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Do individuals recognize cascade behavior of others? – An experimental study

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Abstract

In an information cascade experiment participants are confronted with artificial predecessors predicting in line with the BHW model (Bikchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100, 992–1026). 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

PsycINFO classification: 2340; 3920

Keywords: Informational cascades; Experiments; Bayes' rule

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1. Introduction

Information cascades as modelled by Bikchandani, Hirshleifer, and Welch (1992), henceforth BHW, are 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 or investment 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 decisions of predecessors even though 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 though 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 as a signal for quality. This could unreasonably increase their willingness to pay for best-sellers compared to similar competing products.

The predictions of BHW were confirmed in first experimental tests by Anderson and Holt (1997), henceforth AH. In numerous subsequent experimental studies cascade behavior is analyzed by varying the structure of available information or selling private information.[2]

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. As pointed out in Kübler and Weizsäcker (2005), a common feature of many cascade studies is that length and strength of cascades are correlated, i.e., the rate of deviations from the rational cascade pattern decreases with the number of observed coinciding predictions. Oberhammer and Stiehler (2002) investigate cascade behavior in a simple symmetric design, where even counting leads to correct urn predictions if predecessors behave rationally.[3] In order to get an indication of subjects' probability perceptions, they asked subjects to submit maximum prices they are willing to pay for participating in the prediction game using the BDM procedure (Becker, DeGroot, & Marschak, 1964). These prices generally increase in the length of the cascade.

Error models that include the assumption that subjects incorporate erroneous play of predecessors can account for the observed price increases, as well as for the correlation of length and strength of cascades. However, all these phenomena could also be caused by subjects who do not recognize rational cascade behavior of others due to limited depth of reasoning. This study focusses on the impact of the latter, by excluding the possible effect of presumed erroneous play of predecessors.

[1] For a survey of studies on information cascades see Bikchandani, Hirshleifer, and Welch (1996).

[2] See, e.g., Willinger and Ziegelmeyer (1998), Kraemer, Nöth, and Weber (2006), Nöth and Weber (2003), Celen and Kariv (2004), or Kübler and Weizsäcker (2004).

[3] In the AH experiment, prediction errors increase up to 50% in asymmetric decision situations where simple counting of predecessors' predictions does not lead to a correct urn prediction (Huck & Oechssler, 2000). In these situations the rule "follow your own signal" offers better predictions than Bayesian updating.

One can find numerous examples where deviations from theoretically predicted behavior could be both due to irrational behavior of individuals and to rational responses to the (presumed) irrational behavior of others. To disentangle these two effects, several researchers conducted experiments in which humans interact with artificial players that follow clearly defined decision rules and thus are perfectly predictable. For example, Fehr and Tyran (2001) investigated whether monetary inertia are due to individual money illusion or to rational responses to presumed money illusion of other players. To this end, they let subjects interact both with other human players and with automated agents. Harrison (1989) and Cason (1995) analyzed reasons for off–equilibrium bidding behavior in auction experiments using preprogrammed "Nash bidders", i.e., agents always following the equilibrium bidding strategy.

Pursuing a similar approach, we use a simple cascade design as in Oberhammer and Stiehler (2002) and confront human subjects with computerized predecessors. These artificial agents follow a simple counting rule, thus predict according to BHW, and – by definition – never err. The functioning of the artificial agents is explained to the subjects in detail. Further, as in Oberhammer and Stiehler (2002), the BDM mechanism is used to elicit prices as indicators of subjects' probability perceptions. Using the strategy method, we ask subjects to state their predictions and maximum prices for all possible decision situations. Our procedure results in observing complete individual price setting patterns, and assures that all decision situations are on the equilibrium path.

We find that most subjects predict according to theory 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.

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.

2. Experimental design and procedure

2.1. Experimental scenario

There are two urns, A and B, with five balls each (three black balls and two white balls and vice versa). At the beginning of each round of the game, one urn is randomly chosen with equal probability. 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 BDM mechanism: Subjects' maximum prices are compared to a random price p_r, drawn from a uniform distribution in the interval $[0, 100]$. If the random price is equal or lower than the maximum price ($p_r \leqslant p_{\max}$), the participant is credited the amount resulting from her urn prediction minus the random price. Otherwise, the participant earns nothing.

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.[4] 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. 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. Note that in the applied symmetric information structure this leads to the same urn predictions as Bayesian updating (Anderson & Holt, 1997). Thus, urn predictions of artificial agents are in line with BHW. In case of an equal number of signals in favor of urn A and B, artificial agents decide according to their private signal. This tie-breaking rule simplifies the updating process compared to a randomization between urn A and B, as assumed by BHW.

As described in Section 2.4, we precisely explained the functioning of the artificial agents to our participants. One may object that, by this, we influenced subjects' decision making. Admittedly, we taught participants to predict according to BHW. But note that we are interested in price setting behavior rather than in urn predictions.

2.3. Use of the strategy method

As we wanted to observe complete individual price setting patterns, participants are asked to state their decisions for all situations that may arise from the decisions made by up to five artificial predecessors. Depending on the subject's own position (1–6), the color of the privately drawn ball (black or white), and the history regarding predecessors' predictions, there are 74 decision situations in total (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 (1–6) is randomly determined.
3. For each artificial agent a ball is drawn from the chosen urn. The agents predict according to the defined decision rules. Their predictions are publicly announced.
4. At the (real) subject's position a ball is drawn and the color announced.

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

Finally, the random price is drawn from all integers between 0 and 100 and the payoffs are calculated according to the rules described in Section 2.1.

2.4. Procedure

At the beginning of a session participants were provided with written instructions as well as with a supplementary sheet on the working of the BDM mechanism. The instructions included a detailed description of the artificial agents' decision rules. It was emphasized that their predictions were uniquely determined by these rules. We explained the rules in terms of counting, not in terms of probabilities, in order to make them as traceable as possible. It was also made explicit that all predecessors' decisions were decisions of artificial agents.[5]

After reading the instructions it was demonstrated how the payoff-relevant situation would be determined. Thereby, we repeatedly drew balls (colored table tennis balls) from a randomly chosen urn (opaque blue bags), explained the resulting prediction of the artificial agent, and wrote it on a blackboard. The aim of this procedure was to familiarize the subjects with the formation of a sequence of artificial predecessors' predictions.

Prior to the experiment participants answered several control questions about the decision rules of the artificial predecessors and the working of the price mechanism. Thereby, subjects had to state the prediction that an artificial agent would make in 8 different decision situations. Subjects who answered all questions correctly at first go were credited € 5. This incentive was announced in the instructions. Participants who answered some of the questions incorrectly had to answer these questions again and were encouraged to ask for additional explanation.

In the experiment participants submitted their decisions for all 74 situations sequentially displayed on the computer screen in random order. After the decisions were taken the payoff-relevant situation was determined, the price was randomly chosen, and subjects were paid in cash. 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, balls, dice, and chips with numbers from 1 to 100.

The experiment (using the software toolkit z-Tree, Fischbacher, 2007), was conducted at Humboldt University at Berlin. We ran 4 sessions with a total of 39 subjects, mainly business and economics students. In order to avoid losses a show-up fee of 100 ECU (equivalent to €10) was paid. The experiment lasted about 80 min. Average earnings amounted to approximately €17.

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

[5] Instructions and control questions may be downloaded at http://www.wiwi.hu-berlin.de/institute/wt1/papers/2006/instructions.pdf.

probabilities just depend on the number of signals in favor of urns *A* and *B*. In our setting, these probabilities can be calculated as follows:[6]

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

Thereby, d is defined as the difference between the number of A and B signals. Posterior probabilities increase in the 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. In this case they should always predict according to the ongoing cascade even if their private signal does not match the cascade. Therefore, no further information can be inferred from their predictions. Posterior probabilities remain constant at $\Pr\{\mathrm{A}|d=3\} = 0.77$ after receiving a signal in accordance with the ongoing cascade or at $\Pr\{\mathrm{A}|d=1\} = 0.60$ after receiving an opposed signal.

3.2. Notation

We describe and classify the different situations a subject may be confronted with, as follows: Predecessors' predictions are denoted by capital letters (*A* or *B*), private signals by small letters (*a* and *b*). For example, *ABb* refers to a situation in which a subject acts third in the sequence, sees a ball in favor of urn B 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, depending 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 can gain by ignoring 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 together with the private signal reveal a probability of 0.5 for each urn. Thus, either prediction is in line with rational behavior. Cascade position −2 refers to situations in which equally many predecessors have predicted either urn. Consequently, predecessors' decisions together with the private signal reveal a probability of 0.6 for the urn indicated by the private signal. At cascade position −1, there is already a one-prediction majority for one of the urns among the predecessors and the private signal matches that majority. The probability for predicting correctly is 0.69.

We refer to a player's position *at which a cascade starts* as cascade position 0. A player at cascade position 0 rationally ignores her signal and predicts 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.

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[6] See Anderson and Holt (1997).

Table 1
Decision situations

Private signal	Cascade position	Decision situations	Number
Pro	−3	*Ab*; *Ba*; *ABAb*; *ABBa*; *BAAb*; *BABa*; *ABABAb* *ABABBa*; *ABBAAb*; *ABBABa*; *BABAAb* *BABABa*; *BAABAb*; *BAABBa*	14
	−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
Pro	0	*AAa*; *BBb*; *ABAAa*; *ABBBb*; *BAAAa*; *BABBb*	6
	1	*AAAa*; *BBBb*; *ABAAAa*; *BABBBb*; *ABBBBb*; *BAAAAa*	6
	2	*AAAAa*; *BBBBb*	2
	3	*AAAAAa*; *BBBBBb*	2
Contra	0	*AAb*; *BBa*; *ABAAb*; *ABBBa*; *BAAAb*; *BABBa*	6
	1	*AAAb*; *BBBa*; *ABAAAb*; *ABBBBa*; *BAAAAb*; *BABBBa*	6
	2	*AAAAb*; *BBBBa*	2
	3	*AAAAAb*; *BBBBBa*	2
Total			74

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. Thus, the probabilities of predicting correctly after receiving a pro or a contra signal at cascade positions 1, 2, or 3 equal those at cascade position 0.

There are thus seven cascade positions in total.[7] In Table 1, all cascade positions and the corresponding decision situations are summarized.

3.3. Hypotheses

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. The resulting probability pattern is summarized in panel (a) of Fig. 1.

As for 38 out of 39 subjects (97.4%) we observe highly significant positive correlations between maximum prices and subjective probabilities,[8] we are confident in using the submitted maximum prices to test our hypotheses.

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

[7] 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.

[8] 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. A possible explanation for correlations that are not linear is risk aversion.

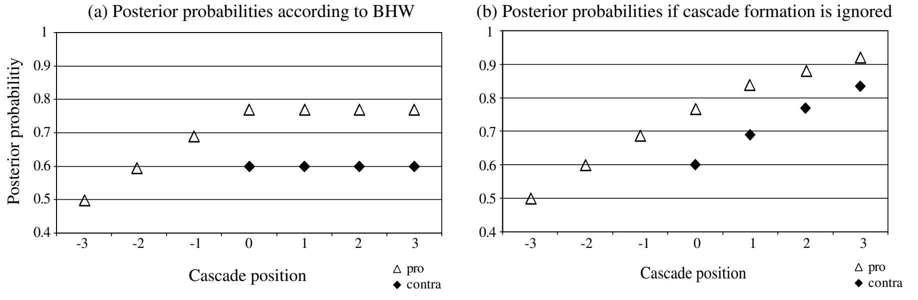

Fig. 1. Posterior probability patterns.

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

Thereby, e.g., we refer to $p_{\max}^{0\text{con}}$ as the willingness to pay of a subject at cascade position 0, who is confronted with a contra signal.

If subjects ignore the formation of a cascade, subjective probabilities increase the longer a cascade continues, as illustrated in panel (b) of Fig. 1. 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) $p_{\max}^{-3\text{pro}} < p_{\max}^{-2\text{pro}} < p_{\max}^{-1\text{pro}} < p_{\max}^{0\text{pro}}$.
Price setting behavior at cascade positions 0–3 is as follows:
(b) $p_{\max}^{0\text{pro}} < p_{\max}^{1\text{pro}} < p_{\max}^{2\text{pro}} < p_{\max}^{3\text{pro}}$,
(c) $p_{\max}^{0\text{con}} < p_{\max}^{1\text{con}} < p_{\max}^{2\text{con}} < p_{\max}^{3\text{con}}$.

Both the BHW and the behavioral hypothesis predict increasing maximum prices from cascade position −3 to cascade position 0. But they differ in the predicted price patterns from cascade position 0–3.

4. Results

4.1. Prediction behavior

The 39 subjects were asked to make decisions for 74 situations. The data set thus consists of $39 \times 74 = 2886$ 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. The rate of seemingly rational predictors sharply increases up to 82.1% (32

Table 2
Prediction errors at different cascade positions

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%]

out of 39) if we include subjects who predicted in line with BHW in at least 95% of the decision situations. Subjects followed their own signal in 77.1% of all tie-breaking situations.[9]

At cascade positions 0–3 rational agents would follow their predecessors even after receiving a contra signal. However, as summarized in Table 2, the error rate in such situations is higher (6.7%) than in cases where the signal coincides with the ongoing cascade (0.6%). When subjects are confronted with pro signals, error rates are similarly low at cascade positions 0–3 (between 0.0% and 1.3%). For contra signals, the error rate at cascade position 0 is higher (12.8%) than at later cascade positions.

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. Thus, longer cascades are more stable. This pattern is in line with numerous cascade studies with interacting human subjects, which are summarized in Kübler and Weizsäcker (2005). However, the rate of deviations from the cascade pattern is generally lower in our experiment. This may be due to the fact that subjects distrust their human predecessors' decision making and thus follow their own signal more often. In addition, our experimental design influenced subjects to predict in line with BHW.

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 in line with BHW. For each of these 2812 predictions we have one maximum price for participating in the prediction game and one subjective probability for making a correct prediction. To give an overview of price setting behavior for different cascade 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).[10] The aggregated results are summarized in Table 3. Fig. 2 illustrates the aggregated price setting pattern.

[9] 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 conducted a pencil-and-paper experiment and used a different signal precision.

[10] 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 her maximum prices are below 10). However, including this observation does not change our findings.

Table 3
Price setting behavior and subjective probability statements

Private signal	Cascade position	Individual average prices			Subjective prob. (in %)			Prob. according to...	
		Mean	Median	SD	Mean	Median	SD	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

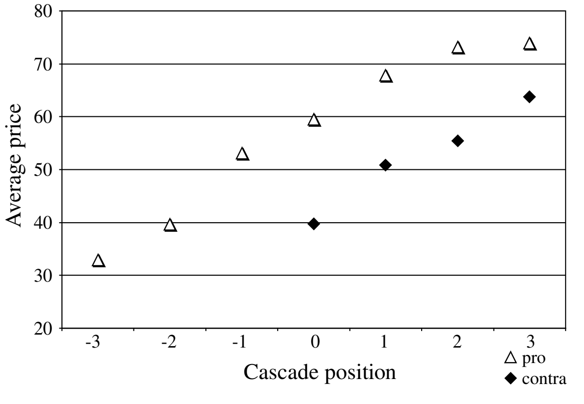

Fig. 2. Average prices for different cascade positions and private signals.

As predicted both by BHW and the 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.[11] At cascade position 3, subjects' average maximum prices and subjective probabilities are higher than predicted by BHW.

We also find that at each cascade position, average subjective probabilities exceed average submitted maximum prices, indicating a certain degree of risk aversion. 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 non-parametric Friedman tests based on individual average prices for each cascade position. Moreover, we used the individual average

[11] Again, Kübler and Weizsäcker (2005) report similar patterns of subjective probability statements from other cascade experiments.

Table 4
Friedman-tests and rank correlations for maximum prices and cascade positions

Friedman test			Spearman rank corr.
Hypothesis (H_0)	χ^2	(sign.)	ρ (sign. 2-tailed)
(a) $p_{\max}^{-3\text{pro}} = p_{\max}^{-2pro} = p_{\max}^{-1\text{pro}} = p_{\max}^{0\text{pro}}$	91.02	(0.000)	0.482 (0.000)
(b) $p_{\max}^{0\text{pro}} = p_{\max}^{1\text{pro}} = p_{\max}^{2\text{pro}} = p_{\max}^{3\text{pro}}$	42.86	(0.000)	0.272 (0.001)
(c) $p_{\max}^{0\text{con}} = p_{\max}^{1\text{con}} = p_{\max}^{2\text{con}} = p_{\max}^{3\text{con}}$	64.45	(0.000)	0.374 (0.000)

prices to calculate the Spearman rank correlation coefficient for each of the three conjectured price/cascade position relationships. The results are presented in Table 4.

Both statistical measures confirm that subjects generally infer information from predecessors' urn predictions (see row a). 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 0–3 if confronted with pro and contra signals, respectively. Applying the same tests to subjective probabilities instead of prices yields the same results.

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. As predictions were in line with BHW in almost 97% of the decision situations and as 77% of the subjects answered all control questions on the artificial agents correctly at first go, we are confident that the results are not due to misunderstanding of the rules. However, to check for any effect of incomprehension, we analyzed the data of 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.

Our findings turn out to be robust. We find similar price and probability patterns for the considered subsample, i.e., the hypothesis according to BHW has to be rejected in favor of our behavioral hypothesis (on the 5%-significance level).

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

Table 5
Individual price patterns

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

[a] Identified price patterns at cascade positions −3 to 0 (column a) and at cascade positions 0–3 when confronted with pro (column b), and 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 Ø.

correlation coefficients between submitted maximum prices and the respective cascade positions for each single participant. According to the significance of the rank correlation coefficients (at the 5% level), subjects are classified as shown in Table 5.

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 0–3 (BHW subjects). 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 0–3. Apparently, these subjects partly ignore the cascade formation. Finally, 5 subjects exhibit a price setting behavior that is not in line with either hypothesis. 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 BHW model.

5. Conclusion

We designed an experiment to test whether individuals recognize cascade behavior of others. Our findings suggest that many do not.

Participants' urn predictions are in line with BHW, but average maximum prices increase the longer a cascade continues. More than two thirds of our subjects obviously ignore cascade behavior of predecessors. In contrast, only 18% set prices in accordance with the BHW model.

In our experiment, subjects are informed about the decision rules of their artificial predecessors. Errors by predecessors are excluded. Of course, this may lead to behavior that differs from behavior in cascades with only human players. 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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