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Do individuals recognize cascade behavior of others? — An Experimental Study — [1]

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Abstract

In an information cascade experiment participants are confronted with artificial predecessors predicting in line with the BHW model (Bikchandani et al., 1992). Using the BDM (Becker et al., 1964) mechanism we study participants' probability perceptions based on maximum prices for participating in the prediction game. We find increasing maximum prices the more coinciding predictions of predecessors are observed, regardless of whether additional information is revealed by these 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

Keywords: information cascades, Bayes' Rule, decision under risk and uncertainty, experimental economics

1 INTRODUCTION

Information cascades as modelled by Bikchandani et al. (1992), henceforth BHW, have become a popular approach to explain herding behavior.[1] The BHW model offers explanations for many economic and social phenomena, such as fashion trends and conformity in consumption decisions. BHW explain herding within a rational choice approach assuming that agents update beliefs according to Bayes' rule. The model shows that in a choice situation under incomplete information it may be rational to follow predecessors and to disregard one's own private information. Hence a cascade starts and no further information is aggregated in the observable decisions. 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 probabilities of making a good decision increase with the length of the cascade even if no further information is aggregated. Thus, boundedly rational behavior of agents would result in an overvaluation of public information and thereby cause further economic distortions. Consumers, for instance, might misinterpret the number of previous sales of a specific product as a signal for quality. This could unreasonably increase their willingness to pay for best-sellers compared to similar competing products. Promotion instruments that refer to the number of sales, e.g. best-seller lists, could then be used for increasing demand or for selling at higher prices.

Cascade phenomena have been the subject of numerous experimental studies. The predictions of the BHW model were confirmed in first experimental tests by Anderson and Holt (1997), henceforth AH. Following AH, most studies investigate cascade behavior by varying the structure of available information or by selling costly private information.[2] Conclusions are drawn from subjects' predictions and buying decisions. The results suggest that individuals, if confronted with more complex decision tasks than in the original AH experiment, tend to overestimate private information and thus to deviate from the rational cascade pattern. Kübler and Weizsäcker (2004) have observed that acquisition rates of costly signals are generally higher than optimal, but decrease in ongoing cascades. Their results suggest that subjects overestimate the error rates of their predecessors and that their depth of reasoning is limited.[3] The authors conclude that "...subjects learn from observing their predecessors' decisions, but...fail to realize that other subjects also learn from observing their respective predecessors".

Oberhammer and Stiehler (2002) investigate whether behavior in cascades reflects Bayesian updating. In their simple symmetric design, even counting leads to correct urn predictions if predecessors behave rationally.[4] Using the BDM procedure (Becker et al., 1964) they

[1]For a survey on theoretical and empirical studies dealing with information cascades see Bikchandani et al. (1996)

[2]See e.g.Willinger and Ziegelmeyer (1998), Kraemer et al. (2006), Kraemer and Weber (2001), Nöth and Weber (2003), Kübler and Weizsäcker (2004).

[3]Kübler and Weizsäcker (2004) use a quantal response model for their analysis. The examination of errors by using quantal response models (McKelvey and Palfrey (1995), McKelvey and Palfrey (1998)) has become increasingly popular for explaining deviations from standard BHW model. For other applications of quantal response equilibria to information cascade models see e.g. Anderson and Holt (1997), Anderson (2001).

[4]In the AH experiment, prediction errors increase up to 50 percent in asymmetric decision situations where simple counting of predecessors' predictions does not lead to a correct urn prediction (Huck and

asked subjects to submit maximum prices they are willing to pay for participating in the prediction game. These maximum prices are used as indicators of subjects' probability perceptions. This procedure allows testing 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. The authors report on prices increasing with the number of predecessors. This price increase also occurs in positions where rational predecessors should have ignored their private signals, i.e. in which their decisions do not reveal additional information. Error models can account for the observed price increases, but the pattern could also be caused by subjects whose depth of reasoning is limited and who thus do not recognize cascade behavior of others. The authors were unable to distinguish between these alternative explanations. Moreover, the decision situations in which individuals had to decide were endogenously determined, so that observing complete individual price patterns was impossible.

To fill these two gaps is the aim of this study. It focuses on individual updating behavior in a cascade design similar to Oberhammer and Stiehler (2002). Subjects are confronted with the same information structure and the BDM mechanism is used to elicit prices as indicators of subjects' probability perceptions. However, we incorporate artificial agents as predecessors, who follow a simple counting rule, thus predict according to BHW, and – by definition – never err. Using the strategy method we ask subjects to state their predictions and maximum prices for all possible decision situations. This results in observing complete individual price setting patterns. By excluding error making of predecessors as an explanation for the observed decisions, we are able to address the question whether individuals recognize cascade behavior of others in isolation.

We find that in these rather simple decision tasks, most subjects predict according to theory (and to simple counting) but many submit increasing maximum prices the more coinciding predictions of predecessors they observe, regardless of whether additional information is revealed by these predictions. We conclude that the majority of participants do not recognize cascade behavior of predecessors.

While we focus on the recognition of predecessors' rational cascade behavior, we do not negate that (assumed) erroneous play of human predecessors also influenced subjects' behavior in other experiments. As our artificial agents never err, we most likely create beliefs about predecessors that are different than in experiments with human players. Therefore, it is no surprise that behavior in this experiment differs in some aspects from behavior reported in other cascade studies.

The remainder of the paper is organized as follows. In Section 2 the experimental design and procedures are described. In Section 3 hypotheses 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. Section 5 concludes.

Oechssler, 2000). In these situations the rule 'follow your own signal' offers better predictions than Bayesian updating. This result suggests that subjects are not always able to apply Bayesian updating in complex decision tasks

2 EXPERIMENTAL DESIGN AND PROCEDURE

2.1 *Experimental Scenario*

There are two urns, A and B, with 5 balls each (3 black balls and 2 white balls and vice versa). In each round of the game, one urn is randomly chosen with equal probability at the beginning of the game. Participants predict the randomly chosen urn. As participants' private information a ball is drawn from the urn and its color revealed. As public information, urn predictions of predecessors (if any) are announced. Participants are credited 100 ECU (Experimental Currency Units) for correct urn predictions and nothing otherwise. 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 opportunity of winning 100 ECU. As an incentive compatible mechanism to elicit subjects' maximum willingness to pay we implement the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964): Subjects' maximum prices are compared to a random price p_r, drawn from a uniform distribution in the the interval [0,100]. 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 is credited the amount resulting from her urn prediction minus the random price (see Table 1).

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

Table 1: Income Calculation.

If participants were risk neutral and maximized their income according to standard expected utility theory the submitted maximum prices would perfectly reflect their winning probability perceptions. But these assumptions are hardly satisfied as many experimental studies on decision making show.[5] However, we are not interested in absolute probability levels, but only in qualitative results. Therefore, prices are a meaningful measure to answer our research question if higher prices reflect higher probability perceptions and vice versa. To check this, we do not only elicit maximum prices but also ask subjects to submit subjective probabilities for the correctness of their urn predictions.

2.2 *Implementation of artificial agents*

In this cascade experiment a subject's predecessors are artificial agents, whose predictions are clearly defined by simple counting, i.e. 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 (Anderson and Holt, 1997). Thus, urn predictions of artificial agents 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

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

their private signal. This tie-breaking rule 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. Admittedly, we taught participants to predict according to the BHW model. But note that we are interested in price setting behavior rather than in urn predictions. By the precise explanation of the artificial agents' decision rule, we wanted to make it as easy as possible for subjects to recognize cascade behavior of predecessors.

2.3 *Use of the strategy method*

Participants are asked to state their decisions for all situations that may arise from the decisions made by up to 5 artificial predecessors. Depending on

- the subject's own position (1 to 6),
- the color of the privately drawn ball (black or white) and
- the history regarding predecessors' predictions

there are in total 74 decision situations (see Section 3.2) for which participants have to submit their urn predictions, maximum prices and subjective probabilities. One of these 74 situations is determined to be payoff relevant as follows:

1. One urn (A or B) is randomly chosen.
2. Subjects' position (1 to 6) is randomly determined.
3. For each artificial agent a ball is drawn from the chosen urn. The agent predicts according to the defined decision rules. This prediction is publicly announced.
4. At the (real) subject's position a ball is drawn and the color announced.

Then the random price is drawn from all integers between 0 and 100. Now the payoffs from the experiment can be calculated according to the rules summarized in Table 1. The implementation of the strategy method has two major advantages: First it allows observing complete individual price patterns. Second, the strategy method causes 'cold', i.e. less emotional responses than spontaneous play and thus helps us to focus on the participants' ability to recognize cascade behavior of others.[6]

[6]For experimental studies on presentation effects see e.g. Brandts and Charness (2000) or Schotter et al. (1994).

2.4 *Procedure*

At the start of a session participants were provided with written instructions as well as with a supplementary sheet on the working of the BDM mechanism demonstrating that strategic behavior does not pay.[7] Questions were answered privately during the experiment.

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

Prior to the experiment participants answered some control questions about the decision rules of artificial predecessors and the working of the price mechanism.[8] Subjects who answered all questions correctly in the first go were paid an additional 5€. Participants were not allowed to proceed to the experiment before all questions were answered correctly.

In the experiment participants submitted their decisions for all 74 situations which were displayed on the computer screen in random order. After the decisions were taken the payment relevant situation was determined, the price was randomly chosen, and subjects were paid according to their decisions.

By using real urns and balls and by the execution of random choices by participants, by demonstrating the choice of the payment-relevant situation before the sessions started and by using pre-experimental control questions we ensured that the structure of the experiment, the decision rules of artificial agents as well as the working of the BDM mechanism were understood by the participants.

The computerized experiment (using the software toolkit z-Tree, Fischbacher (1999)), was conducted at Humboldt University at Berlin. We ran 4 sessions with 9, 12, 7 and 11 participants. The 39 subjects, mainly business and economics students, 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 THEORY, NOTATION AND HYPOTHESES

3.1 *Bayes' rule*

In a symmetric cascade structure in which predecessors update information in line with Bayes' rule and predict according to their private signal in case of a tie, posterior probabilities just depend on the number of signals in favor of urn A and B. According to Anderson and Holt (1997), for the applied design, these probabilities can be derived to be as follows:

$$\Pr\{A|d\} = \frac{1}{1+\left(\frac{2}{3}\right)^{d}} \text{ and } \Pr\{B|d\} = \frac{1}{1+\left(\frac{2}{3}\right)^{-d}} \tag{1}$$

[7] This material may be downloaded at http://www.hu-berlin.de/wt1/papers.
[8] This material may be downloaded at http://www.hu-berlin.de/wt1/papers.

Thereby, d is defined as the difference between the number of A and B signals. Posterior probabilities increase with an increasing difference in favor of the respective urn. Thus, rational subjects would recognize that they should ignore their own signal once a difference of $d = 2(-2)$ can be inferred from the predecessors' predictions. From then on subsequent players would always predict according to the ongoing cascade even if their private signal does not match the cascade, 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.

3.2 *Notation*

To describe and classify the different situations a subject may be confronted with, we first introduce some notation: All possible situations in the decision sequences will be characterized as follows: Predecessors' predictions are denoted by capital letters (A or B), private signals by small letters (a=black ball and b=white ball). For example, ABb refers to a situation in which a subject acts third in the sequence, sees a white ball as her private signal, and observes that one of her predecessors (the first agent) has predicted "A", and one (the second agent) has predicted "B". We denote these situations as "decision situations".

We refer to private signals as either pro or contra signals. The naming is based on what a rational player would do after observing the respective signal: After observing a pro signal, the player predicts the urn suggested by the signal (or is indifferent which urn to choose), after observing a contra signal, she rationally predicts against it. Therefore, as long as no cascade has started, all signals are pro signals, because no player rationally ignores her signal.

We classify decision situations where *no cascade has started yet* as cascade positions -3, -2, and -1. Cascade position -3 refers to a "balanced sample". This means that predecessors' decisions and the private signal together reveal a probability of 0.5 for each urn. Thus, either prediction is in line with rational behavior. Cascade position -2 refers to decision situations in which equally many predecessors have predicted either urn. This means that predecessors' decisions and the private signal together reveal a probability of 0.6 for the urn indicated by the private signal. Finally, at cascade position -1, among the predecessors, there is already a one-prediction majority for one of the urns among the predecessors and the private signal matches that majority. Hence, the probability for predicting correctly is 0.69.

We refer to a player's position *at which a cascade starts* as cascade position 0. This means that a rational player at cascade position 0 is the first to ignore her signal and predict in line with the majority of predecessors in any case. Despite the fact that the optimal decision is unaffected by the private signal, the probability of predicting correctly depends on whether she has observed a pro or a contra signal.

Positions *within the cascade* are referred to as cascade positions 1, 2, and 3. This means that 1, 2, or 3 predecessors have already ignored their private signal and have predicted according to the majority of predictions they observed. Therefore there is no additional information revealed by their predictions. Thus, the probabilities of predicting correctly

FIGURE 1 HERE

Figure 1: Probability pattern according to the BHW model

after receiving a pro or a contra signal at cascade positions 1, 2, or 3 equal those at cascade position 0.

In total there are thus seven cascade positions. Remember that cascade positions are not equivalent to the position in the decision sequence at which a player acts. As an example, consider decision situations *AAb* and *BAAAb* which both belong to cascade position 0.

In Table 2, all cascade positions and the corresponding decision situations are summarized.

Private Signal	Casc. Pos.	Decision Situations	Number
	-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*; *BABAa*	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
pro	1	*AAAa*; *BBBb*; *ABAAAa*; *BABBBb*; *ABBBBb*; *BAAAAa*	6
	2	*AAAAa*; *BBBBb*	2
	3	*AAAAAa*; *BBBBBb*	2
	0	*AAb*; *BBa*; *ABAAb*; *ABBBa*; *BAAAb*; *BABBa*	6
contra	1	*AAAb*; *BBBa*; *ABAAAb*; *ABBBBa*; *BAAAAb*; *BABBBa*	6
	2	*AAAAb*; *BBBBa*	2
	3	*AAAAAb*; *BBBBBa*	2
Total			74

Table 2: Decision Situations.

3.3 *Hypotheses*

Figure 1 shows a representation of posterior probabilities for all cascade positions given pro or contra signals according to the BHW model.

As derived in Section 3.1, posterior probabilities of predicting correctly increase between cascade positions -3 and -1. With the prediction of the agent at cascade position 0, the cascade starts. From then on, probabilities remain constant. As for 38 out of 39 subjects (97.4%) we observe highly significant positive correlations between maximum prices and subjective probabilities,[9] we are confident in using the submitted maximum prices to test our hypotheses.[10]

[9]The Pearson correlation coefficient is significant on the 1%-level for all but one subjects. All significant coefficients are between 0.44 and 0.96, with a median of 0.85. Thus, a majority of subjects exhibit a nearly linear correlation. The non-parametric Spearman's rank-order correlation coefficient is significant on the 1%-level for all 39 subjects.

[10]This correlation does neither need to be perfect nor linear. If, e.g., subjects are risk averse, it may be expected that the correlation exhibits a non-linear pattern.

FIGURE 2 HERE

Figure 2: Probability pattern according to the behavioral hypothesis

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

Price setting behavior at cascade positions -3 to 0 is as follows:
a) $p_{max}^{-3pro} < p_{max}^{-2pro} < p_{max}^{-1pro} < p_{max}^{0pro}$
Price setting behavior at cascade positions 0 to 3 is as follows:
b) $p_{max}^{0pro} = p_{max}^{1pro} = p_{max}^{2pro} = p_{max}^{3pro}$
c) $p_{max}^{0con} = p_{max}^{1con} = p_{max}^{2con} = p_{max}^{3con}$

Thereby, we refer to p_{max}^{0pro} as the willingness to pay of a subject at cascade position 0, who is confronted with a pro signal, etc.

There are many studies indicating that individuals' depth of reasoning is limited.[11] We thus conjecture that even though there is no uncertainty about others' decision making, individuals do not recognize cascade behavior of predecessors in our simple setting. If subjects ignore the formation of a cascade, subjective probabilities increase the longer a cascade continues, as illustrated in Figure 2. From this, we derive our alternative hypothesis.

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

Price setting behavior at cascade positions -3 to 0 is as follows:
a) $p_{max}^{-3pro} < p_{max}^{-2pro} < p_{max}^{-1pro} < p_{max}^{0pro}$
Price setting behavior at cascade positions 0 to 3 is as follows:
b) $p_{max}^{0pro} < p_{max}^{1pro} < p_{max}^{2pro} < p_{max}^{3pro}$
c) $p_{max}^{0con} < p_{max}^{1con} < p_{max}^{2con} < p_{max}^{3con}$

The BHW and the Behavioral Hypothesis both predict increasing maximum prices from cascade position -3 to cascade position 0. But they differ in the predicted price patterns from cascade position 0 to 3.

4 RESULTS

4.1 *Prediction Behavior*

The 39 subjects were independently asked to make decisions for 74 situations. The data file thus consists of 39*74=2886 urn predictions, prices and subjective probabilities. 546 observations are from situations at cascade position -3 where all predictions are consistent with BHW since the posterior probability is 0.5. Of the remaining 2340 urn predictions 2268 (96.9%) are in line with BHW. 14 subjects (35.9%) predicted always in line with the theory.

[11]For depth of reasoning analyses in normal form games see e.g. Ho et al. (1998) or Nagel (1995). For information cascades, Kübler and Weizsäcker (2004) have shown that subjects' depth of reasoning is limited. See our discussion in Section 1.

The rate of seemingly rational predictors sharply increases up to 82.1% (32 out of 39), if we include subjects who predicted in line with the BHW in at least 95% of the relevant situations.[12]

As mentioned in Section 2, our experimental design and procedure indirectly influence subjects to predict in line with BHW. Thus, the high rate of predictions in line with Bayesian updating is not astonishing. Subjects followed their own signal in 77.1% of all tie-breaking situations (with posterior probabilities of 50%).[13]

At cascade positions 0 to 3 rational agents would follow their predecessors even when confronted with a contra signal. However, the error rate in such situations is essentially higher (6.7%) than in cases in which the signal coincides with the ongoing cascade (0.6%). In order to provide insight into the structure of prediction errors in ongoing cascades, we compared error rates at different cascade positions and summarized the results in Table 3. When subjects are confronted with pro signals, error rates are similarly low at cascade positions 0 to 3 (between 0.0% and 1.3%). When confronted with contra signals, the error rate at cascade position 0 is higher (12.8%) than at later cascade positions.[14]

Subjects apparently overvalue their private information at early cascade positions but assign more weight to the sequence of predecessors' predictions the longer the cascade continues.

Cascade position	Number of cases	Number of errors [error rate] after... pro signal	contra signal
0	234	3 [1.3%]	30 [12.8%]
1	234	0 [0.0%]	11 [4.7%]
2	78	0 [0.0%]	0 [0.0%]
3	78	1 [1.3%]	1 [1.3%]
Total	626	4 [0.6%]	42 [6.7%]

Table 3: Prediction errors at different cascade positions

4.2 *Price setting behavior and subjective probabilities*

The question remains whether subjects who predict in line with BHW also recognize that a cascade formation takes place. Thus, in the following, we concentrate on predictions that were in line with BHW. For each of the 2812 correct predictions we have one maximum price for participating in the prediction game and one subjective probability for making a correct prediction. To give a first overview of price setting behavior for different cascade

[12]The remaining (incorrect) predictions do not seem to follow any systematic pattern. In each of the relevant decision situations, one or two subjects made a mistake.

[13]This rate resembles the one in Oberhammer and Stiehler (2002) (79%), but is lower than rates found in Anderson and Holt (1997) and Anderson (2001) (85.4% and 88.5%). However, their design was different to Oberhammer and Stiehler's and ours in a number of characteristics, e.g. they used a non-computerized design and a different signal precision.

[14]This pattern of error rates is in line with the data of Anderson and Holt (1997), Anderson (2001) , and Oberhammer and Stiehler (2002) among others. However, the level of error rates is higher in all those studies. This may be due to the fact that players distrust their human predecessors and thus follow their own signal more often.

positions and private signals, we report average prices and probabilities for each of the 11 different cascade position/signal combinations (7 cascade positions with a pro signal and 4 with a contra signal).[15] The aggregated results are summarized in Table 4. Figure 3 illustrates the aggregated price setting pattern.

FIGURE 3 HERE

Figure 3: Average prices for different cascade positions and private signals

Private signal	Casc. pos.	Individual avg. prices Mean	Median	SD	Subjective prob. (in %) Mean	Median	SD	Prob. according to.. Behav.	BHW
pro	-3	32.9	35.6	18.6	46.2	49.6	8.0	50.0	50.0
	-2	39.7	39.2	17.3	51.6	53.4	9.0	60.0	60.0
	-1	53.1	53.9	17.9	61.8	62.9	9.3	69.2	69.2
pro	0	59.5	60.4	20.2	67.8	68.3	11.1	77.1	77.1
	1	67.8	76.7	22.2	75.5	78.5	11.2	83.5	77.1
	2	73.1	80.0	20.7	81.3	85.0	12.5	88.4	77.1
	3	73.9	81.3	23.9	83.0	87.5	14.9	91.9	77.1
contra	0	39.7	41.0	16.7	49.4	52.5	12.3	60.0	60.0
	1	50.8	50.8	20.5	60.1	61.2	12.9	69.2	60.0
	2	55.5	58.3	23.6	65.9	67.5	15.6	77.1	60.0
	3	63.8	70.3	25.9	74.9	77.5	16.7	83.5	60.0

Table 4: Price setting behavior and subjective probability statements

As predicted by the BHW model and by our behavioral hypothesis, maximum prices increase from cascade position -3 to 0. When information cascades form, the submitted prices at later cascade positions are higher than at earlier positions. This is in line with our behavioral hypothesis. A similar pattern can be observed for the subjective probabilities. At cascade position 3, subjects' average maximum prices and subjective probabilities are higher than predicted by BHW.

As mentioned above, we observe that subjects associate higher probabilities of predicting correctly with a higher willingness to pay for taking part in the prediction game. We also find that at each cascade position, average subjective probabilities exceed average submitted maximum prices, indicating that risk aversion plays a role. The difference between prices and subjective probabilities does not vary systematically over probability levels and cascade positions.

In order to test our hypotheses, we ran nonparametric Friedman tests based on individual average prices for each cascade position. Moreover, we used the individual average prices to calculate the Spearman rank correlation coefficient for each of the three conjectured price/cascade position relationships. The results are presented in Table 5.

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

[15]For the analysis of price setting behavior we excluded observations of one subject whose submitted maximum prices are apparently unsystematic and often on an invariantly low level (85% of his maximum prices are below 10). However, including this observation does not change our findings.

	Friedman test Hypothesis (H_0)	χ^2	(sign.)	Spearman rank corr. ρ (sign. 2-tailed)
a)	$p_{max}^{-3pro} = p_{max}^{-2pro} = p_{max}^{-1pro} = p_{max}^{0pro}$	91.02	(.000)	.482 (.000)
b)	$p_{max}^{0pro} = p_{max}^{1pro} = p_{max}^{2pro} = p_{max}^{3pro}$	42.86	(.000)	.272 (.001)
c)	$p_{max}^{0con} = p_{max}^{1con} = p_{max}^{2con} = p_{max}^{3con}$	64.45	(.000)	.374 (.000)

Table 5: Friedman-tests and Spearman rank correlations for maximum prices and cascade positions

$\rho > 0$ with $p < 0.01$) between submitted maximum prices and the respective cascade positions. This finding is in line with Bayesian updating. However, all other hypotheses derived from the BHW model are rejected (see rows b and c). 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. Applying the same tests to subjective probabilities instead of prices yields the same results.

Observation I *Aggregate price pattern*

1. *In situations where no information cascade has yet formed, the average willingness to pay positively depends on the cascade position (-3 to 0). This is in line with both the BHW model and the behavioral hypothesis.*
2. *The aggregated price setting pattern within cascades is in line with the behavioral hypothesis, i.e. the correlation coefficients between average maximum prices and the cascade position (0 to 3, for both pro and contra signals) are significantly positive.*

One may object that the price pattern may be due to the behavior of some subjects who did not understand the rules of the game and/or the decision rules of artificial agents.

To check whether this objection is justified, we applied the same analysis to the subsample of subjects who predicted in line with BHW in more than 95% of the cases and answered all questions about artificial predecessors correctly at first go.[16]

Our findings turn out to be robust. We find a similar price pattern for the considered subsample, i.e. the hypothesis according to BHW has to be rejected in favor of our behavioral hypothesis.

The use of the strategy method does not only allow to analyze aggregate behavior, but also to obtain complete individual price setting patterns. We calculate Spearman rank correlation coefficients between submitted maximum prices and the respective cascade positions for each single participant. As before, we analyze:

1. maximum prices at cascade positions -3 to 0.
2. maximum prices at cascade positions 0 to 3 if confronted with pro signals.
3. maximum prices at cascade positions 0 to 3 if confronted with contra signals.

[16]Note that some of these control questions referred to situations at which artificial predecessors showed cascade behavior, i.e. predicted against their private signals.

According to the significance of the rank correlation coefficients (at the 5% level), we classify subjects in the following four groups:

- **BHW subjects:** Those who show a significantly positive correlation between cascade positions and maximum prices at cascade positions -3 to 0, but, for both pro and contra signals, no significant correlation at cascade positions 0 to 3.
- **Subjects completely ignoring the cascade formation:** Those who show significant positive correlation coefficients at cascade positions -3 to 0 and, for both pro and contra signals, also at cascade positions 0 to 3.
- **Subjects partly ignoring the cascade formation:** Those who show significant positive correlation coefficients at cascade positions -3 to 0 and, either for pro or contra signals, also at cascade positions 0 to 3.
- **Others:** Subjects who do not show a significant positive correlation coefficient at cascade positions -3 to 0 or who show a significant negative correlation between prices and cascade positions, whose behavior is thus not in line with either hypothesis.

Identified groups	Number of subj.	%	a)	b)	c)	Number of subj.
BHW subjects	7	17.9	+	⊘	⊘	7
Subj. completely ignoring the cascade formation	17	43.6	+	+	+	17
Subj. partly ignoring the cascade formation	10	25.6	+	+	⊘	2
			+	⊘	+	8
Others	5	12.8	⊘	+	+	1
			⊘	⊘	+	1
			⊘	⊘	⊘	2
			+	-	⊘	1
Total	39	100.0				39

*Identified price patterns at cascade positions -3 to 0 (column a) and at cascade positions 0 to 3 when confronted with pro (column b), resp. contra signals (column c). Significant positive (negative) correlations ($p < 0.05$, 2-tailed) between max. prices and cascade positions are indicated by + (-), insignificant correlations by ⊘.

Table 6: Individual price patterns

The results are summarized in Table 6. For 17 subjects (43.6%), all three correlation coefficients are significantly positive, i.e. completely in line with the behavioral hypothesis. For another 10 subjects (25.6%), the correlation coefficient is significantly positive at cascade positions -3 to 0, and, either for pro or for contra signals, also at cascade positions 0 to 3. This indicates that cascade behavior of predecessors is not consistently recognized. Only for 7 of the 39 subjects (17.9%), all three correlation coefficients are in line with the standard BHW model, i.e. significantly positive at cascade positions -3 to 0, but insignificant at cascade positions 0 to 3. Finally, 5 subjects exhibit a price setting behavior that is not in line with either hypothesis: 4 subjects show no significant positive correlation at cascade positions -3 to 0. One subject showed a negative correlation between prices and cascade positions when confronted with pro signals. Overall, price setting behavior of more than two thirds of the subjects indicates that cascade formation is not consistently recognized whereas less than 20% of the subjects show price setting patterns in line with the standard BHW model.

Observation II *Individual price setting patterns*

1. *At cascade positions -3 to 0, almost 90% of participants show a significantly positive rank correlation between submitted maximum prices and cascade positions, indicating that information revealed by predecessors' urn predictions is taken into account.*
2. *Only 17.9% 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.*
3. *For 43.6% 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 behavioral hypothesis, i.e. the correlation coefficients are positive for either pro or contra signals at cascade positions 0 to 3.*

5 CONCLUSION

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. Although urn predictions are in line with BHW, maximum prices increase the longer a cascade continues. More than two thirds of the participants obviously ignore cascade behavior of predecessors. In contrast, only 18% of participants set prices in line with the BHW model.

Participants in our experiment are informed about decision rules used by artificial predecessors. Errors by predecessors are excluded. We are aware that in real life there is uncertainty about behavior of others. Of course, this may influence cascade behavior. But if individuals do not recognize cascade behavior of others in our simple setting with artificial agents, then it is unlikely that they do so when their predecessors are humans.

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