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No. 32

Working Paper Series

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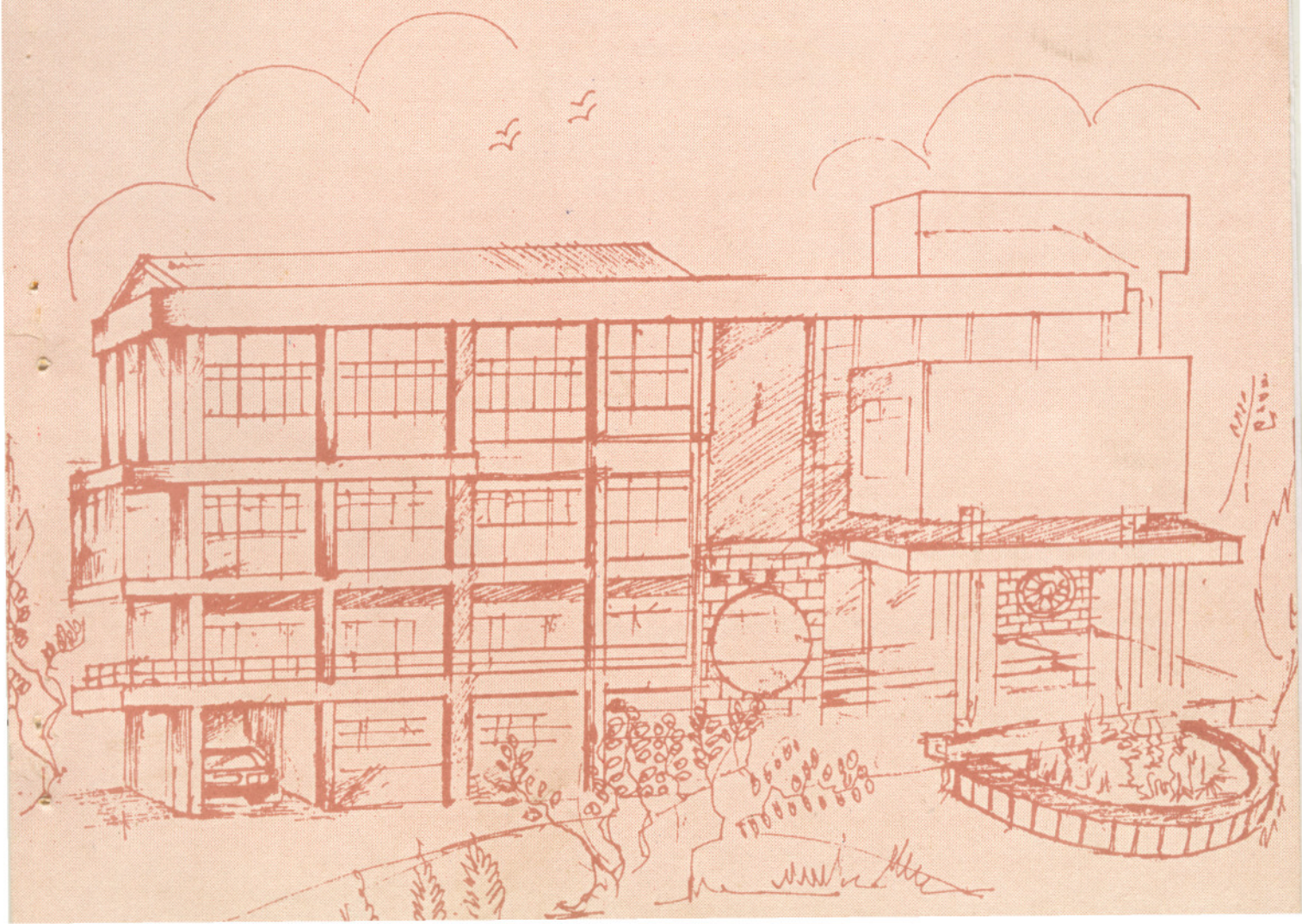
A Laboratory Study of Bullwhip Effect In Distribution Channel



Impact of Learning Effect on Managerial Reaction to Demand Turbulence

A Laboratory Study of Bullwhip Effect In Distribution Channel

R. C. Natarajan
Associate Professor (Marketing)
T. A. Pai Management Institute
Manipal 576 119, Karnataka

Email: cnutraj@mail.tapmi.org

TAPMI WORKING PAPER SERIES NO. 2003 / 01

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T. A. Pai Management Institute

Manipal –576 119, Udupi Dist., Karnataka

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Abstract: Inventory function in distribution channels aims at holding optimal stock that ensures the organization's ability to meet demand without incurring stock-outs keeping inventory-holding costs low. In a situation when consumer demand varies from time to time, inventory management involves forecasting and ordering, keeping in mind the time lag that the channel-mechanism involves. Turbulence in consumer's ordering renders it difficult for the channel to estimate consumer-demand accurately. The difficulty is more when the channel member is farther from the consumer in the channel hierarchy. Under such conditions, variations in consumer-demand lead to amplifications of order quantities along the channel-hierarchy, known as **bullwhip effect**. This paper studies the impact of learning effect on keeping bullwhip effect in check. These two aspects of bullwhip effect have been experimented through a laboratory study and demonstrated in this article. Specifically, it is shown that bullwhip effect will be higher in a situation where the variance in consumer demand is high. It is also demonstrated that learning effect that takes place due to high degree of turbulence enables teams to handle future turbulences better, thus keeping bullwhip effect low. The relevance of this work both to academicians and to corporatist is explained.

Introduction

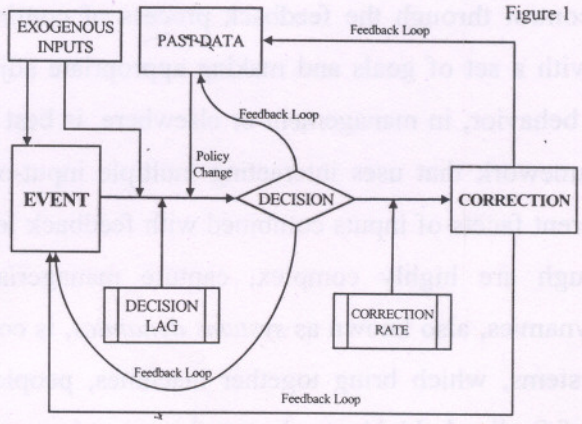
Feedback in communication is an important source of correction. The term "cybernetics" stands for control through the feedback process of continually comparing the existing conditions with a set of goals and making appropriate adjustments. (Forrester, 1964, p. 59). Such a behavior, in management or elsewhere, is best understood when viewed in a systemic framework that uses interacting multiple input-output schemas. Inter-linkages among different facets of inputs combined with feedback loop of past decisions and their results, though are highly complex, capture managerial behavior in near totality. Industrial dynamics, also known as *systems dynamics*, is concerned with problem solving in living systems, which bring together machines, people and organizations. It is the application of *feedback thinking* and control concept in management. (Towill, 1996, p.23) Early research in systems dynamics in management is available with specific focus on systems thinking especially in the area of distribution management and supply chain. The impact of feedback on decision-making has been experimented to study the relation between the focal organization and its environment. (Forrester, 1958, 1964, Sterman 1989, 2001) Further research with application of this approach in management research

appears limited. Much research in the last four decades has been done on either existence of a relationship or the unidirectional cause and effect among variables. Systems-thinking seems to have received much less attention than it deserves. The framework of *Systems Dynamics* holds enormous scope for research in various areas of management, especially the empirical aspects, which can help scholars to model complex managerial behavior with reasonable amount of correctness. (Sterman 2001) In as much as the students of management are potential managers, they form a good sample for analyzing managerial behavior. This paper is an attempt to study an element in behavioral aspects of decision-making, viz., the learning effect of past decisions and its results on future decision-making, based on a laboratory research conducted with the aid of a simulation.

Decision Process

When we consider the psycho-economic aspects of decision-making, managerial behavior can be viewed as non-linear. (Sterman, 1989) *Past data* bears weight on evaluation of future outcome of the decision and therefore impacts the process of decision-making. It is a cumulative outcome of past decision-making, either the decision itself or the result of such decisions. Therefore, current decision-making is a function of both current situation and past data, in addition to the possibility that the event itself is a side effect of past decisions/results. This can be explained with the help of the figure below. When an *event* occurs warranting a decision to cause a correction, the decision is also influenced by past data, certain exogenous inputs and the normal time lag between the event and decision-making. Here, *decision* includes the action of implementing the decision as well. *Decision* can have a causative effect on future events and add to past data cumulatively. *Correction* denotes the outcome of the decision, which is influenced by the rate of

Figure 1



expanded ability to produce results that we want is called "learning". (Senge, 1990, p.142) *Experience ...has ways of boiling over and making us correct our present formulas*. (William James, 1907) The occurrence of *correction* also triggers the event in the next time period, especially in situations where decision-making is an on-going process, thus reinforcing the decision process cycle. The triggered event in the next period may either reflect a better situation or worse depending upon whether the feedback loop is negative or positive one respectively.

Thus, it is important to know the effect of the past decisions on the current event as much as on the desired correction so as to respond accurately to the current event. This, in essence, is the *feedback-loop thinking* which says that in decision making, the impact of past decisions on the environment should be considered as important as the changes in the environment that affect the organization calling for the decision. Closed-loop systems, also known as feedback systems, are characterized by cyclical action-effect process, where a change in environment leads to a decision that results in an action that affects the environment. (Forrester, 1964) *Positive feedback systems* are those where an action triggers a snowballing effect, leading to bigger and bigger event of the same type. *Negative feedback systems* are those where the action in response to the occurrence of an event has such an impact on the system that warrants the opposite action or a reduction in the degree of action in the next period(s), meaning that the event will be smaller in size or degree. These systems are normally known to have a corrective effect on the decisions and actions. Cyclical events reflect existence of negative feedback loop in the system. It is important for managers to consider the feedback effect of their decisions and actions so as to avoid the pitfall of committing over-reaction. However, it has been observed that managers tend to weigh past data less significantly, thus being influenced by the current situation predominantly and a little less by the recent past at best. Though managers may have their rationale for such behavior, right or wrong, it needs to be understood that such a deliberate undermining of the effects of past decisions/results on the environment leads to sub-optimality in management.

Learning Effect

Learning is understood commonly as acquisition of information. Normally, it is defined in terms of *knowledge, skills, interest, motivation,* attitudes etc. (Raia, 1966) A better

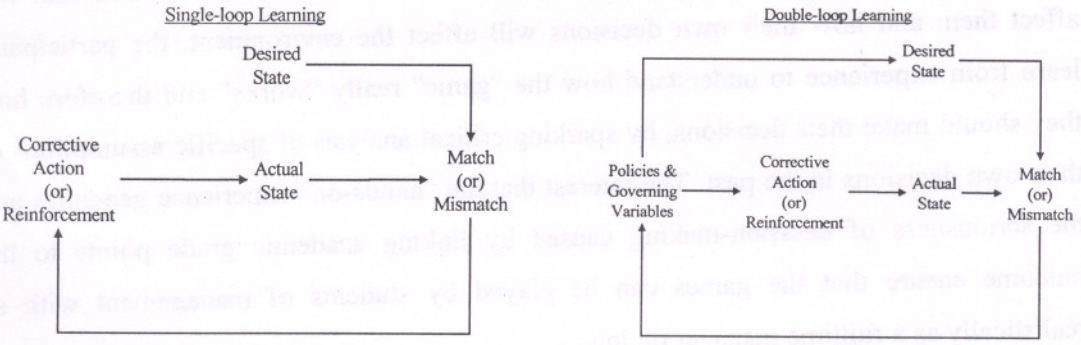
understanding can be that learning is a process whereby knowledge is created through the transformation of experience. (Kayes, 2002, p.139) This acquisition of information through experience and conversion to knowledge can take place in any of the four styles namely, *active experimentation, concrete experience, reflective observation* and *abstract conceptualization.* It is possible to imagine that these styles follow the same sequence in a spiraling cycle, taking the learner to higher planes of knowledge. Though the purpose of this paper is not to analyze the concept of learning, it is necessary to establish what is understood by the term "learning" for the purpose of this study. Learning is *acquired knowledge that expands the ability to produce desired results*. (Senge, 1990, p. 142) This understanding fits the approach of this paper well, where we shall examine the effect of learning on the teams' subsequent decisions to effect a desired correction. Though there does not seem to exist any work directly relating bullwhip effect with learning, there are studies available that have demonstrated that defective products provide significant opportunity for learning and quality improvement. Increase in quality of knowledge is demonstrated to be greater when the process quality is lower. (Li and Rajagopalan, 1998) So, in the context of this experiment, it is intended to associate the ability to reduce bullwhip in later phases with learning. In this paper, the term *learning effect* is used to imply the phenomenon of manifested improvement in performance as a result of acquired experience from difficult conditions preceding the action. That is we believe that greater hardships lead to greater learning.

Research Model

In this research, the impact of *learning* on *decision-policy* was examined. Decision-policy denotes the self-imposed rules that govern the manner in which decisions are taken in response to change in the environment that warrants a corrective action by the participants. Specifically, the impact of learning effect was studied through the effectiveness of it reflected by the outcome of the series of decisions. The understanding, *a priori*, is that when an organization (or a manager) lives through great disturbances, the organization (or the manager) will learn to adapt to disturbances in future more effectively than those organizations that live through relative stability. To test this understanding, two different types of situations were created that provide different levels disturbances in one phase, followed by a phase that has somewhat similar level of

disturbances. Two different sets of "firms" went through these experiences, independently, and their "performances" were considered for analysis.

Learning occurs either when there is a match between the intended outcome of action and the actual outcome or when there is a mismatch. The response to the mismatch may be either programmed or analytical. The former is known as *single-loop learning* and the latter *double-loop learning*. (Argyris, 1999, p.68) In single-loop learning, a mismatch triggers a corrective action. In double-loop learning, the mismatch examines the governing variables of action – what we call policies or governing variables– to lead to an



Suitably adapted from Chris Argyris, *On Organizational Learning*, Blackwell Business Publications, Oxford, 1999,

action. In this case, the response of action cannot be programmed and requires questioning of assumptions, policies and values.

Under conditions that cause single-loop learning behavior, it invariably requires a major disaster to cause a paradigm shift leading to examining the policies and governing variables, and thus the double-loop learning. Without the realization about such a disaster, the firms continue to operate under single-loop learning, blissfully. It was this aspect of paradigm shift that was the purpose of this research. Specifically, the research boiled down to testing the understanding that *firms that face greater disturbances learn to handle future disturbances better than firms that do not*. The firms that face greater disturbances realize the fallacy of single-loop learning much quicker and thus shift to double-loop learning, which is reflected in their corrective actions and the resultant outcomes. Thus, the indicant of learning effect is the effectiveness with which the firms are able to manage disturbance in future, having experienced disturbance once. The research focuses on the relationship between the occurrences of different degrees of

disturbance and the ability to manage disturbance effectively, the latter reflected through reducing the gap between the desired and actual states.

Methodology

Jackson (1959) has outlined the utility of simulations in enabling learning from feedback. In as much as the players are given only partial information about the events that will affect them and how their own decisions will affect the environment, the participants learn from experience to understand how the "game" really "works" and therefore how they should make their decisions, by sparking critical analysis of specific assumptions of their own decisions in the past. The interest that the "hands-on" experience generates and the seriousness of decision-making caused by linking academic grade points to the outcome ensure that the games can be played by students of management with as realistically as a fulltime manager on job.

Games elicit a rich set of behaviors similar to those observed in field studies and limited more by participant background than by game possibilities. This has encouraged persons interested in research to select management games as laboratories for a wide array of research inquiries. (Keys and Wolfe, 1990) For studying the focal behavior of the participants, the game should be sufficiently realistic and the participants should be well aware of the *good* business practice to behave in a reasonably intelligent manner. (Cohen and Rhenman, 1961).

The most interesting research that could be conducted with business games would be research that could tell us something about the way firms behave in reality and not research telling us something about how students behave in a laboratory situation. (Cohen and Rhenman, 1961) Forrester's *Beer Game* (Sterman, 1989) was chosen to carry out this research. The game involves decision making in a supply chain, under zero-communication, except order placing and stock-delivery. The decisions and their outcomes are quantified and are available to the player, thus providing the immediate feedback to them. Invariably, a small spurt in the consumer demand fed by the administrator into the system leads to a massive surge of order placing that amplifies itself up the supply chain. This effect, known as *Bullwhip Effect* is the primary indicator used in this research. The main lessons from the game are (a) structure influences behavior (b) structure in human systems is stable and (c) leverage often comes from new

ways of thinking. (Senge, 1990) The reason for selecting this game was its simplicity in terms of the number of variables to be considered in the game. Since this research is to study the behavioral patterns of firms under different conditions, it was necessary to have a game that clearly highlights the patterns quantitatively. Thus, the *Beer Game* suited the purpose of this research well. The game is known to have yielded consistently similar results in terms of decision-behavior and final results over fifty years, and is credited with the byline *different faces same result*. (Goodwin *et al*, 1994, p. 10) This is indeed a certificate for the reliability of the game as a research instrument when we want to inquire into structure-behavior aspects.

The game was played by each Batch for forty rounds, each round representing a week. The initial scenario was a steady state, where orders, stock-in-pipeline, inventory etc. had been remaining the same for some time. The steady state scenario was continued for the first four rounds, so as to give the participants the feel of playing the game and maintaining records. The author played the role of "Consumer", placing orders and collecting deliveries every round. The initial steady state was set up as shown in the table here. (Sterman, 1989) [1]

	Retailer	**Wholesaler**	**Distributor**	**Factory**
Inventory in hand	12	12	12	12
Order-decision in round-0	4	4	4	4
Order waiting to move out to supplier	4	4	4	4
Pipeline inventory in delay stage-1	4	4	4	4
Pipeline inventory in delay stage-2	4	4	4	4

Ordering sequence was from Consumer to Retailer, Retailer to Wholesaler, Wholesaler to Distributor and Distributor to Factory. The stock movement was the reverse of this sequence. The channel members were supposed to meet their respective customer's orders every round and back order from the available inventory. Failure to do so backlogged their customer's orders and added to their back-order cost, which was double the inventory-holding cost. Thus, there is an indirect incentive to meet the customer's needs. The aim of the channel members was to keep the channel-cost low. There was no

[1] The scenario was somewhat different for the Factory, though the time lag between the order and receipt of stocks was kept uniform at 4 weeks for all members of the chains.

other cost/revenue in the game. As mentioned earlier, the participants would not communicate with other members of the channel. The only interaction among members was either in the form of passing the written order-quantity or passing the chips that symbolized finished products.

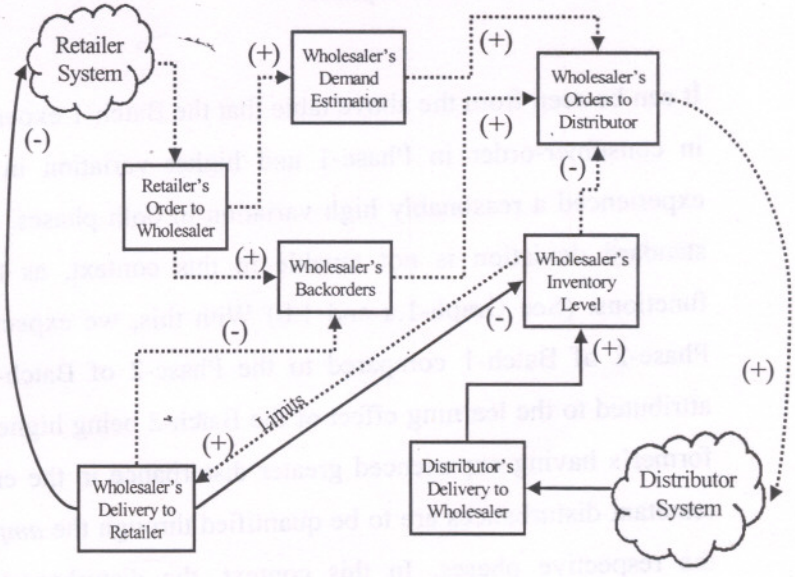
Given the lag in the system, an increase in order received from the retailer witnesses (a) increased order from wholesaler to distributor (b) lack of immediate response from distributor since it takes two weeks for the wholesaler's order to reach the distributor and (c) backorder with wholesaler and therefore lack of response from wholesaler to retailer, thus impelling retailer to increase the order or duplicate it. This leads to an "unreal" demand escalation, thus making the wholesaler to order increased quantity to the distributor. Thus, the negative loop flowing back to the retailer - and thus at every stage of the channel below the factory– causes fluctuations in the chain periodically. Sterman interprets this phenomenon as a consequence of players' systematic irrational behavior or "misperceptions of feedback". (Sterman, 1989, p.337). In some cases, there is a possibility of team(s) fixing a base-stock as the goal-seek for their order-decisions. This is also known as *misused base stock policy*, abbreviated as MBSP. Chen shows the MBSP at any single stage in the channel prevents the others from making rational decisions. (Chen, 1999, p. 1088) Specifically, the double-loop archetype that is used by Flood under the name *Eroding Goals* is most applicable in this context. (Flood, 2000) Under this type, the participant in the simulation not only changes his corrective action but also alters his goal, which is in this context the desired inventory level. This is demonstrated as follows:

> In the steady state scenario at the beginning, the retailer maintains an inventory of 12 units, four units are on the move inward at each of the two stages of delay and four units of orders are on the way out at each of the two stages of delay. When the consumer's order shifts from 4 units to 8 units, its effect on the retailer will be two-fold. Firstly, it will bring down his inventory to eight units at the close of the round, thus warranting him to place an additional order for four more units. If his estimate of demand now shifts to eight units per period, then his desired inventory level will have to be increased as well, to meet the demand anticipated, so as to avoid back-order cost. Thus, he will increase his order to the wholesaler to twelve units at the minimum. That is, an increase in inward order by four

units has resulted in an increase by eight units in outward order, an outflow-inflow ratio of two. This is due to the corrective action being influenced not only by the changed condition but also by the changes effected on the desired goal.

Given the restrictive scenario that the players face in *Beer Game*, the *bullwhip effect* caused by the players' decisions is an apt primary indicator of the performance of the supply chain. (For a thorough understanding of *bullwhip effect*, its causes, measurement etc, see Chen 1999, Chen *et al* 2000, Forrester 1958, 1961 and 1964, Lee *et al*, 1997a, 1997b, 1992, 1993 and 1999, Senge 1990, Sterman 2001 and Young *et al* 1999) It is also possible to quantitatively study the cause and effect between the variables such as incoming order, inventory, and backorder and thus check if there is any marked shift in the *decision-process*. These variables, in their degree of impact on the order-quantity were the set of secondary variables in the study. Though the model of the game implies that demand-estimation of the firm is an important variable affecting the order quantity, the estimation process is an unknown aspect in the game and is prone to high degree of subjective interpretation. To circumvent this, incoming order has been taken as a surrogate measure of demand estimation by the firm. The primary and secondary variables together, were expected to provide a reasonable indicant of *learning effect*.

Beer Game: Wholesaler's Internal Dynamics



In the context of the simulation game, the implications of the testable proposition are that two *batches* and two *phases* were to be devised clearly. The students were divided into two batches of 48 each. Each batch contained six chains, each chain consisting of a factory, a distributor, a wholesaler and retailer and each

of these member-firms being formed by two students. Batch-1 played the simulation during the forenoon and Batch-2 during the afternoon of July 28, 2002. Each batch played the game over forty rounds, each round representing a week. Phase-1 stood for the first twenty rounds and Phase-2 stood for the second twenty rounds, for each batch. The students were not aware of the phases and played the game as if the entire forty rounds were a single series. This eliminated any conscious review and change of decision-policy that may be artificially created in the game.

The input variable by the game administrator was the quantity of consumer-demand, given to the retailer. The inputs were formulated as follows:

	Phase 1	Phase 2
Batch-1	μ_{11}= 7.20 σ_{11}= 1.64	μ_{22}= 13.0 σ_{12}= 3.40
Batch-2	μ_{21}= 10.6 σ_{21}= 4.55	μ_{22}= 10.0 σ_{22}= 4.59

Note: μ and σ denote the arithmetic mean and the standard deviation of consumer-orders during the respective phase. The first suffix stands for the batch and the second suffix stands for the phase.

It can be seen from the above table that the Batch-1 experienced a relatively low variation in consumer-order in Phase-1 and higher variation in Phase-2, whereas the Batch-2 experienced a reasonably high variation in both phases. In strict statistical sense, use of standard deviation is not tenable in this context, as the consumer-orders were step functions. (See Graph-1.a and 1.b) With this, we expect to see a greater turbulence in Phase-2 of Batch-1 compared to the Phase-2 of Batch-2, a phenomenon that will be attributed to the learning effect of the Batch-2 being higher than of the Batch-1 due to the former's having experienced greater disturbance in the environment than the latter. The resultant disturbances are to be quantified through the *amplitudes* of the outward-order in the respective phases. In this context, the disturbances caused in the chain by the decisions reach such extremely high volumes that can cost the firms very highly not only by the endogenous rules of the game but also, in reality, such costs as investments in transportation, capital expenditure in plant-capacity, warehousing etc. Therefore, amplitudes are a better measure for the disturbances than variances due to the former's

ability to capture the extreme point of turbulence whereas the latter checks for the aggregate, a measure that is not relevant to our purpose.

In the context of decision-process, the double-loop thinking works as shown in the diagram here. The players of the game fail to see this pattern consistently, end up thinking in single-loop and cause the splurge in order-placing and inventory holding. When the realization dawns on them about the disaster, the learning effect and double-loop thinking occurs.

The hypotheses were formulated as follows:

H_1 Higher variance in initial consumer demand is related to lower amplitude in orders placed by the retailer in response to subsequent turbulence in consumer demand.

H_2 Higher variance in initial consumer demand is related to lower amplitude in orders placed by the wholesaler in response to subsequent turbulence in consumer demand.

H_3 Higher variance in initial consumer demand is related to lower amplitude in orders placed by the distributor in response to subsequent turbulence in consumer demand.

H_4 Higher variance in initial consumer demand is related to lower amplitude in orders placed by the factory in response to subsequent turbulence in consumer demand.

Findings and Analysis

The data were entered in MS-Office Excel 2000 spreadsheet and the statistical calculations were performed. Though the hypotheses pertained only to the reactive amplitudes, we checked the variances as well. This is because whereas amplitude measures the maximum order placed, which pertains to one-time action, variance may, perhaps, throw light on the dispersion across the entire series. Thus, variance was more a crosschecking mechanism used for this study. The results revealed the following:

The consumer demand in Batch 1 was 2424 units and in Batch 2 was 2472 units, more or less similar demand across the batches. However, the factory's orders in the two batches during the game were 4445 units and 6028 units, manifesting an amplification of 1.83 times and 2.44 times respectively. The amplification of Batch 1 in Phase 1 was 3.67 compared to Batch 2's 4.09, and the amplification in Phase 2 for Batch 1 was 0.81 compared to Batch 2's 0.69. That is the relative amplitude of Factory over Consumer Demand was lower in Batch 1 in Phase 1 compared to Batch 2. However, Batch 2 *shrunk*

their order more than Batch 1 in Phase 2. The orders placed by different levels of the chains – aggregate – in the two batches are summarized below:

Batch 1	Consumer	Retailer	Wh'saler	Distributor	Factory
Phase 1	864	957	1236	2101	3185
Phase 2	1560	1600	1604	1557	1260
Total	2424	2557	2840	3658	4445

Batch 2	Consumer	Retailer	Wh'saler	Distributor	Factory
Phase 1	1272	1820	2615	3163	5199
Phase 2	1200	679	351	457	829
Total	2472	2499	2966	3620	6028

Both batches experienced *bullwhip effect,* as has been the experience world over. Notice the quantity of inventory held at different levels of the chain, though the consumer demand for the batch in total never exceeded 96 units in any period. (Graphs 6.a and 6.b) Batch1 witnessed less degree of turbulence in order volumes in Phase 1 than Batch 1. This can be attributed to the greater turbulence in consumer-demand in phase 1 in Batch 2 than in Batch 1. This phenomenon is true in all but one chain at each level of the chain. (Refer Table 1). The aberration of chain 3 in Batch 1 was caused by a miscalculation by the team playing "Distributor" which also reflected in the ordering by the Factory.

From Tables 1 & 2 it can be noted that the turbulence in consumer-demand in Phase 2 in Batch 1 is actually less than that in Batch 2, given by the fact that the variance is only 560.86 in the former compared to 1603.22 in the latter. However, the Batch 2 had witnessed greater turbulence in Phase 1 compared to Batch 1, who had seen a relative stability between rounds 5 and 20. Thus, in effect, Batch 2 lived through turbulence in both Phases whereas Batch 1 faced turbulence in the second Phase after a stable period in Phase 1. Therefore, the Batch 2 ought to be "experienced" in handling turbulence relatively better than the Batch 1. This aspect is confirmed by the data which shows higher variance of channel members' ordering in Batch 1 in Phase 2 as against the Batch 2 in Phase 2, especially given the fact that the variance of consumer-demand was higher in Batch 2 than Batch 1 in Phase 2. It can be seen from the Graphs 2.a & 2.b that whereas the Batch 1's second peak is larger (following a relative lull for a fairly long period), the Batch 2's second peak is shorter, after having experienced considerable turbulence. Also,

in the cases of Retailer, Wholesaler and Distributor the minimum *relative variance*[2] in Phase 2 for Batch 1 was greater than the maximum relative variance in Phase 2 for Batch 2. However, in the case of Factory, there is one chain in Batch 1 whose relative variance is less than relative variances of two chains in Batch 2. When we eliminate those elements of chains where the orde4rs in Phase 2 was completely zero, then this phenomenon accounts for 10% of the comparisons. That is, 18 out of 20 comparisons for Factory proved that relative variance in Phase 2 for Batch 2 was less than relative variance of Phase 2 for Batch 1. The predominant homogeneity in this phenomenon across the different chains when compared between the two batches (Refer Tables 1 & 2) can be explained only by *learning effect*, since the actual variance of the consumer-demand in Batch 2 in Phase 2 was higher than that for Batch 1 in Phase 2.

The comparison of the two Phases in each Batch needs closer analysis. To what extent the large turbulence in Phase 2 of Batch 1 can be attributed to the increase in the mean consumer-demand is not clear. Though the hypotheses are validated in line with the intuitive understanding that those who live in turbulence learn to handle turbulence better, whether this jump in the mean volume of consumer-demand bore any significant impact on the bullwhip effect is not ascertainable. If one examines Graphs 1a & 1b closer, it can be noted that during the second phase, both the batches experienced a similar upward jump in consumer-order, by eight units, Batch-1 in 21st round and Batch-2 in 26th round. Notably, Batch-2 experienced a greater fall by twelve units in the 31st round. Despite these larger "jerks" in Batch-2, Batch-1 witnessed greater amplitude in the Factory's order in Phase-2. Thus, though the mean consumer demand in Phase-2 was higher for Batch-1, it can be argued that the difference has not caused the greater amplitude in Batch-1 in as much as the "fluctuation" was higher in Batch-2. Therefore,

In order to be absolutely certain that the perceptible difference across the batches is purely due learning effect, a cross-verification through comparing across the batches the amplitudes was done. By this, we mean the ratio between the amplitude of order placed and the amplitude of incoming orders at each level of the channel. While performing this verification, all those cases where the Phase-2 ordering was zero were eliminated. This comparison is available in Tables 4.a and 4.b. Of the rest, the performance of each

[2] *Relative Variance* is calculated as the ratio between the variance of outgoing orders in Phase 2 and the variance of outgoing orders in Phase 1, the latter being the denominator.

member of each chain was compared across the two phases. To check on this aspect, we compared the amplitudes of different members of the chains in both batches in the two phases. The table shows the comparison of amplitudes in Phase 1 (γ_1) with that in Phase-2 (γ_2). (Refer Tables 3.a & 3.b and Graphs 4.a to 5.d)

Batch 1	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	**Chain 5**	**Chain 6**	Tally $\lambda_1 < \lambda_2$
Retailer	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	6 out of 6
Wholesaler	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 = \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	5 out of 6
Distributor	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	---	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	$\gamma_1 < \gamma_2$	5 out of 5
Factory	$\gamma_1 > \gamma_2$	$\gamma_1 < \gamma_2$	---	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	1 out of 5
Batch 2	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	**Chain 5**	**Chain 6**	
Retailer	$\gamma_1 = \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	Nil
Wholesaler	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	Nil
Distributor	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	---	Nil
Factory	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	$\gamma_1 > \gamma_2$	---	---	Nil

From Tables 4.a and 4.b, we can see that the relative amplitudes fell in all cases in Batch 2 whereas this happened only in the case of factory in Batch 1. Batch 1 witnessed generally that the relative amplitude of the channel members increased in Phase 2. This confirms our finding further. This finding conforms to the conclusions reached through modeling of learning curve, where a higher initial endowment of knowledge achieves low cost subsequently. (Doorh *et al*, 1994)

The aspect of *learning effect* is further crosschecked with the decision making process itself. From the diagram shown earlier outlining the decision-dynamics at the wholesaler, it can be understood that the endogenous factors that influence the order decision are inward order (which is a surrogate measure of the firm's demand estimation) and the inventory/backorder. Backorder is nothing but negative inventory and therefore the net inventory can be considered as the independent variable. Systemically, the firms try to correct the "gaps" by responding to inward order and net inventory. But, this is single-

loop thinking and this does not solve the problem for them. Therefore, it is expected that the firms use certain exogenous aspects to question their decision-policy, and this will be reflected by decreased influence of these two variables in the order quantity. When we used multiple regression where inward order and net inventory were considered as independent variables and outward order quantity as dependent variables, we expected to see a reduction in Phase 2 in the number of occurrences where these two independent variables had significant influence on the dependent variable. And this reduction was expected to be higher in Batch 2 than in Batch 1. For such a comparison, we considered only those beta-coefficients that had *t-statistic* of 1.740 or above. (10% confidence level) The comparisons are provided in Table 5. The table throws light on the fact that *inward order* is dismissed by most of the firms as less relevant in their decision making in Phase 2 and this is much more marked in Batch 2 than in Batch 1. Net Inventory however presents a confusing picture, with Batch 1 clearly negating it more frequently in Phase 2 compared to Batch 2. When we compare the β-coefficients of significant *t-statistic* at micro level between the batches, the picture is somewhat hazy. (Tables 6.a to 6.d) However, when we aggregate the data across chains for each batch, then the picture clearly emerges, suggesting that the β-coefficients for Batch-2 are less in magnitude compared to Batch-1, a clear indication that the *endogenous factors affected the decisions of Batch-2 much less in Phase-2 compared to Batch-1, an indication of greater double-loop learning in Batch-2*. The fact that the β-coefficients have changed significantly is an indication that the actions of the firms have been guided by learning in Phase-2 that was exogenous to the system. (Table 7) The noise in factories in Batch-2 can be explained by the fact that inventory did become a significant issue in Batch-2 for the factories who, in aggregate held as much as 2100 cartons in Phase 2 whereas the figure was about 1000 cartons for Batch 1. But it is not surprising that despite a high inventory, Factories in Batch 2 accumulated more stocks in Phase-2, probably since the cost of negative inventory was double that of inventory holding. Whether this can be termed "learning" or "extra-systemic reaction" is an aspect worth pondering over.

Relevance of Findings

The findings from this simulation exercise are two-fold. One is to the industry and the other is to the business schools. These arise mainly from an understanding of the learning process that occurs in the simulated setting. As has been argued earlier in this paper,

whereas Forrester found that the cyclicality was reinforcing and repetitive, the observation in this exercise is one of stabilization over time. That is the initial turbulent reaction was followed by less turbulent reactions. We had attributed this to learning effect in the sense that the experience acquired in the first phase provides inputs about the action-result process, thus moderating the process of response to the changes in the environment. we have shown in the previous section that one of the main reasons for this difference between my findings and Forrester's findings is the fact that in real life the managers are to contend with many variables whereas in this simulation, they were enabled to focus on only one aspect, namely minimization of cost. This opens up an opportunity for learning, and therefore training in the organizations, wherein it becomes necessary first to remove the complexities of real life to provide revelation to the managers. "Complexity" in this context is used to connote dynamic complexity as against detail complexity. (Flood, 2000, p.15) The former concerns the number of static variables whereas the latter concerns the nature of dynamic inter-linkages over time among the variables. The double-loop process explained earlier explains the reaction-process of the participants. Once the reaction-process is clear to them, the participants become aware that their own actions are the cause of the changed environment, they are able to control their reaction-process better. And, the reaction-process is clearer in that scenario when the Phase-1 turbulence of consumer-order is greater. This is because the more frequent turbulence provides more number of the double-loops to the participants to comprehend the nature of their own reaction. The implication of this is that a training program that aims to bring about affective and behavioral changes through experiential learning process can go by the following steps:

1. Building a scenario that is void of dynamic complexity. The detail complexity is first conveyed through cognitive process.

2. The simulation is administered so as to bring about the understanding of the dynamic complexity.

3. Debriefing the participants to work out an exercise that involves explaining the complex situation that they face in real life through depicting the situation firstly with only the detail complexity and then incorporating the dynamic complexity.

Given the established fact in this paper that those with greater chances of facing turbulences learn better, the implication to training programmes in organization for new recruits and for curricular design in business schools for postgraduate courses in management is that experiential method of pedagogy with greater uncertainties built into the problem-issues through simulations can bring about the desired results much faster and better than a slow and evolving method of teaching. With computer software such as *iThink*, *Stella* etc, being available for designing such simulations, pedagogical logistics can no more face bottleneck in using experiential learning methods. This game is a apt tool for laboratory-research in managerial behavior *because the experimental conditions are fully known, controllable and reproducible so that changes in system behavior can be traced directly to their causes*. (Forrester, 1961, p. 45)

Limitations

The study is subject to certain limitations.

a. It is a simulation setting and therefore shortcomings of a simulation vis-à-vis reality continue to exist. Genuine attempts were made, as mentioned earlier, to make the exercise played with equal seriousness as in real life by linking performance to academic grades. However, the seriousness of students towards their grades cannot be said to be the same as their seriousness towards their job, increment or career growth.

b. The game situation is rather contrived, as admitted in earlier writings. The total prevention of any communication is unrealistic compared to real life. Nonetheless, to the extent free and accurate flow of information is not a reality this is admissible.

c. While Chen *et al* used the relative variance (relative to variance in consumer-demand) to measure the quantum of amplification of order, this study has used the ratio between the variances across the batches. The validity of such a measure is not established as much as Chen *et al*'s measurement too is as yet not validated.

d. The finding of *learning effect* leading to better performance can be questioned on semantic grounds. It is possible to argue that the so-called better performance by Batch 2 is actually an exposure in Phase 2 to almost the same situation as in Phase 1, whereas for Batch 1, the two Phases are very different, and therefore, it can be

said that *Batch 1 de facto faced a new situation*. So comparison between the two batches can be questioned.

e. Generalizability of the findings of this study are limited by the l; ack of representative ness of the sample that comprises of only business management students. Moreover, the game provided the students an apt decision-making context but not an organizational context where many more variables need to be contended with. (Keys and Wolfe, 1990)

f. It can be observed from graphs 6.a and 6.b that Batch-1 witnessed a decline in their stock level at the factory around round 23, when the second surge took place. To what extent this negates the learning effect concept is unclear.

Further Research

Since in a complex environment, players can only attend to a small part of the information that is available to them, different patterns of selection (of parts) will lead to different perceptions of tasks, different definitions of action alternatives, different attributions of consequences, and perhaps even different development of systems of values. For greater understanding of the relation between learning and decision/action, in-depth research on the following aspects is needed (Dill and Doppelt, 1962):

1. The process by which players attend to their environment and translate the inputs of information that environment presents. This means a study of the *interpretation of changes in incoming demand* is warranted.

2. The ways in which the players discover and conceptualize alternative ways of achieving the goal and the choice they make among them. This means that a study of *how the players plan to take decisions on the quantum to be ordered given the changes that take place in inward orders* is warranted.

3. The ways in which players use information from their environment and assumptions from prior experience to define *outcomes* of their actions. Given the fact that the specified objective of this game is to minimize inventory cost, this translates into a study of *their understanding of the impact of the changes in inward-demand and inward supplies on their costs.*

This being the first full-scale effort in carrying out this simulation with the purpose of understanding learning effect, the enormous scope that the exercise provides to carry out lab-based research in decision-behavior is encouraging to any research-mind. Specifically, in addition to what is stated above, the exercise can be conducted in various ways, scientifically, to study the following:

- The aspect of "Learning Effect" can be further studied under stochastic demand variation, where in different chains, the same random data can be rearranged in a step function with either a gradual increase to study the difference in ordering behavior of the participants. A priori, it sounds reasonable to believe that a team that gets into a stochastic demand situation will use more accurate estimation techniques than a team that will face step function.

- The effect of changing the time lag, *viz*, order-lag and delivery lag at different stages can be studied by varying the order-movement-delivery lag. A priori, it stands to reason that the greater the lag, the greater will be the bullwhip effect for a given spike in demand that was steady till then.

- The effect of free flow of information among the channel members in optimizing the channel cost. Allowing the channel members within a chain to exchange information freely can enable checking this out. It has been stated that in a centralized information system that permits the channel member to know the shelf-off take at the next downward level enables to avoid bullwhip effect. (Forrester, 1958, p.47; Lee *et al*, 1999)

- The effect of removing one level in the channel in the quantum of bullwhip effect will be an interesting study. It stands to reason that the more the layers of the channel, the greater will be the bullwhip effect for a given spike in consumer-demand. (Forrester, 1958, p.47)

- Effect of removing *backorders* and substitute it with a heftier penalty for lost sales.

- Effect of (a) Incentives to channel to pick up more stocks (b) Price reduction offered to consumers. The latter calls for construction of a fictitious demand function, which introduces complexity in transactions.

- Validity and reliability of the measures such as relative variance (Chen *et al*, 1997) and comparative variance across batches can be studied and established.
- Literature suggests that *pass-order strategy* [3] is the best method under such uncertainty and lack of information flow. This can be tested out among the players with specific instruction to follow this method of ordering, irrespective of the inventory level.
- The effect of random-buying fluctuations in consumer-order, which, *a priori*, will lead to greater amplitude in the factory than that in the case of step function (Forrester, 1958, p.45)
- Given that this paper has established that participants *do* learn from experience in a simulation to perform better, *Beer Game* as a learning tool can be studied upon, with specific focus on systems dynamics in terms of the participants' ability to separately look at the parts, their interrelations and the whole. It is understood that MIT has been undertaking extensive work in Systems Dynamics and it is worthwhile to find out whether any such attempt to relate learning to systems dynamics has been carried out.
- The same research conducted among business executives may eliminate skepticism about laboratory studies involving graduate students, since it may be considered more acceptably as *real managerial behavior*.

In the data presented in this paper, in Batch 1, Factory was exceptional to the trend in as many as four out of five cases. It may be worthwhile to study if learning effect is different at different levels of the channels, in a hierarchical manner.

Conclusion

The purpose of this paper is to check if greater turbulence leads to more learning effect for subsequent correction. It has been hypothesized and found true in this paper that channel's ordering turbulence is higher when sudden turbulence in consumer-demand is high. The turbulence carries itself with a magnifying effect upward in the channel,

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[3] *Pass-order strategy* denotes the manner of deciding the outgoing order by equating to the incoming order of the week. This method is also known as *no-strategy-strategy* and *base-inventory-strategy*.

amplifying the degree of turbulence at the highest part of the channel (Forrester 1958) and this amplification effect is higher in that channel where the turbulence in consumer-demand is higher. Where such turbulences are likely to repeat over time, channels that have experienced greater turbulence adjust their behavior suitably to prevent large amplification during the next turbulence as against those channels who face a relatively calmer consumer-demand pattern, thus proving that learning effect is an important aspect to be considered in the systems dynamics of decision-making. In summary, whereas, in the short run, greater turbulence in consumer-demand causes greater turbulence in the order quantity along the channel, thereby leading to huge inventory (Refer Graphs 6.a & 6.b), it also works through the negative loop mechanism to cause changes in thinking that leads to such decisions which reestablish stability better than milder turbulences. Considering Forrester's observations in the industry that the cyclical fluctuations get reinforced in the long run as seasonality, the results obtained in this simulation experiment point towards the fact that feedback thinking works better when one contends with lesser variables and once in the realm of many variables, other priorities submerge the possibilities of such learning. Perhaps, it may be worth pondering as to the method of expanding the systems dynamics learning to multivariable context systematically. Finally, the paper provides a few tips on the utility of this exercise in training programmes in organization where it is necessary to limit training-variables to bring forth maximum learning.

Reference

Argyris, Chris, 1999. *On Organizational Learning*, Blackwell Business, Oxford, UK.

Chen, Fangruo, (1999). "Decentralized Supply Chains Subject to Information Delays", *Management Science*, Vol. 45, No.8, August, pp. 1076-1090.

Chen, Frank, Zvi Drezner, Jennifer K, Ryan and David Simchi-Levi, (2000). "Quantifying the Bullwhip Effect in a Simple Supply Chain., *Management Science,* Vol. 46, No.3, March.

Cohen, Kalman J. and Eric Rhenman, 1961. "The role of Management Games in Education and Research", *Management Science*, Vol.7 Issue 2, January, pp. 131-165.

Dill, William R. and Neil Doppelt, 1963. "The Acquisition of Experience in a Complex Management Game", *Management Science*, Vol. 10, No. 1, October, pp. 30-46.

Flood, Robert Louis, (2000). *Rethinking The Fifth Discipline*, Rutledge, London.

Forrester, Jay W., (1958). "Industrial Dynamics: A Major Breakthrough for Decision Makers", *Harvard Business Review*, July-August, pp. 37-66

Forrester, Jay W., (1961). *Industrial Dynamics*, The M.we.T. Press, Cambridge, Massachusetts.

Forrester, Jay W., (1964). "The Structure Underlying Management Process", *Academy of Management Proceedings*, pp.58-68

Goodwin, Jack S. and Stephen G. Franklin, Sr., (1994). "The Beer Distribution Game: Using Simulation to Teach Systems Thinking", *Journal of Management Development*, Vol. 13, No. 8.

Jackson, James R. 1959. "Learning from Experiences in Business Decision Games", *California Management Review*, Vol. 1(2), pp. 92-107.

Keys, Bernard and Joseph Wolfe, 1990. "Role of Management Games and Simulations in Education and research", *Journal of Management*, Vol. 16(2), pp. 307-336.

Lee, Hau L., V. Padmanabhan and Seungjin Whang, (1997a). "The Bullwhip Effect in Supply Chains", *Sloan Management Review*, Spring, pp.93-102.

Lee Hau L., V. Padmanabhan and Seungjin Whang, (1997b). "Information Distortion in a Supply Chain: The Bullwhip Effect", *Management Science*, Vol. 43, No. 4, April, pp. 546-558

Lee, Hau L. and Corey Billington, (1992). "Managing Supply Chain Inventory", *Sloan Management Review*, Spring, pp. 65-73

Lee, Hau L. and Corey Billington, (1993). "Material Management in Decentralized Supply Chains", *Operations Research*, Vol. 41, No.5, September-October, pp. 835 – 847

Lee, Hau L. and Seungjin Whang, (1999). "Decentralized Multi-echelon Chains: Incentives and Information", *Management Science*, Vol. 45, No.5, May, pp. 633-640

Li, George and S. Rajagopalan, 1998. "Process Improvement, Quality and Learning Effects", *Management Science*, vol. 44, No. 11, November, pp. 1517-1532.

Raia, Antony P., 1966. "A Study of the Educational Value of Management Games", *The Journal of Business*, Vol. XXXIX No.3, July.

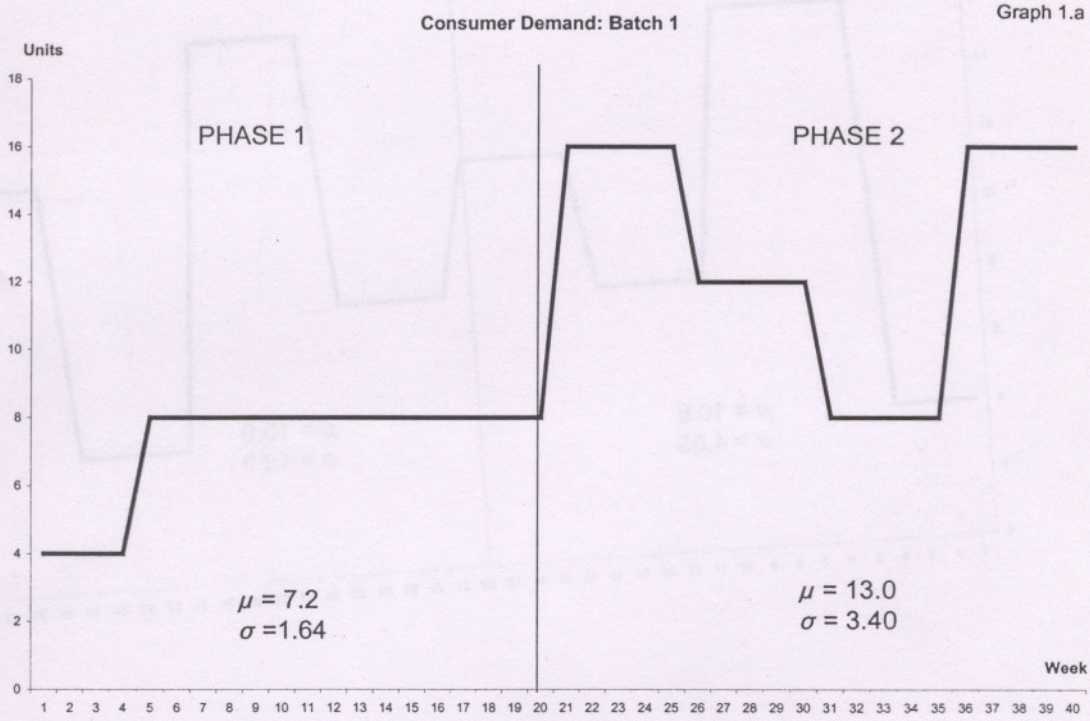
Senge, Peter, (1990). *The Fifth Discipline: The Art & Practice of the Learning Organization*, Century Business, London.

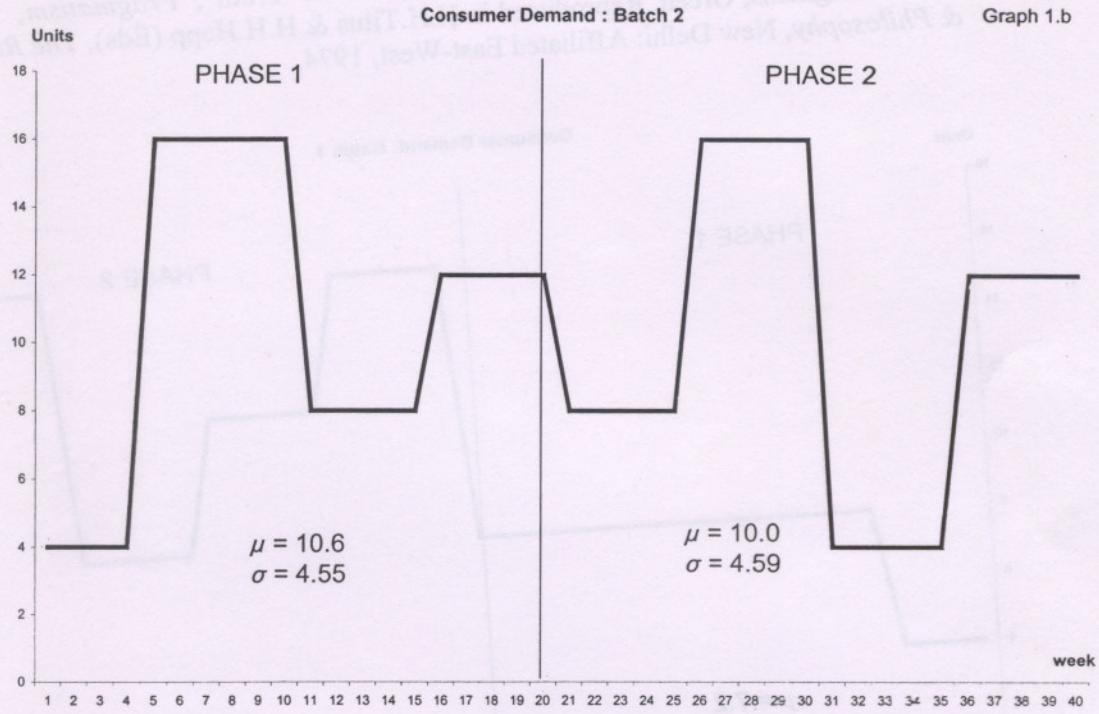
Sterman, John D., (1989). "Modeling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Environment", *Management Science*, Vol. 35, No. 3, March.

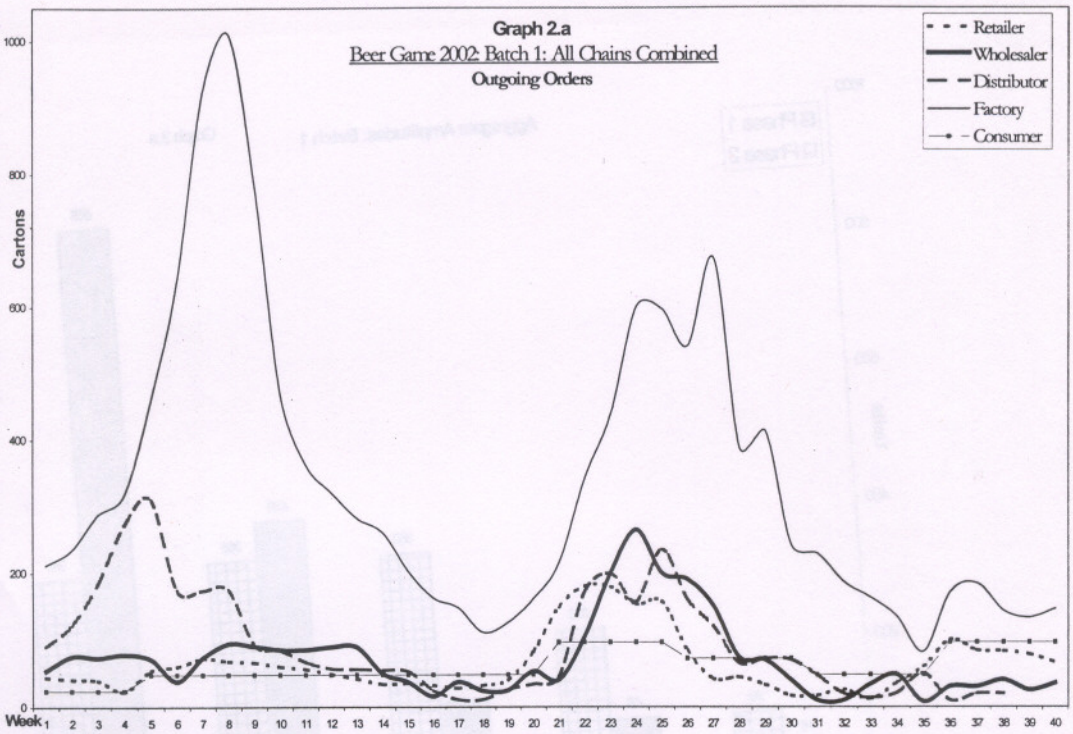
Sterman, John. D., (2001). "System Dynamics Modeling: Tools for Learning in a Complex World", *California Management Review*, Vol. 43, No. 4, Summer, pp. 8-25.

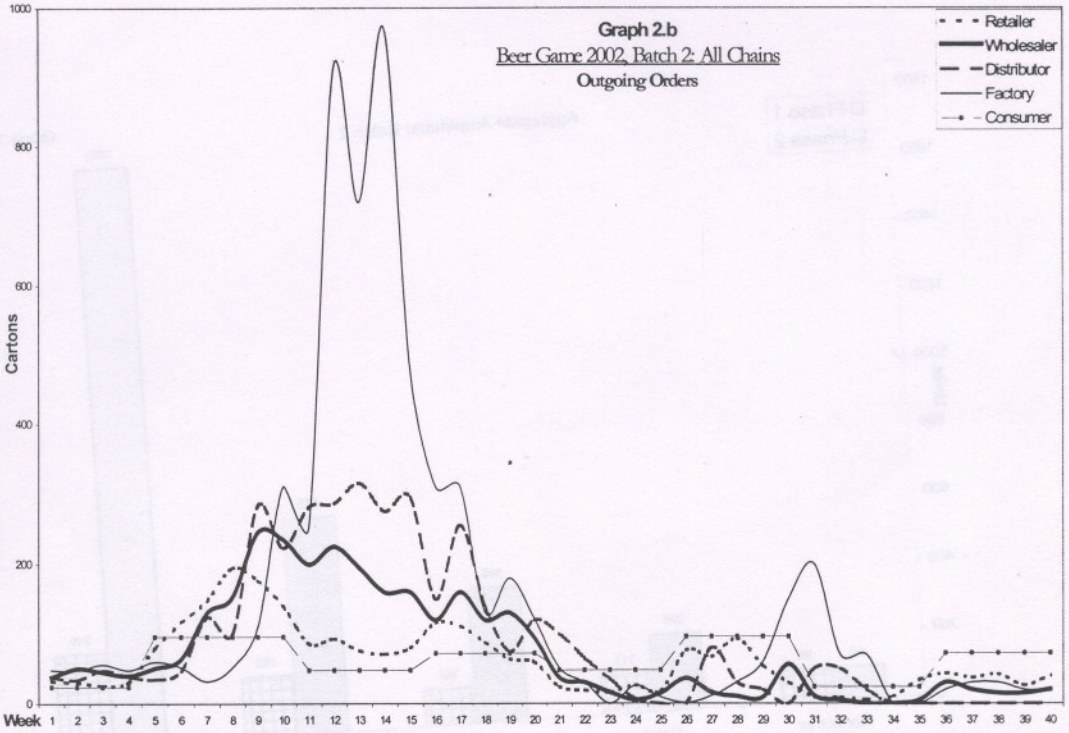
Towill, Denis R., (1996). "Industrial Dynamics Modeling of Supply Chains", *International Journal of Physical Distribution & Logistics Management*, Vol. 26, No. 2, pp. 23-42

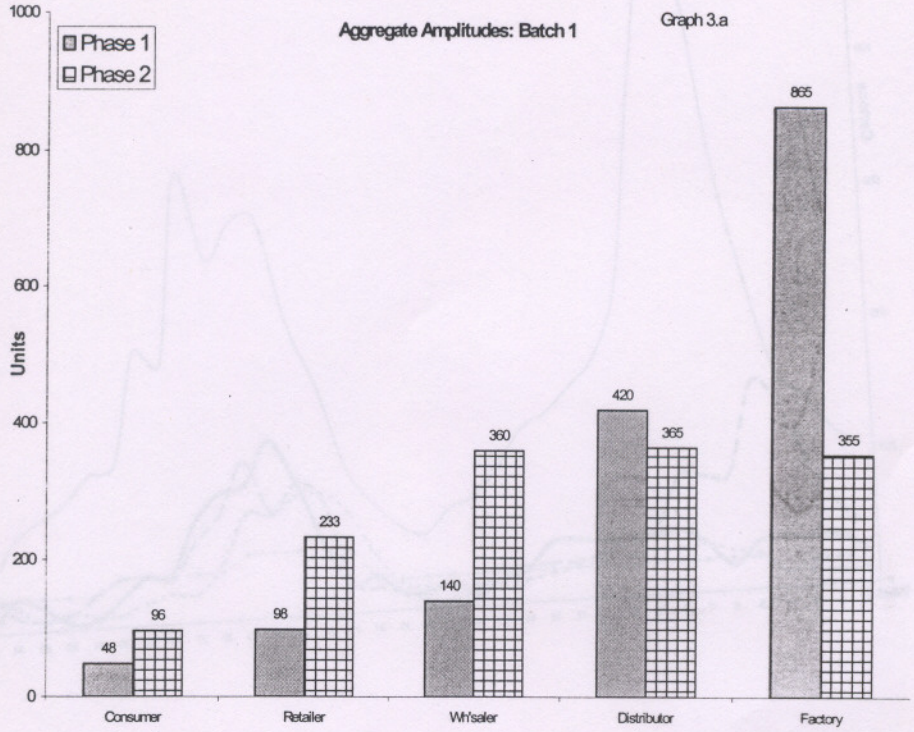
William James, (1907). "Pragmatism's Conception of Truth", *Pragmatism*, New York: Longmans, Green. Reproduced in H.H.Titus & H.H.Hepp (Eds), *The Range & Philosophy*, New Delhi: Affiliated East-West, 1974.

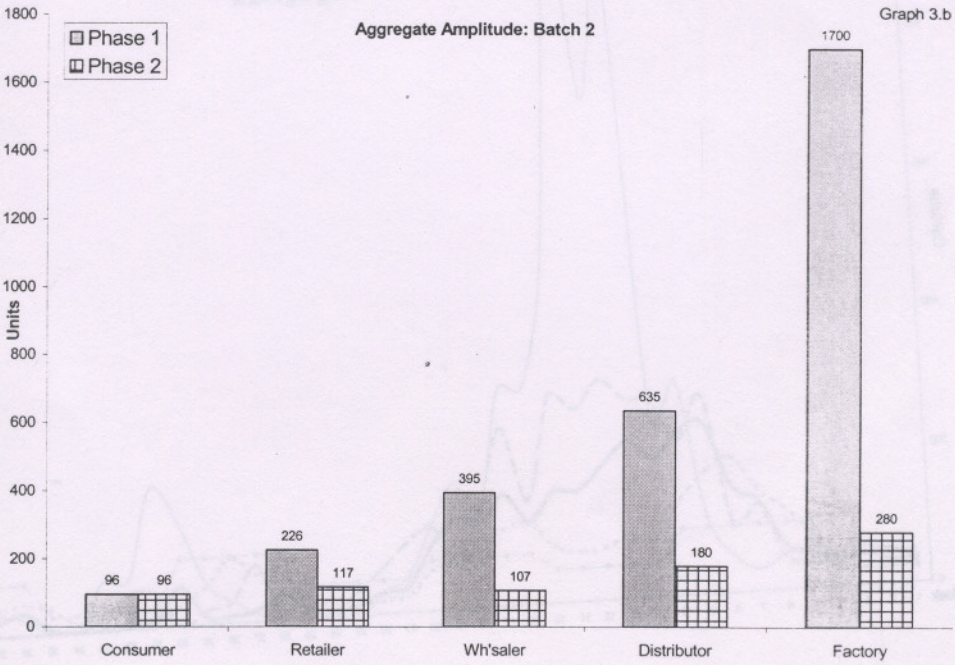


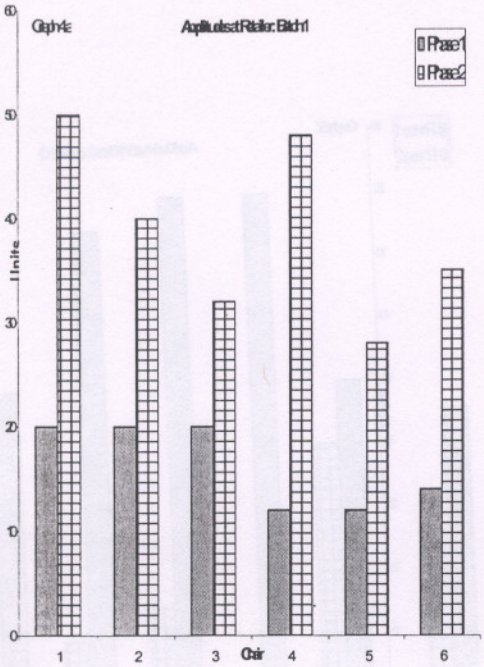

Consumer Demand : Batch 2
Graph 1.b
Units
PHASE 1
PHASE 2
μ = 10.6
σ = 4.55
μ = 10.0
σ = 4.59
week
0
2
4
6
8
10
12
14
16
18
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40

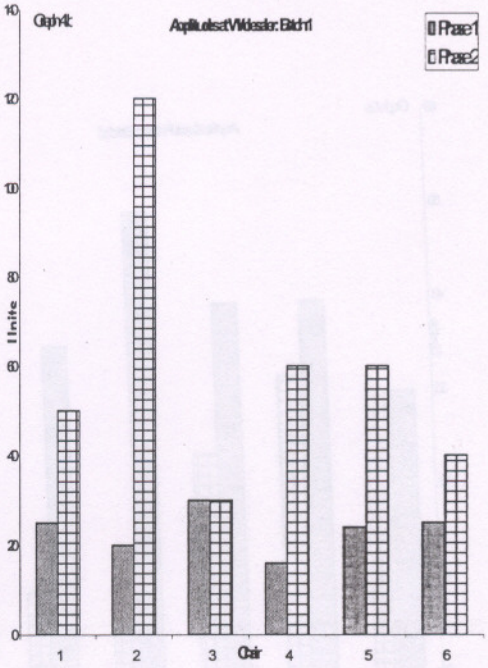

Graph 2.a
Beer Game 2002: Batch 1: All Chains Combined
Outgoing Orders
Retailer
Wholesaler
Distributor
Factory
Consumer
Cartons
Week

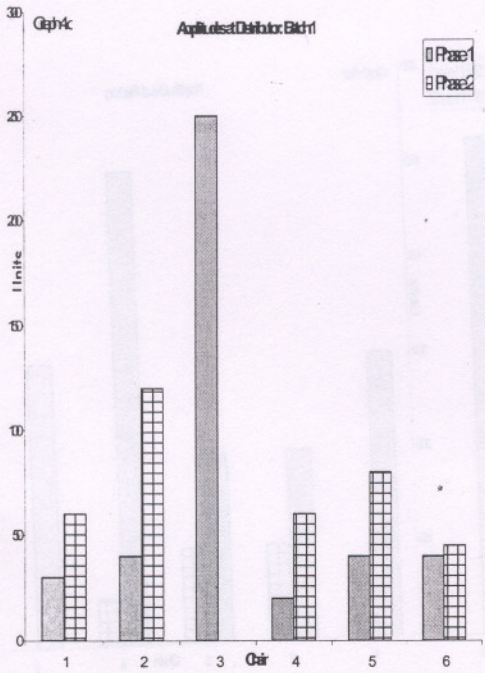

Graph 2.b
Beer Game 2002, Batch 2: All Chains
Outgoing Orders
Retailer
Wholesaler
Distributor
Factory
Consumer
Cartons
Week

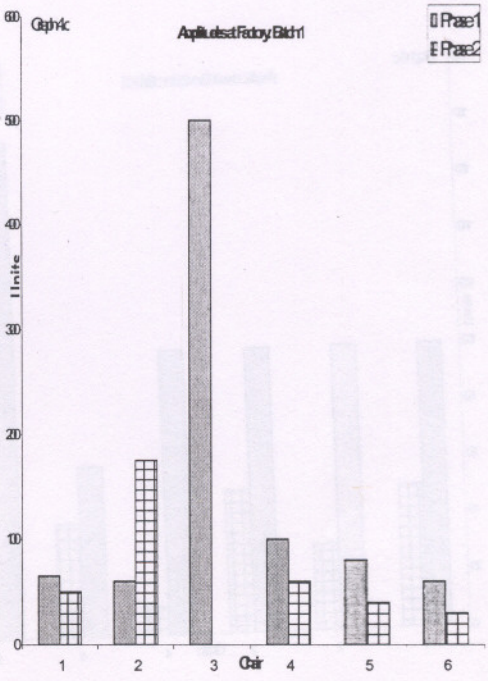

Aggregate Amplitudes: Batch 1
Graph 3.a
Phase 1
Phase 2
Units
1000
800
600
400
200
0
48
96
98
233
140
360
420
365
865
355
Consumer
Retailer
Wh'saler
Distributor
Factory

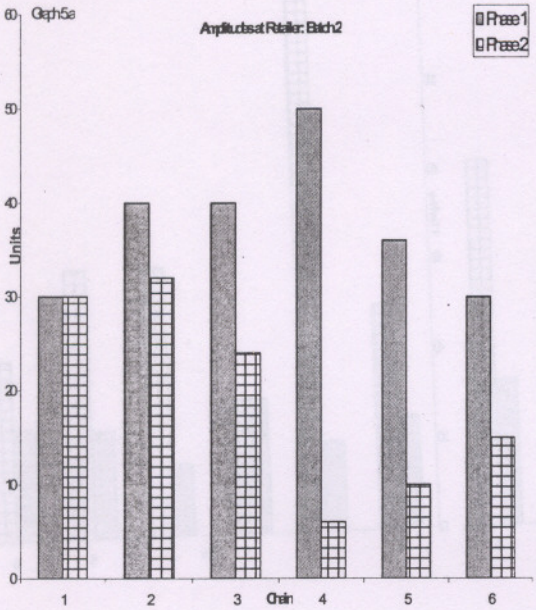

Aggregate Amplitude: Batch 2
Graph 3.b
Phase 1
Phase 2
Units
1800
1600
1400
1200
1000
800
600
400
200
0
96
96
226
117
395
107
635
180
1700
280
Consumer
Retailer
Wh'saler
Distributor
Factory

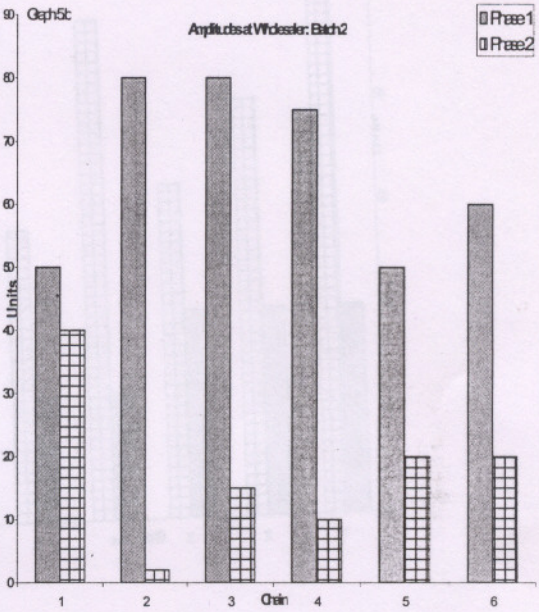

Graph4a
Applicules at Retailor. Batch1
Phase1
Phase2
Unite
Chair
0
10
20
30
40
50
60
1
2
3
4
5
6

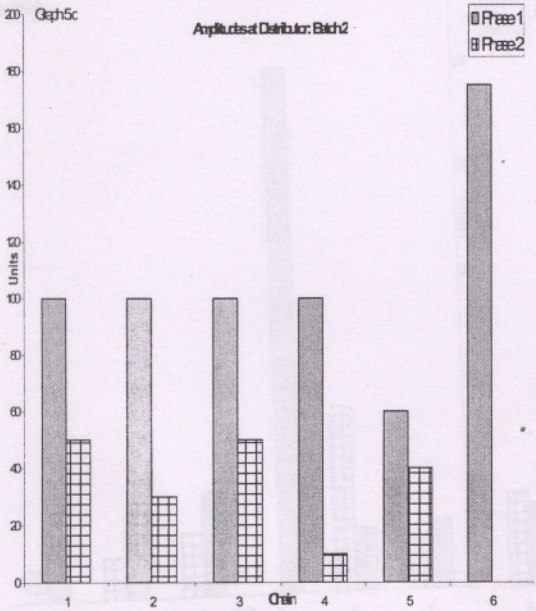

Graph4b
Applicules at Wholesaler. Batch1
Phase1
Phase2
Unite
Chair
0
20
40
60
80
100
120
1
2
3
4
5
6

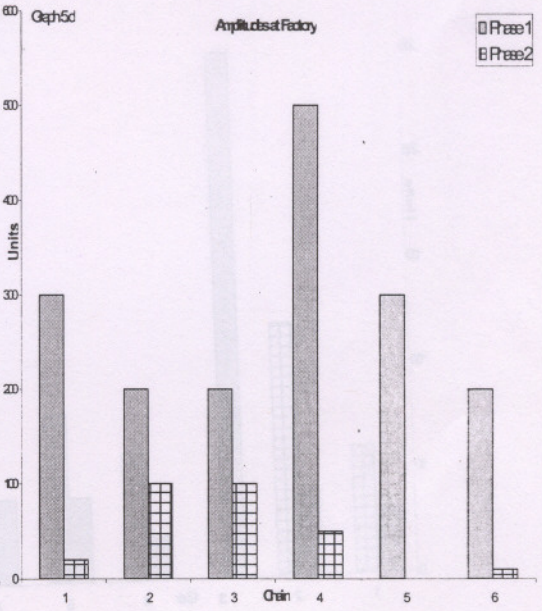

Graph4c
Applicules at Distributor. Batch1
Phase1
Phase2
Unite
Chair
0
5
10
15
20
25
30
1
2
3
4
5
6

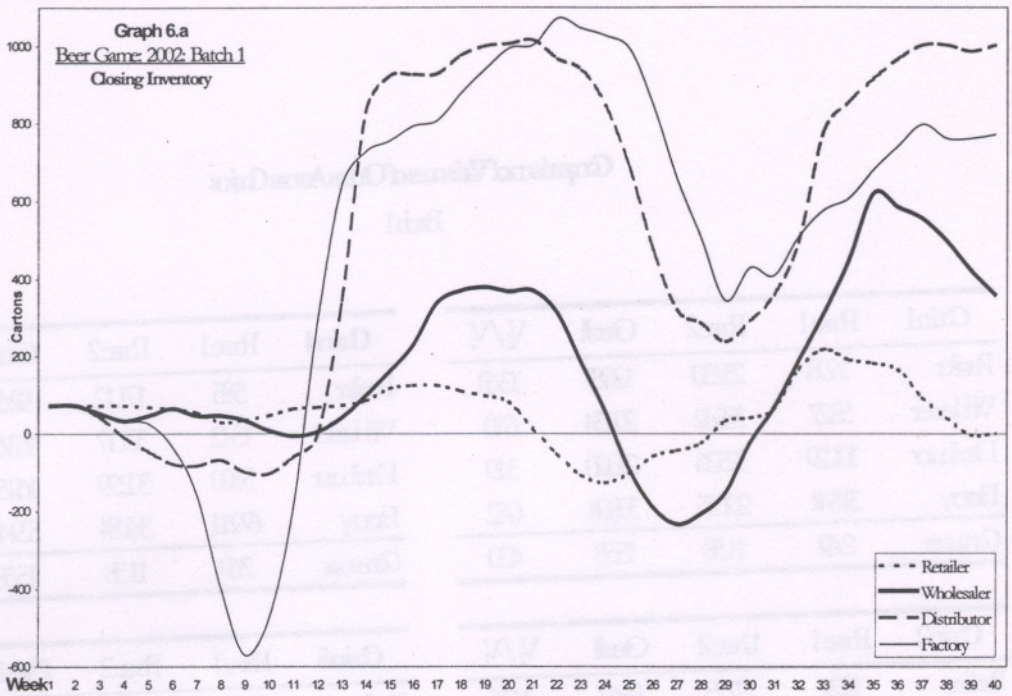

Graph4c
Applicules at Factory. Batch1
Phase1
Phase2
Unite
Chair
0
10
20
30
40
50
60
1
2
3
4
5
6


Graph5a
Amplitudes at Retailer: Batch 2
Phase1
Phase2
Units
Chain


Graph5b
Amplitudes at Wholesaler: Batch 2
Phase1
Phase2
Units
Chain


Graph5c
Amplitudes at Distributor: Batch 2
Phase1
Phase2
Units
Chain


Graph5d
Amplitudes at Factory
Phase1
Phase2
Units
Chain


Graph 6.a
Beer Game: 2002: Batch 1
Closing Inventory
Cartons
Week
Retailer
Wholesaler
Distributor
Factory

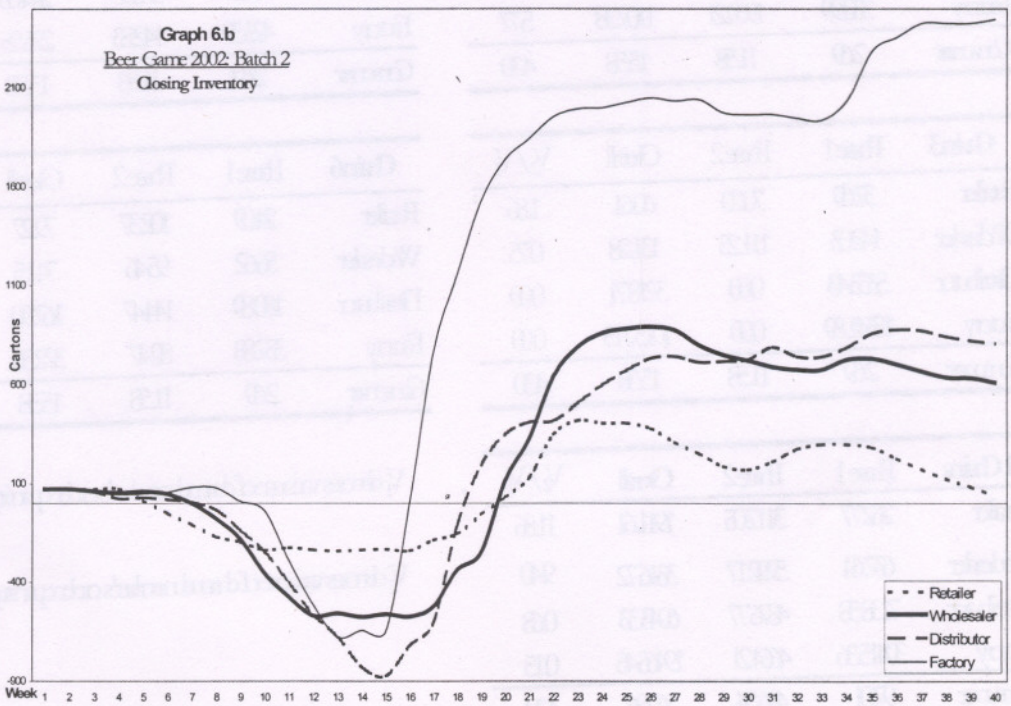

Graph 6.b
Beer Game 2002: Batch 2
Closing Inventory
Cartons
Week
Retailer
Wholesaler
Distributor
Factory

Table 1

Comparison of Variances of Orders Across Chains

Batch 1

Chain 1	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	16.98	23.23.0	126.87	13.68
Wholesaler	58.27	355.42	205.34	6.10
Distributor	101.29	323.36	210.20	3.19
Factory	318.41	261.25	308.04	0.82
Consumer	2.69	11.58	15.58	4.30

Chain 2	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	12.21	172.75	93.62	14.15
Wholesaler	38.94	988.16	523.04	25.38
Distributor	114.73	1237.01	725.00	10.78
Factory	330.99	1909.21	1107.38	5.77
Consumer	2.69	11.58	15.58	4.30

Chain 3	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	37.69	70.20	60.61	1.86
Wholesaler	148.03	111.25	131.28	0.75
Distributor	535.343	0.00	321.871	0.00
Factory	1854.189	0.00	1015.015	0.00
Consumer	2.69	11.58	15.58	4.30

All Chains	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	262.77	3117.05	1911.61	11.86
Wholesaler	637.64	5992.17	3316.72	9.40
Distributor	7138.58	4876.77	6043.33	0.68
Factory	3041.536	4664.21	1946.545	0.15
Consumer	97.01	416.84	560.86	4.30

Chain 4	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	5.85	171.12	92.63	29.24
Wholesaler	15.12	301.17	163.63	19.92
Distributor	37.00	302.99	169.54	8.19
Factory	679.11	381.84	529.44	0.56
Consumer	2.69	11.58	15.58	4.30

Chain 5	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	3.92	68.33	41.48	17.41
Wholesaler	42.73	246.87	143.32	5.78
Distributor	136.37	355.95	244.05	2.61
Factory	423.59	142.83	275.95	0.34
Consumer	2.69	11.58	15.58	4.30

Chain 6	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	24.09	102.37	79.27	4.25
Wholesaler	56.62	95.46	74.15	1.69
Distributor	180.89	144.47	167.90	0.80
Factory	337.88	89.47	322.36	0.26
Consumer	2.69	11.58	15.58	4.30

V_1 denotes variance of channel member's order quantity in Phase 1.

V_2 denotes variance of channel member's order quantity in Phase 2.

Table 2

Comparison of Variances of Orders Across Chains

Batch 2

Chain 1	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	61.09	55.53	69.02	0.91
Wholesaler	156.77	97.63	163.05	0.62
Distributor	668.75	167.11	451.89	0.25
Factory	5789.22	57.89	3214.96	0.01
Consumer	20.67	21.05	20.42	1.02

Chain 2	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	135.75	76.80	111.59	0.57
Wholesaler	482.06	0.20	437.41	0.00
Distributor	858.80	51.32	634.49	0.06
Factory	3846.51	568.53	2426.80	0.15
Consumer	20.67	21.05	20.42	1.02

Chain 3	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	127.00	59.48	92.86	0.47
Wholesaler	409.95	32.83	254.19	0.08
Distributor	772.57	234.98	531.24	0.30
Factory	2247.69	994.47	1580.76	0.44
Consumer	20.67	21.05	20.42	1.02

Chain 4	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	1984.8	1.80	1855.33	0.01
Wholesaler	3942.7	7.57	4257.7	0.02
Distributor	8944.3	16.84	7282.8	0.02
Factory	12070.74	124.74	6833.95	0.01
Consumer	20.67	21.05	20.42	1.02

Chain 5	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	94.52	19.74	152.16	0.21
Wholesaler	178.06	47.69	171.59	0.27
Distributor	338.41	134.21	333.84	0.40
Factory	679.95	0.00	4074.40	0.00
Consumer	20.67	21.05	20.42	1.02

Chain 6	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	72.67	30.20	53.92	0.42
Wholesaler	354.91	24.41	249.87	0.07
Distributor	1683.92	0.00	1083.79	0.00
Factory	2066.22	5.00	1274.91	0.00
Consumer	20.67	21.05	20.42	1.02

All Chains	Phase 1	Phase 2	Overall	V_2/V_1
Retailer	382.426	411.82	371.092	0.11
Wholesaler	388.484	194.59	445.613	0.05
Distributor	1342.765	133.98	1134.692	0.10
Factory	9347.573	289.710	4938.863	0.03
Consumer	239.211	601.05	160.822	0.25

V_1 denotes variance of channel member's order quantity in Phase 1.

V_2 denotes variance of channel member's order quantity in Phase 2.

Table 3.a

Amplitudes of Orders Placed Across Channel (Units)

Batch 1

		Consumer	Retailer	Wh'saler	Distributor	Factory
Chain 1	Phase 1	8	20	25	30	65
	Phase 2	16	50	50	60	50
Chain 2	Phase 1	8	20	20	40	60
	Phase 2	16	40	120	120	175
Chain 3	Phase 1	8	20	30	250	500
	Phase 2	16	32	30		
Chain 4	Phase 1	8	12	16	20	100
	Phase 2	16	48	60	60	60
Chain 5	Phase 1	8	12	24	40	80
	Phase 2	16	28	60	80	40
Chain 6	Phase 1	8	14	25	40	60
	Phase 2	16	35	40	45	30

Table 3.b

Amplitudes of Orders Placed Across Channel (Units)

Batch 2

		Consumer	Retailer	Wh'saler	Distributor	Factory
Chain 1	Phase 1	16	30	50	100	300
	Phase 2	16	30	40	50	20
Chain 2	Phase 1	16	40	80	100	200
	Phase 2	16	32	2	30	100
Chain 3	Phase 1	16	40	80	100	200
	Phase 2	16	24	15	50	100
Chain 4	Phase 1	16	50	75	100	500
	Phase 2	16	6	10	10	50
Chain 5	Phase 1	16	36	50	60	300
	Phase 2	16	10	20	40	
Chain 6	Phase 1	16	30	60	175	200
	Phase 2	16	15	20		10

Table 4.a

Relative Amplitudes of Orders Placed Across Channel (Units)

Batch 1

		Retailer	Wh'saler	Distributor	Factory
Chain 1	Phase 1	2.50	3.13	3.75	8.13
	Phase 2	3.13	3.13	3.75	3.13
Chain 2	Phase 1	2.50	2.50	5.00	7.50
	Phase 2	2.50	7.50	7.50	10.94
Chain 3	Phase 1	2.50	3.75	31.25	62.50
	Phase 2	2.00	1.88		
Chain 4	Phase 1	1.50	2.00	2.50	12.50
	Phase 2	3.00	3.75	3.75	3.75
Chain 5	Phase 1	1.50	3.00	5.00	10.00
	Phase 2	1.75	3.75	5.00	2.50
Chain 6	Phase 1	1.75	3.13	5.00	7.50
	Phase 2	2.19	2.50	2.81	1.88

Table 4.b

Relative Amplitudes of Orders Placed Across Channel (Units)

Batch 2

		Retailer	Wh'saler	Distributor	Factory
Chain 1	Phase 1	1.88	3.13	6.25	18.75
	Phase 2	1.88	2.50	3.13	1.25
Chain 2	Phase 1	2.50	5.00	6.25	12.50
	Phase 2	2.00	0.13	1.88	6.25
Chain 3	Phase 1	2.50	5.00	6.25	12.50
	Phase 2	1.50	0.94	3.13	6.25
Chain 4	Phase 1	3.13	4.69	6.25	31.25
	Phase 2	0.38	0.63	0.63	3.13
Chain 5	Phase 1	2.25	3.13	3.75	18.75
	Phase 2	0.63	1.25	2.50	
Chain 6	Phase 1	1.88	3.75	10.94	12.50
	Phase 2	0.94	1.25		0.63

Relative Amplitude (RA) is calculated by dividing the amplitude of a channel member by that of his predecessor. Thus, RA for Wholesaler is arrived at by dividing the amplitude of Wholesaler by the amplitude of retailer.

Table 5

Comparison of Variable-Significance on Influence of Order Quantity Decision *

Retailer	In Order		Inventory	
	Ph1	Ph2	Ph1	Ph2
Batch 1	3	4	5	3
Batch 2	5	4	4	2

Wholesaler	In Order		Inventory	
	Ph1	Ph2	Ph1	Ph2
Batch 1	2	4	4	3
Batch 2	5	1	3	4

Distributor	In Order		Inventory	
	Ph1	Ph2	Ph1	Ph2
Batch 1	4	4	5	2
Batch 2	6	3	3	2

Factory	In Order		Inventory	
	Ph1	Ph2	Ph1	Ph2
Batch 1	6	3	3	1
Batch 2	6	Nil	1	1

The table lists only those many number of occurences that had significant *t-Stat* for the two beta-coefficients in the regression equations, where Order Quantity decided was taken as a dependent variable and inward order quantity and net inventory (inventory *minus* back order) were taken as independent variables.

The table is to be read as follows:

Among the Distributors in Batch 1, 4 firms had significant influence of their In Order quantity on their outward order decision in Phase I and this number remained in the second phase too, whereas in the same batch, 5 firms had inventory influencing their decision in Phase 1 but only 2 firms experienced it in Phase 2.

* $p \leq 0.10$ in all the tables

Table 6a

BATCH	CHAIN	REGRESSION COEFFICIENTS OF INWARD ORDER & INVENTORY							
		DEPENDENT VARIABLE: RETAILERS OUTWARD ORDER							
		PHASE 1				PHASE 2			
		Inward Order β_1	t	Inventory β_2	t	Inward Order β_1	t	Inventory β_2	t
BATCH 1	1	0.4490	0.8227	-0.4027	-1.8405	1.9537	1.7783	-0.1817	-1.4026
	2	0.7156	1.0721	-0.0899	-0.4593	2.8376	2.9311	0.0772	0.6464
	3	1.7865	3.2506	-0.4535	-5.8618	1.0232	1.4235	-0.1479	-0.8397
	4	0.3664	1.2627	-0.3636	-2.5035	2.1648	4.0952	-0.3236	-5.3429
	5	0.7272	3.0905	-0.2345	-2.7853	1.4000	3.6985	0.3004	3.3231
	6	0.6553	2.8000	-0.3654	-11.8731	0.7259	1.1863	-0.2526	-3.1664
BATCH 2	1	0.5231	1.4581	-0.1446	-2.0063	1.0667	3.2876	0.0078	0.1362
	2	1.8140	4.3294	-0.0957	-1.0396	1.6136	3.3134	0.1119	0.9441
	3	2.1473	5.8118	0.1065	1.9089	1.2238	3.9839	-0.0021	-0.0322
	4	1.6424	4.0334	-0.1721	-4.9986	0.0276	0.4030	-0.0054	-1.0022
	5	0.5664	2.6506	-0.3329	-8.0360	-0.1362	-0.6392	-0.0455	-1.9565
	6	1.3463	3.8494	0.0411	0.7213	0.7521	3.4601	-0.0999	-3.1684

Table6b

BATCH	CHAIN	REGRESSION COEFFICIENTS OF INWARD ORDER & INVENTORY DEPENDENT VARIABLE WHOLESALERS OUTWARD ORDER							
		PHASE 1				PHASE 2			
		Inward Order β_1	t	Inventory β_2	t	Inward Order β_1	t	Inventory β_2	t
BATCH 1	1	0.8748	1.9544	-0.1178	-2.4458	0.8663	5.9589	-0.0787	-2.8217
	2	0.0989	0.1901	-0.5753	-3.2137	0.9238	1.6573	-0.1015	-1.4240
	3	1.3573	5.6847	-0.0704	-3.5957	0.5862	2.6344	-0.1036	-2.1537
	4	0.4453	1.6477	-0.1866	-2.9098	1.2455	5.9008	0.0307	0.6627
	5	-0.7319	-1.0408	-0.2369	-0.6592	0.8347	2.5108	-0.1271	-2.0314
	6	0.5750	1.3146	-0.0896	-1.7072	0.1231	0.5305	-0.0507	-0.6112
BATCH 2	1	1.4626	5.8679	0.0145	0.3084	0.9236	3.6349	0.1368	1.6167
	2	0.5263	3.0278	-0.5320	-8.3354	0.0057	0.6677	-0.0048	-4.0339
	3	1.5979	9.7266	-0.0498	-1.4819	0.1505	1.2480	-0.1391	-4.5819
	4	0.6772	2.4277	-0.1064	-2.1535	-0.0987	-0.2929	-0.0557	-4.4547
	5	0.6599	2.7995	-0.0700	-1.8590	-0.0694	-0.2487	-0.1213	-2.8056
	6	0.6701	1.5244	-0.0911	-1.4839	0.2271	1.0555	-0.0381	-1.4709

Table6c

BATCH	CHAIN	REGRESSION COEFFICIENTS OF INWARD ORDER & INVENTORY DEPENDENT VARIABLE DISTRIBUTORS OUTWARD ORDER							
		PHASE 1				PHASE 2			
		Inward Order β_1	t	Inventory β_2	t	Inward Order β_1	t	Inventory β_2	t
BATCH 1	1	0.6296	2.0732	-0.1284	-1.8510	1.0887	5.5350	0.0714	1.3454
	2	1.3823	6.6375	-0.0865	-3.0091	0.7330	2.9722	-0.0164	-0.2811
	3	0.5496	0.3921	-0.0997	-2.2609		6.5535E+04		6.5535E+04
	4	0.7372	3.1988	-0.1244	-3.1517	0.5518	4.7455	-0.1432	-4.4083
	5	0.6334	1.7001	-0.2342	-2.4643	0.8835	4.5429	-0.0802	-1.1871
	6	0.7790	2.0311	-0.1562	-1.2525	-0.3300	-1.3849	-0.3284	-4.0842
BATCH 2	1	1.0068	3.9989	-0.2278	-4.5720	0.9943	4.3187	-0.0638	-1.1843
	2	1.2275	7.5283	0.0149	0.4188	0.5475	9.3131	-0.0909	-5.0024
	3	1.2477	7.6664	0.0371	1.0884	-0.4433	-0.6004	-0.0143	-0.1707
	4	0.5597	2.2243	-0.0770	-2.2098	-0.0054	-0.0435	-0.1224	-2.5003
	5	1.0544	5.5744	-0.2191	-3.3905	0.7761	6.8178	-0.0054	-0.0699
	6	1.7761	3.1255	0.1113	1.0914		6.5535E+04		6.5535E+04

Table 6d

BATCH	CHAIN	REGRESSION COEFFICIENTS OF INWARD ORDER & INVENTORY							
		DEPENDENT VARIABLE FACTORY OUTWARD ORDER							
		PHASE 1				PHASE 2			
		Inward Order β_1	t	Inventory β_2	t	Inward Order β_1	t	Inventory β_2	t
BATCH 1	1	1.0057	2.3008	-0.0273	-0.3129	0.8902	8.8729	0.0750	2.0592
	2	1.1177	4.5382	-0.0725	-2.1975	0.8752	3.9465	-0.0863	-1.1779
	3	1.8825	5.8500	0.1372	1.5529	Indeterminate			
	4	2.0370	2.5960	-0.1268	-2.3309	0.9905	7.2642	-0.0227	-0.6634
	5	1.3251	5.3943	-0.0588	-1.4357	0.1075	0.6313	-0.0729	-1.2102
	6	0.5152	2.5721	-0.2481	-4.2987	0.0446	0.2094	-0.0149	-0.2682
BATCH 2	1	1.6121	2.8759	-0.1343	-1.3226	0.4066	1.1112	-0.0414	-0.8724
	2	1.3506	2.6377	-0.0766	-0.4457	-0.5779	-0.8958	0.0049	0.0615
	3	1.7986	8.3642	0.1027	1.5613	0.1995	0.4896	-0.1128	-1.7444
	4	1.7541	2.3967	-0.0633	-0.5160	-0.2780	-0.8951	-0.0961	-0.8998
	5	3.0232	4.1150	-0.2419	-3.7002		6.553E+04		6.553E+04
	6	0.5877	2.1743	-0.0253	-0.2217	Indeterminate			

Table 7

Comparison of Variable-Significance on Influence of Order Quantity Decision

Aggregate Scenario

Batch 1	Phase 1				Phase 2			
	Inward Order		Inventory		Inward Order		Inventory	
Value	β	t	β	t	β	t	β	t
Retailers	**0.6730**	2.7317	**-0.4287**	-4.7304	**1.6227**	3.0209	-0.1330	-1.2803
Wholesalers	**0.6666**	2.6895	**-0.1033**	-3.5982	**1.1265**	6.9985	-0.0404	-1.2567
Distributors	**0.6867**	1.1919	**-0.1088**	-3.3460	**0.8005**	5.6279	-0.0154	-0.4333
Factories	**1.3907**	4.5905	-0.0442	-0.7659	**0.8454**	7.8299	-0.0104	-0.2949

Batch 2	Phase 1				Phase 2			
	Inward Order		Inventory		Inward Order		Inventory	
Value	β	t	β	t	β	t	β	t
Retailers	**1.2284**	5.9783	**-0.1348**	-3.0388	**0.7326**	6.0780	0.0301	1.0064
Wholesalers	**0.9977**	7.7558	**-0.0829**	-3.6027	**0.3362**	2.2679	-0.0122	-0.5112
Distributors	**0.9321**	4.1923	**-0.0870**	-1.9291	**0.5858**	2.3339	-0.0228	-0.3584
Factories	**1.6143**	4.4842	**-0.1460**	-2.2796	-0.5021	-1.3445	**-0.1529**	-2.0832

Note: Aggregate scenario is arrived at by collatoral summation of each round's data for each level of the chain acrocs the six chains for each batch separately. Thus, it can be taken to represent the macro scenario of the supply chains during the game periods.

About the Author

R. C. Natarajan holds M.A degree in Economics from JNU and PGDRM from IRMA. He has 15 years work experience in FMCG industry in Sales and Marketing Management. He is Associate Professor (Marketing) in T. A. Pai Management Institute, Manipal since 1999. He handles courses *Distribution Channel Management, Marketing Strategy* and *Presentation Skills*. Currently, he pursues doctoral work in the field of Distribution Management at MAHE, Manipal.