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

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Abstract

Models of herd behaviour and informational cascades were theoretically developed in 1992 respectively by Banerjee (*A simple model of herd behavior*) and Bikhchandani, Hirshleifer and Welch (*A Theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades*). Both articles pointed out the existence of an information externality that causes a welfare loss, and both proposed the idea that destroying an amount of information may turn out in a social improvement. Although this is an old idea and in the last years many features of herd behaviour and informational cascades were studied, this particular aspect was never developed or extensively analysed. In this article we will try to investigate this hypothesis both theoretically and experimentally.

Keywords: Informational Cascades; Individual Decision Making; Experiments; Information Externality

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). This kind of behaviour takes place when agents can augment their information set by looking at other agents' behaviour. Although considered a rational behaviour, it could cause information externalities that result in an aggregate welfare loss (Becker, 1991). In this situation, 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.

Looking at the real world, we have abundant empirical evidence that herd behaviour could lead society 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 decides to follow an action that will eventually result to be incorrect. One obvious example is bubbles in financial markets (Plott, 2002; Hey and Morone 2004). More precisely, if there is a bubble in a market, subjects start to herd. In this case, a bubble is an example of a false run, as sooner or later it will burst.

In this paper we analyse a sequential herd behaviour model departing from Bikhchandani et al. (1992). Essentially our aim is to see if it is possible to avoid informational cascades forcing the first *k* subjects 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 capturated simply by not allowing the first n agents 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)*

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

Even if this idea, according to which destroying an amount of information may turn out in a social improvement, was already proposed, it was never 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 some experimental evidence in Section 3. Section 4 is devoted to the new model. The experimental design and results are introduced, respectively, in Sections 5 and 6. 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 information available to agents, the choices being made, 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). This paper is useful to show the intuition of herd behaviour as well as its strengths and weaknesses.

The basic idea of herd behaviour is very simple: if I have to choose between two unknown restaurants and I have no relevant information about them, I will infer that the best one is the most crowded one and I will join the queue. This behaviour seems rational, but the possibility that also the first customers have no pregnant information at their disposal is crucial.

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)*

Bikhchandani, Hirshleifer and Welch explored the concept of Informational Cascades. Their analysis is devoted not only to explain 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, and 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 developed a model based on Bikhchandani et al. in which some agents receive more accurate information. More precisely, those agents who have to decide immediately after the occurrence of a cascade can observe an additional private signal. They found this mechanism decreases the circumstances in which a cascade can be observed and it breaks off set up herds.

An informational cascade occurs when people prefer to ignore their own piece of information and follow instead what others are doing.

The game in question is a sequential one, with *N* players that have to choose between two options: white and black.

It is possible to understand the structure of the game by comparing it to a game in which we have two urns, urn B and urn W. In urn B there are two **B**lack balls and one white ball, in urn W there are two **W**hite balls and one black ball. One of the two urns is chosen randomly. Player 1 has to observe an extraction from the chosen urn and decide if that one is urn B or urn W. If his/her guess corresponds to the right urn his/her pay off is 1. Otherwise it is 0. Player 2 has to observe an extraction from the same chosen urn as well as player 1's action. He/she then has to choose his/her own action. Player 3 has to observe an extraction in addition to the actions of player 1 and player 2. He/she then has to choose his/her own action and so on. Under these conditions we have:

a. if player 1's signal is B, his/her best guess will be Black;
b. if player 1's signal is W, his/her best guess will be White.

Player 2 should be in one of the following situations:

1. he/she observes that player 1 has played black and his/her own signal is B;
2. he/she observes that player 1 has played black and his/her own signal is W;
3. he/she observes that player 1 has played white and his/her own signal is B;
4. he/she observes that player 1 has played white and his/her own signal is W.

In case (1) the best guess for player 2 is black; in case (2) player 2 will be indifferent between black and white. It is thus assumed that he/she will choose black or white with equal probability, in case (3) player 2 will be indifferent between black and white. It is assumed that she will randomise; in case (4) the best guess for player 2 is black.

Under these assumptions Bikhchandani, Hirshleifer and Welch calculated the unconditional *ex-ante* probabilities of a "White-cascade", "NO-cascade" and a "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 $n = 2m$:

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

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

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

note that the bigger is the probability p the sooner an information cascade will start (figure 1).

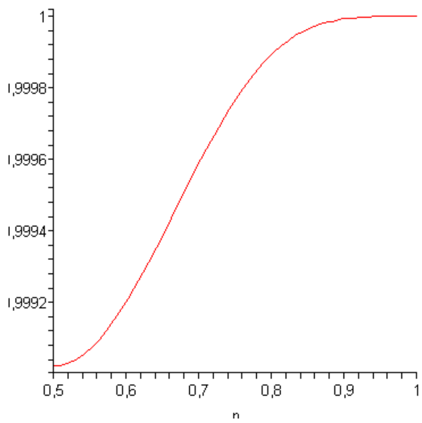

Figure 1: Probability of starting a cascade as a function of p, the correctness of the signal ($N = 10$)

They have also calculated the probability of ending up in the correct cascade after two players have played, given that the chosen urn is **W**hite:

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):

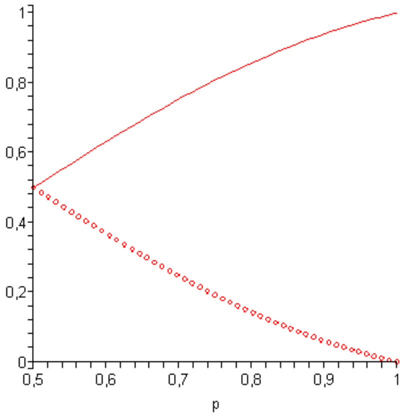

Figure 2: Probability of a correct (continuous line) and incorrect cascade (dotted line) as a function of *p*, the correctness of signal (N = 10)

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).

The first expression is the probability of the correct cascade. It can be shown that this probability is increasing in p and m. Even for very informative signals, the probability of the wrong cascade is remarkably high.

> *The problem with cascades is that they prevent the aggregation of information of numerous individuals. Ideally, if the information of many previous individuals is aggregated, later individuals should converge to the correct action. However, once a cascade has started, actions convey no information about private signals; thus an individual's action does not improve later decisions (Bikhchandani S., Hirshleifer, D., and Welch, I., 1992). (p. 998-999)*

3. Some experimental evidence

Lisa R. Anderson and Charles A. Holt (1997) carried out an experiment on Bikhchandani, Hirshleifer and Welch's model of informational cascades.

In their experiment, exactly as in the theory, students receive private information and have to make a forecast on an unknown event. Their forecasts are public (although the information on which it is based on is private) and they act sequentially. They report that cascades form in about 80% of the cases where the possibility arise. This would suggest a strong tendency to follow the crowd and ignore one's own information. This result provides strong evidence in support of the efficiency loss caused by herd behaviour and informational cascades. In the following paragraphs we will try to investigate if and how avoiding this information externalities is possible.

4. Playing in the darkness: a theoretical approach

Recently, Banerjee and Fudenberg (2004) noted that the inefficient herding of the standard models does not occur if some agents are forced to use their own private information.

Nevertheless, earlier literature did not provide any model able to capture this alteration of the basic models. Therefore, in order to fill this gap, we focused on the specific model developed by Bikhchandani et al. and explored if the assumption that inefficient herding does not occur if some agents are forced to use their own private information is backed by a theoretical model. Before presenting the new model, there are some points that are worth mentioning. First, when talking about 'destroying information', we refer to it in a very narrow sense. In fact, we only mean that the first individuals in the queue are not permitted to observe the decisions taken by others. Second, we make a comparison between the models only from a social point of view. We compare, aggregately, if and under which conditions the probability to make the "right thing" is higher. Obviously, in our model the individuals not allowed to observe the previous decisions are worse-off with respect to the case in which they are allowed to do so, as in the basic models. In this work, however, we leave out this aspect and focus only on the social welfare.

In their model, where all decision makers were allowed to observe the action pursued by their predecessors, Bikhchandani et al. (1992) derived the unconditional *ex ante* probability of a cascade and the *ex ante* probability of no cascade after an even number of individuals n. They also derived the probabilities of ending up in a correct cascade and ending up in a wrong one, as we showed in Section 2. We derive the same probabilities after making some major variations in their model (in Appendix).

To a large extent, we retain all the features of the original model. One of the most important features of this model concerns its direct application to a range of every-day situations. We have N individuals. Each of them has to decide if to adopt or reject a specific behaviour, for example, the use or not of a new technology. They make their choices in a sequential order. All of them know that they have to decide sequentially, but the order is exogenously determined. If they decide to adopt such behaviour, they will pay a cost of adopting, C, which is the same, independently of the subject and his/her place in the queue. Also the gain of adopting, V, is the same for all individuals and is either zero or one. These two events have the same *ex ante* probability to occur.

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

In our case, the major difference from Bikhchandani et al.'s model is that the first k individuals are not allowed to observe the decisions already taken by previous subjects, whereas beginning from the individual $k+1$ in the queue, subsequent individuals can observe the entire sequence, H, of decisions. We could think about it as a game of n stages where in the first k stages the first k individuals play a simultaneous game and in the remaining n-k stages the subjects play a sequential game in which the entire history H become common knowledge.

It is obvious that for the first k individuals, as they can observe only their signals, it would be rational to follow their private information: they will choose to adopt when the signal is 1, and to reject otherwise. Beginning from the subject $k+1$, as showed by Anderson and Holt (1997)[2], each individual should consider which of the two options to follow, basing his/her decision on the actions chosen by all previous subjects and his/her private signal; this means that he/she will choose the action played by the majority of subjects. When a subject is indifferent between the two actions, we assume he/she uses a tie-breaking rule. More precisely we assume that they adopt or reject with equal probability. In other words, when k is an even number, the subject k+1 in the queue will face one of the following two situations: (1.1) if H is made up of a number of adoptions (or rejections) greater than k/2: independently of his/her signal, he/she will decide to adopt (or to reject), starting a herd; (1.2) if H is made up of the

[2] More precisely, Anderson and Holt have showed that the optimal strategy in the Bayesian sense in the cases in which the two events are equally probable and the signals are identically distributed corresponds to the very simple strategy of doing the count of the previous decisions.

same number of adoptions and rejections, the subject will follow his/her signal and the herd will be formed in the next stage. When k is an odd number, the subject in the place k+1 in the queue will face one of the three following situations: (2.1) if H is made up of number of adoptions (or rejections) greater than (k+1)/2: independently of his/her signal, he/she will decide to adopt (or reject). In this case a herd will be formed; (2.2) if his/her signal is in accordance with the decision in H with the higher frequency, but still smaller than (k+1)/2, his/her signal will determine her choice. In this case the herd will be formed in the next stage; (2.3) when the entire history H, summed up to the signal, leads to a misleading situation in which the subject is indifferent, he/she will use the tie-breaking rule described above and the herd will be formed by the next subject.

In our model it is as if the subjects, beginning from the place $k+1$, have an advantage of additional signals: the actions of the first k decision makers. In this manner, we predict a more efficient final result as the society, in this case, has a mechanism that allows to aggregate the information in a more correct way in a successive stage. It is as if the subjects made a more conscious choice when they decide to herd: they can calculate in a more appropriate way the probabilities assigned to the two events, according to the signals that are subjected to specific statistical laws and not only according to the actions that are also influenced by a great range of factors and biases.

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. We show how these were being derived in the Appendix. In this section, we focus only on the comparison between the probabilities. However, we can definitely assert that under our assumption there is a greater probability of no herding and that this probability is growing with k: the greater is the number of individuals 'in the darkness', the higher the probability of no herding is. In this way, the probability of achieving a final inefficient outcome decreases. The following statement, thus, becomes quite obvious: the more efficient a decisional mechanism is, the greater the probability of a correct herd will be observed (or, equally, a smaller probability of a wrong herd), as more individuals, in the aggregate, will choose the correct option.

In figure 3 we have, on the horizontal axis, the probability p of the correctness of the signals and, on the vertical axis, the probability of a correct herd, changing each time the value of k, i.e. the subjects in the darkness, with N = 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 (the dotted curves represent the original model), confirming our hypothesis. Moreover, for every value of k, there is a probability p^* under which the difference between the two models is maximised.

There is also a value of k such that the difference between the two models is maximized, for every value of N. For example, we found, by means of a Monte Carlo simulation[3], that when the population is constituted of $N = 10(20)$ individuals the optimal value of k equals 4(6). Indeed, when we made the graphs (available upon request from the authors), changing each time the size of population N without varying k, there was no notable difference between the situations. Naturally, when the population grows, a greater number of individuals have to be 'in the darkness' in order to allow an improvement from a social point of view. However, this value of k could not be too high, as it will cause deterioration in the situation of the first k individuals, which could not be offset by the improvement in the situation of the n-k subjects follow them (as figure 3 shows).

[3] The simulation provided the percentages of winning for each position in the queue and consisted of 10 millions iterations for each different value of k for some different values of N. To have a measure for the social welfare, we first considered the single percentage of winning as an indicator for individual utility and then summed them up on the entire population.

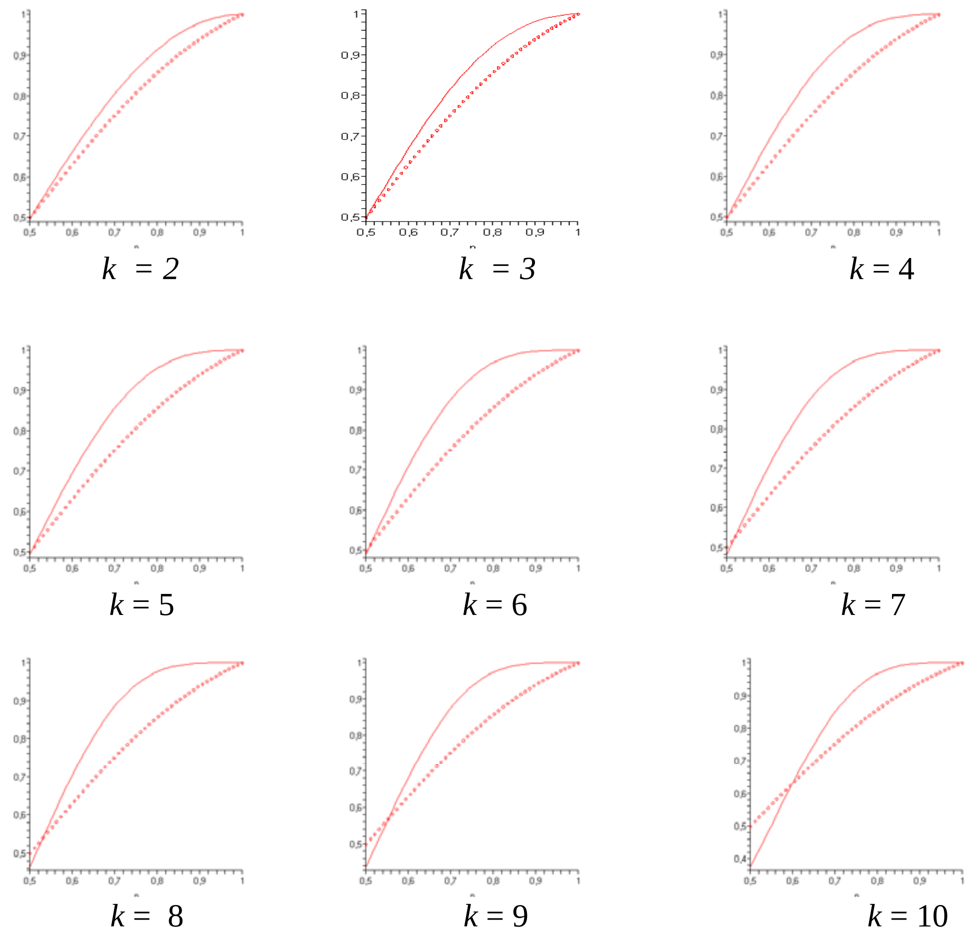

Figure 3: Comparison between the probabilities of a correct herd under the two models when $N = 10$ and for different values of k

5. Experimental details

The next stage of our work was the experimental test of this theoretical prediction. In order to achieve this objective we ran two experimental treatments: in the first we have set the experimental design in accordance with the original model by Bikhchandani et al. where all the subjects were allowed to observe the previous decisions. In the second treatment the first k subjects were forced to play using exclusively their private information. In this way we were able to test the new model by means of comparison with the old one. The experiment was programmed using the Z-tree software of Urs Fischbacher (2002) 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 periods, and 20 real periods. 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). However, 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.

The experiment consisted in a simulation of an investment decision taken by a firm regarding the development (or not) of a new product. In each period, lasting for about two minutes, all the subjects had to take the same decisions sequentially, but the order in which they had to do it was randomly determined and differentiated each time by the programme (to prevent a situation where always the same subjects were in the darkness). Subjects were informed about their turn to play by means of a message on their PC screen. Subjects did not know whether this product would be profitable or not once on the market. There were two equally likely events, the same for each participant: either the product will be successful ($V = 1$), and in this case they will gain 0.5€ - if they had decided to invest - or zero otherwise, or the product will be not successful ($V = 0$), meaning that the right decision - to which was associated a gain of 0.5€ and zero otherwise - could be not developed. We have slightly modified the model by Bikhchandani et al., not considering the cost of adopting C to avoid that the participants at the experiment suffered real losses, also because they had no starting endowment. For each period the programme established the true value of V but did not reveal it to the subjects. Each of them, however, received on her own screen a free-of-charge signal S (a sort of a result of a market survey) informative at $p = 0.75$ about the true value of V. We have already seen that for every value of p, strictly between 0.5 and 1, for $k <= 6$, our model shows a better performance than the original one. These signals took either the value 1 or the value 0 and the subjects knew the value of p. More precisely, we combined these probabilities as shown in Table 1.

In order to choose the experimental parameters, we ran a Monte Carlo simulation that has shown the optimal k, which maximises the social welfare given $N = 10$, is set equal to 4. Consequently, all the subjects in the first treatment as well as the subjects beginning from the fifth position in the second one observed all the actions taken before their own turn to play. Indeed, the screen displayed the following information at all times, in the following order: one’s own turn to play; the position in the queue; where allowed, the decision made by others; and one’s own signal. It was as if, beginning from the fifth player in the second treatment, subjects had five signals (if all the players before her had decided to play rationally, in accordance with their signals). Hiding information for a short time from the subjects, i.e. where the first subjects had to take their decision based only on their own information, may turn out to be a social improvement for a larger number of individuals at the expense of the smaller number of subjects who had to play in the first phase of the game.

	Prob (S=0|V)	Prob (S=1|V)
V=0	0.75	0.25
V=1	0.25	0.75

Table 1: Probabilities associated with signals

At the end of each period, subjects were informed about the right option and about their winning. When all the periods were played, the subjects were paid (given the experimental design, the maximum amount perceived in both treatments could be 10€), and free to leave the laboratory.

6. Results

By running these experiments, there are two main targets we tried to achieve: a) testing if under our theoretical prediction the outcome is socially more efficient also in empirical terms; b) testing to what extent individuals conform to the behaviour of other agents, disregarding their own information, giving us hence the possibility to observe the formation of herds.

The first and the easiest way to test the first question could be achieved comparing the average earnings made by the participants under the two treatments. Indeed, a higher average of earning corresponds to a higher number of times in which the participants have chosen the right option. Given our definition of social efficiency in this work, this result confirms that under our model there is an improvement in social welfare. Particularly interesting is the comparison between the *ex-ante* earnings, as revealed by our Monte Carlo simulation where we have calculated the chances of winning for each position in the queue, and the *ex-post* earnings, namely the actual rewards to the participants during the experiment. These results are shown in Table 2. It is clear that for every position in the decisional queue, the greater average earnings are under treatment 2, both theoretically and empirically. We have not considered as exceptions the lower average earnings assigned to participants holding the third and fourth positions in the queue because the framework itself of the new model suggests us these individuals had worsened their situation passing from the first to the second decisional mechanism. However, also the aggregate average earnings offer a similar pattern, because the worsening in the first positions is offset by a substantial improvement in the later ones.

	Ex-ante earnings		Ex-post earnings	
Position in the queue	Treatment 1	Treatment 2	Treatment 1	Treatment 2
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 2: Theoretical and actual average earnings under the two treatments

We calculated the expected earnings, given the actual signals sequences in the two treatments, and if all participants had adopted the decision in accordance with the rational rules explained

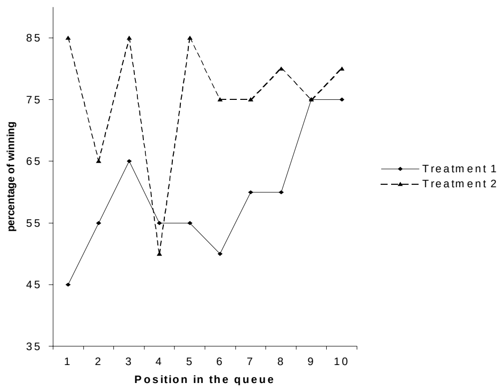

Figure 4: Percentages of winning under the two treatments

in Section 4. If all subjects had behaved in the rational way, the expected total earning under treatment 2 should have been more than 21%, greater than under treatment 1. This is yet another evidence confirming our theory, considering that we can measure the social welfare with a monetary value. Going on with the examination of our experimental data, in figure 4 we report the percentages of winning, depending on the positions held in the decisional queue. Except for the fourth subject in the second treatment, whose case was already explained, under the treatment which produced the new model the percentage is always higher than, or at the most the same as, under the treatment that reproduced the original model. If we consider the percentage of winning as an indication for the individual utility, we may state that the new decisional mechanism is preferable from a social and even from an individual point of view, at least looking at the experimental data.

Now, we turn back to the second purpose of the experiment, which is the empirical evidence of herd behaviour. First, we have considered how many times an imbalance[4] was established between the decisions made by others and an individual's own signal (the typical event in which a cascade could be established) and how the subjects have acted in these cases. We found that in the first treatment there were 20 imbalances but only in 6 cases the individuals have preferred to disregard their own signal (with a percentage of 30%), whereas in the second treatment there were 10 imbalances and even 9 herds (with a percentage of 90%). Consequently, we can deduce that the second decisional mechanism of informational aggregation offers a larger 'psychological' inducement to herd with respect to the first. In this case the subjects have behaved as if the proposed aggregation of information gave them more confidence in the others' decisions, leading to a result conflicting with the theory. Moreover, our experiment has also shown us the 'frailty' of behaviours of this type: also after a rather long herd some individuals have shattered a cascade, cutting a herd off. Now, we compare the theoretical and actual probabilities to not have a herd, to have a correct herd and a wrong herd after N = 10 individuals and for p = 0.75 under the two models. The results we found are summed up in Table 3. The theoretical probabilities are the numerical counterpart of the lines plotted in figure 3 when p = 0.75 and k = 4 and are what we could have anticipated, whereas the actual percentages are indicative of a greater number of occurrences of a herd and of a wrong herd, in opposition with the theory, mitigated by the greater probability of a correct herd, as theory suggests. Two are the possible explanations in support of this: the game was not repeated for enough times, even if it is comparable with the repetitions in other similar experiments; any psychological aspects which could have caused such a behaviour are left out.

	Theoretical Probabilities		Actual Probabilities	
	Original Model	New Model	Treatment 1	Treatment 2
Prob. of no herd	0.0002317	0.00139046(+)	0.5	0.25(-)
Prob. of a correct herd	0.8075051	0.90753078(+)	0.5	0.65(+)
Prob. of a wrong herd	0.1922631	0.09107876(-)	0	0.1(+)

Table 3: Comparison between the probabilities when p = 0.75. In brackets the increase or decrease relative to the original model

Actually, these models are based on the assumption that individuals behave rationally and use Bayes' rule. From the behavioural economics we know instead how human rationality and judgement could be bounded by a certain amount of biases. Actually, even if it seems that in 75% of times the subjects followed the rules explained above, in as high as 15.2% of the times individuals inexplicably failed to make use of the very simple rule to follow their own signal. These conclusions could lead to a better comprehension of human behaviour if economic and psychological aspects could be weigh up wisely in future research.

Finally, the learning process during the experiments is worth mentioning and of some interest. For this purpose, we split the 20 periods in which each treatment consisted of in 4 groups. Then we counted the number of deviations from the optimal strategy in each group relative to the number of the total deviations in each treatment. The findings are presented in figure 5.

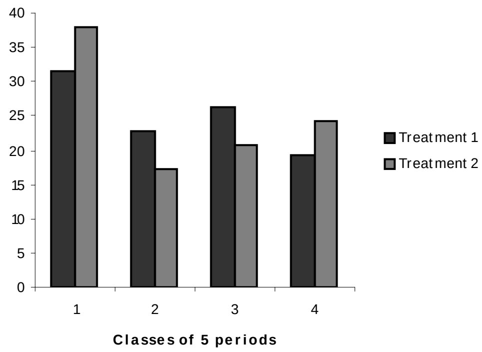

Figure 5: Percentages of deviant strategies in the single classes of periods relative to total deviations

In both of cases, about a third of the deviations were concentrated in the first part of the game, but this percentage of errors is not monotonically decreasing in the course of each treatment. Consequentially, there was no marked learning process by the individuals, but rather a tendency towards a minor percentage of errors.

7. Conclusions

The concern about herd behaviour, observable in a series of social and, more specifically, economic situations, is that it constitutes a negative externality, inflicted on the rest of the population caused by the disregarding of one's own information and an incorrect mechanism of informational aggregation. It thus becomes useful and interesting finding what mechanisms

[4] We have 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 dark'

could be used to eliminate or at least minimise this externality. The paradox whereby burning a piece of information could turn to be a social improvement was worth investigating deeper. This was our task in this paper, achieved through a laboratory experiment, by not allowing some individuals to observe others' actions in a sequence of decisions. Theoretical findings are clear: such a decisional mechanism leads to an informational aggregation in the successive stages able to offset the worsening in the situation of the subjects in the darkness. This could open new challenging scenarios once applied to reality. However, having in mind these theoretical results, the empirical data are rather misleading.

Future lines of research should be laid to incorporate some behavioural devices in these models able to capture the biases in the decisional rules used by the subjects.

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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 the 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 have 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:

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

whereas, when *k* is an odd number:

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

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:

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

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

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

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:

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

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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