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

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Abstract

We examine the explanatory power of cascade models by implementing the BDM-mechanism in a simple cascade experiment in which subject have to decide on the prediction of a randomly chosen urn. Assigned price limits to participate in the prediction game are used as indicators of subjective probabilities. We are thus able to test the explanatory power of the standard BHW model (Bickchandani, Hirshleifer and Welch, 1992) in comparison to cascade models which incorporate individual decision errors. Focusing on stated price limits corresponding to urn predictions in line with both, standard and error BHW models our data indicate that the inclusion of errors does not significantly improve the explanatory power of the standard approach.

JEL Classification: D92, D81, D82

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

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1. Introduction

Many laboratory experiments have been carried out in order to test whether herding behavior can be explained by information cascade models as built by Bikhchandani, Hirshleifer and Welch (1992), henceforth referred to as standard BHW model. The first were Anderson and Holt (1997) who designed an experiment that reflects a cascade information structure by urns and balls. Updating behavior was studied on the basis of urn predictions. The authors 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 tried to gain more insight by replicating cascade experiments as that 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, forthcoming; Willinger and Ziegelmeyer, 1998) or by implementing costly information (e.g. Kraemer, Nöth and Weber, 2000; Kübler and Weizsäcker, forthcoming). They found that in a more complex decision structure a substantial rate of urn predictions and buying decisions cannot be explained by updating behavior in accordance with Bayes' rule only as assumed in the standard BHW model.

A better explanation of experimental data might be achieved if decision errors of others are taken into account. Indeed, econometric models that incorporate individual decision errors (see Anderson and Holt, 1997; Anderson, 2001 or Kübler and Weizsäcker, forthcoming) seem to explain prediction and buying behavior to a higher degree than the standard BHW model. But the question arises whether these econometric models replicate actual urn and buying decisions for the right reasons. Do they really explain the actual updating behavior on which prediction behavior is based?

We present an experiment that enabled us to gather more detailed information on cascade behavior and to compare the explanatory power of the standard BHW model and error models based on Bayesian updating. In particular, we extended a simple cascade experiment using the Becker-DeGroot-Marschak (BDM) mechanism (Becker, DeGroot and Marschak, 1964). We asked subjects to submit maximum prices for participating in the prediction game. The stated price limits are used as indicators of their probability beliefs. Thus, individual updating behavior can be studied in more detail than by previous cascade experiments.[1] Furthermore, we are now able to directly test the explanatory power of econometric models applied to cascade experiments. Participants' urn predictions are used to estimate different error approaches and – based on these estimations – to calculate posterior probabilities for different cascade situations. Expected urn predictions for situations on the equilibrium path are the same for both, standard as well as error BHW models, whereas the respective probability patterns differ significantly. Focusing on stated price limits corresponding to urn predictions in line with both, standard and error BHW models, we will compare resulting price patterns with probability patterns according to the considered models.

The remainder of this paper is organized as follows: Section 2 describes the experimental design and procedure. In section 3, predictions are derived from the considered theoretical models and conditions for using prices as indicators of probability perceptions are discussed. In section 4 results are presented. The paper finishes with a discussion of the results in section 5.

2. Experimental design and procedure

Each experimental session consisted of 20 to 25 rounds of a prediction game. As Anderson and Holt (1997), we used urns and balls in order to implement the basic structure assumed by the underlying information cascade models. Two urns were used, each containing 5 balls: urn A with 2 white and 3 black balls and urn B with 3 white and 2 black balls (see also Figure 2.1).

The rules of the game are as follows: At the beginning of each round one urn is randomly chosen and the sequence of subjects within a group randomly

[1] Nöth and Weber (1999) already asked subjects to submit their probability beliefs but did not provide any monetary incentive.

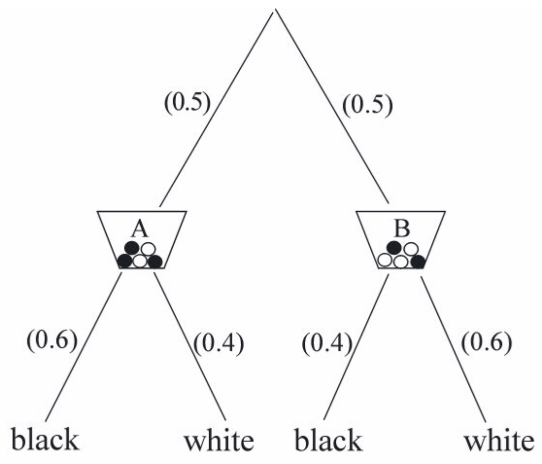

Figure 2.1: Experimental setup

determined. One group consists of 6 persons each of whom has to predict one after another which urn has actually been chosen. Additionally, they have to decide what maximum price they are willing to pay in order 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.[2] In addition, the predecessors' urn 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 own urn prediction. Subjects are paid an amount of 100 ECU (Experimental Currency Unit) for predicting the correct urn and 0 otherwise. We refer to this as mode 1. In the other mode – which is referred to as mode 2 – payoffs additionally depend on the maximum prices 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

[2] Compared to other experiments (e.g. Anderson and Holt, 1997; Kübler and Weizsäcker, 2001) the composition of urns in our experiment leads to rather noisy private signals (see also section 3). This allows us to observe subjects' probability perceptions more distinctly after a cascade has started. In contrast, stronger signals lead to posterior probabilities very close to one and would make it difficult to observe a possible pattern of increasing probability beliefs.

procedure if 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 case 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). This mechanism and its advantages with respect to the task at hand will be explained in more detail in section 3. In Table 2.1 all possible outcomes are summarized.

		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 mode 2.

At the end of each round subjects are informed about the urn that has been actually chosen, the applied payment mode and their resulting income. At the end of the whole session subjects are told their total income.

We used two different payoff modes with probability 0.5 instead of calculating a participant's payoff always according to mode 2, although this would certainly be easier to understand for the participants. The reason for this increased complexity in the experimental setup is that very risk averse subjects might submit a maximum price of 0. In this case they would have no monetary incentive to choose the more probable urn as it is assumed in the considered cascade models, and subjects could thus not trust their predecessors' urn predictions.[3]

The computerized experiment was conducted at Humboldt University of Berlin in July 2000 using the software tool kit Z-Tree (Fischbacher 1990). Both, random drawings of urns and of balls were carried out by the computer. 48 persons, mainly students of the Faculty of Economics were recruited. 8 sessions were conducted, each with groups of 6 persons. Each session lasted on average one and a half hours and two sessions were always conducted simultaneously, which made it impossible for subjects to identify the other group members. 100 ECU corresponded to € 1 and a € 5 participation fee was added to the subjects' final income which averaged about € 8.90. At the end of each session participants were asked to fill in a final questionnaire intended to gain a deeper insight into their decision making process.

[3] Anderson (2001) showed that in fact the monetary payoff matters. She found that error rates significantly increase as the payoff for a correct urn decision decreases from \$2 to \$0.

3. Theoretical predictions

The experimental setup allows to study subjective probability perceptions. The BDM mechanism is applied in order to extract maximum prices which reveal subjects' willingness to pay for participating in the prediction game. Assuming risk neutral subjects maximizing their expected payoffs according to standard expected utility theory the revealed price limits would perfectly reflect subjective probability beliefs. Admittedly, these assumptions are hardly fulfilled, as many experimental studies on individual decision making show (see Camerer, 1995 or Hey, 1991). Nevertheless, for the purpose of this study it is sufficient if submitted maximum prices are positively correlated with subjective probability beliefs. Assuming monotonicity of prices with respect to probability beliefs, probability patterns derived from calculated posterior probabilities on the equilibrium path can be used as benchmarks for the analysis of the revealed price patterns.

In what follows, two classes of cascade models will be introduced as benchmarks for the observed price setting behavior. We start with the explanation of the standard BHW model as our first benchmark. It is based on classical assumptions such as rationality and absense of decision errors. Later on it will be shown how decision errors modify the standard BHW model. We refer to these models as error BHW models and use them as a second benchmark.

3.1. The standard BHW model

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

$$\begin{aligned} \Pr(A|black) &= \Pr(B|white) = \frac{\Pr(white|B)\Pr(B)}{\Pr(white|B)\Pr(B) + \Pr(white|A)\Pr(A)} \\ &= \frac{\left(\frac{3}{5}\right)\left(\frac{1}{2}\right)}{\left(\frac{3}{5}\right)\left(\frac{1}{2}\right) + \left(\frac{2}{5}\right)\left(\frac{1}{2}\right)} \quad (3.1) \\ &= 0.6 \quad (3.2) \end{aligned}$$

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

Color of a ball drawn at position II	Predecessor's predictions at position I A	B
black	$\frac{9}{13}\left(\frac{4}{13}\right)$	$\frac{1}{2}\left(\frac{1}{2}\right)$
white	$\frac{1}{2}\left(\frac{1}{2}\right)$	$\frac{4}{13}\left(\frac{9}{13}\right)$

Table 3.1: Posterior probabilities that urn A (B) is actually chosen at position II.

At position II a subject observes both the color of the ball privately drawn for her and her predecessor's prediction. Table 3.1 summarizes all posterior probabilities for urn A (B) given the predecessor's prediction at position I and the color of the privately drawn ball at position II.

If the posterior probability is 0.5, the urn prediction depends on the tie-breaking rule used by the 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 in this case always follow their private signal.

However, at position III given two equal predictions at position I and II it is always rational to predict the same urn as the predecessors independent of the applied tie-breaking rule and regardless of whether subjects' private signal is in accordance with public information or not. The posterior probabilities following Bikhchandani, Hirshleifer and Welch (Anderson and Holt) are $\Pr(A|black, AA) = 0.72$ (0.77) and $\Pr(A|white, AA) = 0.53$ (0.60), and thus in each case higher than 0.5. Since a subject at position III ignores her private signal given two equal predictions of predecessors, subsequent players cannot obtain any further information from her prediction. A cascade starts and, 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. Therefore, in our experiment a cascade can start theoretically either at position III or V. In the remainder of the paper we refer to positions at which a cascade starts as cascade position 0 and to the subsequent positions as cascade positions 1, 2 and 3, respectively. We refer to the two positions before a cascade starts as cascade

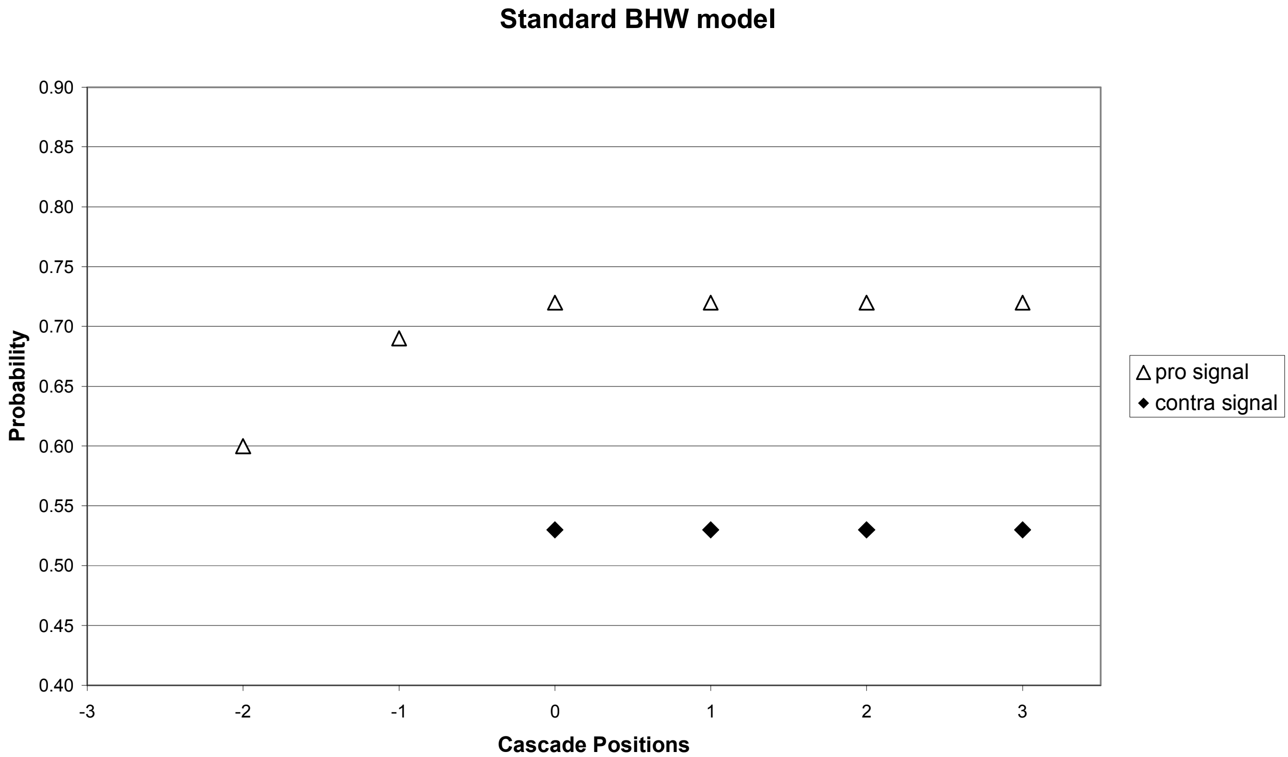

Figure 3.1: Posterior probabilities at different cascade situations according to the standard BHW model.

position -1 and -2. In order to distinguish *positions* at which a participant has to decide from *cascade positions* we index positions with Latin and cascade positions with Arabic letters. Furthermore, we refer to private signals in accordance with the cascade as *pro* signals and the others as *contra* signals. Figure 3.1 shows the probabilities at different cascade situations characterized by cascade position and the respective private signal. Probabilities increase from cascade position -2 to 0 and do not change from cascade position 0 to 3 given pro, resp. contra signals. The displayed probabilities are calculated according to Bikhchandani, Hirshleifer and Welch (1992), applying the tie-breaking rule by Anderson and Holt (1997) would lead to the same characteristics of the probability pattern.

Given the course of posterior probabilities on the equilibrium path according to the standard BHW model the following predictions on the resulting price setting pattern can be derived (assuming monotonically increasing maximum prices in probability beliefs):

Predictions according to the standard BHW model

a) *Prices* $p_{\max}$ *increase from cascade position -2 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 position 0 to 3 if confronted with contra signals.*

3.2. Error BHW models

The standard BHW model presumes that individuals never err in the sense of predicting the less likely urn. Admittedly, there is a lot of evidence in cascade experiments showing that subjects do commit mistakes. In order to examine decision errors in experiments econometric methods (see McKelvey and Palfrey,1995/1998) have been increasingly applied. These methods can also be applied to data from cascade experiments.

Assuming logistically distributed decision errors the probability for predicting an urn is (see also Anderson, 2001):

$$\Pr(R_i = A) = \frac{e^{\lambda \pi_A}}{e^{\lambda \pi_A} + e^{\lambda \pi_B}}$$

The probability $\Pr(R_i = A)$ of choosing urn A depends on the expected income π_A (π_B) for choosing urn A (B) and a precision parameter λ. For $\lambda \to 0$ the probability of choosing a urn approaches 1/2. In this case behavior is random. For $\lambda \to \infty$ the probability of choosing urn A approaches 1 for $\pi_A > \pi_B$ and 0 for $\pi_A < \pi_B$. In this case no decision errors occur.

There are different approaches for the estimation of the precision parameter within the error rate model. Anderson and Holt (1997) as well as Anderson (2001) assume that individuals have rational expectations about their predecessors' behavior, about their predecessors' beliefs about their respective predecessors' behavior, and so on. In contrast, Kübler and Weizsäcker (forthcoming) estimated an error model that allowed for different error rates at different levels of reasoning. Based on a statistical depth-of-reasoning analysis they found that the reasoning gets more and more imprecise on higher levels of the thought process. "In other words, the subjects learn from observing their predecessors' decisions, but they fail to realize that other subjects also learn from observing their respective predecessors" (Kübler and Weizsäcker, forthcoming, p.8).

Based on the prediction data of our experiment we estimated precision parameters for both approaches and find similar results as the researchers cited above.[4] For the rational expectations approach, we find highly significant Lambdas ($p < 0.001$, LR-Test) at all positions (see Table 3.2). However, the likelihood does not improve significantly if we estimate different precision parameters instead of only one Lambda pooled over all positions ($p = 0.07$, LR-Test).

Parameter	λ_{pooled}	λ_I	λ_{II}	λ_{III}	λ_{IV}	λ_V	λ_{VI}
Value	9.19	9.75	10.50	8.63	7.60	10.49	6.94
p-value (LR-Test)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: λ_i indicates the expected error rate at position i.

Table 3.2: Estimated precision parameters for the rational expectations approach.

For the depth-of-reasoning approach we get a similar result as Kübler and Weizsäcker (see Table 3.3).[5] Subjects attribute higher error rates to their predecessors than to themselves ($p = 0.02$, LR-Test), and the reasoning process ends after two steps. Only λ_1 and λ_2 are significantly different from zero. This indicates that individuals have only beliefs about their predecessors but do not consider what their predecessors believe about their respective predecessors and so on.

Parameter	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
Value	9.34	6.60	0.00	106.30	3.91	0.00
p-value (LR-Test)	0.000	0.000	1.000	0.870	1.000	0.976

Note: λ_i reflects the expected error rate at the i-th level of reasoning.

Table 3.3: Estimated precision parameters for the depth-of-reasoning approach.

Having estimated Lambdas we are able to calculate posterior probabilities. Table 3.4 reports the resulting posterior probabilities at different cascade situations according to the considered error approaches. Results regarding the rational

[4] For the estimation of the error rate models we used a gauss procedure which is available on request. It is a modified version of the program developed by Kübler and Weizsäcker (forthcoming) adjusted for our purposes. They also provide a detailed description of the estimation procedure in the appendix part of their paper.

[5] Our results can be compared with the results of the NC treatment in the experiment by Kübler and Weizsäcker (forthcoming). The only difference regarding the information structure is that their subjects were explicitly asked whether they want to obtain a signal at no cost or not.

expectations approach are based on the pooled Lambda, as presented in Table 3.2. Posterior probabilities calculated on the basis of different precision parameters would result in a similar pattern and thus lead to the same conclusions. In contrast to the rational expectations approach, posterior probabilities according to the depth-of-reasoning approach are the same regardless of whether a sequence starts with AA, AB or BA. In addition, Figure 3.2 provides a graphical representation of posterior probabilities at different cascade positions given pro, resp. contra signals.

Error BHW model	Predecessors' predictions	Private signal	Pr(A) at cascade position -2	-1	0	1	2	3
	A, A, A,....	pro	0.60	0.67	0.71	0.73	0.74	0.75
		contra	0.40	0.47	0.52	0.54	0.56	0.57
rational expectations	A, B, A,...	pro	0.59	0.66	0.70	0.72		
approach		contra	0.39	0.46	0.51	0.54		
	B, A, A,....	pro	0.61	0.68	0.71	0.73		
		contra	0.41	0.48	0.52	0.55		
depths-of-reasoning	A, A, A,....	pro	0.60	0.65	0.70	0.75	0.79	0.83
approach		contra	0.40	0.46	0.51	0.57	0.63	0.68

Table 3.4: Calculated posterior probabilities for urn A given predecessors' predictions and the private signal, based on the estimated precision parameters according to both considered error rate models.

Both considered error approaches have in common that posterior probabilities increase not only from cascade position -2 to 0 (as already found for the standard BHW model) but also from cascade position 0 to 3 given pro, resp. contra signals. Comparing the two error approaches one can observe a difference in the marginal increase of posterior probabilities, especially at later cascade positions. Following the rational expectations approach the information content of a predecessor's urn prediction strongly decreases with the ongoing cascade. In contrast, according to the depth-of-reasoning approach each additional urn prediction provides nearly the same additional information, i.e., urn predictions are just taken as a disclosure of private signals but not as a rational sequence regarding urn predictions of preceding players. Thus, the increase of posterior probabilities throughout all cascade positions is nearly linear. However, since we do not assume that price limits perfectly reflect subjective probabilities we are not able to directly compare both error approaches with each other on the basis of the observed price limits.

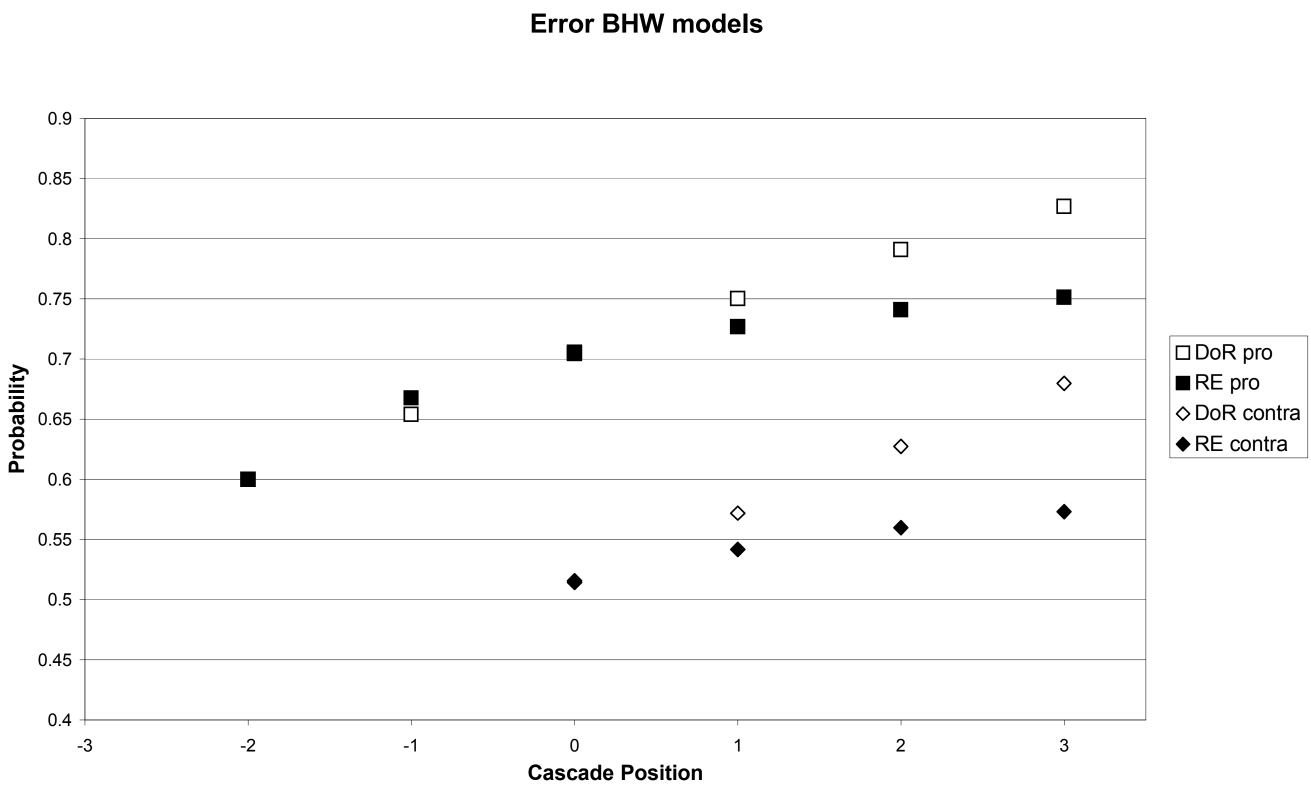

Figure 3.2: Posterior probabilities at different cascade situations according to rational expectations (RE) and depths-of-reasoning (DoR) approach, based on estimated precision parameters.

But assuming a positive relation between price limits and subjective probabilities we are able to derive predictions on the characteristics of the resulting price setting patterns according to both error approaches.

Predictions according to error BHW models

a) *Prices* $p_{\max}$ *increase from cascade position -2 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 if confronted with contra signals.*

4. Results

4.1. Prediction behavior

As can be inferred from Table 3.4 incorporating error rates in Bayesian updating does not change the optimal cascade behavior on the equilibrium path. Thus expected urn predictions according to both standard and error BHW models are the same for cascade positions -2 to 3. 863 out of 1140 urn prediction were made in situations on the equilibrium path and assigned to cascade positions -2 to 3. In further 157 situations urn predictions are submitted in a tie-breaking situation for which the standard BHW model does not provide any clear-cut prediction whereas the considered error models suggest to follow one's own signal. In 125 (79.62%) cases of these situations participants actually followed their own signal. Finally, in further 120 situations participants observed urn predictions of predecessors which obviously deviated from the equilibrium path. In these cases expectations can only be derived from error BHW models. In order to keep the analysis clear we will focus on the 863 situations for which both standard and error BHW models provide clear and coincident expectations about urn predictions.

At first, some general results on urn predictions are summarized in Table 4.1. Almost 90 percent of the considered urn predictions are in line with Bayesian updating. There are, however, striking differences between the error rates at different cascade situations. Regarding pro signals the rate of seemingly rational predictions is about 90 percent at cascade positions 0 and 1, and increases up to about 100 percent at cascade positions 2 and 3. Even more striking is the decreasing error rate if we consider predictions after observing a contra signal. At cascade position 0 almost 40 percent of urn predictions deviate from rational cascade behavior. Even at cascade position 1 in almost 30 percent of urn predictions participants predict according to their own signal instead of following the cascade. In contrast, at cascade positions 2 and 3 about 90 percent of predictions are in line with Bayes' rule. It seems as if more than two confirming urn predictions of predecessors are needed to convince a substantial fraction of subjects to follow the cascade. On the other hand, the high rate of cascade behavior at positions 2 and 3 reveals that heuristics only based on private information cannot explain the observed prediction behavior to a large extent.

Private signal	Cascade position	Number of predictions on the equilibrium path	Number of predictions in line with Bayesian updating	(%)
	-2	312	270	86.54
	-1	156	142	91.02
	0	80	72	90.00
pro	1	55	48	87.27
	2	32	32	100.00
	3	28	27	96.43
	0	74	45	60.81
contra	1	61	44	72.13
	2	31	28	90.32
	3	34	29	85.29
	Total	**863**	**737**	**88.40**

Table 4.1: Prediction behavior for situations on the equilibrium path.

On the individual level we find 31% of participants showing always behavior in line with Bayesian updating. 56% of the subjects showed a very high degree of cascade behavior, with more than 90% of their predictions being in line with theory.

Altogether, the analysis of deviating prediction behavior from what is theoretically expected leads to similar results as already gained by former cascade experiments. Analyzing price setting behavior furthermore enables us to study whether prediction behavior in line with Bayes' rule actually reflects the updating process assumed by the considered cascade models.

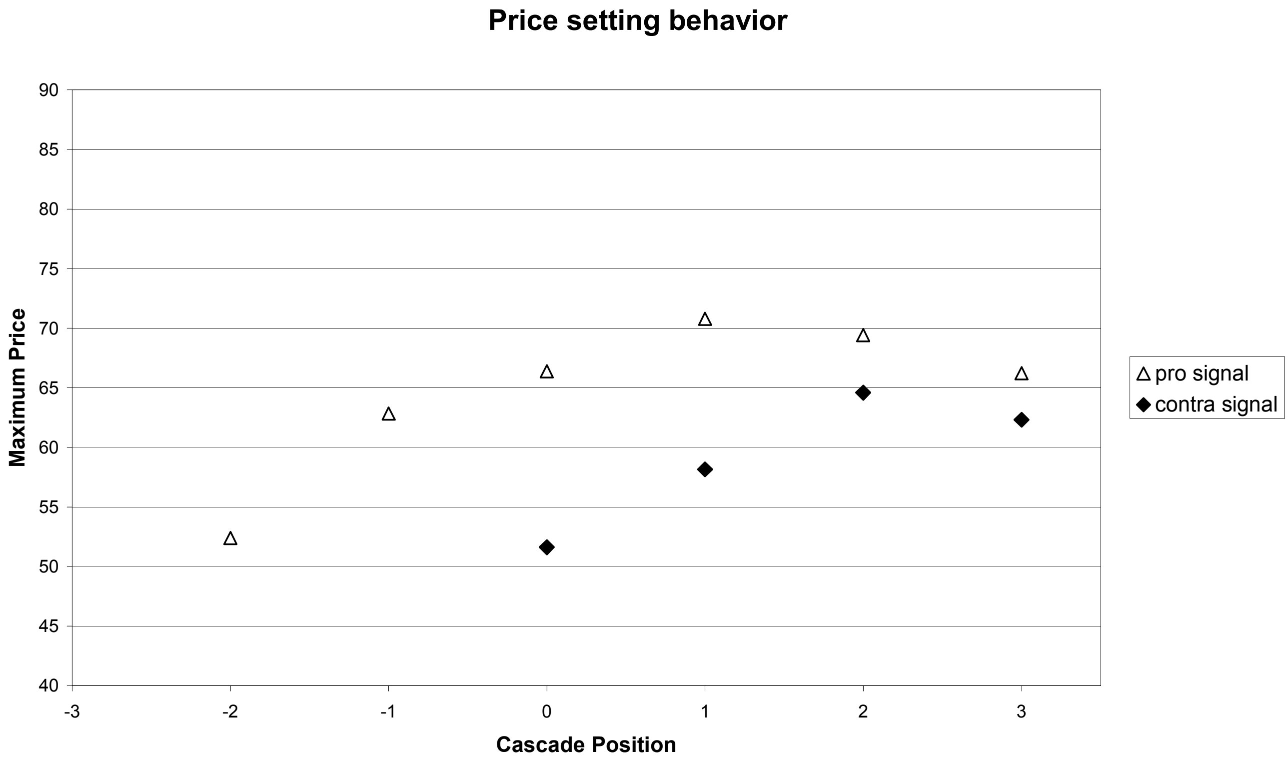

Figure 4.1: Average price limits at different cascade situations.

4.2. Price setting behavior

One essential assumption for using assigned price limits as indicators of subjective probabilities is a positive relation between submitted maximum prices and subjective probability beliefs. The results of a post-experimental questionnaire, in which participants were asked to state subjective probabilities as well as maximum prices for different cascade situations (see Appendix C) support this assumption. Of the 30 subjects for which we were able to calculate correlations, 90 percent showed a positive correlation between maximum prices and probabilities.[6]

In order to get a first impression of the general price pattern we calculated and plotted average prices at each cascade position for pro and contra signals (see Table 4.2 and Figure 4.1). At first glance the observed price pattern rather reflects the predictions derived from error BHW models: Price limits increase even up to cascade positions at which no further information aggregation occurs.

[6] For 18 subjects it was not possible to calculate correlations because either prices or probabilities or both were held constant. It is, however, not possible to specify whether these participants misunderstood the probability concept or the working of the BDM mechanism.

We observe increasing average maximum prices from cascade position -2 up to cascade position 1 if confronted with pro signals and up to cascade position 2 if confronted with contra signals. However, average prices do not monotonically increase throughout the cascade as predicted by the error models. Price limits rather decrease at final cascade positions. Average prices (and median prices) at cascade position 3 if confronted with pro signals are even lower than at cascade position 0.

Private signal	Casc. pos.	Mean	Median	Std.dev.
	-2	52.40	50.00	21.98
	-1	62.84	60.00	23.21
	0	66.39	66.00	25.73
pro	1	70.80	70.00	21.93
	2	69.43	67.00	23.14
	3	66.23	65.00	20.81
	0	51.62	50.00	22.21
contra	1	58.16	50.00	19.05
	2	64.58	60.00	19.26
	3	62.31	60.00	22.28

Table 4.2: Descriptive statistics of price setting behavior in different cascade situations.

In order to check our hypothesis with respect to the considered theoretical models we ran the nonparametric Friedman-statistic to test whether price limits at different cascade situations belong to the same distribution. For each of the 8 (independent) session groups we calculated average prices at each cascade position given pro, resp. contra signals. The session averages are in turn based on individual average prices of the 6 participants per group. We further calculated the Spearman rank correlation between submitted price limits and the respective cascade positions, again based on session averages at the regarded cascade situations. The results are summarized in Table 4.3.

Both standard BHW and error BHW models predict increasing price limits up to cascade position 0 if confronted with pro signals. This pattern is confirmed by our data as can be inferred from line (a). The hypothesis that prices are constant is significantly rejected (Friedman, $p = 0.093$). Price limits significantly increase with the number of confirming predictions by predecessors (Spearman, $p = .005$, 2-tailed). These results indicate that participants generally recognized the additional content of public information at the beginning of a cascade.

	Friedman-test Hypothesis (H0)	χ^2 (sign.)	Spearman rank corr. ρ (sign. 2-tailed)
a)	$p_{\max}^{-2pro} = p_{\max}^{-1pro} = p_{\max}^{0pro}$	4.750 (.093)	.553 (.005)
b)	$p_{\max}^{0pro} = p_{\max}^{1pro} = p_{\max}^{2pro} = p_{\max}^{3pro}$	0.615 (.960)	-.126 (.493)
c)	$p_{\max}^{0con} = p_{\max}^{1con} = p_{\max}^{2con} = p_{\max}^{3con}$	1.800 (.300)	.283 (.130)

Table 4.3: Friedman-test and Spearman rank correlation for different cascade situations.

When considering price limits from cascade position 0 to 3 if confronted with pro signals (see line b) we cannot reject the hypothesis that maximum prices are constant. There is, moreover, no significant correlation between price limits and cascade positions. These findings are in line with the predictions derived from the standard BHW model.

Also for contra signals the hypothesis claiming constant prices from cascade position 0 to 3, as predicted by the standard BHW model, cannot be rejected, although there is a marginally significant positive correlation between price limits and cascade positions (Spearman, $p = 0.065$, 1-tailed).

In addition, we did not detect any statistically significant difference by pair-wise comparison of session average prices at cascade positions 0 to 3 if confronted with pro, respectively contra signals applying the Wilcoxon-signed-ranks test.

Our results can be summarized as follows:

Results (Price setting behavior)

a) *In line with both considered model classes price limits significantly increase from cascade position -2 up to cascade position 0 if confronted with pro signals.*

b) *Considering cascade positions 0 to 3 if confronted with pro signals there is no clear tendency in price setting behavior observable. The hypothesis claiming constant price limits from cascade position 0 to 3 (in line with the standard BHW model) cannot be rejected.*

c) *Considering cascade positions 0 to 3 if confronted with contra signals we find a tendency to increase price limits, supported by a (weakly significant) positive correlation coefficient and monotonically increasing mean ranks. However, the hypothesis that prices are constant cannot be rejected.*

When analyzing price setting behavior only prices are considered for which corresponding urn predictions are in line with the theoretically expected cascade pattern. Prices that correspond to urn predictions not in line with the considered models cannot be taken into account, which implies that the price pattern might be biased. In order to prove the robustness of our results we conducted a similar price analysis for subjects whose urn predictions were always in line with the theoretical models (see Appendix D)[7]. Overall, this analysis leads to the same results as discussed above. Again, we observe a price increase from cascade position -2 to 1 and slightly decreasing prices at later cascade positions if confronted with pro signals. For contra signals average prices increase up to cascade position 1 and are rather constant at later cascade positions. Again, we observe a significant positive correlation between price limits and cascade positions at the beginning, whereas the Spearman rank correlation coefficient does not significantly differ from zero considering price limits for pro signals at cascade positions 0 to 3. For contra signals we also find a marginally significant correlation considering 1-tailed p-values. We thus conclude that our results are robust.

5. Discussion

By implementing the BDM mechanism we succeeded in studying subjects' probability formation less crudely than it has been done in former cascade experiments, whose conclusions were just derived from the observation of urn predictions or buying decisions. We are now able to shed additional light on cascade behavior by investigating assigned price limits as indicators of subjects' probability perceptions. Our design enables us to compare the standard BHW model with econometric models that incorporate individual decision errors based on Bayesian updating.

What do our findings mean in light of the theoretical models presented in section 3? The observed price increase up to cascade position 0 if confronted with pro signals is in line with both considered model classes. It indicates that public signals are generally incorporated in subjects' updating behavior. Simple decision rules, as pure overconfidence (i.e. only private information is taken into

[7] Since for several groups we could not observe price decisions at all cascade situations the Friedman-test could not be applied.

consideration) or simple counting (i.e. only the majority of inferred pro signals is of importance) cannot sufficiently explain the observed behavior since they would result in constant prices at all cascade positions. The significant price increase also shows that participants actually used price limits as an instrument to manage situations perceived as uncertain.

But the price increase as observed at the beginning does not continue throughout the cascade. On the one hand average prices as plotted in Figure 4.1 increase up to cascade positions at which no further information aggregation takes place. This trend is even stronger if subjects are confronted with contra signals. In this sense the incorporation of errors might help to explain cascade data to a larger extent.[8] On the other hand average prices do rather decrease at the final cascade positions. There is no significant relation between the number of coinciding predictions of predecessors and submitted maximum prices if confronted with pro signals and only a weakly positive correlation if confronted with contra signals, such that the hypothesis claiming constant prices at cascade positions 0 to 3 cannot be rejected. Consequently, according to our results the inclusion of errors does not significantly improve the explanatory power of the standard BHW model when explaining updating behavior of subjects who predict in line with the theoretical models.

We consider our experiment to be a first step to implement the BDM mechanism in cascade designs in order to study submitted prices as indicators of subjective probabilities. The results of this study are mainly based on aggregate findings. More insight into the updating process can be gained by analyzing individual price setting behavior. But complete price setting patterns are in our setting hardly observable as the emergence of cascade situations participants are confronted with is endogenous. One possibility to extend the present experimental design would be to confront participants with virtual players whose decisions are determined by certain decision rules. This would enable us to exogenously determine the cascade situation in which a participant has to decide, and thus to gain the necessary amount of individual data needed for a statistically verifiable analysis. To implement such features by keeping the design simple and clear will be the challenge of further experiments.

[8] If we assumed risk neutrality we would be able to directly compare both presented error approaches. In this case the rational expectation approach that results in a decreasing information content of predecessors' urn decisions at later cascade positions would better reflect the observed price setting behavior than the depth-of-reasoning approach by Kübler and Weizsäcker (forthcoming). Remember that the latter approach implies a nearly linear price increase throughout the cascade.

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APPENDIX

A. Instructions (English Translation)

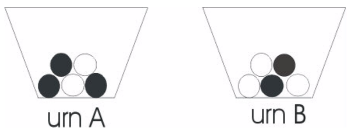
Welcome to our experiment! Please read the instructions carefully! Please do not talk to your neighbors and keep quiet during the whole session! If you have any questions, please raise your hand. We will come to you and help you!

In this experiment you will have to make several decisions. The money you will earn depends only on your decisions and on some random events. The instructions are the same for all participants. The currency is ECU (Experimental Currency Unit) where 50 ECU correspond to DM 1.-. A participation fee of 500 ECU (DM 10) will be added to your final income. The experiment consists of 25 rounds of which all follow the same scheme.

Course of a round

There are two urns, A and B. Urn A contains 3 black balls and 2 white balls. Urn B contains 2 black balls and 3 white balls. One of these two urns is randomly chosen. The random mechanism for choosing the urn works like a coin toss with equal probabilities for both urns.

Now, you have to predict which of the two urns has actually been chosen.



You act together with 5 other participants. The order in which the participants make their decisions is randomly determined at the beginning of each round. When it is a participant's turn, she is asked via her screen to submit her decisions. To do so each participant is provided with certain information that is presented in the next section.

Information

At a participant's turn, a ball is drawn from the chosen urn, and its color is communicated to the participant. After that the ball is put back into the urn. The draw of the ball is random. The probability that a certain ball is drawn is the same for each ball. Furthermore, each participant gets to know the urn predictions of her predecessors. But she does not get to know the colors of the balls that were drawn for her predecessors.

Decisions

Knowing the color of the ball that has been drawn for the participant and the urn predictions of her predecessors each participant has to predict whether urn A or urn B has been chosen and which price $p_{\max}$ she is at most willing to pay to participate in the urn prediction and the according payment chances.

Calculation of the round income

Based on the participant's decisions her round income is calculated. There are two possible modes, mode (1) and mode (2), for calculating the round income. Whether the income is calculated according to mode (1) or mode (2) is determined by a random mechanism similar to a coin toss with equal probability for both modes. The actually chosen mode will be announced at the end of the round. The two modes are explained in detail and summarized in the table below.

- Mode (1): Only your urn prediction is relevant. You receive 100 ECU for a correct urn prediction and 0 otherwise.

- Mode (2): For the case that this mode will be chosen you have to submit a maximum price $p_{\max}$ in addition to your urn prediction. This price limit determines whether you participate in the payoff procedure according to mode (1), that is 100 ECU for a correct urn prediction and 0 ECU otherwise, or not.

Your submitted maximum price $p_{\max}$ will be compared with a random price p_r, that is randomly drawn from all whole-numbered prices between 0 and 100 ECU. The probability that a certain random price is drawn is the same for each price. In case the random price exceeds your submitted maximum price ($p_r > p_{\max}$) you do not participate in the payoff procedure. Your final round income will be 0 ECU, regardless of whether you predicted the correct urn or not. In case the random price does not exceed your maximum price ($p_r \leq p_{\max}$), the payoff is calculated according to mode (1) minus the random price p_r.

Your submitted maximum price $p_{\max}$ indicates how much you are willing to pay at most for the odds described in mode (1). It is always optimal for you to submit your real maximum willingness to pay (see also "The optimal choice of $p_{\max}$") [Appendix B].

- Summary of income calculation:

		Correct urn	Wrong urn
Mode (1)		100 ECU	0 ECU
Mode (2)	$p_r \leq p_{\max}$	100 ECU - p_r	0 ECU - p_r
	$p_r > p_{\max}$	0 ECU	0 ECU

After the participant at the final position has submitted her decisions the round is finished. You will then get an overview over the round providing you with the following:

- the chosen urn

- your own urn prediction

- the chosen mode of income calculation

- in the case of mode (2): the random price p_r

- your round income

Your total income will be the sum of your 25 round incomes plus a participation fee of 500 ECU. Possible negative round incomes will be subtracted from the total income.

Summary

In order to get a better overview of the course of a round, in the following all important steps are summarized:

- random choice of an urn by the computer
- random determination of participants' order
- A ball is drawn and its color is announced to the participant at position 1.
- The participant at position 1 predicts an urn (A or B) and submits her maximum price $p_{\max}$.
- A ball is drawn and its color is announced to the participant at position 2.
- Furthermore, the participant at position 2 gets to know the urn prediction of the participant at position 1.
- The participant at position 2 submits her urn prediction and her maximum price $p_{\max}$.
- A ball is drawn....

After the participant at position 6 has submitted her decisions the round income will be calculated according to the rules described above.

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 DM 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 DM as your maximum price, the following cases could arise:

- $p_r > p_{\max} > p_u$. The random price exceeds the real maximum price, e.g. 6 DM. You would not buy the bottle, irrespective of whether you understate the price or submit your actual maximum price of 5 DM.
- $p_r \leq p_u$. The random price is lower than the submitted understated price, e.g. 2 DM. You would buy the wine for 2 DM, irrespective of whether you submit your actual maximum price of 5 DM or understate the price by assigning 3 DM.
- $p_u < p_r \leq p_{\max}$. The random price lies in between the submitted understated and your real maximum price e.g. 4 DM. In this case you would not buy the wine although you were willing to pay 5 DM and would only have to pay 4 DM.

As you can see, understatement does not pay.

Nor does exaggeration. Assume that you would exaggerate and submit a price p_e of 7 DM. Again there are 3 possible scenarios:

- $p_r \leq p_{\max} \leq p_e$.The random price is lower or equals the real maximum price, e.g. 4 DM. You would buy the wine at a price of 4 DM, irrespective of whether you submit your real maximum price of 5 DM or exaggerate by assigning 7 DM.
- $p_r > p_e$. The random price exceeds the exaggerated price, e.g. 8 DM. You would not buy the wine, irrespective of whether you submit your actual maximum price of 5 DM or exaggerate by assigning 7 DM.
- $p_{\max} < p_r \leq p_e$. The random price lies in between your real maximum price and the submitted exaggerated price, e.g. 6 DM. In this case you would have to pay 6 DM for the bottle although it is only worth to you to pay 5 DM.

Obviously, neither understatement nor exaggeration does pay!

C. Post-experimental questionnaire

By the computerized post-experimental questionnaire participants were asked (without monetary incentives) to predict the chosen urn and to state subjective probabilities and price limits for the following cascade situations:

No.	Cascade situation characterized by	
	predictions of predecessors	color of the ball
1	-	black
2	-	white
3	A	black
4	A	white
5	AA	black
6	AA	white
7	AAA	black
8	AAA	white
9	AAAA	black
10	AAAA	white
11	AAAAA	black
12	AAAAA	white

D. Further statistics (regarding those participants who always predicted in line with the standard BHW model)

- Descriptive statistics of price setting behavior:

Private signal	Cas. pos.	Mean	Median	Std. dev.
	-2	44.78	47.00	17.52
	-1	55.31	60.00	22.44
	0	59.65	60.00	25.94
pro	1	79.00	80.00	18.35
	2	76.64	75.00	19.13
	3	67.55	75.00	22.89
	0	47.96	50.00	19.52
contra	1	60.53	65.00	21.02
	2	59.00	60.00	9.17
	3	59.40	56.00	17.55

Note: Only data of those subjects who always predicted in line with the standard BHW model are included.

- Spearman rank correlation between average price limits and the respective cascade positions at different cascade situations:

	Considered price limits at different cascade situations	Spearman rank corr. ρ (sign. 2-tailed)
a)	$(p_{\max}^{-2pro}; p_{\max}^{-1pro}; p_{\max}^{0pro})$	.477 (.021)
b)	$(p_{\max}^{0pro}; p_{\max}^{1pro}; p_{\max}^{2pro}; p_{\max}^{3pro})$	.090 (.670)
c)	$(p_{\max}^{0con}; p_{\max}^{1con}; p_{\max}^{2con}; p_{\max}^{3con})$	.292 (.156)

Note: Only data of those subjects who always predicted in line with the standard BHW model are included.