



‘Herd’ Behavior and the Bull Whip Effect: Information Access, or Risks and Rewards?

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ABSTRACT

“Information cascades” occur in sequential decision-making process, where the second person who ignores their own information in favor of going along with the decision of the first person could induce others to follow, sometimes even when those earlier decision-makers are misinformed. Suppliers and retailers have observed in recent years that minor variations in customer demand may cause widespread gyrations – the bullwhip effect - in inventory levels and back-orders, which increase in magnitude as the (mis)information is transmitted across the supply chain. Traditionally, the problem has been defined as information-based and has been addressed by providing increased visibility across the supply chain, at best a partial remedy. Given that for most firms the sales and marketing department is the nexus of the organization, one possible explanation for the bullwhip effect could lie in the risk-sharing and payoff policies of supply chain players.

This paper presents the theoretical basis for an experiment that tests the effect of the prevailing reward system on the frequency information cascades. Proof of the main hypothesis would imply that more equitable sharing of risks and payoff in supply chain alliances can actually reduce the impact of the bullwhip effect, a new perspective on the phenomenon.

1. THE BULLWHIP EFFECT

In a sequential supply chain decision-making process, small variations in consumer demand have been observed to cause increasingly larger gyrations in inventory and back-order levels as the information is relayed backwards across the supply chain, away from the retailer. This phenomenon, the “bullwhip effect” is believed to be the result of one of four supply chain related causes (Lee, Padmanabhan and Whang, 1997):

- (i) *Demand signal processing*: where a retailer incorrectly interprets a temporary surge in one period as a signal of an increase in future demand;
- (ii) *Response to rationing*: where in the case of rationed supplies, the retail may pad orders to ensure additional safety stock as a buffer against possibility stock-outs;
- (iii) *Order batching*: demand distortion that can result either from the periodic review process, or the processing cost of a purchase transaction, where the retailer could order an amount up to the volume of the previous cycle’s demand; and
- (iv) *Price fluctuations*: in instances where a retailer faces independent and identically distributed demand in each period, this could generate the bullwhip effect.

Mitigation measures focus on greater visibility for supply chain members, calling for more transparent data sharing (Lee, Padmanabhan and Whang, 1997; Eleni and Ilias, 2005; Wang, Jai and Takahashi, 2005). Some researchers are not as optimistic re this solution (Dejonckheere, Disney, Lambrecht and Towill, 2004). Firstly, most supply chain *success* stories are at best anecdotal (Bechtel and Jayaram, 1997), and given the predominance of the sales and marketing functions of the firm and the preponderant concern with sales maximization, firms may be easily enticed into abandon common supply-chain efficiency objectives in favor of more selfish gains. Supply chain management entails three distinct component processes: first, planning involves sophisticated demand forecasting that guide sourcing, manufacturing and operations. Next, these high level strategic plans are translated into tactical level action plans at the execution and transactional levels of the organizations, allowing for some degree of interpretation and modification which could initiate the “cascades” identified in supply chains as “the bullwhip effect.” The lure of the possibility of increased sales may lead to defection by any supply chain member, choosing instead to pursue individual goals that bear the prospect of higher rewards (Reddy 2001). As information regarding this act of defection travels further up the supply chain amended forecasts become more and more exaggerated and the bullwhip effect takes shape.

Banerjee’s “herd-behavior” model (1992) refers to the associated decision-action of following the majority, where subjects choose to ignore their own information even when it may be correct, in favor of following others’ lead, sometimes even when those others are misinformed. In a *sequential* decision-making process, the decision of the second person to ignore their own information in favor of going along with the decision of the first could induce the rest of the chain to go along with the popular decision, resulting in an “information cascade.” Subsequent researchers (Anderson and Holt, 1997) have claimed that their laboratory findings supported Banerjee’s conclusions, while yet others have proposed alternate explanations. This paper proposes yet another possible explanation: given that both “herd-member” and first-mover strategies are valid and rational strategies, one possible explanation could lie in the reward policies used in these laboratory experiments. Subjects may be simply reacting according to the underlying system of risk and rewards of the options they face.

Next follows a brief explanation of Bayesian rule and how they relate to the concept of information cascades. Then we examine some laboratory and other experiments that are believed to either support or refute the argument that information cascades are at the root of the issue and outline a methodology to test the influence of the reward structure used in the experiment.

2. INFORMATION CASCADES AND ‘HERD’ THEORY

The basic decision-making principle involved here is an inference technique that provides for reasoning under uncertainty, called Bayesian belief networks, which in turn is based on Bayes’ theorem. Bayesian reasoning infers that statements can be represented by variables which may take on many probabilistic values rather than simply *true* or *false*. Bayesian inference requires an initial estimate of the belief value of each variable, called *prior probabilities* which is then updated to represent a revised belief value as new information is received, using the Bayes’ inversion formula:

$$P(\chi | e) = a\lambda_e(c) \times P(\chi).$$

This rule allows computation of the revised probability of a variable χ given the occurrence of some event e , believed to be a signal of the event χ (Morawski, 1989). The likelihood ratio $\lambda_e(\chi)$ is one of a vector of possibilities and gives the level of certainty with which each possible state of c is indicated given the occurrence of an event e . The symbol a is a normalization constant that ensures that the probabilities sum to one.

The term “herd externality” conveys the potentially negative impact of this phenomenon (Banerjee, 1992). The very act of trying to use information contained in others’ decision makes each person’s decision less reflective of their own information, and in turn less informative to others (possibly an explanation for the amplification observed in the bullwhip effect. In equilibrium this “reduced informativeness” may be so severe that it may be more beneficial to constrain some decision-makers to using only their own information. The outcome of this herd behavior may be inefficient *even when* the individuals themselves earn the anticipated reward for their decisions.

Bikhchandani, et al, (1992) used a similar concept to model the dynamics of imitative decision processes, but defines its presence as an *optimizing* behavior by a decision-maker who *chooses* to disregard his own information and follow the action of those preceding him; thus cascades could explain uniform behavior as well as fads, although the phenomenon can often be mistaken. The outcome may not always be socially desirable, but a reasoning process that takes into account the decision of others is seen as totally *rational*, even when the individual places no value on conformity in itself. In that sense, their paper serves as an extension of Banerjee’s line of argument.

3. PROPOSED ALTERNATIVE EXPERIMENT

There are several possible alternative arguments for explaining the development of cascades. One argument (Anderson and Holt, 1996, 1997) holds that human subjects frequently deviate from rational Bayesian inferences in controlled experiments, especially when they are provided with simple heuristic rules-of-thumb. Alternatively, several non-Bayesian-based explanations for conformity can be offered. For example, psychologists and decision theorists have discovered a tendency among subjects to prefer an alternative that maintains the “*status quo*.” This would be evident of an irrational bias if the decision-maker’s private information is at least as reliable as the information available to the people responsible for establish the existing condition. However, in the case where it is reasonable to believe that this status quo was established on the basis of good information or bad experiences with alternatives, it should be viewed as a rational selection.

Yet other researchers contend that contrary to Bayes’ rule, individuals may simply ignore prior and base-rate information in revising beliefs, thereby reducing their options to a heuristic choice between “following the majority” and “follow your own signal” (Grether, 1980; Huck and Oechssler, 2000). The question of what determines the *final* heuristic choice is addressed in this research. In past experiments subjects were rewarded for simply providing what is determined as the correct response by the experimenters. Could it be that the incidence of information cascades as observed is a figment of the reward system itself?

Methodology of Proposed Experiment

The proposed experiment runs as follows: an individual observes a private signal, a , or b , that reveals information about which of two equally likely events, A or B , has occurred. Each signal is informative in that there is a probability of $2/3$ that it matches the corresponding event. This setup can be physically replicated by placing balls of two distinct colors, perhaps, in opaque cups labeled A or B , as shown in the following Andersen and Holt (1996):

Cup A: Dark, Dark, Light
Cup B: Light, Light, Dark

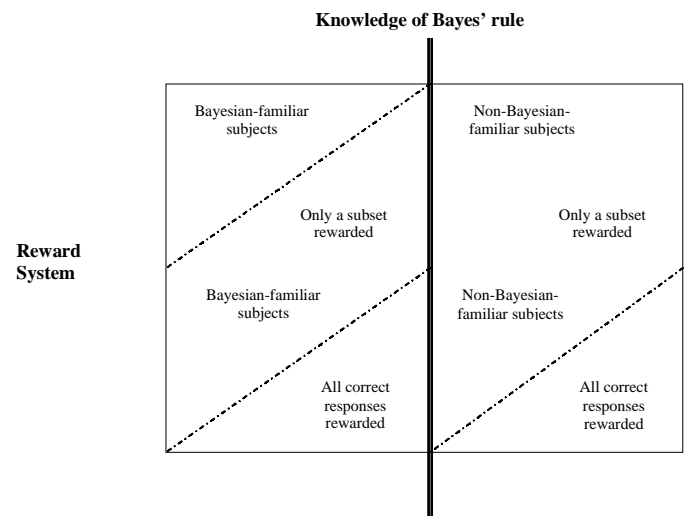
Note that since two of the three balls in Cup A are dark-color this means that there is a posterior probability of $2/3$ that a chosen ball came from Cup A if it is dark-color, and $1/3$, if it is light-color, and similarly for Cup B.

Individuals are then approached in a random order to receive a signal (draw a ball) and make a decision as to the event (cup) with which the signal is associated. The *decision* is announced publicly when it is made, while ensuring that the actual *signal* (the color of the ball) is not revealed. Each individual earns a fixed, cash reward for choosing the correct event, so a person wishing to maximize expected utility will always choose the event with the higher posterior probability. For the first decision-maker, the only private information would be that provided by the draw; but subsequent decision-makers would have not only their private information, but the announced decision of those that preceded them.

We propose a 2x2 factorial analysis experiment (Figure 1) with the two treatments of interest being “*knowledge of Bayes’ rule*” and “*system of rewards*.” We expect to employ a total of 72 subjects comprising two main groups. One group will represent those familiar with Bayes’ rule. As an additional measure, this group then will be re-familiarized with the topic and reminded that they should consider it as a relevant option - although not required to be utilize. A second group of 36 students will represent those who have never been exposed to the concept of Bayes’ rule. These major groups will be further subdivided: in one segment all correct responses will be rewarded; in the other, only a subset of the correct decisions will be rewarded. All four segments will run concurrently.

The actual experiment will be comprised of a number of sessions each involving groups of 6 subjects. This means that ultimately there will be 3 separate sequential groups assigned to each of the four categories of subjects (Figure 1). Each subject will receive a fixed nominal fee for

Figure 1. Proposed 2x2 experimental design – information cascades



participation at beginning of the experiment. In addition, and as an incentive for maintaining high levels of interest during the experiment, winners will be rewarded with a chip after each session, which they would then cash in at the end.

An information cascade can occur whenever the first two decision-makers choose the same event, which makes it an attractive optimizing option for all subsequent decision-makers to follow suit. A cascade can also form if the first two decisions differ but the next two match. In sum, an imbalance of two decisions favoring any one of the events could muddle the informational content of any subsequent individual signal, causing that subject to ignore their own signal and go along with those preceding. In those segments where only a subset of the correct answers are rewarded, potential information cascades will be limited in size to either 3 or 4 subjects at most, whereas in those segments where all correct decisions are reward, information cascades can potentially involve all 6 participants of a session. But we are interested in a comparison of the frequency with which identifiable incidents of information cascades occur between the segments, rather than the size of the cascade.

We do not expect that information cascades would be significantly influenced by a lack of understanding of Bayes' rule although our experiment includes this possibility as a control. On the other hand if, as we expect, information cascades are more reflective of heuristic decision making based on maximizing rewards, then we would see a more distinct variation in the level of frequency, based on the reward system, being higher in the case where all correct decisions are rewarded. This would indicate that the decision space is being reduced to a simpler landscape in which decisions are based on perceived risk and reward. The question of potential reward would determine whether the subject's motivation is gaining early mover advantage or is willing to settle for being a "member of the herd." Each subject will be asked to complete an exit questionnaire in which, among other things they would be asked to identify the decision process they used, and to approximate the frequency with which this method was used.

Supply chain arrangements are based extensively on contracts, but to what extent these contracts proactively aim to address the issue of the bullwhip effect is questionable, given the accepted definition for this issue. The results of this experiment could be an important initial step in guiding more effective contractual arrangements in supply chains.

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