rules applied by predecessors.

References

[1] L. R. and C. A. Holt (1997): "Information Cascades in the Laboratory", *American Economic Review*, 87 (5), 847-862.

[2] Anderson, L. R. (2001): "Payoff Effects in Information Cascade Experiments", *Economic Inquiry*, 39, 609-615.

[3] Avery, C. and P. Zemsky (1998): "Multidimensional Uncertainty and Herd Behavior in Financial Markets", *American Economic Review* 88 (4), 724-48.

[4] Becker, G. M., DeGroot, M. H. and J. Marschak (1964): "Measuring Utility by a Single-Response Sequential Method", *Behavioral Science* 9, 226-232.

[5] Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992): "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades", *Journal of Political Economy* 100, 992-1026.

[6] Bikhchandani, S., Hirshleifer, D. and Welch, I. (1996): "Informational Cascades and Rational Herding: A Annotated Bibliography", Working Paper, UCLA/Anderson and Michigan/GSB.

[7] Brandts, J. and G. Charness (2000): "Hot vs. Cold: Sequential Responses in Simple Experimental Games", *Experimental Economics* 2, 227-238.

[8] Camerer, C. (1995): "Individual Decision Making" in Handbook of Experimental Economics, Princeton University Press, 587-674.

[9] Cipriani, M. and A. Guarino (2001): "Herd Behavior and Contagnion in a Laboratory Financial Market", Working Paper, New York University.

[10] Drehmann M., Oechsler, J. and A.Roider (2002): "Herding and Contrarian Behavior in Financial Markets - An Internet Experiment", mimeo.

[11] Fischbacher, U. (1999): "z-Tree. Zurich Toolbox for Readymade Economic Experiments", Working Paper No. 21, University of Zurich (1999).

[12] Hey, J. D. (1991): "Part II: Experiments on Individual Decision-making under Risk" in Experiments in Economics, Basil Blackwell Ltd, 35-92.

[13] Ho, T., Camerer, C. and K. Weigelt (1998): "Iterated Dominance and iterated best response in experimental 'p-beauty contests", *American Economic Review* 88(4), 947-969.

[14] Huck, S. and Oechssler, J. (2000): "Informational Cascades in the Laboratory: Do They Occur for the Right Reasons?", *Journal of Economic Psychology* 21, 661-667.

[15] Kraemer, C., Nöth, M., and M.Weber (2001): "Information Aggregation with Costly Information and Random Ordering: Experimental Evidence", Working Paper, University of Mannheim.

[16] Kraemer, C. and M. Weber (2001): "To Buy or Not To Buy: Why do Poeple Buy too Much Information?", Working Paper, University of Mannheim.

[17] Kraemer, C. and M. Weber (2002): "How do poeple control for weight, strength and quality of segregated vs., aggregated data? Experimental evidence", Working Paper, University of Mannheim.

[18] Kremer, T. and M. Nöth (2000). "Anchoring and Adjustment in Information Cascades: Experimental Evidence", Working Paper, University of Mannheim.

[19] Kübler, D. and Georg Weizsäcker (forthcoming): "Limited depth of reasoning and failure of cascade formation in the laboratory", *Review of Economic Studies*, forthcoming.

[20] Nagel, R. (1995): "Unravelling in guessing games: An experimental study." *American Economic Review* 85, 1313-1326.

[21] Nöth, M. and M. Weber (2001): "Information Aggregation with Random Ordering: Cascades and Overconfidence", *Economic Journal,* forthcoming.

[22] McKelvey, R D. and T. R.Palfrey (1995): "Quantal Response Equilibria for Normal Form Games", *Games and Economic Behavior* 10, 6-38.

[23] McKelvey, R D. and T. R.Palfrey (1998). "Quantal Response Equilibria in Extensive Form Games", *Experimental Economics* 1(1), 1-41.

[24] Oberhammer, C. and A. Stiehler (2003): "Does cascade behavior in information cascades reflect Bayesian Updating?", Papers on Strategic Interaction (1), Max Planck Institute for Research into Economic Systems.

[25] Safra, Z., Segal, U. and A. Spivak (1990): "The Becker-DeGroot-Marshak Mechanism an Non-Expected Utility", *Journal of Risk and Uncertainty* 3, 177-90.

[26] Schotter, A., Weigelt, K. and C. Wilson (1994): "A Laboratory Investigation of Multiperson Rationality and Presentation Effects", *Games and Economic Behavior* 6, 445-468.

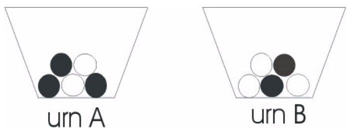
[27] Willinger, M. and A. Ziegelmeyer (1998): "Are more Informed Agents Able to Shatter Information Cascades in the Lab?" In P. Cohendet, P. Llerma, H. Stahn, and G. Umbhauer (eds.), The Economics of Networks: Interaction and Behaviours, Springer-Verlag.

A. Instructions (English Translation)

Welcome to our experiment! Please read these instructions carefully. Do not talk to your neighbors during the experiment. If you have any questions, please raise your hand. We will come to you and help you.

The amount of money you will earn in this experiment depends on your decisions and on some random events. The instructions are the same for all participants. The currency is ECU (Experimental Currency Unit). 100 ECU equal 10 Euro.

The experiment is carried out in the following scheme: There are two urns, A and B. In urn A there are five black balls and four white balls. In urn B there are five white and four black balls. One of these urns is chosen randomly. You have to find out which of the urns has been chosen.



Up to five artificial agents act one after the other before you make your decision. In case of an artificial agent´s turn a ball is drawn out of that urn that has been chosen at the beginning of the experiment. The color of the ball is announced to the agent and the ball is put back into the urn. It is, furthermore, announced to each agent which urns has been predicted by the agents that acted before them. Knowing the color of the drawn ball and the choices of the preceding agents the agent predicts one of the urns according to the following decision rules:

- Generally all agents predict the urn which got the majority of all votes (including their own).

- "Votes of the predecessors" are their decisions for urn A or B. The acting agent´s vote is added to these. It is only determined by the color of the ball drawn for him. A black ball means a vote for urn A. A white ball means a vote for urn B.

- If an agent decides first, his choice is only determined by his own vote, i.e. by the color of the ball which has been drawn for him. If a black ball is drawn, he chooses urn A. If a white ball is drawn, he chooses urn B.

- If there is no majority of votes (equal number of votes in favor of A and B), the agents decide according to their own vote.

It can be your turn to decide at the positions 1 to 6. Also for you a ball is drawn from the urn that has been chosen randomly at the beginning of the experiment and you are told the color of the ball. Furthermore, you are told the urn predictions of all artificial agents that have acted at previous positions.

Depending on:

- the position at which you act (1 to 6),

- the color of the ball drawn for you (black or white) as well as on

- the predictions of urns of your artificial predecessors

  there are 74 different situations for which you have to take your decisions.

These situations are provided by the computer in random order. In each of these situations you have to decide:

- which one of the urns you predict

- what maximum price $p_{\max}$ you are willing to pay to participate in the urn prediction with the according payoff chances.

At the end of the experiment one of the 74 situations will be chosen randomly and your payoff will be calculated according to your decisions in this situation.

Income Calculation: Generally you obtain 100 ECU for every correct urn prediction and nothing for a wrong prediction, i.e. 0 ECU. The following mechanism determines, whether and to what price you will participate in the urn prediction: The maximum price $p_{\max}$ you have submitted is compared to a random price p_r, which is randomly drawn from all integer prices between 0 and 100 ECU. The probability with which a certain price is drawn is the same for each price.

- If the random price exceeds your maximum price ($p_r > p_{\max}$) you do not participate in the payment. Then your payoff is 0, regardless whether your urn prediction was right or wrong.

- If the random price is lower or equal to your maximum price ($p_r > p_{\max}$), you obtain your payment according to your urn prediction (100 or 0 ECU) minus the random price p_r.

Your submitted maximum price $p_{\max}$ thus determines how much you are willing to pay at maximum to participate in the urn prediction and the according payment chances. It is always optimal for you to submit your real maximum price (also see "The optimal choice of $p_{\max}$"). [Appendix B]

Additionally all participants obtain a participation fee of 100 ECU which is set off against the earned income. The resulting incomes are summarized in the following table (participation fee in parantheses):

	Correct urn prediction	Wrong urn prediction
$p_r \leq p_{\max}$	100 ECU - p_r (+100 ECU)	0 ECU - p_r (+100 ECU)
$p_r > p_{\max}$	0 ECU (+100 ECU)	0 ECU (+100 ECU)

The choice of the payment-relevant situation with all the applicable random mechanisms is carried out "live" in the laboratory. First the position at which you act is determined randomly by dice (points = position). An urn is chosen randomly. Then balls are drawn from the chosen urn (and put back) for your artificial predecessors. Their decisions are determined in accordance with those decision rules specified above. If it is your turn a ball is drawn from the urn and the color of this ball announced to you. By this way exactly one situation is determined for which your decisions are payment-relevant. The random price is drawn from an urn which contains exactly 101 chips numbered 0 to 100.

The experiment starts with a "warm-up" round to demonstrate the course. Before the experiment starts we ask you to answer some control questions. Participants who answer all questions correctly at the first trial receive an extra payment of 50 ECU in addition to their experimental income. The experiment starts after all questions have been answered correctly by all participants. After the decisions for all 74 situations have been taken by all participants the payment-relevant situation will be determined according to the random process described above. Your payment will be calculated and paid out in Euro.

B. Supplementary sheet: The optimal choice of $p_{\max}$ (English Translation)

In the price mechanism used in this experiment it is always the best strategy to submit your real maximum price. It is neither profitable to exaggerate nor to understate the price.

Example: Assume that you are willing to pay a maximum price $p_{\max}$ of € 5 for a bottle of wine. The price mechanism in this experiment (with an uniformly distributed random price p_r in the interval between 0 and 100) determines whether and at which price you obtain the bottle of wine.

If you understated the price e.g. by submitting a price p_u of € 3 as your maximum price, the following cases could arise:

- $p_z > p_{\max} > p_u$. The random price exceeds the real maximum price, e.g. € 6. You would not buy the bottle, irrespective of whether you understate the price or submit your actual maximum price of € 5.

- $p_z \leq p_u$. The random price is lower than the submitted understated price, e.g. € 2. You would buy the wine for € 2, irrespective of whether you submit your actual maximum price of € 5 or understate the price by assigning € 3.

- $p_u < p_z \leq p_{\max}$. The random price lies in between the submitted understated and your real maximum price, e.g. 4 €. In this case you could not buy the wine although you were willing to pay € 5 and would only have to pay € 4.

As you can see, understatement does not pay.

Nor does exaggeration.

Assume that you would exaggerate and submit a price p_e of € 7. Again there are 3 possible szenarios:

- $p_r \leq \cdot p_{\max} \leq p_e$.The random price is lower or equals the real maximum price, e.g. € 4. You would buy the wine at a price of € 4, irrespective of whether you submit your real maximum price of € 5 or exaggerate by assigning € 7.

- $p_r > p_e$. The random price exceeds the exaggerated price, e.g. € 8. You would not buy the wine, irrespective of whether you submit your actual maximum price of € 5 or exaggerate by assigning € 7.

- $p_{\max} < p_r \leq p_e$. The random price lies in between your real maximum price and the submitted exaggerated price, e.g. € 6. In this case you would have to pay € 6 for the bottle although it is only worth to you to pay € 5.

Obviously, neither understatement nor exaggeration does pay!

C. Cascade situations

Assignment of possible situations subjects are confronted with to cascade situations analysed in the paper:

Cascade situation		Situations	Num.
Private signal	Cascade situation	characterized by predecessors predictions (capitals) and private signals (a=black ball and b=white ball)	
	-3	Ab; Ba; ABAb; ABBa; BAAb; BABa; ABABAb; ABABBa; ABBAAb; ABBABa; BABAAb; BABABa; BAABAb; BAABBa	14
pro	-2	a; b; ABb; ABa; BAb; BAa; ABABb; ABABa; ABBAb; ABBAa; BAABb; BAABa; BABAb; BABAb	14
	-1	Aa; Bb; ABAa; ABBb; BAAa; BABb; ABABAa; ABABBb; ABBAAa; ABBABb; BABAAa; BABABb; BAABAa; BAABBb	14
	0	AAa; BBb; ABAAa; ABBBb; BAAAa; BABBb	6
	1	AAAa; BBBb; ABAAAa; ABBBBb; BAAAAa; BABBBb	6
	2	AAAAa; BBBBb	2
	3	AAAAAa; BBBBBb	2
contra	0	AAb; BBa; ABAAb; ABBBa; BAAAb; BABBa	6
	1	AAAb; BBBa; ABAAAb; ABBBBa; BAAAAb; BABBBa	6
	2	AAAAb; BBBBa	2
	3	AAAAAb; BBBBBa	2
Total			74

D. Pre-experimental control questionnaire

Using a computerized control questionnaire participants were asked to answer questions on both, on the decision rules of artificial agents as well as on the working of the BDM mechanism. The experiment did not continue until all participants answered all questions correctly. In addition, an extra payment of € 5 was provided to participants who answered all questions correctly at the first trial. The questions regarding artificial agents and BDM-mechanism are summarized below.

- Artificial Agents: Participants were asked to to state artificial agents' urn predictions (A or B) for the situations summerized in the following table (characterized by agents position, decision of her predecessors and color of the privately drawn ball):

No.	Agents' position	Predictions of predecessors	Color of the privately drawn ball	Correct answer
1	1		black	A
2	3	AB	white	B
3	4	ABB	black	A
4	4	AAA	white	A
5	3	BA	white	B
6	1		white	B
7	3	BB	black	B
8	2	B	black	B

- Price Mechanism: Participants were asked to state whether they will participate in the urn prediction and the corresponding payment chances (Yes or No) and to calculate the resulting income from the experiments in the situations summerized the following table (characterized by maximum price, random price and correctness of the urn prediction).

Max. price $p_{\max}$	Random price p_r	Urn prediction	Participation (correct answer)	Resulting income (correct answer)
60	71	correct	No	0
50	35	wrong	Yes	- 35
70	50	correct	Yes	50

In addition, subjects were asked to state the optimal choice of the maximum price assuming that they are willing to pay 50 ECU at maximum (correct answer: 50 ECU).

E. Further statistical analyses

E.1. Statistics on price setting behavior

In the following tables and describtives and test statistics are summerized for those 23 participants who

1. showed more than 95% of urn predictions in line with the BHW model and
2. answered all questions about artificial predecessors at the first time.

- Descriptive statistics of price setting behavior and subjective probability statements:

Private Signal	Cas. pos.	Individual average prices Mean	Median	Std. dev.	Ind. subj. probabilities Mean	Median	Std.dev.
	-3	30,36	28,57	19,11	42,27	46,79	12,14
	-2	38,06	24,28	17,20	49,13	51,21	10,67
	-1	54,00	54,29	18,12	60,43	61,64	9,60
	0	60,34	61,00	22,09	66,34	66,67	12,19
Pro	1	69,42	77,50	21,37	76,67	76,67	10,99
	2	70,76	75,00	20,52	62,98	77,50	31,74
	3	72,78	80,00	21,66	64,43	82,50	31,99
	0	39,92	40,83	15,82	47,61	50,00	12,07
Contra	1	50,25	50,00	19,47	58,65	60,00	12,45
	2	55,00	52,50	23,31	52,08	62,50	26,31
	3	63,98	70,00	25,40	57,55	69,00	29,46

- Friedman-test and Spearman rank correlations regarding price limits at different cascade situations:

	Friedman-test Hypothesis (H0)	χ^2 (sign.)	Spearman rank corr. ρ (sign. 2-tailed)
a)	$p_{\max}^{-3pro} = p_{\max}^{-2pro} = p_{\max}^{-1pro} = p_{\max}^{0pro}$	55.852 (.000)	.509 (.000)
b)	$p_{\max}^{0pro} = p_{\max}^{1pro} = p_{\max}^{2pro} = p_{\max}^{3pro}$	19.366 (.000)	.208 (.046)
c)	$p_{\max}^{0con} = p_{\max}^{1con} = p_{\max}^{2con} = p_{\max}^{3con}$	11.314 (.000)	.367 (.000)

E.2. Statistics regarding subjective probabilities

- Friedman-test and Spearman rank correlations regarding subjective probabilities at different cascade situations:

	Friedman-test Hypothesis (H0)	χ^2 (sign.)	Spearman rank corr. ρ (sign. 2-tailed)
a)	$p_{\max}^{-3pro} = p_{\max}^{-2pro} = p_{\max}^{-1pro} = p_{\max}^{0pro}$	92.937 (.000)	.642 (.000)
b)	$p_{\max}^{0pro} = p_{\max}^{1pro} = p_{\max}^{2pro} = p_{\max}^{3pro}$	68.809 (.000)	.447 (.001)
c)	$p_{\max}^{0con} = p_{\max}^{1con} = p_{\max}^{2con} = p_{\max}^{3con}$	69.033 (.000)	.635 (.000)