Does Cascade Behavior in Information Cascades Reflect Bayesian Updating? — An Experimental Study —*

Clemens Oberhammer and Andreas Stiehler

Humboldt-University of Berlin
Department of Economics and Business Administration
Spandauer Str. 1
D - 10178 Berlin, Germany

May 23, 2001

Abstract

Updating behavior in cascade experiments is usually investigated on the basis of urn prediction. But urn predictions alone can only provide a very rough information on individual updating behavior. Therefore, we implement a BDM mechanism. Subjects have to submit maximum prices that they are willing to pay to participate in the prediction game. This enables us to study subjects' probabilty formation less crudely. The results show that in many situations herding occurs in accordance with the standard BHW model but cannot be explained neither by rational Bayesian updating nor by heuristics identified in former cascade experiments.

*Financial support by the Deutsche Forschungsgemeinschaft through the Sonderforschungsbereich 371 "Quantification and Simulation of Economic Processes" at Humboldt University is greatfully acknowledged. The authors also wish to thank D. Kübler, W. Güth and all other participants at the experimental economics seminar at Humboldt University for their helpful comments.

1. Introduction

Information Cascades are often used to explain economic decision behavior in sequential decision structures when individuals ignore their private signal due to the aggregation of public information. Bikhchandani, Hirshleifer and Welch (1992) derived an economic model which explains the occurrence of information cascades just by rational Bayesian updating. We refer to their model as the standard BHW model. Experiments have been carried out in order to test individual updating behavior as assumed by this model. In the standard experimental design subjects have to predict sequentially which urn out of two was randomly drawn. The urns contain a certain number of white and black balls. As private information a ball is randomly drawn from the chosen urn and the colour is announced to the subject. Additionally, participants are informed about the predictions of their predecessors. Conclusions from these experiments are usually drawn from subjects' urn predictions. Since urn predictions alone can only provide a very rough information on individual updating behavior our idea is to implement the BDM mechanism. Thus, we asked subjects to submit maximum prices they are willing to pay for participating in the prediction game. Interpreting submitted maximum prices as indicators of subjects' probability beliefs we can gain more insight in individual updating behavior.

Just on the basis of urn predictions Anderson and Holt (1997) observed a high proportion of individual decisions in line with Bayes' rule. These findings led them to the conclusion that "Individuals generally used information efficiently and followed the decisions of others when it was rational" (Anderson and Holt , 1997, p. 859). Other experimenters try to gain more insight by replicating cascade experiments as by Anderson and Holt with different information structures, for instance by varying the strength of the private signal (e.g. Kremer and Nöth, 2000;

Nöth and Weber, 1999; Willinger and Ziegelmeyer, 1998). Their results generally indicate a strong bias for overconfidence.[1] Moreover, they identify simple heuristics that are able to generate high efficiency rates. Nöth and Kremer (2000) refer to the heuristic, mostly used by participants as "Anchoring and Adjustment". In recent experiments it has been tried to gain more insight by implementing costly information (e.g. Kraemer, Nöth and Weber, 2000; Kuebler and Weizsaecker, 2000). Even though, the results of these experiments provide more insight in individual updating behavior than Anderson and Holt, they are still restricted to urn predictions and buying decisions, respectively. In order to study individual updating behavior less crudely we need to observe perceived probabilities of subjects when deciding within a cascade. Nöth and Kremer already asked subjects to submit probabilities, but did not provide any incentive to participants to answer seriously. Moreover individuals vary in the interpretation of "probabilities", as pointed out by Davis and Holt (1993).

By implementing the BDM mechanism we study subjects' probability formation based on prices rather than on probabilities. We find that even subjects whose urn predictions were always in line with the standard BHW model did not update information according to it. Instead, they increased prices even within cascades when theoretically no information aggregation occurs. Also other heuristics, identified in former experiments, are not able to explain the observed price setting pattern. Our conclusion is that in many situations herding occurs in accordance with the standard BHW model but the observed updating behavior cannot be explained by the standard BHW model or heuristics identified in former cascade experiments.

The remainder of this paper is organized as follows: In section 2 we describe our experimental design. In section 3 the procedure is explained. In section 4 we discuss theoretically which decision and price setting behavior one should expect according to Bayes' rule. We also explain the conditions for using prices as indicators of probability perceptions. At the end of the section we formulate some hypotheses about individual behavior. In section 5 our findings are presented and discussed. Finally, in section 6 some conclusions are drawn from our findings.

[1] Overconfidence was also found in another cascade experiment by Kraemer, Nöth and Weber (2000) who implemented fixed cost for private signals.

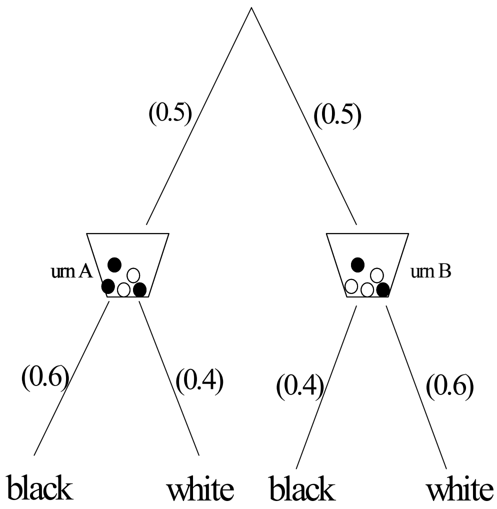

Figure 2.1: Experimental Setup

2. Experimental Design

One session consists of 20 to 25 rounds. In the same way as Anderson and Holt, we use urns and balls in order to implement the basic structure as assumed in underlying information cascades models. Two urns are used, containing 5 balls each; urn A with 2 white and 3 black balls and urn B with 3 white and 2 black balls (see also figure 2.1).

At the beginning of each round one urn is randomly chosen and the sequence of subjects within a group randomly determined. One group consists of 6 persons who have to predict in sequence which urn is actually chosen. Additionally, they have to decide what maximum price they are willing to pay to participate in the prediction game.

At a participant's turn she is asked to submit her decisions. We provide each participant with a private signal by telling her the color of the ball that has randomly been drawn for her from the chosen urn and afterwards been replaced into the urn. In addition, predecessors' predictions are announced. After the last subject has made her decisions the payment mode for this round is randomly determined. There are two possible payment modes:

With a probability of 0.5 participants' payoffs are only based on their urn prediction. Subjects are paid an amount of 100 ECU (Experimental Currency Unit) just for predicting the correct urn and 0 otherwise. We refer to this mode

		correct prediction	wrong prediction
mode 1		100	0
mode 2	$P_{\max} \geq P_R$	$100 - P_R$	$0 - P_R$
	$P_{\max} < P_R$	0	0

Table 2.1: Payoff calculation according to mode 1 and 2.

as mode 1 or prediction game as used above. In the other mode – we refer to it as mode 2 – payoffs additionally depend on the maximum price participants submitted in order to participate in the prediction game. The payment mechanism works as follows:

A uniformly distributed random price between 0 and 100 ECU is drawn. A subject participates in the payoff procedure when her maximum price $P_{\max}$ equals or exceeds the random price P_R. In this case she receives the payoff as in mode 1 (100 ECU for a correct prediction and 0 otherwise) and has to pay the random price. In the case that the random price exceeds the maximum price the subject does not participate and, therefore, earns 0 ECU. The random price mechanism is known as the BDM - mechanism (Becker, DeGroot and Marschak; 1964). The mechanism and its chances for the task at hand will be explained in more detail in section 4. In table 2.1 all possible outcomes are summarized.

At the end of a round each subject is told the chosen urn, the applied payment mode and her resulting income. At the end of the whole session each subject is told her total income.

3. Procedure

In contrast to Anderson and Holt we run our experiment in the computer laboratory which enables us to gain more data and to assure that participants make their decisions anonymously. The experiment was run at Humboldt University of Berlin in July 2000. 48 persons, mainly students of the Faculty of Economics were recruited. We conducted 6 sessions, each with 2 groups of 6 persons. Each session lasted on average one and a half hours and two sessions were always conducted at the same time, which made it impossible for subjects to identify the other group members. 50 ECU correspond to 1 DM. A 10 DM participation fee was added to the subjects' final income which averaged about 17.81 DM. At the end of each session participants were asked to fill in a final questionnaire which should help us gain more insight in their decision making process. In order to discuss parameter settings we first have to explain our assumptions necessary for the analysis of price setting behavior. This will be done in section 4.

		decision at position I	
		A	B
color of ball	black	$\frac{9}{13}(\frac{4}{13})$	$\frac{1}{2}(\frac{1}{2})$
drawn at position II	white	$\frac{1}{2}\left(\frac{1}{2}\right)$	$\frac{4}{13}\left(\frac{9}{13}\right)$

Table 4.1: Posterior probabilities that urn A (B) is actually chosen at position II.

4. Theoretical Expectations

4.1. Predictions and Probabilities

In this section it is shown how rational Bayesian updating is applied in information cascade models. Based on this we formulate some expectations about prediction behavior in our experiment. Assuming rational behavior a subject should always predict the urn that is more probable. The probability that an urn is actually chosen is calculated by Bayes' rule. In our experiment we implement a symmetric setup; e.g. the probability for observing a black (white) ball when actually urn A (B) is chosen is always 0.6.

The only information a subject observes at position I is the color of the ball which is privately drawn for her. The posterior probability that urn A (B) is actually chosen given an observed black (white) ball is calculated as follows:

$$\Pr(A/black) = \Pr\left(B/white\right) = \frac{\frac{1}{2}\frac{3}{5}}{\frac{1}{2}\frac{3}{5} + \frac{1}{2}\frac{2}{5}} = 0.6\ . \tag{4.1}$$

Therefore, applying Bayes' rule it is rational to predict urn A (B) if a black (white) ball is observed.

At position II a subject observes both, the color of a ball which is privately drawn for her and her predecessor's prediction. Table 4.1 summarizes all posterior probabilities for urn A (B) given the predecessor's predictions at position I and the color of the privately drawn ball at position II.

Given a posterior probability of 0.5 the urn prediction depends on the tie-breaking rule used by a subject. In the model of Bikhchandani, Hirshleifer and Welch (1992) it is assumed that individuals randomize with equal probability between urn A and B whereas Anderson and Holt (1997) suppose that subjects always follow their private signal.[2] At position III given two equal predictions at

[2] Assuming a small fraction of prediction errors at position I it is rational to follow the private signal.

position I and II it is always rational to ignore one's private signal and to predict the same urn as the predecessors regardless of the tie-breaking rule presented above. The posterior probabilities at position III following the Anderson/Holt approach are calculated as follows:

$$\Pr(A/black, AA) = \frac{\frac{1}{2}\left(\frac{3}{5}\right)^3}{\frac{1}{2}\left(\frac{3}{5}\right)^3 + \frac{1}{2}\left(\frac{2}{5}\right)^3} = 0.77 \tag{4.2}$$

$$\Pr(A/white, AA) = \frac{\frac{1}{2}\left(\frac{3}{5}\right)^2 \frac{2}{5}}{\frac{1}{2}\left(\frac{3}{5}\right)^2 \frac{2}{5} + \frac{1}{2}\left(\frac{2}{5}\right)^2 \frac{3}{5}} = 0.6 \tag{4.3}$$

The respective probabilities following the Bikhchandani, Hirshleifer and Welch approach are $\Pr(A/black, AA) = 0.72$ and $\Pr(A/white, AA) = 0.53$. Therefore, in both cases it is rational to ignore one's private signal and to follow the predictions of one's predecessors. Since the subject at position III ignores her private signal, subsequent deciders cannot infer any further information from her prediction, i.e., no further aggregation occurs. Consequently, the probabilities for urn A (B) at all subsequent positions are the same as at position III.

Given two different predictions at position I and II the situation at position III is the same as at position I, i.e., the a priori probability for urn A (B) is 0.5. Thus, in our experiment a cascade can start theoretically either at position III or V. In the remainder of the study we refer to these positions where cascades start always as cascade position 3 and the subsequent positions as cascade positions 4, 5 and 6, respectively. We refer to the two positions before the cascade starts as cascade position 1 and 2. Figure 4.1 shows the probabilities at different cascade positions for each signal assuming the Anderson/Holt tie-breaking rule.[3]

We refer to private signals that are contrary to public information as contra signals and the others as pro signals.

Recently, Koessler and Ziegelmayer (2000) have shown that relaxing the assumption about the used tie-breaking rule allows for other equilibria in which information cascades are not necessarily observable. Therefore, they recommend to implement an asymmetric design in cascade experiments. By doing this, situations with posterior probabilities of 0.5 can be avoided and cascade behavior

[3]The pattern that probabilities do not change from cascade position 3 to 6 given the same private signal is the same assuming the Bikhchandani/Hirshleifer/Welch tie-breaking rule.

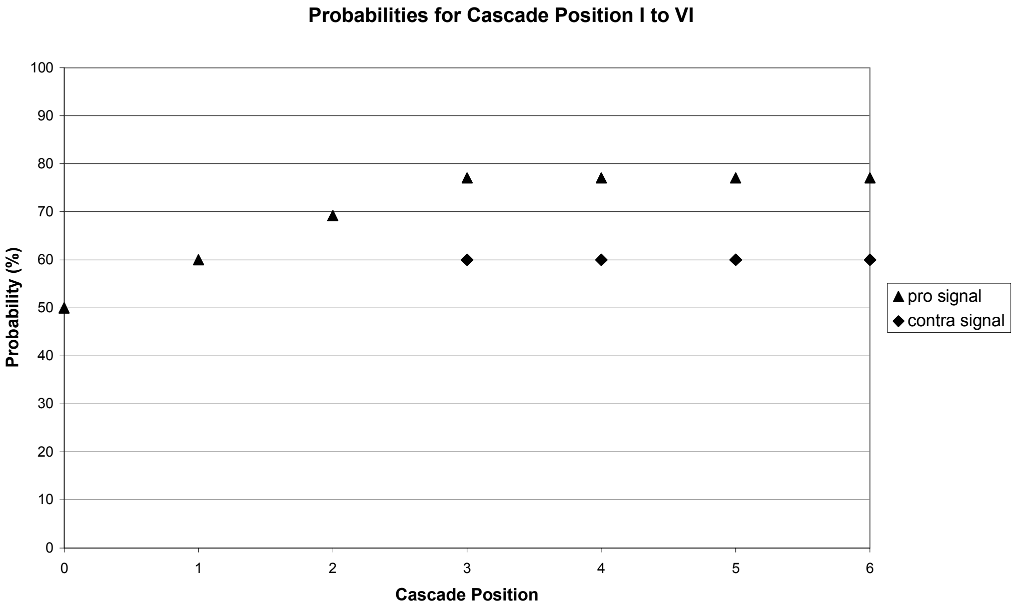

Figure 4.1: Posterior probabilities at different cascade positions given different private signals assuming the Anderson/Holt tie-breaking rule.

clearly identified. However, in all equilibria worked out by Koessler and Ziegelmayer no information aggregation takes place from cascade position 3 to 6. In this case we also have to expect constant prices. Therefore, our analysis does not depend on assumptions about a certain tie breaking rule. Implementing an asymmetric design would not contribute to our questions but rather complicate our experimental setup.

4.2. Prices as Indicators for Probabilities

Former cascade experiments provide evidence that many subjects seem to use rather simple decision rules instead of Bayes' rule and show a significant bias toward overconfidence.[4] Overconfident subjects put too much weight on their private signal relative to the public information. Most of these findings are based on the observation of subjects' urn predictions, for instance different decision rules are usually inferred from predictions which are not in line with Bayes' rule. Since predictions provide only rough information about subjects' beliefs, our idea is to use prices as an indicator for the subjects' probability perceptions. Therefore,

[4]See for example Nöth and Weber (1999) and Kremer and Nöth (2000).

we applied the BDM mechanism in order to extract maximum prices that reveal subjects' willingness to pay for participating in the prediction game. Assuming risk neutral subjects the revealed maximum prices would perfectly reflect subjects' probability beliefs. But even if one only assumes that maximum prices monotonously increase in subjects' probability beliefs we are still able to compare subjects' beliefs at different cascade positions. Actually, for our purpose it is sufficient if a higher maximum price reflects a higher probability belief and vice versa.

Regarding the analysis of the observed price setting behavior we will focus on individuals who always predict in line with the standard BHW model. By implementing the BDM mechanism we are now able to study whether these subjects actually update information according the theoretical model. Following, we will discuss some price patterns, that we can expect in the case that individuals either update information according to the standard BHW model or according to heuristics identified in former cascade experiments.

- *The standard BHW model*

Since we restrict our analysis of the price setting behavior on subjects who always predict in line with the standard BHW model we can also expect that these subjects update information according to it. One important assumption of this model is that subjects recognize that no information is aggregated once a cascade has started. If the standard BHW model actually describes updating behavior in the laboratory, according to figure 4.1, assuming monotonously increasing prices in probability beliefs and given a certain private signal, subjects should submit the same price at cascade positions 3 to 6.

- *The error BHW model*

Former cascade experiments show that individuals err sometimes by not predicting in accordance with the standard BHW model. Incorporating these errors into the standard BHW model would change the expected price pattern. In this case we had to expect increasing prices throughout the cascade given a certain signal. Since predictions after cascade position 3 now contain additional information, perceived probabilities would increase with the length of the cascade. Additionally, we had to expect lower prices at cascade position 3 given a contra signal than at cascade position I [5]. In the further study we refer to this model to the error BHW model.

[5] See Anderson (2000).

- *Anchoring and Adjustment*

Nöth and Weber (1999) identify an anchoring and adjustment heuristic that is able to explain a high proportion of deviations from the cascade pattern. Subjects use their private signal as an anchor and their predecessors' predictions for adjustments. It is reasonable to assume that this heuristic is also used by participants who always predict in line with the standard BHW model. Since we choose a symmetric design an anchoring and adjustment heuristic can lead to prediction behavior in accordance with the standard BHW model. In this case we also have to expect increasing prices throughout a cascade.

- *Counting*

Another heuristic called counting would lead to a similar price pattern. The greater the majority of inferred and observed pro signals compared to observed and inferred contra signals the higher is the probability of the predicted urn. Doing this, individuals ignore that their predecessors might just have followed their predecessors.[6] Otherwise, one might argue that just the existence of the majority of pro signals is of importance. We refer to this heuristic as simple counting. In this case we have to expect constant prices from cascade position 3 on, regardless whether the private signals are pro or contra.

As can easily be seen, all alternative heuristics presented above lead to similar price patterns with increasing prices towards later cascade positions. Thus, we are able to separate Bayesian updating from alternative decision rules but we cannot identify the heuristic that is actually used in case of increasing maximum prices.

Having explained the assumptions necessary to analyze price setting behavior and formed some expectations regarding the heuristics used by the participants we are now able to discuss the private signal strength chosen in our setup. As private signal strength we choose probabilities of $\frac{2}{5}$ and $\frac{3}{5}$, respectively. Using quite noisy signals, as we do, generates rather low posterior probabilities. Given that subjects' beliefs increase, even after a cascade has started, low posterior probabilities allow us to observe this pattern more distinctly. Signal strength of $\frac{2}{3}$ and $\frac{1}{3}$, respectively, as Anderson/Holt used lead to posterior probabilities very close to one and, therefore, a possible pattern of increasing probability beliefs might be difficult to observe.

[6] See Anderson and Holt (1997).

private signal	expected predictions in line with BR	actually observed
all	1,140	985 (86.4%)
pro	915	821 (89.7%)
contra	225	164 (72.9%)

Table 5.1: Expected and actually observed predictions in line with Bayes' rule dependent on the private signal.

5. Results

5.1. Prediction Behavior

Following our theoretical framework, cascade behavior can be observed if a subject's prediction is inconsistent with her private signal but in line with the standard BHW model. Moreover, the situation may occur that a subject deviates from the cascade pattern, e.g., she does not follow her predecessors within a cascade. In order to compare some of our findings with those of Anderson and Holt (1997) we first follow their reasoning that a deviating decision reveals the private signal. Therefore, we define as cascade behavior predictions that are inconsistent with private signals due to an imbalance of previous inferred signals. This means, that we firstly include all observations even when former observations deviate from the equilibrium path as assumed by the standard BHW model.

Table 5.1 shows some general findings concerning prediction behavior. As Anderson and Holt we also found a high degree of cascade behavior. When an imbalance of previous inferred signals occurred cascade behavior was observed in 104 of 132 rounds. We also found a high degree of predictions seemingly in line with Bayes' rule. Of all 1,140 predictions 985 (86,4%) were in line with rational Bayesian updating behavior, but considering only situations when it was rational to predict against the private signal only 73% of the predictions were in line with Bayes' rule. Figure 5.1 summarizes the results.

Studying prediction behavior on an individual level we found that 31% of the subjects (15) predicted always in line with the standard BHW model. 56% of the subjects showed a very high degree of seemingly rational behavior. More than 90% of their predictions were in line with the standard BHW model. Compared to the two thirds of subjects always submitting predictions in line with the standard BHW model in the Anderson/Holt experiments the proportion of seemingly rational subjects in our experiment was significantly lower. This may be due to the

Cascade Position	Expected cascade behavior	Actually observed	in %
3	74	46	62,2
4	49	34	69,4
5	31	28	90,3
6	34	30	88,2
Total	188	138	73,4

Table 5.2: Expected and actual cascade behavior at different cascade positions.

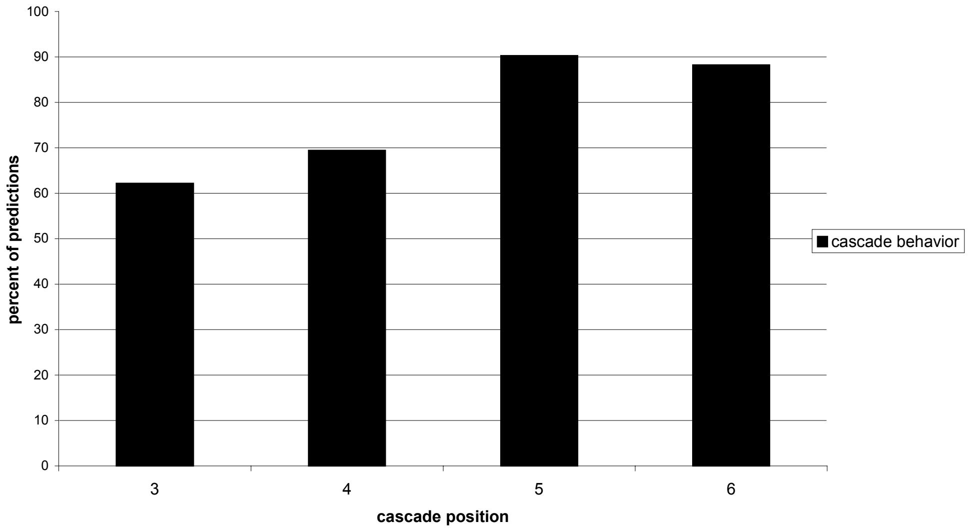

Figure 5.1: Cascade behavior at different cascade positions.

lower signal strength applied in our experiment. Moreover, we run 25 instead of 15 rounds which certainly increases the probability that prediction errors occur.[7]

In order to keep our analysis clear the remainder of this study is focused on decisions made within cascades that follow our theoretical framework. Therefore, we exclude all decisions that follow predictions deviating from the equilibrium path. In 188 situations cascade behavior could be observed theoretically. Of these 188 situations we actually observed 138 in which subjects predicted against their private signal but in line with standard BHW. As table 5.2 and figure 5.1 shows the rate of cascade behavior varies depending on the cascade position.

More than 30% of predictions are not in line with Bayes' rule up to cascade position IV. This indicates that subjects put too much weight on their private

[7] Additionally, the different results could also be explained by differences of the experimental setup as well as of the experimental environment, e.g. computer laboratory versus classroom.

signal. On the other hand there are about 90% of the predictions at cascade position V and VI that show cascade behavior. It seems like it needs more than two predecessors predicting the same urn to convince a substantial fraction of subjects not to follow their private signal. This pattern highly corresponds to the "Anchoring and Adjustment" heuristic found by Nöth and Weber in which one's own private information provides the anchor and the adjustment is based on the available public information whereas many subjects put too much weight on their private signal. Moreover, the high rate of cascade behavior at positions V and VI reveals that a heuristic only based on private information cannot explain the observed prediction behavior to a large extent. Generally, the results on prediction behavior, presented above, show similar patterns as already worked out in former cascade experiments. The question still remains if subjects who always predict in line with the standard BHW model also update information as theoretically assumed. In order to get more insight in their updating behavior we now want to analyze the price setting behavior of these subjects. For this purpose, we consider only price decisions of subjects who always predicted in line with the standard BHW model. In the further study we refer to these subjects as BHW subjects. At the end of this section we enhance our study on price decisions of subjects not always predicting in line with the standard BHW model. Due to our simple information structure we are not able to subdivide these subjects in subgroups regarding their updating heuristic. Therefore, we just present some of these findings without interpreting them in greater detail.

5.2. Price Setting Behavior

Analyzing price setting behavior enables us to study whether subjects update information according to the models and heuristics presented in section 4.2. In this section we first want to present some results from our postexperimental questionnaire that are crucial to prove the assumptions for using maximum prices as indicators for probabilities. Then we give a first overview by presenting some descriptive statistics based on average prices followed by a regression analysis. The results will be compared with the expectations according to the presented models and heuristics. At the end of this section we present some results of individuals that did not always predict in line with the BHW model.

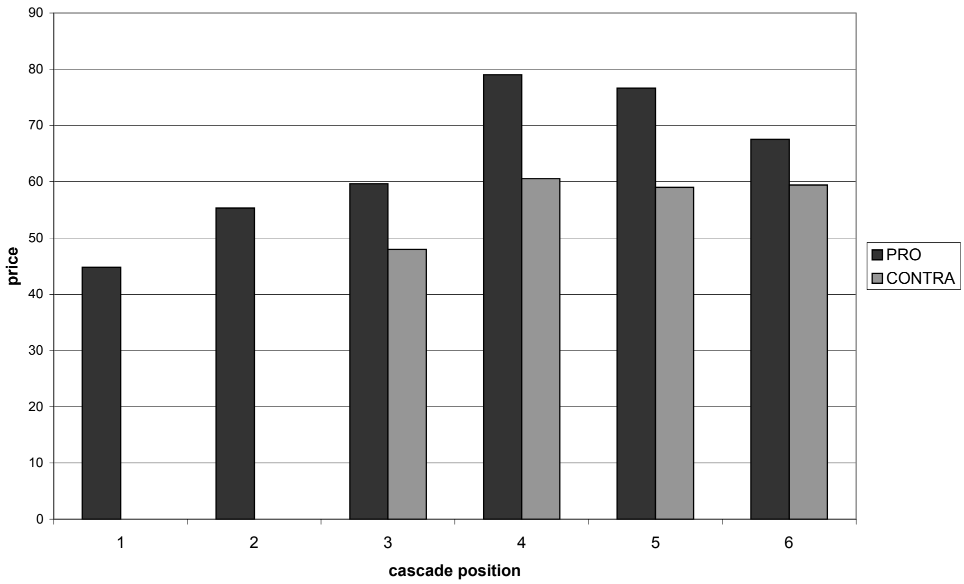

Figure 5.2: Average maximum prices for pro and contra signals at different cascade positions for BHW subjects.

One essential assumption for using maximum prices as indicators of probability beliefs is a positive relation between submitted maximum prices and subjects' probability beliefs. In order to test this assumption we confronted participants with a final questionnaire. They were asked to state their probability beliefs as well as maximum prices for different cascade situations. For 30 subjects (out of 48) we were able to calculate correlations. 90% of them showed a positive correlation between maximum prices and probabilities. For 18 subjects it was not possible to calculate correlations because either prices or probabilities or both were held constant. Of the 15 BHW subjects 13 showed a clearly positive relationship between prices and probabilities. The other two subjects held prices constant.[8] Thus, the assumptions necessary for our further analysis seem to be satisfied.

In order to get a first impression of price setting behavior of subjects whose urn predictions were always in line with the standard BHW model we calculated and plotted average prices at each cascade position separately for pro and contra signals (see table 5.3 and figure 5.2).

[8]Excluding these two subjects from our analysis does not change the results presented below. Thus, we do not exclude them from our analysis.

signal	cas. pos.	mean	median	std. dev.
PRO	1	44.7838	47.00	17.520
	2	55.3103	60.00	22.44
	3	59.6522	60.00	25.8397
	4	79.0000	80.00	18.3521
	5	76.6429	75.00	19.1255
	6	67.5455	75.00	22.8926
CONTRA	3	47.9600	50.00	19.5245
	4	60.5294	65.00	21.0152
	5	59.0000	60.00	9.1652
	6	59.4000	56.00	17.5512

Table 5.3: Average maximum prices for pro and contra signals at different cascade positions for BHW subjects.

	variable	coefficient	std. error	t	sign. 2-tailed
BHW	POS4	15.637	4.166	3.754	0.000
adj. R^2: 0.502	POS5	11.320	4.622	2.449	0.016
F-value: 5.942	POS6	12.456	5.049	2.467	0.015
sign. 0.000	CONTRA	-14.570	3.213	-4.535	0.000

Table 5.4: Regression analysis for BHW subjects

Figure 5.2 shows that prices increase up to cascade position 4. Towards later cascade positions prices are slightly decreasing but still higher than at cascade position 3. It seems that the standard BHW model does not explain actual updating behavior in our experiment.

In order to present a statistically verifiable analysis we run a regression analysis with price as dependent and dummies for each cascade position (using cascade position 3 as reference point) and one dummy for contra signals[9] as independent variables. Since we cannot assume that all individuals have the same willingness to pay given a certain probability, we additionally implement a dummy for each subject.[10] We control also for time influences but do not find any significant influence (F-test sign. 0.952). The result of the regression analysis is shown in table 5.4.

[9] One might argue that the influence of a contra signal varies at different cascade positions. Therefore, we run also a regression analysis with additional dummies for contra signals at each cascade position. These dummies are not significantly different from zero.

[10] In the presented regression analysis we assumed the same price pattern for all subjects. In order to test whether this assumption can be justified we run an additional regression analysis with dummy variables for each subject at each cascade position and tested whether this led to a significant improvement. The incremantal F-test did not show a significant improvement compared to the presented regression analysis (sign. 0.987).

	variable	coefficient	std. error	t	sign. 2-tailed
BHW	POS1	-21.391	4.602	-4.648	0.000
PRO SIGNAL	POS2	-14.111	4.849	-2.910	0.004
adj. R^2: 0.563	POS4	16.076	5.324	3.019	0.003
F-value: 9.750	POS5	14.692	5.619	2.615	0.010
sign. 0.000	POS6	7.120	6.397	1.113	0.268

Table 5.5: Regression analysis for BHW subjects and pro signals incorporating also cascade position 1 and 2.

It can be seen that our first impression is confirmed. BHW subjects set a significantly higher price at cascade position 4, 5 and 6 than at cascade position 3. After position 4 prices remain rather stable and, as expected, a contra signal has a significant negative effect on the price.

Price setting behavior for contra signals can only be observed from cascade position 3. In order to study price setting behavior also at cascade positions 1 and 2 we run an additional regression analysis only for pro signals incorporating cascade position 1 and 2. The result is shown in table 5.5.

There is a significant price increase throughout the first three cascade positions. Interestingly, we observe an even stronger (although not significant) price decrease after cascade position 4. At cascade position 6, given a pro signal, prices are not significantly higher than at cascade position 3. Obviously, subjects who always predict in line with the standard BHW model do not update information according to it. In contrast to the standard BHW model subjects increase prices even after cascade position 3.

The question arises if an error BHW model is able to explain the observed price setting pattern of BHW subjects? As reported in the previous section participants erred sometimes by not predicting in line with the standard BHW model. Subjects could have incorporated these errors of their predecessors and for this reason aggregated information even at later cascade positions. In our opinion an error BHW model is not able to explain the observed price setting pattern. First, if subjects incorporated their predecessors' error rates they should have increased their prices also beyond cascade position 4. We observed, however, rather decreasing prices after cascade position 4. Secondly, subjects should submit higher prices at cascade position 1 than at cascade position 3 after observing a contra signal.[11]

[11] See Anderson (2000).

Actually, in our experiment only two out of 9 subjects submit on average a higher price at cascade position 1 than at cascade position 3 after observing a contra signal. The others submit either the same (2 subjects) or a higher maximum price (5 subjects).

As reported in section 4.2 in former cascades experiments certain heuristics have been identified that are able to explain a high proportion of observed prediction behavior. Can the observed price setting behavior of BHW subjects in our experiment be explained by these heuristics? If subjects employed an anchoring and adjustment or a counting heuristic given a private signal prices should increase from cascade position 3 to 6. But we observe only increasing prices from cascade position 1 to 4 and rather decreasing prices afterwards. If subjects applied a simple counting heuristic prices would increase up to position 3 and would be constant afterwards. Also this heuristic is not confirmed by the observed price setting pattern.

In summary, neither the considered models (with or without incorporating error rates) nor heuristics that have been identified in former experiments are able to explain the observed price setting pattern of subjects who always predicted in line with the standard BHW model. Before turning to the discussion of alternative explanations in section 6 we want to present some findings of subjects not always predicting in line with the BHW model.

Again, we restrict our analysis to predictions in line with the standard BHW model. First we run a similar regression analysis as for BHW subjects. The only difference is that we introduce an additional contra dummy for each cascade position since the price pattern for pro and contra signals differs significantly (see table 5.6).

In the case of pro signals prices do not increase after cascade position 3 but rather decrease, whereas in the case of contra signals we observe significantly higher prices at cascade position 5 and 6 compared to cascade position 3 but no increase from cascade position 3 to 4. As expected a contra signal has a significant negative influence on the submitted price.

We additionally run a regression analysis for pro signals including cascade position 1 and 2. Prices increase significantly from cascade position 1 to 2 and from 2 to 3 and are constant afterwards. For pro signals it seems that subjects

	variable	coefficient	std. error	t	sign. 2-tailed
Subjects not always predicting in line with BHW	POS4	-1.027	3.777	-0.272	0.786
	POS5	-6.772	4.198	-1.613	0.109
	POS6	-1.662	4.973	-0.334	0.739
	CONTRA	-13.273	4.129	-3.215	0.002
adj. R^2: 0.677	CONTRA4	2.902	5.944	0.488	0.626
F-value: 8.991	CONTRA5	23.044	6.482	3.555	0.000
sign. 0.000	CONTRA6	14.879	6.947	2.142	0.034

Table 5.6: Regression analysis for subjects not always predicting in line with the standard BHW model.

whose predictions were not always in line with the standard BHW model updated information in accordance with the standard BHW model. When observing a contra signal it seems to make a significant difference whether three or four predecessors predict the same urn. However, to investigate updating behavior of these subjects in more detail we would have to form subgroups of subjects who employ a similar updating heuristic. Unfortunately, this is not possible due to our simple information structure .

6. Discussion

By implementing a BDM mechanism we succeeded to study subjects' probability formation less crudely than it was done in former cascade experiments, where conclusions were just derived from the observation of urn predictions. We are now able to investigate cascade behavior in more detail of subjects who always predict in line with the standard BHW model. We show that even if their prediction behavior seems to confirm updating behavior as assumed by the BHW model, BHW subjects do not update information in accordance to it. Furthermore, the observed price patterns cannot be explained by the incorporation of prediction errors in the standard BHW model nor by heuristics identified in former cascade experiments.

It is not possible to identify one certain updating rule from our data since there are at least two possible explanations for the observed price patterns. From our data we find, that BHW subjects increase price limits up to position 4. It is interesting, that towards later cascade positions prices seem to decrease. Obviously, when deciding at cascade position 1 to 4 subjects trust the additional information revealed by the predictions of their predecessors. They do not recognize that no information aggregation takes place from cascade position 3 on. When deciding at later cascade positions BHW subjects start to distrust the additional information provided by the predictions of their predecessors. From our data we get some hints that at very late cascade positions subjects seem to realize the way of information aggregation as assumed by the standard BHW model and lower their prices accordingly. However, this is just one possible explanation of our data. One could also assume that subjects doubt their predecessors' decisions at early cascade positions and, therefore, need the public signals of at least three predecessors to be totally convinced. Further experiments that allow for the observation of longer cascades have to be run in order to prove which explanation turns out to be right.

The data we provided for subjects not always predicting in line with BHW can give some hints for further analyses but cannot be used to study applied updating rules since we cannot identify them. In order to study also the updating behavior of those subjects, it is necessary to implement a subtler information structure. This allows to subdivide subjects in homogenous groups on basis of the observed prediction behavior. Therefore, the implementation of a subtler information structure by keeping the design simple and clear will be the challenge of future experiments.

References

[1] Anderson, L. R. (2000). "Payoff Effects in Information Cascade Experiments." *Economic Inquiry.* Forthcoming.

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

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

[4] 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.

[5] Davis, D. D. and Holt C. A. (1993). *Experimental Economics.* Princeton, NJ: Princeton University Press.

[6] 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.

[7] Koessler, F. and Ziegelmayer, A. (2000). "Tie-breaking Rules and Informational Cascades: A Note." Manuscript.

[8] Kraemer, C., Nöth, M., and Weber M. (2000). "Information Aggregation with Costly Information and Random Ordering: Experimental Evidence." Manuscript.

[9] Kremer, T. and Nöth, M. (2000). "Anchoring and Adjustment in Information Cascades: Experimental Evidence." Manuscript.

[10] Kübler, D. and Weizäcker, G. (2000). "Limited Depth of Reasoning and Failure of Cascade Formation in the Laboratory." Manuscript.

[11] Nöth, M. and Weber, M. (1999). "Information Aggregation with Random Ordering: Cascades and Overconfidence." Manuscript.

[12] Willinger, M. and Ziegelmeyer, A. (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.