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A Simple Note on Informational Cascades

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Abstract:

Seminal models of herd behaviour and informational cascades point out existence of negative information 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 try to fill this gap, investigating both theoretically and experimentally whether and to which extent destroying information can improve welfare. Our empirical results show that this decisional mechanism actually leads to a behaviour more consistent with the theory that in turn produces the predicted efficiency gain.

JEL: *C91; D62*

Keywords: *Informational cascades; information externality; individual decision making; experiment*

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1 Introduction

Part of social learning is related to an apparently naive behaviour known as *herd behaviour* (Banerjee, 1992) or *informational cascades* (Bikhchandani, Hirshleifer, and Welch, 1992 – BHW, henceforth). Peculiarity of these models, however, is that they view agents' imitative behaviour as perfectly rational, even though characterized by imperfect information.

This behaviour takes place when agents can augment their information set by looking at other agents' behaviour. Although rational, it could cause information externalities that result in an aggregate welfare loss (Becker, 1991). In this situation, the individual rational behaviour may well result in a non-optimal strategy from an aggregate point of view.

Looking at the real world, we have abundant empirical evidence for informational cascades. Actually, one of the most attractive features of these kinds of models concerns their direct application to a range of every-day situations. Just to cite an example, we can refer to bubbles in financial markets (Plott, 2002).

The idea underlying these models is simple. Consider the case in which I have to choose between two unknown restaurants and I have no relevant information about them. However, I can infer that the most crowded is the best and I will choose to join the queue. This behaviour is rational, but the possibility that first customers have no pregnant information as well is crucial.

BHW point out the conformity of followers in a cascade contains no informational value (p. 998-999), and this argument has been demonstrated by some empirical evidence (Anderson and Holt, 1997; Allsopp and Hey, 2000).

Aim of this paper is investigating the possibility to mitigate informational cascades' negative effects forcing the first k subjects in a queue to play only according to their private information. For this purpose, we analyse a sequential model departing from BHW's model in some relevant parts and then we experimentally investigate if "*society may actually be better off by constraining some of the people to use only their own information*" (Banerjee, 1992; p. 798).

The paper is structured as follows. Section 2 is devoted to the new specification of the standard model. The experimental design and results are introduced, respectively, in Sections 3 and 4. Section 5 concludes.

2 Theory

In addition to the seminal papers on herd behaviour and informational cascades (Banerjee, 1992; Bikhchandani et al., 1992), even more recently a paper on word-of-mouth learning (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. Nevertheless, earlier literature did not provide any model capturing this feature. Therefore, in order to fill this gap, we develop a new specification departing from the standard model as advanced in BHW. We retain the main features of the original model. We have a population of $I = \{1, \ldots, N\}$ individuals. Each individual $i \in N$ has to decide whether to adopt or not a specific behaviour, for example, the adoption or not of a new technology. All individuals make their choices in a sequential and exogenously determined order. The gain of adopting, V, is the same for all $i \in N$ and is either zero or one. These two events have the same *ex-ante* probability to occur.

However, each individual i privately observes a conditionally i.i.d. signal about V. This signal s is either 0 or 1: 1 is observed with probability $p > ½$ if the true value is 1, and with probability $1-p$ otherwise.

Under our specification, the first k ($< N$) individuals in the queue are not allowed to observe the decisions already taken, whereas the entire history of decisions is commonly known to the last N-k individuals. We can think of this game as of 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[†]. 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.

In our specification it is as if individual i, with $i = k+1$, …, N has an advantage of additional signals. In this manner, we therefore expect our specification to lead to a more socially efficient final outcome, as the society has a mechanism that allows to aggregate the information in a later stage and in a more correct way.

[†] More precisely, Anderson and Holt (1997) show that the optimal strategy in a Bayesian sense whenever the two events are equally probable and signals identically distributed corresponds to the very simple strategy of doing the count of the previous decisions, one's own signal included.

In their model, where all decision makers are allowed to observe their predecessors' action, BHW derive 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 derive the probabilities of ending up in a correct cascade and ending up in a wrong one. We derive the same probabilities after having taken in consideration the fact that the first k players acting only based on their own signal s. We show our main results in the Appendix. At this point, however, it may be more illustrative to compare probabilities of ending up in a correct cascade (to a some extent, it can be consider as an index of efficiency) under the two specifications for some different parameter values (k, number of players observing only their own signal; p, probability of signal correctness; n, number of players having made their choice after which the probability is assessed). Figures are shown in Table 1.

Table 1 Probability of a correct cascade: Comparative static analysis and comparison between models[‡]

***P* = .75 – *n* = 100**	(*k* = 10)	(*k* = 56)	(*k* = 98)
BHW	.8077	.8077	.8077
Our specification	.9690	.9999	.9999

(*k* = 6) - *p* = .75	*n* = 10	*n* = 100	*n* = 1000
BHW	.8075	.8077	.8077
Our specification	.9333	.9370	.9370

(*k* = 56) – *n* = 100	*p* = .55	*p* = .85	*p* = .99
BHW	.5664	.9011	.9949
Our specification	.7778	.9999	1.000

At a first glance, it is evident that probability of ending up in a correct cascade is higher under our specification throughout. Entering into details, we can point out that as *k* increases (top panel), probability of a correct cascade becomes not statistically different from 1, whereas under the standard model the probability is quite high, but never reaches this level. Other results are more obvious, in the sense

[‡] In the first row different parameter values at which probabilities are computed. In boldface, parameters held constant for each comparative static exercise. Different values of *k* in parentheses since relevant only to our model.

that probability of a correct cascade is monotonically increasing in the number of subjects that have already made a decision (n, middle panel) and in the signal correctness (p, bottom panel) under both the two specifications, but nevertheless always higher under ours.

Probably it may be interesting to combine results regarding the effect of changes in signal correctness and number of subjects that act with no clue regarding previous decisions. We perform these comparative static exercises varying simultaneously p and k, while keeping N - the number of individuals in the population – constant. Consequently, we have the opportunity to note that for each value of k there is a probability p^* under which the difference between the two specifications is maximised. The converse is also true.

3 Experimental design

In order to test empirically whether the new specification of the model allows to achieve a social improvement, we ran two computerized treatments at the laboratory of ESSE at the University of Bari. The control treatment was set in accordance with the original model (T1, henceforth), whereas in the second treatment we test the new specification, with the first $k = 4$ subjects forced to play basing their decision exclusively on their private information[§] (T2, henceforth).

The experiment was programmed using the Z-tree software (Fischbacher, 1999). Each treatment lasting for about an hour was made up of 22 periods, of which 2 were trial ones. The trial periods were necessary for subjects to become friendly with the experiment, providing them also the opportunity to ask questions about the instructions (available on request). The final payment was made on only the 20 real periods and paid at the end of each treatment.

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

In the experiment, subjects acted as entrepreneurs and their task was to decide to invest in a new product or not. The order in which they chose sequentially was randomly determined period by period[**].

[§] As we noted above, there is an optimal value for k^* for each parameter combination. We determined the optimal k^* with a Monte Carlo simulation. This simulation provided the winning percentages for each position in the queue, provided that we consider the individual winning percentage as a proxy for individual utility. The simulation consisted of 10 millions iterations for each different value of k, setting N and p at 10 and .75, respectively. We get a measure for social welfare summing up individual winning percentages over the entire population, and we picked the case in which this indicator was at its maximum.

However, subjects did not know whether this product would be profitable or not once on the market. Whenever they made the right decision, they gained 0.5€, and zero otherwise[††]. For each period the programme established the true value of V but did not reveal it to subjects. Each of them, however, received a free-of-charge signal s about V (a sort of a result of a market survey). These signals took either the value 1 or the value 0 and the signal correctness (p = .75) was common knowledge. The screen displayed these details: one's own turn to play; the position in the queue; where allowed, the decision made by predecessors; and one's own signal. At the end of each period, subjects were informed about the right option and their payoff. When all periods were played, subjects were paid and free to leave the laboratory. Average payoff was 6.75€.

4 Results

We start this section showing some data at individual level. In each position, taking into account predecessors' decisions and the signal realization, we determine which action should be chosen according to the theory. Consequently, we categorize as

[**] They were informed about their turn via a message on their PC screen.

[††] More precisely, 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 no investment (the right decision in this scenario), and zero otherwise.

rational behaviours in accordance with it (in our simple set-up, the optimal strategy in a Bayesian sense corresponds to the count, as explained in footnote 1) and whenever subjects adopted the tie breaking rule if indifferent, regardless of the fact that it produces a cascade or not. At the individual level, we classify as cascade the case where "an imbalance of previous inferred signals causes a person's optimal decision to be inconsistent with his or her private signal" (Anderson and Holt, 1997; p. 851). As regards behaviours categorized as irrational, namely, inconsistent with the theory, we discriminate the case in which it can be rationalized somehow – following her own signal – from the case it cannot be explained whatsoever. Results in Table 2.

Table 2 Summary of behaviours observed in the experiment (individual level)

	rational			irrational	
		whose cascade		not	signal-
		correct	wrong	rationalized	keeping
T1	146	4	16	33	21
T2	171	12	8	24	5

From the table it can be clearly noted that the new specification may be effective in driving a more consistent behaviour (73% in T1 vs. 85.5% in T2).

However, though lower, among the occurrence of irrational behaviours in T2 the percentage of behaviour that cannot be explained in any case is higher than in T1 (61.1% in T1 vs. 82.7% in T2). Moreover, it interesting that while observing the same occurrence of cascade behaviour under the two treatments (20 in each), the percentage of a correct cascade is up to three times higher in T2. Finally, we observe that cascade behaviour is rather fragile (individuals do not choose to conform to the mass, still when their all predecessors made the same choice), and that often they also choose to play against their own signal, especially when they are the first in the queue.

At this point, in order to test our hypothesis, namely that under the new specification of the model the outcome is socially more efficient, we compare the average earnings under two treatments. Particularly interesting is the comparison between the *ex-ante* earnings, as it would have been if all individuals behaved according to the theory, given the actual signal realization during the experiment, and the *ex-post* earnings, the actual payoffs obtained by participants during the experiment. Results in Table 3.

Table 3 Average earnings for each position and for each treatment

Position in the queue	*Ex-ante* earnings		*Ex-post* earnings	
	T1	T2	T1	T2
1	0.225	0.4	0.225	0.425
2	0.325	0.35	0.275	0.325
3	0.3125	0.475	0.325	0.425
4	0.33125	0.375	0.275	0.25
5	0.34375	0.4	0.275	0.425
6	0.34375	0.4125	0.25	0.375
7	0.34375	0.4125	0.3	0.375
8	0.34375	0.40625	0.3	0.4
9	0.34375	0.425	0.375	0.375
10	0.34375	0.425	0.375	0.4
TOTAL	**3.25625**	**4.08125**	**2.975**	**3.775**

First, we note a statistically significant difference between the two treatments (Wilcoxon rank-sum test for *ex-ante* earnings: -3.835, *p-value* = .0001; for *ex-post* earnings: -3.755, *p-value* = .0059). Interestingly, each experimental treatment is not statistically different from its theoretical counterpart (Wilcoxon rank-sum test for BHW and T1: 1.614, *p-value* = .1066; for our specification and T2: 1.190, *p-value* = .2340). Second, for each position in the queue, we observe always higher average earnings under T2[‡‡].

[‡‡] The lower average payoff for the fourth position cannot be considered as an exception. Indeed, under our specification the first k (except for the first) individuals observe their situation worsened

In order to give an additional insight into the social efficiency gain, we can consider the percentage of winning as a useful proxy for individual utility, and then compare this index under the two treatments. In figure 1 we report the index for each different position held in the decisional queue.

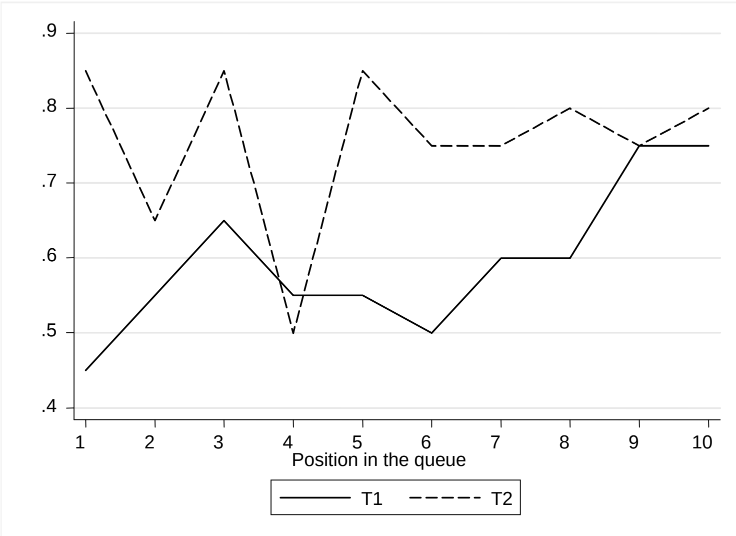

Figure 1 Percentages of winning

Except for the fourth subject in the second treatment (see footnote 6), under the second treatment the percentage is always higher than, or at the most the same as,

passing from the first to the second treatment, even if the deterioration of their situation is more than offset by the improving of the remaining *N-k* individuals, for an appropriate choice of the value *k*.

under the first treatment. Looking at the graph, we may state that the new decisional mechanism is preferable from a social and even individual point of view.

4.1 Econometric analysis

Finally, we estimate a very simple learning model. Specifically, we constructed a model that links decisions in the experiment to a set of determinants, as follows. Firstly, the presence of learning is investigated by the use of the variable *Time* (the period number) and the variable $Time^2$, to test for concavity of learning. Moreover, in order to gain further insight, we test for the presence of directional learning (or Cournot behaviour; Selten and Buchta, 1998) by using the *Correctwon* variable (a dummy variable equal to 1 if in the most recent period the subject made the theoretically correct decision and won) and *Correctlost* variable (a dummy variable equal to 1 if in the most recent period the subject made the theoretically correct decision and lost). Our dependent variable, *Correct*, is a dummy variable equal to 1 whenever subjects make the decision consistent with the theory, 0 otherwise. Consequently, we run a probit estimation procedure. Results in Table 4.

Table 4 Maximum Likelihood probit estimation[§§]

Dep. Variable: Correct	Marginal Effect	Std. Error	p-value
Time	.02199	.01628	0.177
Time^2	-.00084	.00075	0.264
Correctwon	-.13474	.05139	0.011
Correctlost	-.22575	.08449	0.004
T2	.15977	.04393	0.000
Log likelihood	-217.271		
Pseudo R^2	0.0478		
NOBs	400		

We note no trend in observing a more consistent decisions over time (in fact, *Time* is not statistically significant), consequently, concavity for learning is not statistically significant, either. Even directional learning is not a firm determinant of learning. Indeed, even if both *Correctwon* and *Correctlost* are significant, nevertheless *Correctwon* does not present the correct direction (positive sign) in our analysis. In fact, we expect probability of making the correct decision increasing if in the previous period subject made correct decision and won.

[§§] Note that the reported significance levels assume independent observations, though this is unlikely to be the case.

Interestingly, on the other hand, the dummy variable for the treatment T2: the decisional mechanism implemented in this treatment is actually effective in increasing probability of making the correct decision by 16%.

5 Conclusions

Negative informational externality produced by phenomenon of informational cascade has attracted concern in economic literature. Consequently, it may be of a some interest to find mechanisms useful in eliminating or at least in minimising this externality. The paradox whereby burning a piece of information in a first stage of the sequential decisional process could turn to be a social improvement in a later stage was indeed worth investigating. This was our task. Our empirical results show that this decisional mechanism actually leads to a behaviour more consistent with the theory that in turn produces a social improvement. If supported by further analyses – aimed, for example, to design an implementable self-enforcing mechanism - our result may open new challenging scenarios once applied to reality.

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Appendix

Our analysis was structured in several stages: first, probabilities were derived varying each time the value of k – number of individuals acting with no clue regarding previous actions. Then, since constant regularities were present, we were able to generalize the model for any k.

The probability of NO-cascade after $n = 2m$ individuals is simply the probability of observing the same number of the two kinds of signals, $s = 0$ and $s = 1$. In our specification it becomes, whenever k is an even number:

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

(1.a)

whereas, whenever k is odd:

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

(1.b)

At this point it is of greater importance to consider how the probability of ending up in a correct cascade after $n = 2m$ individuals becomes, whenever k is an even number:

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

(2.a)

and whenever k is odd:

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

(2.b)

Finally, consider the probability of ending up in a wrong cascade after n = 2m individuals, whenever k is an even number:

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

(3.a)

and whenever k is odd:

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

There are some points we have to clarify: in eq. (2.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. (3.a) we have to work out the expansion until the *1-p* exponent is strictly greater than the *p* one. For example, in (3.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. (2.b) and (3.b) we have to follow a very similar rule as in (2.a) and (3.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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