

# The Bullwhip Effect—Impact of Lead Time, Information Quality, and Information Sharing

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**Abstract**— A simple system dynamics model of a traditional supply chain system is investigated. Particularly, the effect of lead time, information quality and information sharing also remanufacturing lead-time and the return rate on the inventory variance and the generation of bullwhip effect were studied. Our results clearly showed that the bullwhip in the closed loop supply chain is bigger than one in traditional supply chain and foreign to the collection rate and the inventory variance in every stage decrease when the quality of information and the information sharing is introduced into the traditional supply chain. Furthermore, we found that the bullwhip effect in the closed loop supply chain will increase when the short term lead time of remanufacture cycle time increase.

**Index Terms**— BWE (Bullwhip Effect), Supply Chain.

## I. INTRODUCTION

The operating phenomenon known as the “Bullwhip Effect” (BWE) is affected by the flow of information upstream through the supply chain. The Bullwhip Effect is the amplification of the demand or order variance up the supply chain, from customer to factory, as demand information passes back through the supply chain. The phenomenon is shown in Figure 1, which is generated by plotting 100 orders placed by each node of a simulated supply chain. The analogous amplification is due to effects of deteriorating process quality and overtime as a result of a “meltdown” incident. The BWE has a number of consequences on the operation of a supply chain. Because of the higher variance, more safety stocks have to be carried with consequently more investment, extra production capacity, and increased storage space. Periods of intense resource utilization are followed by periods of underutilization.

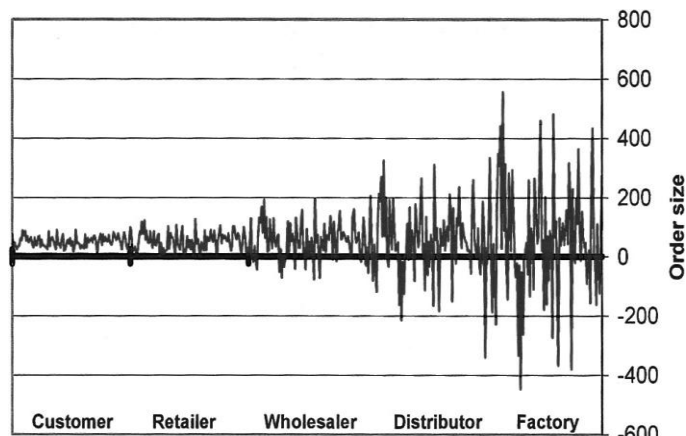
This oscillation shows that the supply chain harness enough resources to meet the inflated peak periods.

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**Figure 1** Illustration of the Bullwhip Effect from Time Series Data.

## II. GOALS AND CONTRIBUTION TO THE LITERATURE

The literature indicates that much of the BWE is due to erratic human behavior, it indicated that the BWE is caused by “strategic interactions among rational supply-chain members,” whereas others take a systems dynamics approach relating a supply chain’s structure, policies, and interactions to demand variability amplification. The current state of investigation of the BWE involves restrictive assumptions about many aspects of the supply chain. The constant lead-time assumption is especially restrictive in light of the variable lead times actually present in many supply chains. Another characteristic of Bullwhip-related studies is the focus on two-stage supply chains, with customer-retailer being the first stage, and retailer-manufacturer the second. Other than Forrester’s simulation model and the Beer Game, Bullwhip research has so far generally focused on these two-stage scenarios. In our research, we create a serial supply chain simulation model to determine order-up-to levels and order quantities for each stage. we create a series of experiments that employ factors related to lead-time variation, information quality, and information sharing. Our purpose is to gain insights to help reduce overall variability within a supply chain. We model serial supply chains and wish to answer the following questions:

1. What is the effect of lead times in supply chains?
2. What is the extent to which information sharing helps?
3. What impact does the quality of information on the BWE ?

## III. LITERATURE REVIEW

### Approaches to Analyzing the Bullwhip Effect

The original characterization of the BWE is due to Forrester (1958, 1961), who employed a continuous simulation system called ‘DYNAMO’ to simulate a four-node production-inventory-distribution system.

Forrester described the behavior of the system under various internal conditions and its response to external changes and shocks. His underlying theme was that the structure, policies, and interactions within a supply chain cause variability amplification. This approach is also employed in the simulation-driven works of Towill (1991), Wickner, Towill, and Naim (1991), and Towill, Naim, and Wickner (1992) and, to a lesser extent, of Bhaskaran (1998). Bhaskaran analyzed a manufacturing supply chain using simulation and showed how the various components interacted with each other, concluding that the lack of coordination in supply chains led to inventory fluctuations and to a high average inventory level. This involves representing the relationships within a supply chain, such as replenishment policies, as a set of transfer functions. These transfer functions can then be used to relate the output of the system (orders) to the input (demands) by utilizing the z-transform of the output and input variables (Dejonckheere et al. 2004).

#### IV. INVESTIGATION AND METHODOLOGY

##### Factors Investigated

##### Lead-Time Variation.

The first factor deals with the modeling of supply chain lead times, which previous investigations of the BWE have restricted to constant values. We investigate various levels of leadtime variation, using the distribution to represent stochastic lead times. We create four scenarios based on different levels of the coefficient of variation for the lead-time.

##### Information Quality Level.

The second factor is the “quality” of information available or chosen. This information is used directly in lead-time demand forecasting and inventory parameter updating. It may also affect the order streams, inventory levels, stockouts, and other aspects of a supply chain. We distinguish between four information quality levels (IQL) that may be used for updating the order-up-to point: levels 0, 1, 2, and 3.

##### Level 0. IQL0

Means no new information is used. This is the case where there is no new information collected to aid in updating, or possibly the case where the demand and lead-time distributions are known and thus the “best” order-up-to value can be chosen in advance, with no need for any updating.

##### Level 1. IQL1

Assumes that the histories of incoming demands and of lead times are available. Information on lead-time variance is not used in updating the inventory policy parameters, which could be due to a mistaken assumption of constant lead times or the belief that lead-time variation is not important.

##### Level 2. IQL2

Assumes that the histories of incoming demands and of lead times are available, but in this case an estimate of lead-time variance is generated and used for up-dating the inventory policy parameters.

##### Level 3. IQL3

Assumes that the inventory manager tracks and stores the final lead-time demand realizations for each order. Forecasts should be more accurate and exhibit less “nervousness” when employing IQL3, since the final realizations of lead-time demand are used instead of the intermediate surrogate data of lead time and demand.

##### Information Sharing.

The first two factors were lead-time variation and information quality level. The third factor is information sharing. With no information sharing, each node generates its own forecast, based on local information, and the forecast is then used to generate a new order-up-to value, and consequently, the order size for the current period. The idea of information sharing is that if the nodes were aware of the current customer demands, they would make forecasts with that information and fine-tune their inventory system parameters accordingly. Since the customer’s demand order stream will have a variance less than or equal to the variance of the orders coming from the downstream partner, the assumption is that a node using customer information will smooth the fluctuations in the order-up-to level and the resulting order stream will have a lower variance.

#### V. SUPPLY CHAIN MODEL

We employ single-stage lead times with the entire delay occurring during transportation. We assume that any information delay, or the delay necessary for the order to “get into the right hands,” is zero. We also assume that the time to fill an order once it is received (order processing delay) is also zero. The mean lead times at the customer, retailer, wholesaler, distributor, and factory are 0, 4, 4, 4, and 4 time units, respectively, not including the review period,  $R=1$ . We assume that these delays are gamma-distributed.

##### Lead-Time Demand

Let  $X$  be the demand during the protection period  $L+R$ . Then  $X$  has mean  $\mu_X$  that we estimate by  $\bar{X}$ , and variance  $\sigma_X^2$  that we estimate by  $S_X^2$ . Hence,  $X$  for an order placed at time  $t$ , is the convolution

$$X_t = \sum_{i=0}^{L+R} D_{t+i} \quad (1)$$

#### VI. SCOPE OF INFORMATION

With no information sharing, supply chain nodes possess only local information and are “blind” to what is going on outside their level. Each node’s supply chain knowledge-base is derived from the incoming demand flow coming from the downstream partner and the outgoing flow of orders being placed with the upstream partner. With information sharing, each node in the supply chain receives information on customer demand, in addition to orders from its downstream supply chain partner. The nodes make no assumptions

regarding the demand or lead-time distribution, except that the lead time is stationary. Each node makes all assessments based only on the available data and attempts to adjust its actions to adapt to the “current” conditions. So, for example, even though customer demand is *iid*, and thus the mean and variance do not change over time, the retailer does not “know” this and will update the inventory policy parameters using forecasts based upon the most recent demand information.

### Inventory Policy.

The order-up-to point,  $S$ , is determined using typical inventory management methods, which include the normal approximation in setting the safety stocks. Thus,  $S$  is the base stock that allows the system to meet the demand during the time period  $L+R$ . We use a safety factor of  $z=2.0$  (service level of 97.72%) in calculating

$$S = X + z s_X \quad (2)$$

### Forecasting and Estimation.

When updating, we use forecasts of the lead-time demand mean ( $X$ ) and its standard deviation ( $s_X$ ) to set an order-up-to level that would yield a desired service level. How we forecast  $X$  and  $s_X$  depends on the information available, i.e., which IQL is used.

## VII. ANALYSIS

### The Impact on the *BWE* of Not Updating Inventory Parameters

We determine that with no updating, i.e., when we employ IQL0, then no variance amplification occurs. Each of the eight scenarios that utilize IQL0 show no *BWE* at all. But since IQL0 has a known impact, we now exclude it from our experimental analysis. Thus, for the remaining factors and factor levels, we analyze 24 scenarios (3 information quality levels x 4 lead time variance levels x 2 information sharing levels) instead of the initial 32.

### The Impact on the *BWE* of Information Sharing

Our results with regard to information sharing confirm much of what has been found when analyzing simpler systems. We will find information sharing does not eliminate the *BWE*. We find information sharing to be the most significant factor at all stages of the supply chain except the retailer's. The exception of the retailer is expected, since the advantage of information sharing is that all stages receive customer demand information, which the retailer has whether information is shared or not. When observing the experimental means, we see that the use of information sharing decreases the total variance amplification at the wholesaler

### The Impact on the *BWE* of Information Quality

We start by noting again that all scenarios utilizing IQL0 no updating of order up to level showed no Bullwhip Effect whatsoever, and were excluded from further analysis. We analyze the remaining three information quality levels (IQL1, IQL2, and IQL3). When observing total variance amplification, we find information quality to be significant at

all of the supply chain. In general, we find IQL2 to be the biggest aggravator of the Bullwhip Effect. We recognize that IQL2, which uses demand rate ( $D$ ) and lead time ( $L$ ) data to forecast the lead-time demand, will result in forecasts with greater variability than IQL1 or IQL3. Forecast variability leads to “nervousness” of the order-up-to level, which results in the *BWE*.

## VIII. RESULT

Given our supply chain structure, regular updates of the order-up-to level are a necessary condition for the Bullwhip Effect (*BWE*). We see this by its absence with no updating. We conclude that the initiation of the *BWE* is due to the manager's attempts to adjust the inventory policy to correspond to the latest data. These adjustments cause system “nervousness,” which is a precursor to the *BWE*. We do not believe adjustments to inventory policies are always detrimental. It may have a positive influence on cost and service aspects of the system, but they do lay the groundwork for the variance amplification of demand.

Information sharing reduces total variance amplification and stage variance amplification. We find that information sharing decelerates the *BWE* as we go up the supply chain, which could be the result of planning ahead, since the upper supply chain would be responding to customer demand information before the demands actually show up in the form of an order from the downstream partner. Information sharing protects a supply chain against failures. When observing *BWE* differences between the models when not using information sharing. We attribute this to the cascading effect that failures (stockouts) at the upper may have on multiple downstream nodes. When information is shared, the cascading phenomenon disappears. Information quality is an important factor in *BWE* formation and we see that better information quality reduces it. We believe that information quality drives the *BWE* by affecting the stability and accuracy of the lead-time demand forecasting process. Less stable or accurate forecasting processes will result in less accurate and more variable order-up-to levels, which result in greater order variability. At the outset, we posed three research questions: what is the effect of stochastic lead times in supply chains; to what extent does information sharing help in attenuating the Bullwhip Effect; and what is the effect of the quality of information available. We hope that we have answered these questions satisfactorily in this experiment.

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