Fragility of Information Cascades: An Experimental Study using Elicited Beliefs *

Anthony ZIEGELMEYER[†] Frédéric KOESSLER[‡] Juergen BRACHT[§] Eyal WINTER[¶]

Abstract

This paper examines the occurrence and fragility of information cascades in two laboratory experiments. One group of low informed participants guess sequentially which of two states has been randomly chosen. In a matched pairs design, another group of high informed participants make similar guesses after having observed the guesses of the low informed participants. In the second experiment, participants' beliefs about the chosen state are elicited. Bayesian rationality predicts the emergence of information cascades in the group of low informed participants and the systematic collapse of these cascades in the group of high informed participants. In line with the existing experimental evidence, we find that the behavior of low informed participants is qualitatively in line with Bayesian rationality which implies that information cascades systematically emerge in our experiments. The tendency of low informed participants to engage in cascade behavior increases with the number of identical guesses. Our main finding is that *information cascades are not fragile.* One-third of laboratory cascades are broken by high informed participants and the empirical probability of collapse averages to about 15% for the situations where five or more identical guesses are observed. Participants' elicited beliefs are strongly consistent with their own behavior and suggest that the more identical guesses participants observe the more they believe in the state favored by those guesses.

KEYWORDS: Information cascades; depth-of-reasoning analysis; elicited beliefs; experimental economics; fragility.

JEL CLASSIFICATION: C72, C92, D82.

1 Introduction

In recent years a great deal of attention has been focused on situations in which the existence of informational externalities leads to a loss of social welfare. In these situations, Bayesian rational individuals with limited information share that information with others through their choices, and the attempt to take advantage of the information of their predecessors prevents individuals from exploiting their private information in a socially optimal way. This likely consequence of social learning is what has been called *information cascades* (Banerjee, 1992 and Bikhchandani, Hirshleifer, and Welch, 1992). An information cascade occurs when the accumulated evidence from previous choices is so conclusive that individuals rationally herd without regard to their private

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[†]Max Planck Institute for Research into Economic Systems, Strategic Interaction Group, Jena, Germany. *E-mail:* ziegelmeyer@mpiew-jena.mpg.de

[‡]Paris School of Economics and CNRS. *E-mail:* koessler@pse.ens.fr

[§]University of Aberdeen Business School. *E-mail:* juergen.bracht@abdn.ac.uk

[¶]Center for Rationality and Interactive Decision Theory, Hebrew University of Jerusalem.

information. In an information cascade, choices do not convey private information, the benefit of diversity of information is lost, social learning stops completely and the failure of information aggregation is spectacular. Information cascades have been proposed as explanations of a variety of phenomena, such as fads, fashions, booms and crashes.[1]

As emphasized by Bikhchandani et al. (1992) (henceforth BHW), in the Bayesian Nash equilibrium of information cascade models, *the convergence of behavior is idiosyncratic and fragile*. Individuals quite rapidly converge upon one choice on the basis of some but very little information. In fact, a choice is fixed upon when the accumulated evidence from previous choices grows to be just enough to overcome an individual's private information pointing in the opposite direction. The next individual is also just barely willing to ignore her private information and all further individuals do the same thing, i.e., they are in a cascade. Since choices are uninformative once a cascade has started, only the information of a few early choices is aggregated and the informativeness of a cascade does not rise with the number of similar choices. Thus, a small bulk of evidence causes the vast majority of individuals to make one choice over the other, which might be the wrong one. But the fallibility of information cascades causes them to be fragile meaning that incorrect decisions can be rapidly reversed, e.g., by the arrival of a little extra information. These two consequences of social learning are the two sides of the same coin, and they constitute the departure point of our experimental study.

We examine the occurrence and fragility of information cascades in two laboratory experiments. In each decision making round, a random choice is made between two (almost) equally likely states and the randomly chosen state is not revealed to the participants. Low informed participants guess sequentially which state has been chosen, with each participant observing all previous guesses and a low-accuracy signal (correct with probability 2/3). In a matched pairs design, high informed participants observe the guesses of the low informed participants and a high-accuracy signal (correct with probability 4/5). Each participant is incentivized to correctly guess the randomly chosen state. In the second experiment, participants' beliefs about the chosen state are elicited. Bayesian rationality predicts the emergence of information cascades in the group of low informed participants and the systematic collapse of these cascades in the group of high informed participants. In other words, a low informed participant who observes an established pattern of identical guesses should rationally herd without regard to her private information whereas a high informed participant should guess against this established pattern when her signal points in the opposite direction.

The behavior of low informed participants is qualitatively in line with Bayesian rationality which implies that information cascades systematically emerge in our experiments. In situations where Bayesian rationality predicts a guess inconsistent with the one based only on the private signal, low informed participants rationally herd without regard to their private signal slightly less than 70% of the time. Moreover, participants' tendency to engage in cascade behavior increases with the number of identical guesses, ranging from less than 65% after two identical guesses to 100% after seven identical guesses. On the contrary, the behavior of high informed participants strongly contradicts Bayesian rationality which implies that collapses of long information cascades are almost absent. One-third of laboratory cascades are broken by high informed participants and the empirical probability of collapse averages to about 15% for the situations where five or more identical guesses are observed. Our experiments provide strong evidence that information

[1]Since choices are the words for the transmission of information between individuals, information cascades occur only if the information space is large relative to the choice space. Smith and Sorensen (2000) provides the most comprehensive and exhaustive analysis of social learning in situations where players observe the full sequence of past choices, and establishes that the failure of information aggregation is not a robust property. However, as rightly argued by Chamley (2004), which reviews a large spectrum of economic models, the inefficiency of social learning is a robust conclusion. Acemoglu, Dahleh, Lobel, and Ozdaglar (2008) addresses how the social network structure, which determines the observations of each individual, affects information aggregation.

cascades occur in the laboratory and that as the number of identical guesses increases the fragility of laboratory cascades rapidly vanishes. This evidence is supported by our analyzes of the large data set on elicited beliefs. Participants' elicited beliefs are strongly consistent with their own behavior and suggest that the more identical guesses participants observe the more they believe in the state favored by those guesses. High informed participants believe more strongly than low informed participants that the informativeness of a laboratory cascade rises with the number of identical guesses.

We attempt to understand participants' behavior by estimating an error-rate model that uses logistic response functions to determine guess probabilities and allows for different error rates on different levels of reasoning about others' behavior. The results of our depth-of-reasoning analysis suggest that participants apply medium chains of reasoning. They learn from observing their predecessors' guesses and realize that other participants also learn from observing their respective predecessors. However, participants' reasoning gets rather imprecise on the highest level since participants think that others attribute to their respective predecessors twice the participants' error rate. Additionally, low informed participants attribute a significantly higher error rate to their predecessors whereas high informed participants attribute a significantly lower error rate to their predecessors as compared with their own. Participants' behavior can be explained along the lines of our estimated model. Compared to Bayesian rational individuals, low informed participants discount the evidence conveyed by guesses which are not part of an information cascade and they do not fully discount the evidence conveyed by guesses which are part of an information cascade. The reasoning process of low informed participants explains why they do not systematically engage in cascade behavior after having observed a few identical guesses but do so after having observed many identical guesses. Compared to low informed participants, high informed participants do not discount the evidence conveyed by any guess, whether it is part of an information cascade or not, which explains why long herds have such a low empirical probability of collapse.

Related Literature

We selectively survey the experimental literature on information cascades and establish that the behavioral patterns observed in our study are well in line with the existing evidence.[2] The most prominent theoretical rationalizations of the experimental regularities are presented in the discussion section of this paper.

In a seminal study, Anderson and Holt (1997) (henceforth AH) presents three experiments to investigate the emergence of information cascades in the laboratory. In the baseline experiment, there are six participants and two urns which are equally likely to be chosen. Urn A contains 2 balls labeled a and 1 ball labeled b while urn B contains 2 balls labeled b and 1 ball labeled a. In each decision making round, one urn is randomly chosen and participants guess sequentially which urn has been chosen, with each participant observing all previous guesses and a single draw from the chosen urn (signal correct with probability 2/3). At the end of the round, the randomly chosen urn is publicly revealed and participants who guessed correctly get \$2 while those who did not get nothing. The procedures of the second experiment extend those of the baseline experiment by adding either one or two public draws after the fourth guess. The procedures of the third experiment are identical to those of the baseline experiment except that urn A contains 6 a balls

[2] We focus on laboratory studies which, similarly to our study, are based on BHW's specific model. Other experimental studies relied on alternative frameworks to distinguish between information cascades and herding (Celen and Kariv, 2004) and to investigate herding in financial markets (Drehmann, Oechssler, and Roider, 2005; Cipriani and Guarino, 2005).

and 1 b ball while urn B contains 5 a balls and 2 b balls.

Though AH find clear evidence that information cascades occur in the laboratory, participants do not always rationally ignore their private signal and follow an established pattern of previous guesses. For example, in the baseline experiment, participants rationally follow the herd in only 70% of the cases.[3] These deviations from Bayesian rationality are more prevalent after the observation of two identical guesses (64% of cascade behavior) than after the observation of five identical guesses (80% of cascade behavior).[4] From now on, we refer to the participants' reluctance to engage in cascade behavior after a few identical guesses as to the "overweight-phenomenon". Compared to what Bayesian rationality prescribes, participants seem to overweight their private information relative to the public information of their predecessors' guesses. Like in AH's baseline experiment, we observe the overweight-phenomenon in our group of low informed participants and the phenomenon basically disappears once the evidence conveyed by predecessors' guesses is strong i.e. enough participants made the same guess.

AH's second experiment helps finding out whether laboratory cascades collapse due to the public release of information as predicted by Bayesian rationality. Laboratory cascades collapse only in 5 of the 13 situations in which participants are endowed with multiple draws contradicting the established pattern of identical guesses. This evidence is also well in line with our own findings.[5]

In the third experiment, where signal b is much more informative than signal a, more deviations from Bayesian rationality are observed.

Kübler and Weizsäcker (2004) examines the robustness of laboratory cascades to the introduction of costly signals in AH's baseline experiment, i.e. participants decide whether to obtain private information or not, at a small but non-zero cost. According to Bayesian rationality, only the first participant in the decision making sequence should buy a private signal and all subsequent participants should simply imitate the first guess. These predictions perform poorly in organizing the experimental data. Indeed, participants buy too many signals suggesting that they do not consider the first participant's guess strong enough evidence (this finding is clearly related to the overweight-phenomenon). However, most participants follow the majority of guesses once the evidence conveyed by the predecessors' guesses is strong. Again, we observe the same phenomenon among our low informed participants.

Kübler and Weizsäcker successfully explain these observations by conducting a statistical depth-of-reasoning analysis. The estimated error-rate model does not impose the rational expectations assumption according to which players have a correct perception of other players' error rates, or that they have a correct perception of other players' perceptions of third players, and so on. Their estimation results clearly indicate that participants apply only short chains of reasoning and that the perceived error rates get larger and larger on higher levels of reasoning, pointing at a consistent underestimation of others' degree of rationality.[6] Our own statistical error-rate analysis is directly borrowed from this earlier work and the comparison of the two sets of estimation results indicates

[3]Several laboratory studies show that AH's baseline experiment results replicate. Anderson (2001) as well as Hung and Plott (2001) establish that AH's observation that information cascades occur in the laboratory is robust to changes in payoffs and experimental settings. Additional evidence in favor of the cascade phenomenon is reported by Alevy, Haigh, and List (2007) which compares the behavior of market professionals from the floor of the Chicago Board of Trade with that of college students in the gain and loss domain of earnings.

[4]We report our own computations of the frequencies of cascade behavior since AH does not discuss the correlation of length and strength of laboratory cascades.

[5]Note that AH does not report on the empirical probability of collapse of laboratory cascades since very few situations of potential collapse are observed.

[6]Kraemer, Nöth, and Weber (2006) evaluates private information acquisition behavior in an experimental setting with two signal accuracies and obtains identical results.

that our low informed participants exhibit less distortion in the perception of their predecessors (the estimates for the high informed participants might not be comparable). However, this discrepancy between the two estimated models has few noticeable consequences in terms of behavior since our low informed participants think that others attribute to their respective predecessors twice the participants' error rate.

Goeree, Palfrey, Rogers, and McKelvey (2007) extends AH's baseline experiment by considering long sequences of guesses, respectively 20 and 40, and two values of the signal accuracy, respectively 5/9 and 6/9. Their experimental results can be summarized as follows: (i) Pure laboratory cascades, i.e. two identical guesses not canceled out by previous guesses which induce herd behavior for the remaining participants in the sequence, are rarely observed. The occurrence of pure laboratory cascades decreases with the length of the sequence of guesses and increases with the signal's accuracy; (ii) Laboratory cascades are almost always broken by participants with contradictory private signals (signals pointing in the opposite direction to the accumulated evidence from previous guesses); (iii) The longer a pure laboratory cascade the more likely participants with contradictory private signals herd; and (iv) In the majority of cases, after an incorrect laboratory cascade is broken the new laboratory cascade which emerges is a correct one, i.e. laboratory cascades are self-correcting.

Goeree et al.'s results and our own results complement each other. First, the third result corroborates and extents to long sequences of guesses our finding that participants engage more in cascade behavior after longer herds.[7] Second, our finding that the fragility of laboratory cascades rapidly vanishes as the number of identical guesses increases indicates that Goeree et al.'s third result is valid not only when, according to Bayesian rationality, participants are endowed with signals which they should disregard but is also valid when participants are endowed with signals which they should *not* disregard. Of course, the fact that long herds have a low empirical probability of collapse does not imply that laboratory cascades cannot collapse at all. Still, laboratory cascades are not fragile in the sense predicted by Bayesian rationality which might be a concern for social welfare (though Goeree et al. rarely observe pure laboratory cascades, they report an empirical probability of collapse of less than 10% after a dozen of identical guesses in case the signal accuracy is 6/9). In the discussion section of this paper, we come back to this issue.

The remainder of the paper is structured as follows. Section 2 outlines the basic theory. Section 3 discusses the experimental design. In Section 4 we give an exhaustive analysis of participants' guesses and belief reports. Section 5 presents some theoretical rationalizations of the behavioral patterns observed in information cascade experiments. Section 6 concludes.

2 An Information Cascade Game with Low and High Informed Players

In this section we present a simple information cascades game based on BHW's specific model. First we consider a low informed setup in which the unique equilibrium outcome is characterized by a high occurrence of information cascades. Next we introduce a high informed player to demonstrate the fragility of information cascades.

[7] Kübler and Weizsäcker (2005) also documents this regularity and shows that the correlation of length and strength of pure laboratory cascades is robust to changes in experimental cascade games.

2.1 Low Informed Setup

There are two payoff-relevant states of Nature (henceforth states)—state α and state β, two signals—signal a and signal b, and two possible guesses—"guess state α" simply denoted by A and "guess state β" simply denoted by B. Players have a common prior belief on the state space $\{\alpha, \beta\}$ where $\Pr(\alpha) = 1 - \Pr(\beta) = 0.55$.[8]

Nature moves first and chooses a state which remains unknown to the players. We denote this state by ω and refer to it as the true state. Players have to guess whether $\omega = \alpha$ or $\omega = \beta$. Players make their guesses in sequence and the order in which players make their guesses is exogenously specified. Player 1 guesses in period 1, player 2 guesses in period 2, and so forth. Before making his guess, each player i both observes a single draw from an urn, which constitutes his private signal $t_i \in \{a, b\}$, and the public history of guesses of all preceding players $1, 2, \ldots, i-1$. If the state is α then each player draws a ball from an urn which contains two a balls and one b ball. If the state is β then each player draws a ball from an urn which contains two b balls and one a ball. Therefore, conditionally on the true state, players' signals are i.i.d. and the conditional probabilities are given by $\Pr(t_i = a \mid \omega = \alpha) = \Pr(t_i = b \mid \omega = \beta) = 2/3$ and $\Pr(t_i = a \mid \omega = \beta) = \Pr(t_i = b \mid \omega = \alpha) = 1/3$. Guessing the true state, i.e., making guess A in state α or making guess B in state β, yields 10 whereas guessing the wrong state yields -5.

For $i \geq 2$, let $\{A, B\}^{i-1}$ be the space of all possible period i histories of guesses chosen by the $i-1$ predecessors of player i. Denote by h^{i-1} an element of $\{A, B\}^{i-1}$, i.e., h^{i-1} is a sequence of guesses up to player $i-1$. Let $\mu_i : \{a, b\} \times \{A, B\}^{i-1} \to [0, 1]$ be player i's belief (conditional probability given past observed guesses and his private signal) that the state is α. player i's belief is given by

$$\mu_i(t_i, h^{i-1}) = \frac{\Pr(t_i \mid \alpha)\ \Pr(\alpha \mid h^{i-1})}{\Pr(t_i \mid h^{i-1})},$$

where probabilities are computed with respect to players' strategies and the prior. Given a history h^{i-1}, a signal t_i and a belief $\mu_i(t_i, h^{i-1})$, player i's expected utility is given by $15\mu_i(t_i, h^{i-1}) - 5$ (respectively $15(1 - \mu_i(t_i, h^{i-1})) - 5$) if his guess is A (respectively B).

In equilibrium, players update their beliefs in a Bayesian rational way by observing their signal and their predecessors' guesses and they maximize their expected utility given these beliefs. Player 1 guesses in accordance with his signal. If player 2 observes an A guess then he guesses A too even if his private signal is b. As the same argument applies for all the rest of the sequence, it is here that an information cascade results. On the contrary, if player 2 observes a B guess then he predicts in accordance with his signal. If player 3 observes two B guesses then he follows his predecessors' guesses even if he is endowed with an a signal. This implies that the rest of the sequence joins the herd. Once a cascade has started the further guesses are uninformative. In other words, after an A guess not canceled out by previous guesses, whatever their positions in the sequence the beliefs of two followers are identical when endowed with the same private signal. Similarly, after two B guesses not canceled out by previous guesses, whatever their positions in the sequence, the beliefs of two followers are identical when endowed with the same private signal.

The only history which does not lead to an information cascade is $BABABA\ldots$. Table 1 reports the probability of having no information cascade after any even number of players lower than eight. There is a less than 5% probability that the fifth player's guess in the sequence depends on his signal.

[8]Contrary to BHW's specific model, the two payoff-relevant states are not equally likely. This difference has the advantage that tie-breaking rules are useless which implies that the equilibrium outcome is unique.

Number of players	Probability of no cascade
2	0.222
4	0.049
6	0.011
8	0.002

Table 1: Probability of no cascade after any even number of players lower than eight.

2.2 High Informed Setup

In this setup we assume that one and only one of the players receives a more informative signal about the state. We use the subscript $j \neq i$ to refer to this player and we denote his signal $t_j \in \{a_S, b_S\}$. If the state is α then player j draws a ball from an urn which contains four a balls and one b ball. If the state is β then player j draws a ball from an urn which contains four b balls and one a ball. Therefore, player j's signal has a higher accuracy than player i's signal: $\Pr(t_j = a_S \mid \omega = \alpha) = \Pr(t_j = b_S \mid \omega = \beta) = 4/5$ and $\Pr(t_j = a_S \mid \omega = \beta) = \Pr(t_j = b_S \mid \omega = \alpha) = 1/5$.

In equilibrium, whatever his position in the sequence, player j guesses in accordance with his signal. Indeed, player j's high-accuracy signal is twice as informative as player i's signal. If player j observes an A cascade and receives a b_S signal then his signal overweighs the a signal and the priors ($\mu_j(b_S, A) = 0.38 = \mu_i(b, \emptyset)$), and player j guesses in accordance with his signal. If player j observes a B cascade and receives an a_S signal then his signal and the two b signals just cancel out. This leaves player j with a belief which equals the prior one ($\mu_j(a_S, BB) = \Pr(\alpha)$). Hence the rational guess is A. Of course, if player j either observes a $BABA\ldots$ sequence or if player j's signal is in accordance with what he has observed then he has to follow his signal too. The interesting result is that, whatever the type of information cascade that has started, the high informed player j breaks the cascade when endowed with a contradictory signal (contrary to a low informed player i).

3 Experimental Procedures

Two experiments were run on a computer network at the laboratory of experimental economics in Strasbourg (LEES) using 96 undergraduate students from the University of Strasbourg. No participant had any training in game theory or economics of information. Each experiment was made up of three sessions that took between $1\frac{1}{2}$ and $2\frac{1}{4}$ hours. Sixteen participants took part in each session (plus one participant who acted as a assistant). Participants were randomly assigned to a computer terminal, which was physically isolated from other terminals. Communication, other than through the decisions made, was not allowed. Participants were instructed about the rules of the game and the use of the computer program through written instructions, which were read aloud by the assistant. A short questionnaire and one dry run followed.[9] Participants, on average, earned approximately 126 French francs (including a show-up fee of 15 French francs), which was paid to them in cash at the end of the session.[10]

[9]The dry run was added in order to give some experience to the participants about the computer program. Participants did not make guesses in this dry run. In each session, at least 22 participants read the instructions on their own, listened to the assistant reading the instructions aloud, and answered a questionnaire. The questionnaire mainly checked participants' understanding of the calculation of earnings. Participants who made mistakes in answering the questionnaire were paid 30 French francs and were replaced by participants who were randomly selected among those who made no mistakes on the questionnaire. Thus, in each session, all 16 participants who were retained for participation in the remainder of the experiment had made no mistakes on the questionnaire.

[10]\$1 was approximately 7.5 French francs at the time of the experiment.

In the first experiment participants played the simple information cascades game described in Section 2, fifteen times in the same group. In each decision making round, we implemented this setup in the following way. We built two "lines" of participants, a "low line" and a "high line". The low line was constituted by nine participants whereas the high line was only made of seven participants, and participants in the high line were only in positions from three to nine. At the beginning of the round, a random choice was made between state α and state β, and the probability of choosing state α was 55%. Participants were then chosen in a random order to observe a single draw from a selected urn. Balls tagged a or b were put in urns labeled A and B and drawn on the computer screen to represent participants' signals. In the low line the signal's strength, which indicates the probability that this signal is correct, was equal to 2/3 whereas in the high line it was equal to 4/5. Thus, in the low line on each participant's computer screen appeared a ball drawn from an urn containing 3 balls, two "correct" balls and an "incorrect" one. In the high line on each participant's computer screen appeared a ball drawn from an urn containing 5 balls, four "correct" balls and an "incorrect" one. This information structure was common knowledge as being part of the instructions which were read aloud by the assistant. In particular, each participant knew on which type of private information quality (signal strength either of 2/3 or 4/5) was based each previous guess. Whatever his line, each participant observed the previous guesses of the participants *in the low line*. Finally, participants were asked to make a public guess about the identity of the selected state. Each participant received 10 French francs for a correct guess and −5 French francs otherwise. At the end of each round uncertainty about the true state was resolved to allow for controlled learning. During a session a participant always belonged either to the low line or to the high line. Table 2 summarizes the progress of a typical decision making round.

Period	Participant's position in the low line	Participant's position in the high line	Observed history
1	1		$\emptyset$
2	2		1st guess in the low line
3	3	1	1st to 2nd guess in the low line
4	4	2	1st to 3rd guess in the low line
⋮	⋮	⋮	⋮
9	9	7	1st to 8th guess in the low line

Table 2: Typical decision making round.

Our innovative design has nice features. First, it allows us to collect a lot of data concerning the potential situations where a cascade should be broken (107 cascade breaks should have been theoretically observed). Second, one can investigate whether participants' behavior, both the low and high informed types, rely on the position in the decision queue. Third, as low and high informed participants observe the same history, a highly controlled comparison between low informed and high informed participants' behavior can be made.

In the second experiment we replicated Experiment 1 but we also elicited participants' beliefs about the randomly chosen state. For the sake of comparison of participants' behavior between the two experiments, the same random events, i.e., urns used and private signals, were maintained to run one session in each experiment.

Eliciting Beliefs

In each period of the second experiment participants in the low line were asked to key in a probability vector which represents their beliefs that state α or state β was randomly chosen at the beginning of the round. Participants in the high line reported their beliefs until the period of their guess. For example, if in a given round a participant in the high line held position 5 then he only reported 5 beliefs. The first elicitation of a participant's belief was made just after he received his signal and before making guess A or B. Otherwise, participants' beliefs were elicited at the beginning of each period, i.e., after having observed the previous periods' guesses. Of course, in period 1, except for the participant who received a signal, participants' beliefs should reflect the priors. This procedure of beliefs' elicitation allowed us to collect a 9×9 matrix of beliefs for the low line and 7 vectors of beliefs for the high line, whose length goes from 3 to 9, for each decision making round.

Participants' belief reports were rewarded on the basis of a quadratic scoring rule function.[11] Thus, participant i reported his beliefs in period n by keying in a vector $\mu_{in} = (\mu_{in}^{\alpha}, \mu_{in}^{\beta})$ indicating his belief about the probability that the state randomly chosen at the beginning of the round is α or β.[12] In period n, the payoff to participant i when state α was randomly chosen and μ_{in} is the reported belief vector is given by

$$\Pi_{\alpha} = 0.25 - \frac{1}{8}\left((1-\mu_{in}^{\alpha})^2 + \left(\mu_{in}^{\beta}\right)^2\right) = 0.25\left(1 - \left(\mu_{in}^{\beta}\right)^2\right). \quad (1)$$

The payoff to participant i when state β was randomly chosen is, analogously,

$$\Pi_{\beta} = 0.25 - \frac{1}{8}\left(\left(1-\mu_{in}^{\beta}\right)^2 + (\mu_{in}^{\alpha})^2\right) = 0.25\left(1 - (\mu_{in}^{\alpha})^2\right). \quad (2)$$

It can easily be demonstrated that this reward function provides an incentive for risk-neutral participants to reveal their true beliefs about the randomly chosen state (see Murphy and Winkler, 1970 for more details).[13] The payoffs from the assessment task were all received at the end of the experiment.[14] We made sure that the amount of money that could potentially be earned in the assessment part of the experiment was not large in comparison to the game being played. In this respect, the maximum amount that could be earned in the assessment task of Experiment 2 was only 33.75 French francs as compared to the theoretical expected payoff of the decision task: 90 French francs for a low informed participant and 100 French francs for a high informed participant. Table 3 summarizes the features of both experiments.

[11] Belief elicitation using a quadratic scoring rule is widely employed in experimental economics (see for example Nyarko and Schotter, 2002). Offerman, Sonnemans, van de Kuilen, and Wakker (2009) show how proper scoring rules can be generalized to modern theories of risk and ambiguity, and can become valid under risk aversion and other deviations from expected value. They also report experimental results suggesting that it is desirable to correct participants' reported probabilities elicited with scoring rules if only a single large decision is paid, but that this correction is unnecessary with many repeated decisions and repeated small payments.

[12] In the experiment μ_{in}^{α} and μ_{in}^{β} were keyed in as numbers in [0,100], so are divided by 100 to get probabilities.

[13] While payoffs are maximized by a truthful revelation of beliefs, reporting equal probabilities for each state would guarantee the largest minimal payment ("secure" stated beliefs). Risk aversion could induce participants to behave in such a way. We did neither observe a bias toward flat beliefs' vectors (risk averse participants) nor toward extreme beliefs' vectors (risk loving participants) in our data.

[14] For the sake of understanding, instead of presenting Equations (1) and (2) to the participants, we included in the instructions a table summarizing the respective payoff depending on the pair of beliefs reported and the chosen state.

	Elicitation of beliefs	Line	Total number of participants	Number of rounds per session	Total number of guesses	Total number of belief reports
Experiment 1 (3 sessions)	No	Low	27	15	405	0
		High	21	15	315	0
Experiment 2 (3 sessions)	Yes	Low	27	15	405	3645
		High	21	15	315	1890

Table 3: Experimental design.

4 Results

First, we analyze participants' guesses and show that, in accordance with Bayesian rationality, information cascades develop consistently in the low line. However, these information cascades rarely collapse in the high line which contradicts Bayesian rationality. Second, we study the dynamics of elicited beliefs and their consistency with the guesses. Participants' belief reports are strongly consistent with their own behavior and suggest that the more identical guesses participants observe the more they believe in the state favored by those guesses. Finally, we attempt to understand participants' behavior by conducting a depth-of-reasoning analysis.

In the game of Section 2, theoretical predictions are clear: The equilibrium outcome is unique. Nevertheless, whereas equilibrium decisions for high informed players are unique whatever the history of guesses, low informed players' equilibrium strategies rely on interpretations of observable off the equilibrium path decisions.[15] As there is no unique prediction off the equilibrium path, we only consider decisions following a history that could be part of an equilibrium outcome (histories are still included after out-of-equilibrium guesses as long as those guesses do not lead to an history that cannot be part of an equilibrium outcome). We obtain very similar results by considering participants' guesses on and off the equilibrium path and assuming that each participant believes that a deviation from the equilibrium path by a participant reveals that participant's private signal.

A *cascade situation* is a situation where a guess (A or B) constitutes an established pattern, and a participant's signal does not coincide with the established pattern. Let n_{i-1} be the number of a signals less the number of b signals that can be inferred from an equilibrium history h^{i-1}. Formally, player i in the low line (respectively player j in the high line) is in a cascade situation if either $n_{i-1} = 1$ and $t_i = b$ (respectively $t_j = b_S$) or $n_{i-1} = -2$ and $t_i = a$ (respectively $t_j = a_S$).

[15]In equilibrium, high informed players always follow their private signal since, whatever the history of guesses, at most two private signals can be inferred in favor of a state (assuming that interpretations of out-of-equilibrium guesses are common knowledge). For example, assume a (off the equilibrium path) B prediction is observed after one or several A predictions (from which only one a signal is inferred). The first-after-deviation-player either interprets the deviation as essentially uninformative or as largely revealing the deviator's private signal (the case where the deviation is interpreted as revealing a confirmatory signal is identical to the first case). In the first case, he cascades and his A prediction does not reveal any private information which implies that the second-after-deviation-player is in the same situation as the first-after-deviation-player. In the second case, the first-after-deviation-player follows his private signal which implies that the second-after-deviation-player follows his signal after history ABB and the remaining players cascade after history ABA. Finally, the third-after-deviation-player is in the same situation as the first player after history $ABBA$ whereas the remaining players cascade after history $ABBB$. In summary, inferred private signals cancel out after history $ABBA$, history $ABA \ldots A$ leads to the inference of either 1 a signal or two a signals and a b signal (or a signal favoring state β but with an accuracy slightly lower than a b signal), and two b signals are inferred from history $ABBB \ldots B$.

Given a cascade situation in period i, a *cascade behavior* is observed in the low line if player i guesses A when $n_{i-1} = 1$ and guesses B when $n_{i-1} = -2$. Similarly, given a cascade situation in period j, a *cascade break* is observed in the high line if player j guesses B when $n_{i-1} = 1$ and guesses A when $n_{i-1} = -2$.

Four remarks concerning participants' guesses and beliefs before discussing in details the emergence and fragility of information cascades. First, the overall relative frequency of guesses which are neither in line with Bayesian rationality nor in agreement with the private signal is extremely small in the low line (less than 4 percent) but quite large in the high line (about 20 percent) where the two benchmarks always make similar predictions. Second, only slightly more than half of the observed histories are equilibrium histories (54 percent). Third, in all cases but three, a deviation from the equilibrium path by a low informed participant reveals that participant's private signal (51 cases). Finally, one might argue that in the second experiment risk-averse participants have an incentive to hedge with their stated beliefs against adverse outcomes of their guesses. We find no clear evidence for hedging since elicited beliefs are almost systematically in line with guesses (see footnote 20) and participants' guesses in both experiments are similar.

4.1 Emergence of Information Cascades: Decision Data in the Low Line

We denote by n_{CS} the total number of cascade situations. The relative frequency of cascade behavior is the ratio $\frac{n_{CB}}{n_{CS}}$, where n_{CB} is the total number of cases in which a low informed participant, placed in a cascade situation, guesses in contradiction with his signal. The relative frequencies of cascade behavior for each session in both experiments are given in Table 4. Information cascades emerge in our experiments since cascade behavior is observed 69% of the time overall. Apparently, there is a difference between the relative frequency of cascade behavior in Experiment 1 and the relative frequency of cascade behavior in Experiment 2. However, applying a robust rank-order test (Siegel and Castellan, 1988, p. 137), we cannot reject the null hypothesis of no difference between the two relative frequencies at the significance level of 10 percent (U statistic of 2.348).[16] In the rest of the section, we pool the data of both experiments when discussing participants' guesses in the low line.

It is useful to point out that random decisions yield a relative frequency of cascade behavior equal to 50%. According to χ^2 tests, the observed behavior in cascade situations is significantly different from both the theoretical predicted behavior and a random behavior based on coin flips at the 5 percent level.

We now examine participants' tendency to engage in cascade behavior depending on the number of identical guesses i.e. the depth of the cascade. Figure 1 represents the relative frequencies of cascade behavior as a function of $|n^A - n^B|$, where n^d is the number of guesses $d \in \{A, B\}$ taken up to the current period. After an A guess, only 24% of the participants follow the trend when they receive a contradictory signal. After two similar guesses not canceled out by previous guesses, the relative frequency of cascade behavior increases markedly and reaches 64%. When the absolute difference between the number of A and B guesses attains 7, the proportion of cascade behavior is identical to the theoretical one: 100% of the participants follow the established pattern.[17]

[16] We have checked the robustness of the conclusion by conducting a two-sample t-test with equal variances and a two-sample Mann-Whitney test. The two-sided t-test gives a p-value of 0.107; the Mann-Whitney test gives a p-value of 0.127. The conclusion is also confirmed by a probit regression on individual-level data in both lines with robust standard errors (237 observations). Though significant, the impact of belief elicitation on the participants' propensity to engage in cascade behavior is negligible (marginal effect of -0.063 with p-value of 0.032).

[17] In the last period, the relative frequency of cascade behavior decreases. Though we have no convincing explanation for such an anomaly, participants' elicited beliefs also reflect this "end-game" behavior (see the next subsection).

Experiment	Session	Cascade behavior
1	1	85%
	3	83%
	5	70%
	Average	79%
2	2	61%
	4	44%
	6	73%
	Average	59%

Table 4: Relative frequencies of cascade behavior in equilibrium histories.

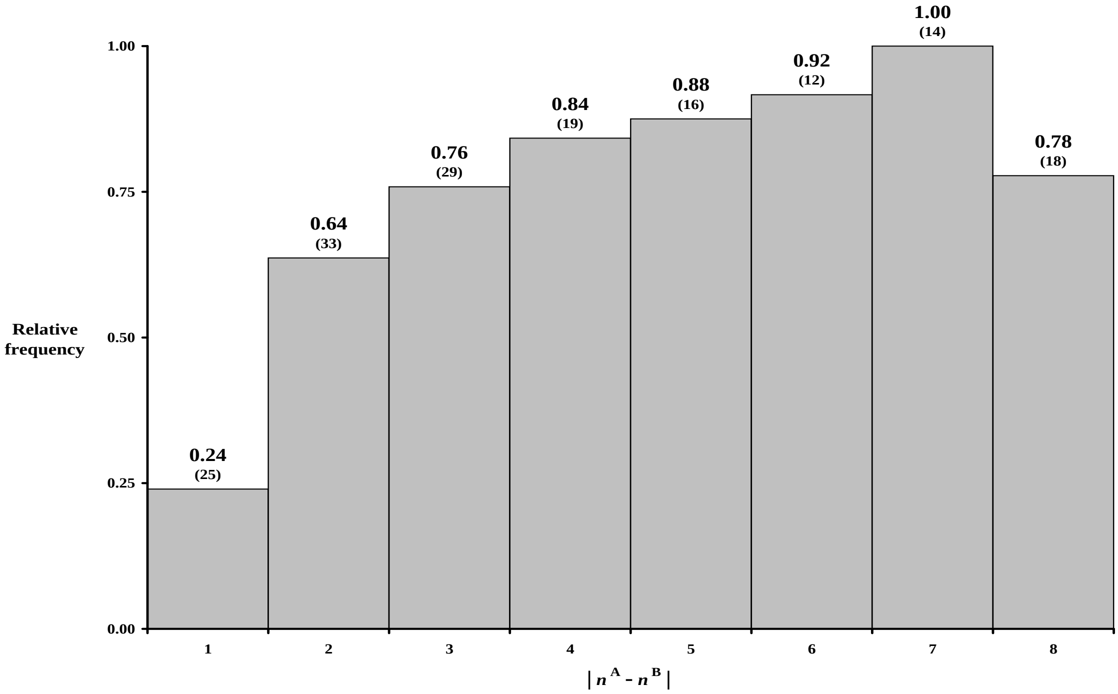

Figure 1: Relative frequencies of cascade behavior in equilibrium histories (numbers of cascade situations are indicated in parentheses).

4.2 Fragility of Information Cascades: Decision Data in the High Line

We define the relative frequency of cascade break as the ratio $\frac{n_{SC}}{n_{CS}}$, where n_{SC} is the total number of cases where a high informed participant, placed in a cascade situation, guesses in accordance with his signal and in contradiction with the majority of previous guesses. The relative frequencies of cascade break for each session in both experiments are given in Table 5. Overall, in only one third of the situations, a participant who has a strong signal contradicting the established pattern breaks the cascade.[18] In the rest of the section, we pool the data of both experiments when discussing

[18]Applying a robust rank-order test, we cannot reject the null hypothesis of no difference between the relative frequency of cascade break in Experiment 1 and the relative frequency of cascade break in Experiment 2 at the significance level of 10 percent (U statistic of 0.182). We have checked the robustness of the conclusion by conducting a two-sample t-test with equal variances and a two-sample Mann-Whitney test. The two-sided t-test gives a p-value of 0.732; the Mann-Whitney test gives a p-value of 0.827.

participants' guesses in the high line.

Experiment	Session	Cascade break
1	1	27%
	3	26%
	5	53%
	Average	35%
2	2	20%
	4	42%
	6	32%
	Average	31%

Table 5: Relative frequencies of cascade break in equilibrium histories.

Figure 2 shows the relative frequencies of cascade breaks depending on the depth of the cascade. At least half of the information cascades are broken in case an imbalance of at most 3 guesses in one direction is observed whereas, on average, less than one six of the information cascades are broken as soon as an imbalance of at least 4 guesses in one direction is observed.

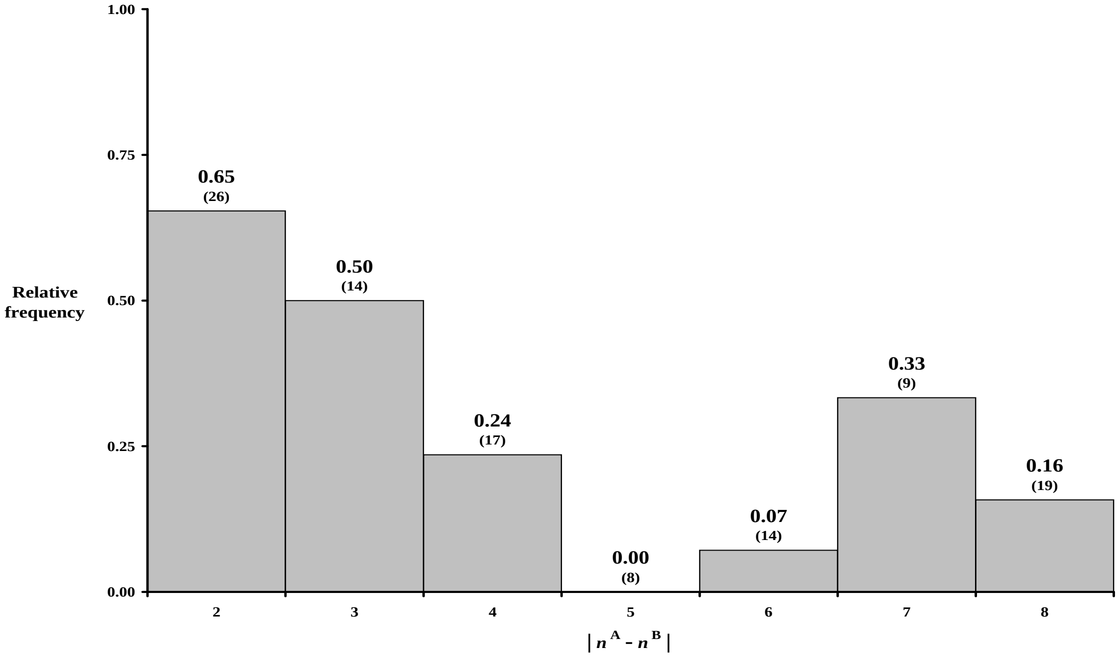

Figure 2: Relative frequencies of cascade break in equilibrium histories (numbers of cascade situations are indicated in parentheses).

4.3 Dynamics of Beliefs

In this subsection we look at the dynamics of elicited beliefs. We show that, in contradiction with Bayesian rationality but in accordance with actual behavior, participants do not consider guesses belonging to an information cascade as uninformative.

Elicited beliefs in the first period

Table 6 summarizes the average beliefs in the first period (standard deviations are given in brackets). Those participants did not observe any guess yet but some of the low informed participants were endowed with a private signal. Actual beliefs in the first period, with or without private information, are very close to the theoretical ones. Participants seem to apply Bayes' rule when thinking about others is not necessary.

	No signal 675 obs. (both lines)	Signal a 26 obs. (low line)	Signal b 19 obs. (low line)
Session 2	54% (0.12)	78% (0.17)	33% (0.22)
Session 4	51% (0.12)	62% (0.18)	36% (0.10)
Session 6	55% (0.14)	61% (0.15)	37% (0.22)
Average elicited beliefs	53% (0.13)	66% (0.18)	35% (0.18)
Theoretical beliefs	55%	71%	38%

Table 6: Average beliefs in the first period.

History dependent elicited beliefs

Figure 3 shows the dynamics of participants' beliefs, before being endowed with a private signal, in a cascade with an established pattern of A guesses (respectively B guesses) when the depth of the cascade $n^A - n^B$ (respectively $n^B - n^A$) increases. From a theoretical point of view, as public information stops accumulating once a cascade has started, players' beliefs stay constant whatever the depth of the cascade (grey line). Clearly, the dynamics of stated beliefs for participants without private information do not reflect this theoretical feature (empty diamonds). On the contrary, participants' beliefs increase when the depth of the cascade increases and the dynamics of actual beliefs are very close to the dynamics of "Private Information" (PI) beliefs, i.e., to the dynamics of beliefs that players would have if it was mutually known that all players follow their private signal (full circles).

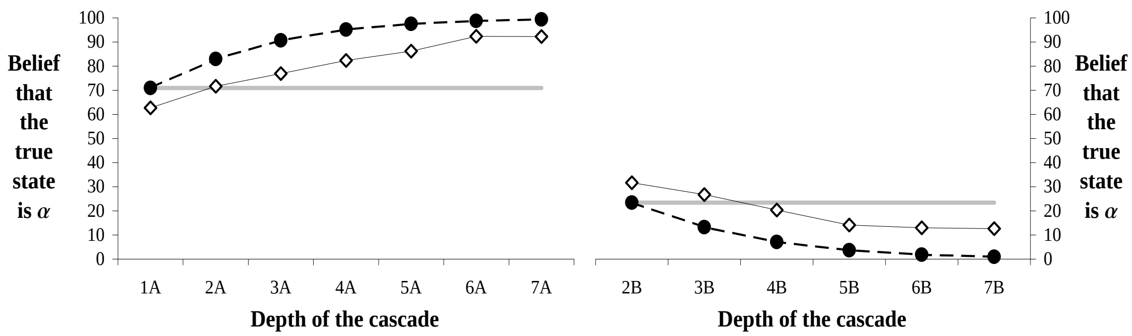

Figure 3: Dynamics of beliefs in A and B cascades without private signal (low and high line).

The observation that the relative frequency of cascade behavior increases with the depth of the cascade seems to be explained by the fact that participants' beliefs do not stay constant in a cascade. To see the link between the relative frequency of cascade behavior and the way participants update their beliefs we represent in Figure 4 the dynamics of the low informed participants' beliefs when the depth of the cascade increases and their (low quality) signal contradicts the established pattern of guesses.[19] When the majority of previous guesses are A and the private signal is b, participants' belief is greater than 50% (grey line) only after a depth of 2 but largely greater than 50% with a depth larger than 3. The same phenomenon appears with a majority of previous B guesses, albeit beliefs cross 50% only after a depth of 3 (instead of 2 in a sequence with a majority of A). This explains why participants rarely engage in cascade behavior with a depth of 1 but very frequently with a depth greater than 3.

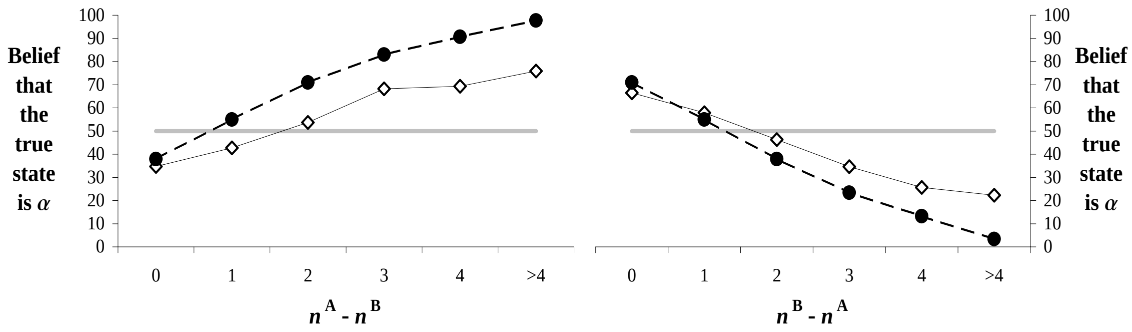

Figure 4: Dynamics of beliefs with a weak contradictory signal (low line).

Similarly, the fact that the relative frequency of cascade break decreases with the depth of a cascade can also be explained by the way participants update their beliefs. Figure 5 shows the dynamics of high informed participants' beliefs when the depth of the cascade increases and their signal contradicts the established pattern of guesses. In both cases (majority of previous A guesses and majority of previous B guesses), participants believe more in the state favored by the majority of previous guesses than in their own contradictory signal after a depth of 3. This explains why participants rarely break a cascade of depth 3 or more even with a strong contradictory signal.[20]

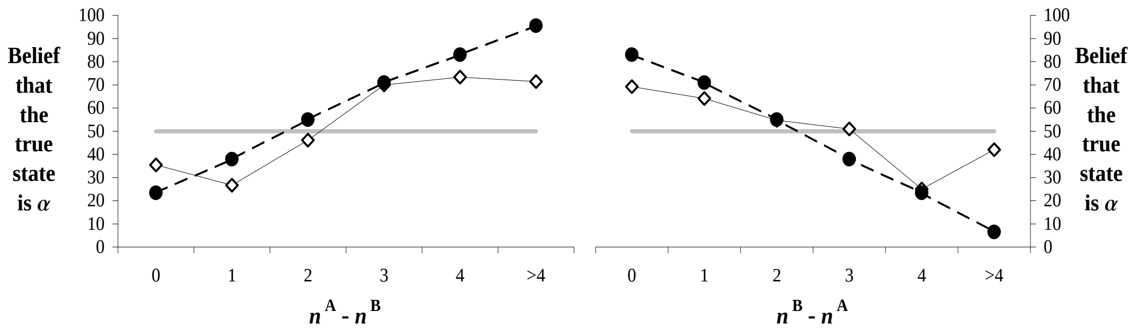

Figure 5: Dynamics of beliefs with a strong contradictory signal (high line).

4.4 A Statistical Error-Rate Analysis

A natural candidate to explain low informed participants' deviations from Bayesian rationality are errors. If the likelihood of an error is inversely related to its cost then most deviations from

[19]For depths strictly greater than 4 we only report the average of participants' beliefs since the number of observations falls from 117 with no previous guess to 15 with depth 5. In this way, we consider 54 observations for depths strictly greater than 4.

[20]Note that in both lines participants' guesses are highly consistent with their beliefs (about 97% of the time), i.e., participants maximize their expected payoff given their beliefs.

Bayesian rationality occur in situations where Bayesian rationality predicts a guess inconsistent with the one based only on the private signal. Indeed, in such situations, a deviation following a confirmatory signal is more costly than a deviation following a contradictory signal. Errors constitute a plausible rationalization to the overweight-phenomenon, namely that low informed participants do not systematically engage in cascade behavior after having observed a few identical guesses. To rationalize the fact that low informed participants engage in cascade behavior after having observed many identical guesses, a further step in the reasoning process of the participants is necessary: Participants know that others make guess errors which are monotone in payoffs, they know that other participants know it, and so on. Generalizing Bayesian rationality by allowing for noisy optimizing behavior while maintaining the internal consistency of rational expectations defines McKelvey and Palfrey's (1995) quantal response equilibrium (QRE) (in our context, the monotone agent quantal response equilibrium; see McKelvey and Palfrey, 1998). Since the seminal work of AH, several experimental papers have suggested QRE as an alternative theory of behavior to Bayesian rationality, and the literature has focused on the logit specification (LQRE) because players' behavior is determined by a single parameter, the sensitivity to payoff differences, with a natural "rationality" interpretation.[21] In LQRE, low informed players often guess according to their contradictory private signal after having observed a few identical guesses not only because of the small cost of the deviation but also because they discount the evidence conveyed by the observed guesses. Consequently, social learning never stops since low informed players do not fully discount the evidence conveyed by later guesses. Still, once a long sequence of identical guesses is observed, low informed players assign a large probability to the state favored by those guesses and they often engage in cascade behavior.

Though the dynamics of beliefs and guesses of low informed participants can be rationalized by LQRE, high informed participants do not "better respond" to rational expectations about the underlying distributions. Indeed, high informed participants endowed with a contradictory signal assign an extreme belief to the state favored by many identical guesses, which explains the low empirical probability of collapse, but such extreme beliefs are clearly at odds with the predictions of LQRE.[22] In an attempt to rationalize low and high informed participants' behavior we conduct a depth-of-reasoning analysis, along the lines of Kübler and Weizsäcker (2004). We estimate an error-rate model that uses logistic response functions to determine guess probabilities and allows for different sensitivities to payoff differences on different levels of reasoning about others' behavior.[23]

Participants are assumed to predict urn A with probability

$$\Pr(A \mid t_i, h^{i-1}, \lambda_1) = \frac{\exp\left(\lambda_1\left(15\mu_i(t_i,h^{i-1})-5\right)\right)}{\exp\left(\lambda_1\left(15\mu_i(t_i,h^{i-1})-5\right)\right)+\exp\left(\lambda_1\left(15(1-\mu_i(t_i,h^{i-1}))-5\right)\right)},$$

and urn B with the complementary probability. The parameter λ_1 captures the sensitivity to

[21] Haile, Hortacsu, and Kosenok (2008) show that evaluating the predictive success of QRE in a single game is uninformative *without* strong a priori restrictions on distributions of payoff perturbations. The logit specification imposes such restrictions and limits the number of observable phenomena in an information cascades game.

[22] This observation is true whatever the level of the sensitivity to payoff differences. If the sensitivity to payoff differences is large then high informed players infer much information from the first guesses (first one guess in an A herd and first two guesses in a B herd) but very little from later guesses. If the sensitivity to payoff differences is small then high informed players infer little information from any observed guess. In both cases, high informed participants always assign a higher belief to the state favored by their private signal unless an extremely long sequence of identical guesses is observed.

[23] The failure of LQRE to account for the documented regularities in social learning experiments has been often reported in the literature. Among others, Huck and Oechssler (2000) and Nöth and Weber (2003) point out that participants' reluctance to engage in cascade behavior is not solely due to their scepticism about others' capacity to learn in a Bayesian rational way. In a recent meta analysis of social learning experiments, Weizsäcker (2008) clearly demonstrates that QRE does not organize well the bulk of the experimental evidence.

payoff differences of the participants. Participants are assumed to attribute a sensitivity to payoff differences λ_2 to the guesses of the other participants. In addition, when participants consider the reasoning that other participants attribute to others' reasoning, they assign another sensitivity to payoff differences, λ_3. Additional higher-level sensitivities are assigned to longer chains of reasoning. Under the restriction that the data generating process is correctly specified by Bayesian rationality, the true value of the sensitivities should be infinity. Under the restriction that the data generating process is correctly specified by the LQRE, the true value of the sensitivities should be the same ($\lambda^C > 0$).

Table 7 shows the maximum likelihood estimation results. The top panel displays the results for LQRE and the bottom panel displays the results of the level-of-reasoning model. The left (right) panel shows the results on the data from the low (high) line. For each line, results are shown for the pooled data, and for experiment 1 and 2 separately.[24] At the 5% significance level, sensitivities to payoff differences λ_1 and λ_2 are significantly different from 0 in all six subsets of the data. The sensitivity to payoff differences λ_3 is significantly different from 0 in all subsets of the data except from the high line in experiment 2. The sensitivity to payoff differences λ_4 is not significantly different from 0 in all six subsets of the data. At the 5% significance level, sensitivities to payoff differences λ_1 and λ_2 are significantly different from the estimate of the sensitivity at the lower reasoning level, on both pooled data sets.

The results of our depth-of-reasoning analysis suggest that participants apply medium chains of reasoning. They learn from observing their predecessors' guesses and realize that other participants also learn from observing their respective predecessors. However, participants' reasoning gets rather imprecise on the highest level since participants think that others attribute to their respective predecessors twice the participants' error rate. Additionally, low informed participants attribute a significantly higher error rate to their predecessors whereas high informed participants attribute a significantly lower error rate to their predecessors as compared with their own. Thus, our estimation results confirm those of Kübler and Weizsäcker (2004) since low informed participants attribute a significantly lower "rationality" to their predecessors compared with their own. They also extend them since high informed participants attribute a significantly higher "rationality" to their low informed predecessors compared with their own which suggests that the perception of others' rationality is affected by the participant's information endowment. The reasoning process of low informed participants explains why they do not systematically engage in cascade behavior after having observed a few identical guesses but do so after having observed many identical guesses, and the reasoning process of high informed participants justifies the low empirical probability of collapse of long cascades.

5 Discussion

Experimental economists have established the anatomy of failure in social learning environments. After few identical guesses participants often follow their contradictory signal but they (almost) systematically engage in cascade behavior once many predecessors made the same guess. Several alternative theories of behavior to Bayesian rationality account for the prevalence of the overweight-phenomenon and its attenuation in long pure laboratory cascades. We present below the most

[24]To construct hypotheses tests, we conduct a simulation study. We generate a set of simulated guesses, based on the maximum likelihood estimates and the sample size used in our experiment. We re-estimate the model and obtain a vector of maximum likelihood estimates of the simulated data. We repeat the process a large number of times. We obtain a distribution that resembles the sampling distribution of the maximum likelihood estimator. The standard errors are obtained by the sample standard deviation. Confidence intervals are obtained by deleting values of the appropriate number of estimates from the sorted array of maximum likelihood estimates.

	Low Line			High Line		
	Pooled Data	Exp. 1	Exp. 2	Pooled Data	Exp. 1	Exp. 2
λ^C	**3.44**	**3.85**	**3.11**	**1.98**	**2.27**	**1.77**
$-$LL	212.40	95.17	115.88	204.16	87.39	114.95
λ_1	**3.49**c	**3.55**	**3.51**c	**1.97**c	**2.42**	**1.63**c
	[3.07 4.18]	[2.95 4.66]	[2.95 4.40]	[1.59 2.32]	[1.99 3.96]	[1.22 2.06]
	[3.11 4.06]	[3.02 4.47]	[2.97 4.26]	[1.66 2.29]	[2.08 7.38]	[1.34 2.00]
λ_2	**2.52**b,c	**3.62**c	**1.81**a,b,c	**5.34**a,b,c	**3.87**a,b,c	**6.43**a,b,c
	[2.02 3.51]	[2.49 17.30]	[1.40 2.72]	[3.35 17.32]	[2.50 8.54]	[2.86 89.30]
	[2.03 3.45]	[2.56 8.16]	[1.46 2.48]	[3.58 9.99]	[2.68 7.38]	[3.12 35.90]
λ_3	**1.81**b	**2.01**	**0.97**a,b,c	**0.86**a,b	**0.92**a,b	-0.32
	[0.87 4.12]	[1.04 5.93]	[0.52 2.47]	[0.47 1.55]	[0.38 2.21]	[-21.42 1.25]
	[1.00 2.86]	[1.16 4.71]	[0.59 2.06]	[0.53 1.43]	[0.50 1.85]	[-13.77 0.88]
λ_4	2.30	1.65	-2.61	0.60	0.84	—
	[-1.75 30.97]	[-2.15 20.00]	[-20.00 1.87]	[-20.02 3.17]	[-8.38 20.00]	
	[-1.30 24.67]	[-1.95 19.60]	[-19.50 1.48]	[-20.00 2.96]	[-5.68 19.01]	
$\lambda_{5,6,7,8,9}$	—	—	—	—	—	—
$-$LL	207.43	92.91	111.20	161.80	66.78	90.60

Table 7: Sensitivity to payoff differences estimates; 95% and 90% confidence intervals in brackets; negative log-likelihood ($-$LL). Parameter values in bold indicate sensitivities that are significantly different from 0 at conventional error levels. Parameter values with a subscript "a" ("b") indicate sensitivities that are significantly different from the corresponding common error rate, λ^C, at a 5% (10%) level. Parameter values with a subscript "c" indicate sensitivities that are significantly different from the estimate of the sensitivity at the lower reasoning level, at the 5% level.

prominent of these alternatives and we investigate which ones account for our new evidence. We end this section by discussing the actual allocative efficiency in both lines.

As already mentioned, LQRE has been suggested early in the experimental literature as an alternative theory of behavior to Bayesian rationality. LQRE accounts for the overweight-phenomenon and its attenuation in long pure laboratory cascades which means that its predictions are qualitatively in line with the behavior of our low informed participants. However, LQRE's predictions do not agree with the participants' behavior in the high line. There are basically two ways to modify LQRE in order to improve its predictive success in social learning experiments. In this paper, as initially suggested by Kübler and Weizsäcker (2004), we relax the rational expectations assumption and show that, compared with their own, low informed participants attribute a significantly lower rationality to their predecessors whereas high informed participants attribute a significantly higher rationality to their low-informed predecessors. Not only do we confirm the earlier findings according to which the perception of others' rationality is biased but our estimation results suggest that this perception is affected by the participant's information endowment. A second possible extension of LQRE has been suggested by Goeree et al. (2007) and assumes that players update their beliefs in a non-Bayesian way which is commonly know. Players overweight their private information i.e. count their private signal as k signals where $k \in (1, \infty)$ when forming their beliefs. Such an extension retains the rational expectations assumption but gives up the fact that players better respond. Our experimental results suggest that the overweight-parameter is not commonly known since high informed participants have different expectations than low informed participants about the rule used by low informed participants to update their beliefs.[25]

With the help of a meta data set of 13 experimental studies on BHW's specific model, Weizsäcker (2008) shows that participants are unsuccessful in learning from others in information cascade games since they underestimate the informational content of their predecessors' guesses. In situations where it is empirically optimal for participants to contradict their private signal, they make the appropriate guess in less than half of the cases. The behavior of low informed participants confirms this finding. We compare the proportion of correct guess among the actual guesses of the low informed participants with the proportion of correct guess among the guesses of Bayesian rational players who interpret a deviation from the equilibrium path as revealing the deviator's private signal. Overall, slightly more theoretical guesses are correct than actual guesses (81.36% vs. 77.28%). The difference is entirely explained by the suboptimal play of low informed participants endowed with an incorrect private signal. If low informed participants would overweight their private information relative to the public information of their predecessors' guesses *and* successfully learn from others then they would do worst than Bayesian rational players early in the sequence but would do better over time as more and more information gets revealed. In fact, the accuracy of actual guesses does not improve over time compared to the accuracy of theoretical guesses. In the first four periods (respectively last four periods) of the decision making sequence, the proportion of correct theoretical guesses is 12% higher (respectively 14% higher) than the proportion of correct guesses made by low informed participants endowed with an incorrect private signal. The proportion of correct theoretical guesses is almost identical to the proportion of correct guesses made by low informed participants endowed with a correct private signal at any point in the decision making sequence. On the contrary, slightly less theoretical guesses are correct than actual guesses made by high informed participants (76.19% vs. 78.25%) and the improvement in guess accuracy only occurs in situations where high informed participants are endowed with an incorrect private signal. Overall, the proportion of correct theoretical guesses is 45% lower than the proportion of correct guesses made by high informed participants endowed with an incorrect private signal (it is 17% lower in the third period and 72% lower in the ninth period). The proportion of correct theoretical guesses is 11% higher than the proportion of correct guesses made by high informed participants endowed with a correct private signal (it is 7% higher in the third period and 12% higher in the ninth period). In contrast with low informed participants, high informed participants are successful in learning from others and they behave efficiently when engaging in cascade behavior.

6 Concluding Remarks

We examine the occurrence and fragility of information cascades in two laboratory experiments. In each decision making round, a random choice is made between two (almost) equally likely states and the randomly chosen state is not revealed to the participants. Low informed participants guess sequentially which state has been chosen, with each participant observing all previous guesses and a signal correct with probability 2/3. In a matched pairs design, high informed participants observe

[25]Two recent theoretical papers derive predictions in numerous social learning environments assuming that players are boundedly rational. Guarino and Jehiel (2009) investigates the behavior of players who choose according to the Analogy Based Expectation Equilibrium (ABEE) using the payoff-relevant analogy partition (this implies that there are only two analogy classes, one for each state). Eyter and Rabin (2009) investigates the implications of naïve herding according to which players believe that each predecessor's guess reflects solely his private information. Both approaches predict that the beliefs of players become extreme when they observe long sequences of identical guesses and the low empirical probability of collapse of long herds. However, both approaches fail to explain the overweight-phenomenon.

the guesses of the low informed participants and a signal correct with probability 4/5. In the second experiment, participants' beliefs about the chosen state are elicited.

The fragility of laboratory cascades rapidly vanishes as the number of identical guesses increases. Said differently, the behavior of high informed participants deviates from Bayesian rationality in situations where Bayesian rationality predicts a guess *consistent* with the one based only on the private signal. This result complements the main finding in earlier experimental cascade games, the overweight-phenomenon, according to which participants' behavior deviates from Bayesian rationality essentially in situations where Bayesian rationality predicts a guess *inconsistent* with the one based only on the private signal. Additionally, earlier experimental studies have established that participants' tendency to engage in cascade behavior increases with the number of identical guesses i.e. participants endowed with *weak* contradictory signals guess *more* in accordance with Bayesian rationality when the evidence conveyed by previous guesses is strong. Due to this behavioral pattern, some authors have interpreted their experimental data as a clear support for Bayesian rationality (among others, Anderson and Holt, 1997 and Hung and Plott, 2001). We show that participants endowed with *strong* contradictory signals guess *less* in accordance with Bayesian rationality when the evidence conveyed by previous guesses is strong. This evidence is corroborated by the analysis of participants' elicited beliefs which suggests that the more identical guesses participants observe the more they believe in the state favored by those guesses.

Compared to Bayesian rational players, low informed participants guess suboptimally when endowed with an incorrect private signal since they underestimate the informational content of their predecessors' guesses. In contrast, high informed participants are successful in learning from others and the remarkable stability of laboratory cascades reflects their efficient behavior. Further experimental studies should investigate the efficiency of participants' behavior in social learning environments with long decision making sequences and numerous signal accuracies.

References

Acemoglu, D., M. Dahleh, I. Lobel, and A. Ozdaglar (2008): "Bayesian Learning in Social Networks," MIT LIDS Working Paper 2780.

Alevy, J., M. Haigh, and J. List (2007): "Information Cascades: Evidence from a Field Experiment with Financial Market Professionals," *Journal of Finance*, 62, 151–180.

Anderson, L. (2001): "Payoff Effects in Information Cascade Experiments," *Economic Inquiry*, 39, 609–615.

Anderson, L. and C. Holt (1997): "Information Cascades in the Laboratory," *American Economic Review*, 87, 847–862.

Banerjee, A. (1992): "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107, 797–818.

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

Celen, B. and S. Kariv (2004): "Distinguishing Informational Cascades From Herd Behavior in the Laboratory," *American Economic Review*, 94, 484–497.

Chamley, C. P. (2004): *Rational herds: Economic models of social learning*, Cambridge, Cambridge University Press.

Cipriani, M. and A. Guarino (2005): "Herd Behavior in a Laboratory Financial Market," *American Economic Review*, 95, 1427–1443.

Drehmann, M., J. Oechssler, and A. Roider (2005): "Herding and Contrarian Behavior in Financial Markets: An Internet Experiment," *American Economic Review*, 95, 1403–1426.

Eyter, E. and M. Rabin (2009): "Rational and Naive Herding," CEPR Discussion Paper 7351. London, Centre for Economic Policy Research.

Goeree, J., T. Palfrey, B. Rogers, and R. McKelvey (2007): "Self-Correcting Information Cascades," *Review of Economic Studies*, 74, 733–762.

Guarino, A. and P. Jehiel (2009): "Social Learning with Coarse Inference," Mimeo.

Haile, P., A. Hortacsu, and G. Kosenok (2008): "On the Empirical Content of Quantal Response Equilibrium," *American Economic Review*, 98, 180–200.

Huck, S. and J. Oechssler (2000): "Informational Cascades in the Laboratory: Do they Occur for the Right Reasons?" *Journal of Economic Psychology*, 21, 661–671.

Hung, A. and C. Plott (2001): "Information Cascades: Replication and an Extension to Majority Rule and Conformity Rewarding Institutions," *American Economic Review*, 91, 1508–1520.

Kraemer, C., M. Nöth, and M. Weber (2006): "Information Aggregation with Costly Information and Random Ordering: Experimental Evidence," *Journal of Economic Behavior & Organization*, 59, 423–432.

Kübler, D. and G. Weizsäcker (2004): "Limited Depth of Reasoning and Failure of Cascade Formation in the Laboratory," *Review of Economic Studies*, 71, 425–441.

——— (2005): "Are Longer Cascades More Stable?" *Journal of the European Economic Association (Papers and Proceedings)*, 3, 330–339.

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

——— (1998): "Quantal Response Equilibria for Extensive Form Games," *Experimental Economics*, 1, 9–41.

Murphy, A. and R. Winkler (1970): "Scoring Rules in Probability Assessment and Evaluation," *Acta Psychologica*, 34, 273–286.

Nöth, M. and M. Weber (2003): "Information Aggregation with Random Ordering: Cascades and Overconfidence," *Economic Journal*, 113, 166–189.

Nyarko, Y. and A. Schotter (2002): "An Experimental Study of Belief Learning Using Elicited Beliefs," *Econometrica*, 70, 971–1005.

Offerman, T., J. Sonnemans, G. van de Kuilen, and P. Wakker (2009): "A Truth-Serum for Non-Bayesians: Correcting Proper Scoring Rules for Risk Attitudes," *Review of Economic Studies, forthcoming.*

Siegel, S. and N. J. Castellan (1988): *Nonparametric Statistics for the Behavioral Sciences*, McGraw-Hill, New York.

Smith, L. and P. Sorensen (2000): "Pathological Outcomes of Observational Learning," *Econometrica*, 68, 371–398.

Weizsäcker, G. (2008): "Do We Follow Others When We Should? A Simple Test of Rational Expectations," Mimeo.

Ziegelmeyer, A. (2001): "Informational Externalities and Sequential Interactions: Experimental Evidence on Social Learning," Unpublished Ph.D. thesis. Louis Pasteur University, Strasbourg.