Is playing alone in the darkness sufficient to prevent informational cascades?

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Abstract

Seminal models of herd behaviour and informational cascades point out the existence of information negative externalities, and propose to destroy information in order to achieve social improvements. Although in the last years many features of herd behaviour and informational cascades have been studied, this particular aspect has never been extensively analysed. In this article we investigate, both theoretically and experimentally, whether and to which extent destroying information can improve welfare.

JEL Classification: C92

1. Introduction

Part of social learning is related to an apparently *naive* human behaviour known as herd behaviour (Banerjee, 1992) and informational cascades (Bikhchandani et al., 1992). These kinds of behaviour occur when agents can increase their information set by looking at other agents' choices. Although viewed as rational, such behaviour can cause information externalities that result in an aggregate welfare loss (Becker, 1991). Hence, the *individual* rational behaviour, i.e., trying to gain by looking at others' actions, may well result in a non-optimal strategy from an *aggregate* point of view. The basic idea of herd behaviour is very simple: if one has to choose between two unknown restaurants and has no relevant information about them, (s)he will consider the most crowded one as the best and will join the queue. This behaviour is rational but leads to an inefficient outcome if the first customers have no pregnant information. In this regard, even Keynes (1965) argued that:

> *Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally. (p 158)*

There exists abundant empirical evidence showing that herd behaviour may lead society either into a true run, i.e., situations in which everyone, doing what everyone else is doing, will do the "right thing", or into a false run, i.e., situations where everybody follows an action that will eventually result to be incorrect. Typical examples of a false run are bubbles in financial markets (Plott, 2002; Hey and Morone, 2004; for a survey, see Bikhchandani and Sharma, 2001).

In this paper we analyse a sequential herd behaviour model that is based on Bikhchandani et al. (1992)'s work. Our main aim is to investigate whether informational cascades can be avoided by forcing the first *k* subjects in a sequence of *N* players to play only according to their private information. This hypothesis was already advocated by Bikhchandani et al. (1992):

> *… a cascade regime may be inferior to a regime in which the actions of the first n*[1] *individuals are observed only after stage n+1. (p. 1009)*

Banerjee (1992) has also considered the same idea:

> *… in ex ante welfare sense society may actually be better off by constraining some of the people to use only their own information. (p. 798) … some of its advantages* [the right choices always gets revealed] *can be captured simply by not allowing the first n agents*

[1] In our work we indicate the number of the subjects in the darkness with *k*.

> *to observe anybody else's choice when they are making their own choice. The rest of population is then allowed to choose sequentially, with each person observing the choices made by all her predecessors. (p. 881)*

Although the hypothesis according to which destroying information may turn out in a social improvement was already proposed, it has never been extensively analysed neither theoretically nor experimentally.

The paper is structured as follows. In Section 2 we show Bikhchandani et al.'s results, while we report on some earlier experimental evidence in Section 3. Section 4 is devoted to the new model. The experimental design and results are introduced in Sections 5 and 6, respectively. Section 7 concludes.

2. A simple model of Informational Cascades: a dichotomy choice model

Models of herd behaviour and informational cascades often make strong assumptions about the available information, the choices to make, the timing of decisions, and the symmetry of equilibrium. A simple example is provided by Banerjee's "Herd Behaviour and the Reward for Originality" (1989), which shows the intuition of herd behaviour as well as its strengths and weaknesses.

Bikhchandani, Hirshleifer and Welch explore the concept of informational cascades. Their analysis is devoted to explain not only conformity among agents but also "rapid and short-lived fluctuations such as fads, fashions, booms and crashes". They point out that the conformity of followers in a cascade contains no informational value. In this sense, the cascade is fragile and can be upset by the arrival of new public information (note that if superior information does not arrive it is impossible to reverse the cascade). This particular aspect was experimentally investigated by Willinger and Ziegelmeyer (1998). The authors develop a model based on Bikhchandani et al. in which some agents receive more accurate information[2]. They find that this mechanism decreases the occurrence of cascades and breaks off herding.

An informational cascade occurs when people prefer to ignore their own piece of information and follow what others are doing. The game involves N players who must decide sequentially between two options: urn B (for black) and urn W (for white). In urn B there are two black balls and one white ball, whereas in urn W there are two white balls and one black ball. One of the two urns is randomly chosen. Player 1 draws a ball, and then guesses the chosen urn. Her payoff is 1 if her guess is correct and 0 otherwise. Player 2 observes player 1's choice, draws a ball from the same urn, and then makes her choice. Player 3 observes both previous players' choice, draws a ball and makes her choice, and so on until player N. Rationality requires player 1 to choose the black (white) urn when she draws a black (white) ball.
Player 2 therefore faces one of the following scenarios:

1. she observes that player 1 has chosen the black urn, and draws a black ball;
2. she observes that player 1 has chosen the black urn, and draws a white ball;
3. she observes that player 1 has chosen the white urn, and draws a black ball;
4. she observes that player 1 has chosen the white urn, and draws a white ball.

A rational player 2 should choose the black urn in scenario (1) and the white urn in scenario (4). In scenarios (2) and (3), she should be indifferent between the two urns, and assign equal probability to each of them.

Under these assumptions, Bikhchandani, Hirshleifer and Welch calculate the unconditional *ex-ante* probabilities of "White-cascade", "No-cascade" and "Black-cascade" after two individuals have played:

White = $\frac{1-p+p^2}{2}$ (1);

No = $p-p^2$ (2);

Black = $\frac{1-p+p^2}{2}$ (3);

and after an even number of players $n = 2m$ have played:

[2] More precisely, those agents who have to decide immediately after the occurrence of a cascade can observe an additional private signal.

White = $\frac{1-(p-p^2)^m}{2}$ (4);

No = $(p-p^2)^m$ (5);

Black = $\frac{1-(p-p^2)^m}{2}$ (6),

where *p* is the probability of observing a correct signal. Note that the bigger *p* is, the sooner an information cascade can start (figure 1).

Bikhchandani, Hirshleifer and Welch calculate also the probability of ending up in the correct cascade after two players have played, given that the chosen urn is **W**:

White = $\frac{p(p+1)}{2}$ (7);

No = $p(1-p)$ (8);

Black = $\frac{(p-2)(p-1)}{2}$ (9);

and in the general case (figure 2):

White = $\frac{p(p+1)\left[1-(p-p^2)^m\right]}{2(1-p+p^2)}$ (10);

No = $(p-p^2)^m$ (11);

Black = $\frac{(p-2)(p-1)\left[1-(p-p^2)^m\right]}{2(1-p+p^2)}$ (12).

Equation (10) is the probability of observing a correct cascade. Although this probability increases in *p* and *m*, even for very informative signals (*p* close to 1), the probability of a wrong cascade (equation (12)) remains remarkably high.

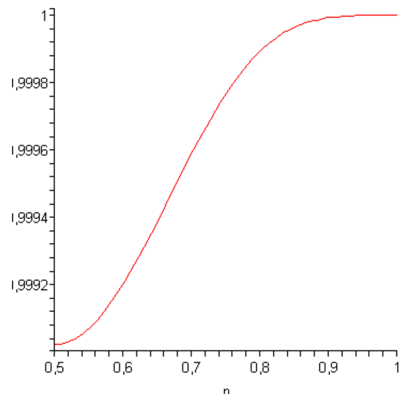

Figure 1. Probability of starting a cascade as a function of *p*, the correctness of the signal (*N* = 10)

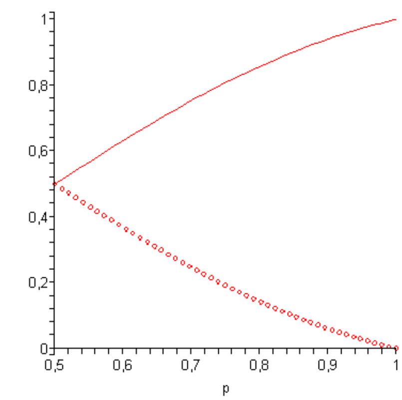

Figure 2. Probability of a correct (continuous line) and incorrect cascade (dotted line) as a function of *p*, the correctness of signal (*N* = 10)

3. Some experimental evidence

In the past decade, many features of herd behaviour and informational cascades have been studied experimentally. This strand of research was started out by Anderson and Holt (1997), and Allsopp and Hey (2000). In the first experiment, based on Bikhchandani, Hirshleifer and Welch's model, students received private information, and had to forecast, publicly and sequentially, one of two unknown events. They report that cascades occur frequently. In Allsopp and Hey's experiment, based on Banerjee's work, subjects could receive no signal and had to choose among ten options. They find that herding does not occur as often as Banerjee's theory predicts, and that individuals' behaviour is parameter-dependent.

Over the years, researchers have been mainly investigating the reasons for herding and the possible ways to reduce the phenomenon. For instance, Huck and Oechssler (2000) find that observed cascades are due more to the heuristic "follow your own signal" than to Bayesian updating. Noth and Weber (2003) assert that subjects' overconfidence may avoid non-revealing informational cascades. Hung and Dominitz (2004) report that public announcements subsequent to a cascade affect expectations.

Turning to the ways proposed to reduce this information externality, Anderson (2001) advocates the importance of rewarding incentives. Sgroi (2003) shows that cascades do not disappear if subjects can delay their decision. By looking at herd behaviour in a market context, Hey and Morone (2004) find that herding can arise also in a market that may be misled by misinformed individuals. Finally, Kübler and Weizscher (2004) show that costly signals induce far from equilibrium behaviour, and that subjects apply short chains of reasoning.

The experiment by Çelen and Kariv (2004) is worth mentioning separately because it was the first to show the difference between herd behaviour and informational cascades.

4. Playing in the darkness: a theoretical approach

Banerjee and Fudenberg (2004) note that the inefficient herding of the standard models does not occur if some agents are forced to use their own private information. Nonetheless, earlier literature has not been able to alter the classical models so as to capture this feature. In order to fill this gap, we focus on Bikhchandani et al.'s work and explore whether Banerjee and Fudenberg's claim is supported by a theoretical model.

Before presenting the new model, two points need to be mentioned. First, we speak of 'destroying information' in a very narrow sense as we mean that the first individuals in the sequence are not allowed to observe others' decisions. Second, we compare Bikhchandani et al.'s model to ours only from a social viewpoint, and investigate, on aggregate, if and under which conditions our model provides a higher probability to "do the right thing[3]". Obviously, in our model, those who cannot observe previous decisions are worse off than those who can to do so. However, we leave out this aspect and focus only on social welfare, defined as the sum of individual payoffs.

In their model, where all decision makers were allowed to observe the action pursued by their predecessors, Bikhchandani et al. (1992) derived the results shown in Section 2. We derive the same probabilities after making some major variations in their model (see the Appendix).

To a large extent, we retain all features of the original model. We have a set of $I = \{1, \ldots, N\}$ individuals. Each individual $i \in N$ has to decide whether to adopt or not a specific behaviour, e.g., a new technology. All individuals make their choices in a sequential and exogenously

[3] Spike Lee (1989).

determined order. If they decide to adopt the specified behaviour, they pay a positive cost, *C*, which is the same for all $i \in N$, independently of their position in the sequence. The gain of adopting, *V*, is also the same for all $i \in N$ and is either zero or one. These two events have the same *ex ante* probability to occur.

Moreover, each individual *i* privately observes a conditionally independent and identically distributed signal about the gain of adopting. This signal is either 0 or 1, where 1 is observed with probability *p* strictly greater than ½ if the true value is 1, and with probability 1–*p* otherwise.

Our model departs from Bikhchandani et al.'s model in that the first *k* (< *N*) individuals are not allowed to observe previous decisions, whereas the entire history of decisions is commonly known to the last *N*–*k* individuals. We can think of this game as an *N*-stage game where the first *k* individuals play simultaneously and the remaining *N*–*k* sequentially.

As the first *k* individuals can observe only their own signal, rationality requires them to follow their private information: they should take on the new behaviour if the signal is 1, and reject it otherwise. In contrast, the remaining *N*–*k* individuals should base their decision on both their own signal and all past decisions, thereby choosing the most frequently observed action.[4] In case of indifference, we assume that individual *i* with *i* = *k*+1 , …, *N* follows the tie-breaking rule of adopting or rejecting with equal probability.[5]

Compared to Bikhchandani et al.'s model, our model allows individual *i* with *i* = *k*+1 , …, *N* to aggregate information in a more accurate way as he/she can calculate the probability of each event on the basis of precise statistical laws rather than on the basis of earlier possible biased actions. We therefore expect our model to lead to a more socially efficient final outcome.

At this point our prediction becomes worth testing. We will tackle this task checking how the probabilities in the original model change under our modification (see the Appendix). In this section, we focus only on the comparison between the probabilities. However, we can

[4] Anderson and Holt (1997) demonstrate the rationality of such a strategy.

[5] The situation faced by individual *k*+1 depends, therefore, on whether *k* is even or odd. Assume, for instance, that *k* is an even number. In this case, individual *k*+1 will confront one of the following two situations: (1.1) if he/she observes that one of the two options has been chosen more than *k*/2 times, he/she will decide to follow the most recurrent option, independently of his/her own signal, therefore starting a herd; (1.2) if he/she observes that the two options have been chosen in equal number, he/she will follow his/her own signal, and the herd will start with individual *k*+2. Assume now that *k* is an odd number. In this case, *i*=*k*+1 will face one of the following three situations: (2.1) if he/she observes that one of the two options has been chosen more than (*k*+1)/2 times, he/she will decide on the most frequent option, independently of his/her private signal, and a herd will be formed; (2.2) if the frequency of the most recurrent option is exactly (*k*+1)/2 and agrees with individual *k*+1's private signal, the latter will determine the individual's choice and the herd will start with the next individual/stage; (2.3) finally, if the frequency of the most recurrent choice is (*k*+1)/2 but contradicts *k*+1's own signal, he/she will be indifferent between the two options and will use the above described tie-breaking rule; also in this case, the next individual will start herding.

definitely assert that under our assumption there is a greater probability of no herding and that this probability is growing with k: the greater the number of individuals ‘in the darkness’, the higher the probability of no herding, and the lower the probability of an inefficient final outcome. The following statement, thus, becomes obvious: the more efficient a decisional mechanism is, the greater the probability of a correct herd. Therefore, more individuals, in the aggregate, will choose the correct option.

The various graphs in figure 3 show the probability of a correct herd as a function of the

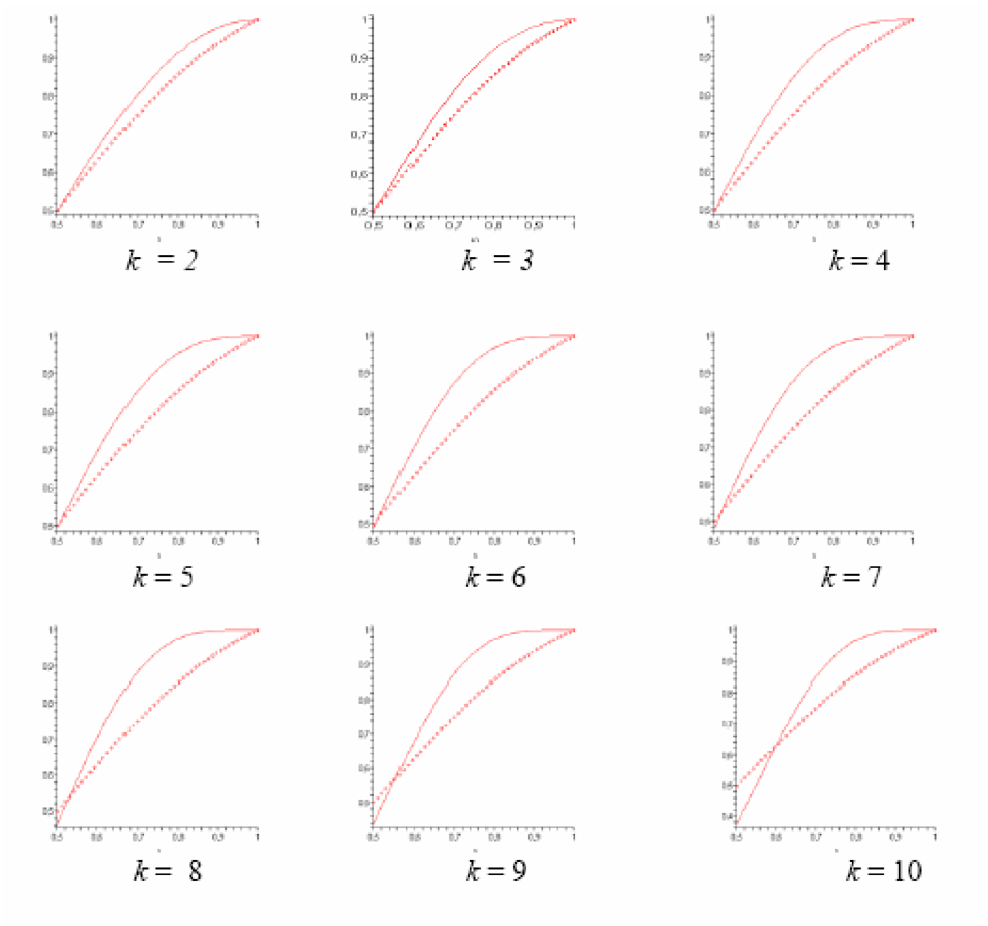

Figure 3. Comparison between the probabilities of a correct herd under the two models when N = 10 and for different values of k

probability p of the correctness of the signals when k varies between 2 and 10 and N is kept constant to 10. For almost all values of p, or at least when the signal is informative enough, the probability of a correct herd is always greater under our model (continuous lines) than under the original model (dotted lines), thereby confirming our hypothesis. Moreover, for every value of N, there exists a pair (k*, p*) such that the distance between the models is maximised. For example, by means of a Monte Carlo simulation[6], we found that for $N = 10$ (20), $k^* = 4$ (6). Changing N but not k yields no notable difference between the models. An increase in the population size requires an increase in the number of individuals ‘in the darkness’ in order to improve social welfare. However, this value of k should not be too high since there is a clear trade-off between the welfare of the first k individuals and the welfare of the remaining n-k individuals (as figure 3 shows).

5. Experimental details

To test experimentally this theoretical prediction, we ran two treatments. The control one replicated the design by Bikhchandani et al. The experimental treatment imposed ‘darkness’ on the first k subjects as explained in the previous section. The experiment was programmed using the Z-tree software of Urs Fischbacher (1999) and was run at the laboratory of ESSE at the University of Bari.

Each treatment, lasting for about an hour, was made up of 22 periods, 2 of which were trial ones. The trial periods were necessary for subjects to become friendly with the treatment, allowing them to ask questions about the experiment’s instructions (available on request). The final payment was made on only the 20 real periods and paid at the end of each treatment.

In each session we had $N = 10$ subjects, sitting next to a PC terminal connected by a net. The subjects could not see each other or communicate. All of them were undergraduate students in Economics not familiar with previous similar experiments.

Subjects in the experiment were asked to decide whether to invest in a new product or not. In each period, lasting for about two minutes, subjects played sequentially in a randomly determined order (to prevent the same subjects to be always in the darkness). They were informed about their turn via a message on their PC screen. Subjects did not know whether the new product would be profitable or not. There were two equally likely events. If the product was successful ($V = 1$), they would gain 0.5€ in case of investment, and zero otherwise. If the product was not successful ($V = 0$), they would gain 0.5€ in case of non investment (the right decision), and zero otherwise. To exclude losses by participants, we did not consider the cost of adopting as Bikhchandani et al. did. In each period the true value of V was exogenously determined but not revealed to the subjects, who saw only a free-of-charge signal S (a sort of a result of a market survey) that had a probability $p = 0.75$ of being correct.

[6] The simulation (10 millions of iterations for each different value of k and for some different values of N) provided the percentages of being in a correct cascade given one’s position in the queue.

As to the values of the experimental parameters, we set $N = 10$ and $k^* = 4$. In every period of the control treatment, subjects were informed about: their own turn to play, all previous guesses, and their own signal. In the 'darkness' treatment, information about previous guesses was hidden to the first four subjects in the sequence. At the end of each period, subjects were informed about the true value of V, and their period-payoff. When all periods were played, the subjects were paid and could leave the laboratory. The experiment lasted about 40 minutes. Average earnings were 7€.

6. Results

Our experimental set-up allows us to investigate a) whether the hypothesised gain due to playing in the darkness is empirically supported, and b) whether individuals do herd.

The easiest way to test the first question is to compare the participants' average earnings under the two treatments. Table 1 shows that per-period average earnings are always greater in the darkness treatment than in the control one.[7]

	Monte Carlo earnings		Experimental earnings	
Position in the queue	Control	Darkness	Control	Darkness
1	0.3750	0.3750	0.2250	0.4250
2	0.3750	0.3750	0.2750	0.3250
3	0.3985	0.3750	0.3250	0.4250
4	0.3985	0.3750	0.2750	0.2500
5	0.4030	0.4480	0.2750	0.4250
6	0.4030	0.4480	0.2500	0.3750
7	0.4035	0.4530	0.3000	0.3750
8	0.4035	0.4530	0.3000	0.4000
9	0.4040	0.4540	0.3750	0.3750
10	0.4040	0.4540	0.3750	0.4000
SUM	3.9680	4.2100	2.9750	3.7750

Table 1. Theoretical and actual average earnings under the two treatments

[7] Note that the first four subjects in the darkness treatment play simultaneously. Hence, their order does not matter.

Figure 4 reports the winning frequencies for each position in the queue. Since the first four subjects in the darkness treatment played a simultaneous game, we average frequencies over the first four positions. If winning frequency is interpreted as winning probability, maximization of expected utility (regardless of its functional form) should yield the subjects to choose the action with the highest winning probability. The frequencies are never lower in the darkness treatment than in the control. Our experimental data suggest that playing in the darkness is preferable even from an individual point of view.

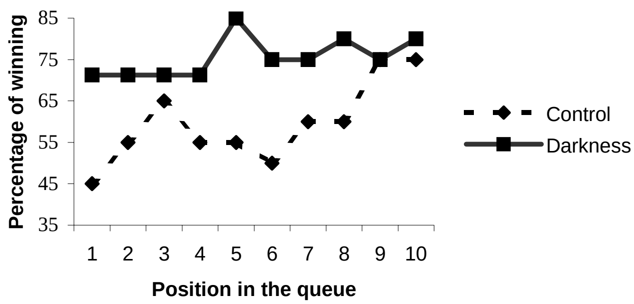

Figure 4. Percentages of winning under the two treatments

Now, we turn to analyse the occurrence of herding. First, we consider how many times an imbalance[8] between previous players' decision and private signal was observed, and how subjects solved this indifference problem. As regards the control treatment, we find that in 6 out of 20 imbalances individuals preferred to disregard their own signal. In contrast, in the darkness treatment, 9 out of 10 imbalances lead to herding. Consequently, we can deduce that, as compared to the former, the latter decisional mechanism of informational aggregation guides subjects towards more conformity. Nevertheless, in line with previous studies (cf., Anderson and Holt, 1997; Allsopp and Hey, 2000), we find that cascades are fragile.

Next, we compare the theoretical and actual probabilities not to have a herd, to have a correct herd, and to have a wrong herd for $N = 10$ and $p = 0.75$. The results are reported in Table 2. The theoretical probabilities are the numerical counterpart of the lines plotted in figure 3 when $k = 4$. They show, not surprisingly, that the probability of herding is almost the same in the two treatments, and that correct herding is more likely under darkness. The figures in the last

[8] We considered the cases in which the actions of the two immediately precedent individuals were against one's own signal. Moreover, for the case of the fifth individuals in the second treatment, we have considered the imbalance established between one's own signal and at least three same actions of the subjects 'in the darkness'.

two columns of the table are more interesting. In the experiment, either herding-type behaviour occurs more frequently if subjects play in the darkness.

	Monte Carlo Probabilities		Experimental Probabilities	
	Original Model	New Model	Control	Darkness
Prob. of no herd	0.00023	0.001390	0.5	0.25
Prob. of a correct herd	0.80751	0.907531	0.5	0.65
Prob. of a wrong herd	0.19226	0.091079	0	0.1

Table 2. Comparison between the probabilities when $p = 0.75$.

Finally, in figure 5 we analyze the learning process. For each treatment, we divided the 20 periods into 4 groups. Given the total number of deviations from the optimal strategy, we calculated the percentage of deviations in each single group.

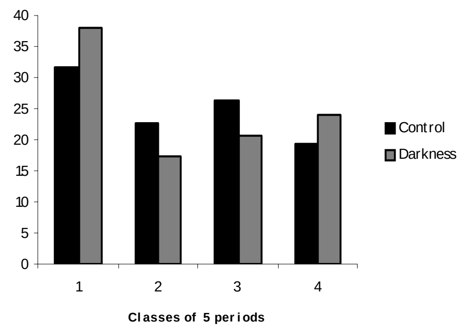

Figure 5. Percentages of deviant strategies in the single classes of periods relative to total deviations

In both treatments, though a third of the deviations are concentrated in the first 5 periods, the percentages are not monotonically decreasing over time. Consequentially, there is no marked learning process, but rather a tendency towards a minor percentage of decision errors.

7. Conclusions

Herd behaviour, as observed in a series of social and, more specifically, economic situations, is a clear failure of informational aggregation that results in a negative externality (i.e., herd externality). Thus, finding mechanisms to eliminate or, at least, mitigate this externality is important. In this paper, we investigated theoretically and experimentally the apparent paradox whereby burning a piece of information could turn to be a social improvement. The first *k* subjects have access only to one piece of private information. Our theoretical findings are clear: such a decisional mechanism leads to a more efficient outcome as compared to the standard model. The welfare gain of the last *N – k* subjects offsets the welfare loss of the first *k* subjects that play 'in the darkness'. Although this may open new challenging scenarios once applied to reality, our experimental findings are sometimes at odds with our theoretical predictions.

AKNOWLEDGMENTS

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Appendix

Our analysis was structured in several stages: first, probabilities in (1)-(12) were been derived varying each time the value of *k* of subjects in the darkness. Then, having noted some constant regularities, we were able to generalize the model for a general number of *k*.

Under the new specification of the model, the probabilities in (1)-(3) are the same and we decided to leave out them here. The probability in (5), i.e. the probability of NO-cascade after $n = 2m$ individuals, is simply the probability of observing the same number of the two types of signals. In our model it becomes, when *k* is an even number:

$$\frac{k!}{\left(\frac{k}{2}\right)!\left(\frac{k}{2}\right)!} p^m (1-p)^m \quad \text{(1.a);}$$

whereas, when *k* is an odd number:

$$\frac{1}{2}\left[\frac{(k+1)!}{\left(\frac{k+1}{2}\right)!\left(\frac{k+1}{2}\right)!}\right] p^m (1-p)^m \quad \text{(1.b).}$$

The probabilities of a White-cascade or a Black-cascade in (4) and (6) are not conditional on the chosen urn, so they have the same expression. For example, the probability of a White-cascade after six individuals is the probability of a White-cascade after two individuals plus the probability of not being in a cascade after two individual multiplied by the probability of a White-cascade after another two individuals plus the probability of not being in a cascade after another two individuals multiplied by the probability of a White-cascade after another two individuals. The probabilities put in such a calculation depend on the value of *k*. The probability of a White-cascade, after *k* individuals, when *k* is even:

$$\frac{1-\dfrac{k!}{\left(\frac{k}{2}\right)!\left(\frac{k}{2}\right)!}p^{\frac{k}{2}}(1-p)^{\frac{k}{2}}}{2} \quad (2.a);$$

when *k* is odd, after *k+1* individuals:

$$\frac{1-\dfrac{1}{2}\left[\dfrac{(k+1)!}{\left(\frac{k+1}{2}\right)!\left(\frac{k+1}{2}\right)!}\right]p^{\frac{k+1}{2}}(1-p)^{\frac{k+1}{2}}}{2} \quad (2.b).$$

Also the probability in (7)-(9) are the same than under the original model. Now, of greater importance it should be to consider in our model how the probability of ending up in a correct cascade in (10) after $n = 2m$ individuals becomes, when *k* is an even number:

$$[p+(1-p)]^k+\frac{k!}{\left(\frac{k}{2}\right)!\left(\frac{k}{2}\right)!}p^{\frac{k}{2}}(1-p)^{\frac{k}{2}}\frac{p(p+1)}{2}\left[\frac{1-\left(p-p^2\right)^{m-\frac{k}{2}}}{1-\left(p-p^2\right)}\right] \quad (3.a);$$

and when *k* is an odd one:

$$[p+(1-p)]^{k+1}+\frac{1}{2}\left[\frac{(k+1)!}{\left(\frac{k+1}{2}\right)!\left(\frac{k+1}{2}\right)!}\right]p^{\frac{k+1}{2}}(1-p)^{\frac{k+1}{2}}\frac{p(p+1)}{2}\left[\frac{1-\left(p-p^2\right)^{m-\frac{k+1}{2}}}{1-\left(p-p^2\right)}\right] \quad (3.b).$$

Finally, the probability of ending up in a wrong cascade in (12) after $n = 2m$ individuals, when *k* is an even number, under new model is:

$$[(1-p)+p]^k+\frac{k!}{\left(\frac{k}{2}\right)!\left(\frac{k}{2}\right)!}p^{\frac{k}{2}}(1-p)^{\frac{k}{2}}\frac{(p-2)(p-1)}{2}\left[\frac{1-\left(p-p^2\right)^{m-\frac{k}{2}}}{1-\left(p-p^2\right)}\right] \quad (4.a);$$

and when *k* is an odd number:

$$\left[(1-p)+p\right]^{k+1}+\frac{1}{2}\left[\frac{(k+1)!}{\left(\frac{k+1}{2}\right)!\left(\frac{k+1}{2}\right)!}\right]p^{\frac{k+1}{2}}(1-p)^{\frac{k+1}{2}}\frac{(p-2)(p-1)}{2}\left[\frac{1-\left(p-p^{2}\right)^{m-\frac{k+1}{2}}}{1-\left(p-p^{2}\right)}\right] \quad (4.b).$$

There are some points we have to clarify: in eq. (3.a), we have to work out the the *k*-th binomial power expansion in the first term until the *p* exponent is strictly greater than the *1-p* one, whereas in eq. (4.a) we have to work out the expansion until the *1-p* exponent is strictly greater than the *p* one. For example, in (4.a), if $k = 6$, we have to work out until *1-p* is raised to the fourth power and *p* to the second one.

Also in eq. (3.b) and (4.b) we have to follow a very similar rule as in (3.a) and (4.a): we have to work out the the *k+1*-th binomial power expansion in the first term until the two exponents are equal, but we have also to quarter the corresponding term.

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