UNDERSTANDING THE FINANCIAL CONSEQUENCES OF THE BULLWHIP EFFECT IN A MULTI-ECHelon SUPPLY CHAIN

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INTRODUCTION

The Bullwhip Effect (Forrester 1961; Lee, Padmanabhan, and Whang 1997) has been studied extensively because of its ability to explain excess inventory in supply chains. In addition, some studies have attempted to quantify the financial effects of the demand variance amplification and inventory increases that characterize the effect (Metters 1997). On the other hand, there is mixed evidence about the aggregate prevalence of the Bullwhip Effect and its consequences (Cachon et al. 2007). But even aggregate studies admit the likelihood of variance amplification as supply chain participants are positioned further from final customers. Therefore, this article’s primary objective is to develop and implement a system dynamics model that allows an analysis of the financial consequences of the Bullwhip Effect in a trans-border setting. We employed typical planning policies and reported operating and financial parameters to investigate how a relatively complete supply chain performs, both in terms of inventory and service variability (the Bullwhip Effect), and in terms of total cost including inventory and service penalty costs.

To analyze the problem, we first outline a base case scenario using supply chain characteristics as reported by a real firm, in this case a Mexican electronics supplier to U.S. automobile assemblers. After establishing the financial levers embedded in this firm’s current supply chain, we use system dynamics (Forrester 1961; Towill 1996) simulation techniques to evaluate which supply chain strategies will have the largest effect on the Bullwhip Effect Index (BE) (Metters 1997), and system costs. Furthermore, sensitivity analysis suggests some interesting, counter-intuitive results. The implications of these findings are further developed as we test how lead time reduction can mitigate the Bullwhip Effect in the simulated setting.

In some supply chains, the Bullwhip Effect can drive 13 %-25 % of operating costs (Lee et al. 1997). Thus “taming” the Bullwhip Effect can have a major impact on firm costs and knowing where to invest effort and resources for this purpose should be a high priority for supply chain managers. We believe that we can show some innovative approaches to an important problem. The remainder of this article will be divided as follows. The next section will review some of the literature about performance measures, cost drivers, and supply chain strategies to be analyzed. Then we will construct and analyze a simulation model that shows how these strategies affect a standard measure of the Bullwhip Effect and further affect supply chain costs. The article concludes with some thoughts on the appropriate measurement techniques for demand variance inflation, as well as the limitations of this work, and suggestions for further research.
LITERATURE REVIEW

Measuring the Bullwhip Effect and Its Structural Precursors

In order to control a process or outcome, it is necessary to define the scope of the process, the process outcome, and a measure of process efficiency and/or effectiveness (Supply Chain Council 2007). Since the Bullwhip Effect seems to be endemic to most stages of the supply chain, we first trace the supply chain process perspective that underlies our investigation. Then we indicate the expected outcomes of this process from both an effectiveness and efficiency perspective. Our focus in this article is efficiency as manifested in operating costs. Hence we go on to discuss both previous work connecting the Bullwhip Effect to supply chain costs, as well as drivers of the Bullwhip Effect which can be found throughout the supply chain process.

The Supply Chain Process—Scope

Although there are many treatments of the overall supply chain process (Chopra and Meindl 2007; Lambert et al. 2005; Supply Chain Council 2007), we employed a version of the SCOR framework as the basis for investigating the consequences of the Bullwhip Effect on overall cost. Specifically, we considered the following stages of a particular company’s supply chain:

Procurement or Source in the SCOR framework refers to obtaining raw materials and components as inputs to a manufacturing procedure. In our case, inputs to the production process were provided “Just-in-Time” and the manufacturer incurred no raw material holding cost.

Production or Make in the SCOR framework refers to converting raw materials and components into a finished good (saleable product). Inventory, for this portion of the supply chain, is work-in-process (WIP).

Transport or Deliver in the SCOR framework refers to moving finished goods inventory from manufacturing site to final customer. In this research, transportation includes both moving product from plant to distribution center, and from distribution center to customer.

Sales is also associated with the Deliver part of the SCOR framework, but includes the actual selling price as part of the model. We add this process to the SCOR framework in order to determine projected profit as part of our investigation.

The Supply Chain Process—Outcome and Measurement (based on variation in the Bullwhip Effect)

One of the best known characteristics of the supply chain process, as outlined in the SCOR model, is the Bullwhip Effect, or the amplification of demand variance through the supply chain. This increase in demand variability is also called the Forrester Effect (Forrester 1961) and has received consideration from many academics (Lee et al. 2004). The generally accepted measure of the magnitude of the Bullwhip Effect is the Bullwhip Effect Index (Dejonckheere et al. 2003; Sterman 1989):

\[ BE = \frac{\sigma^2_{\text{production}}}{\sigma^2_{\text{sales}}} \]

BE is the Bullwhip Effect Index. The numerator is the variance of the amount of product manufactured over a given day of time, and the denominator is the variance in sales to final customer over the same day of time. Notice that both numerator and denominator should be in common units of finished goods, such as cases, and be measured over similar time periods. Notice also that this particular definition of the Bullwhip Effect Index measures the amplification of demand variability between sales and production, but that any two stages of the supply chain could be represented in this manner, as long as the numerator refers to a stage of the supply chain process that precedes the stage in the denominator.

In terms of cost increases, a common outcome attributed to the Bullwhip Effect, estimates vary depending on the importance and value of inventory in the particular supply chain, as well as the imputed inventory carrying cost
for the inventory. Metters (1997) finds that eliminating the Bullwhip Effect can improve profitability from 15-30% for a product with 40% margins over production costs, 33% annual inventory holding costs, and 13% cost of capital. Sterman (1989) shows that the total system costs from “Beer Game” results can be “five to ten times the cost of optimal policies” (Metters 1997). A well-known study by Kurt Salmon Associates in 1993 found that as much as $30 billion in inventory could be removed from the grocery industry supply chain through better matching of supply and demand at all levels. Published reports of inventory inflation and excess cost due to variance amplification have included companies such as HP (Davis 1993), Barilla (Hammond 1994), Procter and Gamble (McKenney and Clark 1995), and Campbell Soup (Fisher 1997).

Although Forrester (1961), Sterman (1989), and Lee et al. (1997) set out convincing evidence that individual supply chains are characterized by variance amplification, the evidence at the aggregate, or industry level, is more difficult to interpret. Economists such as Blanchard (1983) and Blinder (1986) found that production variance in manufacturing industries seemed to be greater than sales variance in retail industries. Cachon et al. (2007) examine industry level data. They attempt to identify industries where variance amplification dominates demand smoothing efforts, versus industries which do not explicitly demonstrate demand variance amplification. Although they do not find consistent evidence of the Bullwhip Effect at an industry level, they emphasize that industry level variance data probably reflect both the Bullwhip Effect and any industry efforts to mitigate the Bullwhip Effect, such as production smoothing. Cachon et al. (2007) call for more investigation into individual firm and individual product data, and it is in that spirit that we proceed.

Precursors to the Bullwhip Effect—Extended Order Cycle Times/Lags in the Supply Chain

Lags in supply chain execution and long cycle times were identified early as potential drivers of the Bullwhip Effect and the associated increased inventory (Blackburn 1991; Forrester 1961; Lee et al. 1995; Metters 1997). This is not surprising since supply chains, like other operating systems, have to obey Little’s Law (Hopp 2008):

\[
\text{Average Inventory} = \text{Throughput} \times \text{Cycle Time}
\]

Actual cycle time is the result of both innate characteristics of the supply chain, such as distance and manufacturing time, as well as the “human” aspect of the supply chain, which encompasses information lags, production planning rules, labor availability (e.g. limits on overtime), etc.

Based on Little’s Law, one approach to minimizing inventory would be to reduce cycle time to the greatest extent possible (Cachon and Terwiesch 2009). For a total supply chain, this implies Just-in-Time operation at every level of the supply chain and thus maximum coordination and visibility. Such an approach is advocated throughout the Toyota Production System and also involves minimizing variability in the supply chain, thus reducing safety stock as well as cycle stock inventory.

However, the necessity of maximizing return on assets while satisfying customer requirements results in familiar complications for both production and demand planners. For example, one approach to minimizing cycle time would be long production runs of a single product, since that eliminates setup times while guaranteeing that product is available. However, if such production is not actualized as throughput (i.e. sold), then inventory in the system increases. Another possibility for minimizing inventory is to match production exactly to customer demand (assuming customers will wait)—a pure make-to-order supply chain, implemented through Just-in-Time purchasing and production. But this approach may result in limited throughput, unused capacity, and depressed return on owned assets, such as manufacturing plants and warehouses.

Thus, we suggest that every supply chain has a cycle time/throughput/inventory combination which best matches demand at lowest total cost. In our exemplar supply chain we account for both information and transportation lags, as well as production times, setup times, and other eventualities. We also use realistic values for the cost of inventory, capital, finished goods, and associated delivery services. Finally, we assign a value to shortage costs based on our conversations with the specific case company.

Once the base cost model has been determined, we test the outcomes of a variety of supply chain strategies. Our objective is to understand how variability, as measured through the Bullwhip Effect Index, can affect overall
supply chain costs. In turn, we seek to determine how a key precursor to the Bullwhip Effect—variation in cycle times—manifests in the Bullwhip Effect, and affects supply chain financial performance under different strategies.

Although others have quantified the penalties associated with the Bullwhip Effect (Hammond 1994; McKenney and Clark 1995; Metters 1997), we know of no other attempts to compare supply chain outcomes of various strategies specifically through overall supply chain cost models and cycle times. Managerially, as Hopp (2008) points out, it is important to understand the implications of reducing cycle times and whether there is a “best” value, since customer service, inventory, and cycle time are inextricably linked. Furthermore, it may be useful to understand where the financial leverage points are in supply chains, since that is likely to be the best place to invest time, effort, and other resources. But locating financial leverage points also requires realistic, accessible models, which can be used to evaluate alternative strategies.

MODEL AND ANALYSIS

Supply Chain Cost Model

North Electronics (NE), the Mexican subsidiary of a multinational auto parts supplier, is the manufacturer anchoring the supply chain we analyze in detail. NE ships some 200 products to U.S. assembly plants, but we chose a single representative item for this analysis. This company was the subject of a previous study (Carranza and Villegas 2006a) and volunteered data based on extensive semi-structured interviews and company records. In particular, the company made available actual sales data, realistic prices, and backorder penalties. Company executives also reviewed costs at various facility levels and provided a “reality check” on operational parameters such as transportation times, production times, and other company policies.

We model the supply chain process from the plant forward to final customer, which means the product:

1) Begins as raw material;
2) Is finished in the production facility;
3) Is stored in a plant warehouse;
4) Is transported to, and stored in, a distribution center in the U.S.; and finally
5) Is sold and delivered to a customer.

We decided to use the System Dynamics methodology because it highlights the importance of both information and product flows, and both of these flows have been typically asserted as integral causes of the Bullwhip Effect (Forrester 1961; Lee and Whang 2006; Sterman 1989). Since we will be using the System Dynamics approach to modeling (Towill 1996), we specify the rules used by each decision-maker in the supply chain. Then we specify inputs and shipments or sales and sum the costs accumulated in the model over time. We specifically do not allow variability in the time lags incorporated in this model, again following typical System Dynamics practice (Towill 1996). For another example of this approach, see Carranza and Villegas (2006a). A diagram of the model can be found in Figure 1, which was generated by Powersim, the simulation software package used in this research. This base model reflects current company practice, but with minimal information lags and transportation and storage times. The base model is the starting point for testing the outcomes of various supply chain strategies. Specific parameter values can be found in Table 1.

We model supply chain cost by combining activity costs such as production and transportation with inventory cost associated with the various participants in the supply chain. In particular, we calculate the following costs (Figure 2) over 200 days.
The input parameters to the model are shown in Table 1 below. All unit values are based on a single part.

**TABLE 1**

**INPUT PARAMETERS FOR NE MODEL**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw Material Cost (includes receiving)</td>
<td>$150 per part</td>
</tr>
<tr>
<td>Setup</td>
<td>$50 per shift</td>
</tr>
<tr>
<td>Reconfiguration Cost (i.e. interrupting a shift)</td>
<td>$100 per instance</td>
</tr>
<tr>
<td>Work In Process Inventory Value</td>
<td>$180 per part</td>
</tr>
<tr>
<td>Finished Good Inventory Value</td>
<td>$200 per part</td>
</tr>
<tr>
<td>Transportation Cost from Plant to U. S. RDC</td>
<td>$20 per part</td>
</tr>
<tr>
<td>Transportation Cost from DC to Customer</td>
<td>$5 per part</td>
</tr>
<tr>
<td>Selling Price</td>
<td>$300 per part</td>
</tr>
<tr>
<td>Out of Stock Penalty</td>
<td>$500 per part</td>
</tr>
<tr>
<td>Discount Rate %</td>
<td>0.3 % per day (day)</td>
</tr>
<tr>
<td>Production Capacity per Shift</td>
<td>300 units</td>
</tr>
</tbody>
</table>

(Note that inventory carrying cost for Work in Process and Finished Goods was not available from the target company and thus has been omitted.)
THE COST MODEL CALCULATIONS

\[ \text{RawMatl\_cost} = \sum_{t=0}^{200} \frac{1}{(1 + i_r)^t} (150 * \text{RMunits} + i_{cc} * \text{RMunits} * 150) \]

\[ \text{Production\_cost} = \sum_{t=0}^{200} \frac{1}{(1 + i_r)^t} (50 * \text{production} + 100 * \text{shifts} + i_{cc} * (200 * \text{DC} + 180 * \text{Plant}) \]

\[ \text{TransporttoRDC\_Cost} = \sum_{t=0}^{200} \frac{1}{(1 + i_r)^t} (20 * \text{Shipments} + i_{cc} * 200 * \text{In\_Transit}) \]

\[ \text{Dlvry\&FG\_cost} = \sum_{t=0}^{200} \frac{1}{(1 + i_r)^t} (5 * \text{Sales} + i_{cc} * 300 * \text{RDC}) \]

\[ \text{Penalties} = \sum_{t=0}^{200} \frac{1}{(1 + i_r)^t} (500 * (\text{demand\_orders} - \text{Sales})) \]

\[ \text{Total\_Cost} = \text{RawMatl\_Cost} + \text{Production\_Cost} + \text{Transportation\_Cost} + \text{Dlvry\&FG\_cost} + \text{Penalties} \]

Each equation in the above model, except for the Total Cost equation, has two parts. The first part is activity-driven. For example, the first term in the Raw Material Cost equation is 150*RMunits, where each RMunit represents the amount of raw material purchased for one part, and $150 is the cost for this amount of raw material. The second term is the inventory carrying cost rate, $icc, multiplied by the number of units of raw material in inventory, RMunits, and the cost per unit, $150. Recall, however, that NE suppliers own the raw material inventory until it enters the production process. Hence there is no raw material inventory cost in the base model. Noteworthy, under production cost, there are separate inventories for work in process (Plant) and finished goods (DC), since finished goods are stored in the plant distribution center. Transportation cost to the field distribution centers includes the transportation cost per unit, $20, plus the inventory carrying cost for in transit units. Delivery and Finished Goods Cost is the sum of the $5 per shipment for delivery from RDC to customer, plus the cost of Finished Goods not yet sold. We value finished goods in the field at sales price, based on the subject company’s policies. Penalties are assessed each time the supplier cannot completely fulfill demand, and the penalty per unit is $500, again reflecting NE’s sense of the cost of backorders and/or lost sales. All costs are discounted at .3 % per day to obtain present value since the simulation is iterated over 200 days. The number of shifts is computed based on 300 units per shift for production capacity, again consistent with NE experience. Appendix A shows the equations and initial conditions for the base simulation model. Table 2 shows the distribution of costs under the base model scenario and reflects the results of combining actual demand with NE’s stated initial conditions, and initially specified order up to quantities over 200 days (day by day results are available from the lead author).

Not surprisingly material purchase cost makes up over half the total supply chain expense, since there are relatively small transportation and production lags in this model and NE is essentially an electronics assembly operation. Note also that under the base scenario, NE incurred large out of stock penalties amounting to over 12 % of total cost. In fact, NE was unable to fulfill customer requirements in only 14 instances of the 200 days, but the extremely heavy per unit penalties added up quickly. Of the remaining 36 % of total cost, one-third is inventory cost, and the other two-thirds is primarily transportation and production cost. Most logistics texts highlight the need for trading off transportation and inventory cost (Coyle et al. 2008), and Little’s Law implies the same trade-off; i.e. faster (and more expensive) transportation for lower inventory. But the high level of expense driven by purchasing and stockout costs in this instance shows the importance of a total supply chain perspective. Therefore, we investigate total supply chain costs based on the amplification of demand variance all the way back at the production process using BE, the Bullwhip Effect Index, and then consider profitability.
TABLE 2

BASE MODEL COST DISTRIBUTION RESULTS

<table>
<thead>
<tr>
<th></th>
<th>Inventory</th>
<th>Activity</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production</td>
<td>2.87 %</td>
<td>16.50 %</td>
<td>19.37 %</td>
</tr>
<tr>
<td>Purchasing</td>
<td></td>
<td></td>
<td>51.00 %</td>
</tr>
<tr>
<td>Transportation</td>
<td>5.44 %</td>
<td>6.30 %</td>
<td>11.74 %</td>
</tr>
<tr>
<td>Sales</td>
<td>4.27 %</td>
<td>1.50 %</td>
<td>5.77 %</td>
</tr>
<tr>
<td>Penalties</td>
<td></td>
<td></td>
<td>12.12 %</td>
</tr>
<tr>
<td>Total</td>
<td>12.58 %</td>
<td>24.30 %</td>
<td>100 %</td>
</tr>
</tbody>
</table>

Since there are minimal lags in this initial model, the results can be seen to inform an “efficient frontier” for NE with the specified parameters (Hopp 2008). Thus, as we apply different supply chain strategies to this multi-echelon supply chain, any differences should be attributable to the strategies themselves, rather than inefficiencies in current supply chain operations. In the latter part of the article, we introduce more realistic lags to test whether the effects of the strategies change under more realistic conditions.

Supply Chain Strategies

We investigate the behavior of the network under four different supply chain strategies. Each strategy is simulated over 200 days and a variety of levels of safety stock targets and the Bullwhip Effect Index (BE). The very simple logic rules we are using to drive the simulation share certain similarities to the full-scale control processes that enterprises implement (with the names APS, TOC, Kanban, and ERP), but they are by no means fully reflective of all the complexities in a real world application. Costs, inventories, and safety stock are tabulated for each scenario to gain insight into how the Bullwhip Effect drives overall service and costs in a multi-echelon supply chain setting. We find that minimizing the Bullwhip Effect, while intuitively appealing, may not always result in the lowest supply chain cost. As Hopp (2008) and others have observed, low system variability is critical to minimizing inventory and enhancing responsiveness. Determining whether this “fact of life” is manifested in a correspondingly low BE and cost under a variety of supply chain strategies is a primary objective of this research.

Villegas and Barrar (2006) simulated results of similar strategies. However, where Villegas and Barrar used stylized demand signals, we employ actual demands experienced by NE. The strategies and their essential characteristics are summarized in Table 3.

TABLE 3

SUPPLY CHAIN STRATEGIES IN THIS RESEARCH

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Kanban</td>
<td>Yes</td>
<td>SS, Upper level</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>ERP</td>
<td>Yes</td>
<td>Market, SS, Upper level</td>
<td>No</td>
<td>Yes (at all levels)</td>
</tr>
<tr>
<td>APS</td>
<td>Yes</td>
<td>SS, Upper level, Forecast</td>
<td>Yes</td>
<td>In the forecast</td>
</tr>
<tr>
<td>TOC</td>
<td>Yes</td>
<td>SS, Upper level</td>
<td>No</td>
<td>Yes (in production)</td>
</tr>
</tbody>
</table>
In the above table, “SS” indicates that we use a target safety stock level as a trigger point for reorders, and “Upper level” indicates that the next level up in the supply chain places orders to the preceding level. “Market” indicates that the ERP planning algorithm uses final demand to determine when to launch production, while “Forecast” drives the planning algorithms in APS. As noted above, the scenarios assume minimal delays, which are typically associated with information lags in the supply chain.

Villegas and Barrar (2006) lay out the detailed assumptions and fundamental difference equations for each of these strategies in a retail customer setting. Our model includes more detail at the plant level, but follows their lead otherwise. Hence, we only summarize the key points here. Details are available from the lead author.

Kanban refers to inventory policies which drive shipments based on a combination of orders from the next level of the supply chain (upper level), and location safety stock assumptions. For example, under the Kanban scenario, the plant ships to the plant warehouse based on the needs of the plant warehouse, the plant warehouse submits orders based on demand from the distribution center, etc. The plant launches production based on warehouse orders, its inventory position, and the availability of raw material. Safety stock targets, order (or produce) up to quantity, and production lot size are inputs to this scenario. Forecasting is not part of this strategy.

ERP is a strategy where all levels of the supply chain have visibility to final demand. Thus, all the decision variables that determine order size involve the latest market demand, as well as specified safety stock levels, although the timing of shipment for each order is time-phased based on specified information transfer delays at each level of the supply chain. Here again, decision criteria do not include forecasts.

Advanced Planning and Scheduling (APS) combines visibility of the latest market demand with forecasting to explicitly account for delays in the supply chain. Thus, the procurement manager, who is furthest from final demand, bases his/her decisions on the latest demand, plus forecasts over the planned supply chain cycle time. In contrast, the distribution manager bases his/her decisions on the latest demand, plus forecasted demand over the lead time from distribution center to final customer. Manufacturing, manufacturing’s warehouse, and distribution center managers, all update their forecasts based on the latest sales/demand results, but each has a different forecast horizon.

Finally, Theory of Constraints (TOC), models the supply chain strategy based on Goldratt’s well-known insights (Goldratt and Cox 2004). Here, the factory always produces to actual demand, which is known in “real time.” However, actual shipments may be affected by the safety stock levels chosen by each site. In addition, there is some delay between when the factory receives the demand information and when production to replace the demand becomes available at the plant warehouse.

The simulations for each strategy were made with the demand pattern of an actual company (Carranza and Villegas 2006b). The simulations involved 200 days, and initial input parameters were those in Table 1 above. We obtained a range of values for BE by varying the safety stock target, which applies to each inventory holding point in the supply chain. As is to be expected from other research, increasing safety stock is associated with more variability and higher BE (Metters 1997). Figure 3 illustrates this result. Note that if the safety stock target is set below 2000 units, the supply chain cannot meet demand, so we have labeled this region of Figure 3 the “Penalty Zone.” As we will show below, these penalties overwhelm other costs at low safety stock levels. Also note that the TOC scenario shows little variation of the BE with increasing safety stock targets, since it is essentially a “make-to-order” strategy. Also, because of the information inherent in this supply chain, TOC requires significant initial safety stock to avoid completely outsized penalties.

Table 4 summarizes the cost results for the various safety stock levels and the associated Bullwhip Effect Index values. Purchase costs are not included, as they are the same under all strategies. The five scenarios under each strategy represent five levels of safety stock targets from 1,000 up to 5,000 units. Penalties are calculated based on the number of units short for each day over the 200 day time horizon. For base case purposes, we assume seven days lag time from plant to customer, and 1.5 days cycle time for manufacturing. As expected, given the high shortage cost of $500 per unit per day, penalties are a major cost factor until enough safety stock is set up to alleviate or eliminate shortages. The need to “never shut down an assembly plant” is well-accepted in the automotive business, as evidenced by extremely high contractual penalties for every hour a plant is out of service.
In the previous graph, TOC does not have penalties. The line with “x” as its marker shows the SS levels that generate penalties for the other scenarios (ERP 5000, Kanban 4000, APS, 2000).

Having established that BE increases with safety stock targets for these specific supply chain strategies, we then charted the cost behavior associated with variation in BE. Table 4 and Figures 4 and 5 show the results for the Kanban, ERP, APS, and TOC supply chain strategies respectively, including penalties. The Bullwhip Effect Index scale varies for each model. The optimal value for the cost function is between 3 and 5 for Kanban and APS, approximately 8 for ERP, and essentially indeterminate for TOC, again reflecting TOC’s make-to-order process.

The first somewhat surprising result is that a higher Bullwhip Effect is not, of itself, a driver of significantly increased costs, especially if stockout penalties are sizable. As both Table 4 and Figures 4 and 5 indicate, higher inventories and a higher Bullwhip Effect Index are associated with relatively small changes in the supply chain costs we consider, especially once target inventory levels are high enough to eliminate penalties for Kanban, APS, and ERP strategies. The model results of increased inventory targets and/or increased Bullwhip Effect Index values seem to differ based on the supply chain strategy simulated. Finally, as both Table 4 and the figures show, there is some “flattening” of effect as BE and/or SS increases. In particular, for this supply chain structure, cost (net of penalties) seems to increase most as SS goes from 2000 to 3000, at least for Kanban, ERP, and APS strategies. Note also that BE increases the most for that increment for Kanban and ERP, but not for APS. Thus, sharing forecasts is effective in this context, both in mitigating the BE, and in keeping costs down, as expected (Lee and Whang 2006). Increasing inventory targets has a differential effect for each strategy on both costs and the BE. For Kanban, increasing SS targets from 2000 to 5000 units results in a quadrupling of BE and a 29% increase in cost before penalties. For ERP, the same increase in inventory target is associated with over a 100% increase in BE and a 7% increase in cost before penalties. Finally, for APS, increasing SS targets from 2000 to 5000 results in about a 15%
increase in BE and 3% increase in total cost. Clearly, choice of supply chain strategy has a strong influence on the importance and magnitude of BE, and that influence is not linear with safety stock target variation.

### TABLE 4

**SUPPLY CHAIN COSTS UNDER VARIOUS STRATEGIES AND INVENTORY TARGETS**

<table>
<thead>
<tr>
<th></th>
<th>Production</th>
<th>Dlvry</th>
<th>Transport</th>
<th>Total Wio</th>
<th>Penalties</th>
<th>Total w/Penalties</th>
<th>BE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Kanban</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SS target = 1000</td>
<td>3401</td>
<td>372</td>
<td>1350</td>
<td>5122</td>
<td>32485</td>
<td>37607</td>
<td>0.34</td>
</tr>
<tr>
<td>SS target = 2000</td>
<td>5557</td>
<td>627</td>
<td>2223</td>
<td>8407</td>
<td>11667</td>
<td>20074</td>
<td>1.58</td>
</tr>
<tr>
<td>SS target = 3000</td>
<td>8547</td>
<td>783</td>
<td>2522</td>
<td>9952</td>
<td>1970</td>
<td>11921</td>
<td>2.94</td>
</tr>
<tr>
<td>SS target = 4000</td>
<td>6628</td>
<td>879</td>
<td>2787</td>
<td>10486</td>
<td>0</td>
<td>10486</td>
<td>4.52</td>
</tr>
<tr>
<td>SS target = 5000</td>
<td>7053</td>
<td>939</td>
<td>2881</td>
<td>10884</td>
<td>0</td>
<td>10884</td>
<td>6.14</td>
</tr>
<tr>
<td><strong>ERP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SS target = 1000</td>
<td>5325</td>
<td>575</td>
<td>2104</td>
<td>8005</td>
<td>15270</td>
<td>23275</td>
<td>2.05</td>
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<tr>
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<td>6651</td>
<td>768</td>
<td>2870</td>
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<td>2010</td>
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<tr>
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<td>10625</td>
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<td>26450</td>
<td>31594</td>
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</table>

The Bullwhip Effect and Safety Stock in Practice

We now modify the models used above to reflect operational realities and practices at North Electronics (NE). It turns out that NE’s base supply chain operation does not fit exactly into any of the four archetypes we studied above, and of course, there are typically longer delays than the modest values in our previous models. Specifically:

1. In the case of NE, both the procurement manager and the production manager use the same forecast in their decisions to buy raw material or make product, respectively. Each also uses the same safety stock level in the calculation, which compares the sum of the forecast plus safety stock target vs. raw material inventory (procurement) or plant plus plant warehouse inventory (production). Neither the Theory of Constraints, ERP, nor the Kanban strategy, utilize forecasts. The APS strategy employs different forecast horizons for the procurement and production managers respectively.

2. NE estimated that typical transportation time is closer to 14 days than 7, while production time, given contention with other products, should be put into the model at 5.5 days, vs. 1.5 days.
3. Each of the four strategies was simulated as before, but with the additional delays incorporated into the decision rules and cost calculations. The NE process was also simulated under its specific decision rules and the same estimated delays. The results are shown in Figure 6, which indicates considerable differences in costs under the various supply chain strategies. Notice also that the range of safety stock targets and associated BE values is somewhat different for each strategy, because the longer delays change the safety stock levels necessary to avoid significant penalties for shortages.

FIGURE 4
BE INDEX VERSUS TOTAL COST IN KANBAN AND ERP MODELS

FIGURE 5
BE INDEX VERSUS TOTAL COST IN APS AND TOC MODELS
The most striking finding from this part of the modeling exercise is that NE’s mixed strategy seems to outperform any of the four “pure” strategies. Note that the base model has a much lower range of safety stock levels for analysis. The safety stock levels shown in Figure 6 were chosen in each case to encompass the minimum cost scenario, which emerged from simulations across a wider range of safety stock test levels. For example, a TOC run with safety stock target of 7000, far below the range shown in Figure 6, resulted in total costs of nearly $41 million. Also, as shown above, a simulation using the APS strategy and 8000 for a safety stock target resulted in sizable penalties and total cost over $50 million. Hence the advantage of the base model appears to be its ability to operate with high service levels at much lower safety stock targets than those of the pure strategies, when realistic delays are introduced into the models.

Table 5 shows changes in model results if delay times for transportation and production starts are increased, as well as a measure of the “robustness” or cost range of the model results over the chosen safety stock range (Hopp and Spearman 2000). Percent increases are relative to the initial model, which had delays of 1 day for the production at factory level. Note that each supply chain strategy seems to have strengths and weaknesses, especially when transportation and production delays are varied. In particular, the TOC strategy seems to be very stable with respect to production delays, probably because it explicitly deals with production bottlenecks. On the other hand, TOC has the highest percent increase with respect to additional transport time, presumably because the transportation delays are not planned for specifically under this strategy. Interestingly, the optimal “base” strategy seems relatively cost sensitive to both production and transportation delays, suggesting that minimizing inventory in this setting leaves relatively less slack for dealing with operating problems. Table 6 is a qualitative summary and ranking of the various strategies on several criteria. Strategies are listed from the most desirable value on the particular characteristic to the least desirable value. Thus, the base strategy seems to lead to the lowest optimum
cost, but is second worst in terms of stability to increased transportation or production delays. Details of the specific runs are available from the first author.

### TABLE 5

**SENSITIVITY ANALYSIS OF MODEL RESULTS**

<table>
<thead>
<tr>
<th>Model</th>
<th>Safety Stock Range Analysis</th>
<th>Lowest Cost (millions $)</th>
<th>Cost Range Max/Min (%)</th>
<th>Cost Increase with Longer Transport Time (%)</th>
<th>Cost Increase with Longer Production Delay (%)</th>
<th>Optimal Safety Stock Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOC</td>
<td>17000-21000</td>
<td>38.13</td>
<td>26</td>
<td>41</td>
<td>0</td>
<td>20000</td>
</tr>
<tr>
<td>Kanban</td>
<td>5000-14000</td>
<td>37.49</td>
<td>36</td>
<td>8</td>
<td>19</td>
<td>5000</td>
</tr>
<tr>
<td>APS</td>
<td>8000-13000</td>
<td>35.64</td>
<td>46</td>
<td>13</td>
<td>0.1</td>
<td>9900</td>
</tr>
<tr>
<td>ERP</td>
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<td>154</td>
<td>15</td>
<td>33</td>
<td>5000</td>
</tr>
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<td>Base</td>
<td>1000-5000</td>
<td>30.49</td>
<td>37</td>
<td>26</td>
<td>29</td>
<td>2000</td>
</tr>
</tbody>
</table>

### TABLE 6

**RANKING OF SUPPLY CHAIN STRATEGIES**

<table>
<thead>
<tr>
<th>COST OPTIMUM</th>
<th>TRANSP. TIME STABILITY</th>
<th>PRODUCTION TIME VARIABILITY</th>
<th>COST STABILITY OVER SS VARIATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>Kanban</td>
<td>TOC</td>
<td>TOC</td>
</tr>
<tr>
<td>ERP</td>
<td>APS</td>
<td>APS</td>
<td>Kanban</td>
</tr>
<tr>
<td>APS</td>
<td>ERP</td>
<td>Kanban</td>
<td>Base</td>
</tr>
<tr>
<td>Kanban</td>
<td>Base</td>
<td>Base</td>
<td>APS</td>
</tr>
<tr>
<td>TOC</td>
<td>TOC</td>
<td>ERP</td>
<td>ERP</td>
</tr>
</tbody>
</table>

Given the superior performance of the base setup, as well as its high level of sensitivity to cycle time variations, we decided to test an additional approach to improve performance by mitigating the Bullwhip Effect. As Hopp and Spearman (2000) and others have noted, releasing orders only when production capacity is available will minimize cycle time, because waiting in queues will be nearly eliminated. By Little’s Law, minimizing cycle time will also minimize work-in-process, assuming constant throughput. Since production will thus be extremely level, the numerator of BE, and thus BE itself, will be low also. We also applied this procedure to the APS, ERP, and Kanban strategies. The results are shown in Table 7 and Figure 7. In Table 7, the optimal performance, when orders are released based solely on inventory needs, is shown as a benchmark for comparison. Target safety stock levels are in parentheses under the BE values. The costs shown are for a transportation lag of seven days. Increasing the lag to 14 days still resulted in consistent savings for the minimum cycle time scenarios.

Figure 7 illustrates the other potential supply chain benefit for leveling production through holding the order release. In comparison with Figure 6, system cost performance exhibits higher stability over a range of safety stock targets (and BE).
TABLE 7
ORDER RELEASE, BE, AND COST COMPARISONS

<table>
<thead>
<tr>
<th>Model</th>
<th>Inventory Driven Order Release</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cycle Time</td>
<td>BE (SS)</td>
</tr>
<tr>
<td>Base</td>
<td>1.5</td>
<td>1.24 (3000)</td>
</tr>
<tr>
<td>APS</td>
<td>4.8</td>
<td>6.9 (9900)</td>
</tr>
<tr>
<td>ERP</td>
<td>3.4</td>
<td>1.9 (5000)</td>
</tr>
<tr>
<td>Kanban</td>
<td>10.7</td>
<td>27.4 (9000)</td>
</tr>
</tbody>
</table>

FIGURE 7
COST FOR CAPACITY DRIVEN ORDER RELEASE BY SAFETY STOCK TARGET AND STRATEGY
CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

One well-accepted method for improving supply chain performance and cost is reducing overall variability. Perhaps the best known consequence of variability is the Bullwhip Effect, and the best documented measure of the Bullwhip Effect is the Bullwhip Effect Index (BE). Therefore, we decided to investigate how focusing on BE as a key metric might lead to improved supply chain results. Our results, based on modeling a real-world supply chain under a variety of supply chain strategies, were somewhat surprising. First, we found evidence that managing to a goal for the Bullwhip Effect Index is no guarantee of either low cost or low inventory levels. The usefulness of the proposed metric seems to vary widely, depending on the supply chain strategy chosen and the specifics of the supply chain itself. The multi-echelon supply chain we studied is relatively generic; with a plant, a distribution center, and a customer. We incorporated delays that ranged from minimal to moderate. Nevertheless, the behavior of costs and inventory differed based on our supply chain strategy as the Bullwhip Effect Index was varied. Kanban, ERP, and APS strategies all resulted in “threshold” behavior. As Figures 4 and 5 show, penalty costs dominated at low levels of variability, dropped quickly as inventory targets (and thus the BE) increased, and then were fairly stable even at high values of BE. Kanban and ERP thresholds for BE were quite different, but similar for inventory targets. APS required somewhat less inventory to eliminate penalties. Finally, TOC procedures seem to entail very high levels of inventory to eliminate penalties, even though this make-to-demand strategy matches production and customer orders and thus has a very low BE. We also note (Tables 3, 5, and 6) that realistic lags in the network highlight the strengths and weaknesses of the various strategies, as well as indicating what kinds of inventory and associated BE might be necessary for each strategy to be effective in the real world of long lead times and sizable penalties for poor performance. Finally, we found that waiting to release production orders until capacity was available uniformly, improved cost performance in our network, even in comparison to the optimal results for releasing orders whenever inventory dropped below safety stock targets. Furthermore, waiting for capacity generally improved the predictability of costs over a range of safety stock targets. In other words, physical flows were smoother if orders were not released until capacity was available in the next stage.

In summary, we find that classifying a supply chain according to its variability using the Bullwhip Effect Index is only a first step toward control and process improvement. Managers have to look at how their choice of strategy and order release drives this metric. They also have to evaluate the inventory investment necessary to satisfy variable customer demands under these strategies. As always, customer needs and company costs must be balanced. Although mitigating the Bullwhip Effect is certainly helpful in simplifying managerial tasks and lowering inventories, we have shown that a low BE cannot be the complete answer in a world of increasingly demanding customers. Under certain strategies, visibility to market demand is very helpful, but even then, supply chain managers’ choices can result in unexpected results.

Future Research

There are several lines of research that can arise from this research. As others have pointed out, variability in supply chains has multiple sources beyond the demand variability and production release rules we used. For example, forecast accuracy, or lack of it, has been shown to exacerbate the Bullwhip Effect, and it would be interesting to understand its influence under the four strategies in this article. Furthermore, there are certainly other strategies than the prototypes in this article. Even our subject company’s operation did not fit neatly into these well-known procedures. So it would be appropriate to replicate our exercise across a variety of hybrid strategies and variations in lag times. In particular, we used a constant safety stock target across all levels of the supply chain. Independent companies are unlikely to agree to this synchronization without looking at alternatives. We would also look to incorporating inventory carrying costs in the model, provided we can get an agreement from decision-makers on their magnitude. Finally, we did not incorporate variability in lag times into our models. Yet cross-border supply chains run a significant risk of intermittent customs delays, and thus we would suggest incorporating that likelihood into future research.

Most firms and supply chain managers understand that no single metric can guarantee success. On the other hand, many studies over the years have shown that variability increases cost and jeopardizes customer service unless it can be controlled. We also find that increasing variability, as manifested in a larger Bullwhip Effect, is associated with higher costs. But, the higher inventory levels may be necessary to satisfy customers who are several levels removed from the product manufacturer. A responsible supply chain manager has to choose not only a strategy, but also inventory targets and a tolerable level of variability in his/her network. As we have seen in this article, these
choices are not necessarily easy or straightforward, but the Bullwhip Effect Index may be one aid to better understanding and performance.

**Appendix A- Base Model Equations**

```plaintext
init Distr_center = 5000
flow Distr_center = +dt*arrivals
         -dt*Sales
init In_transit = 5000
flow In_transit = +dt*Shipping
         -dt*arrivals
init Plant = 500
flow Plant = -dt*Finishing_product
         +dt*Launching_product
init RM = 8500
flow RM = -dt*Launching_product
         +dt*Procurement_orders
init Warehouse = 1500
flow Warehouse = -dt*Shipping
         +dt*Finishing_product
aux arrivals = DELAYPPL(Shipping,7,0)
aux Finishing_product = DELAYPPL(Launching_product,1.5,0)
aux Launching_product = IF(prod_mgr>RM,RM,prod_mgr)
aux Procurement_orders = PULSE(proc_mgr,1,3)
aux Sales = IF(demand>Distr_center+arrivals,Distr_center+arrivals,demand)
aux Shipping = IF(dist_mgr<Warehouse+Finishing_product,dist_mgr,Warehouse+Finishing_product)
aux demand =
GRAPH(TIME,0,1,[600,0,0,0,0,0,0,0,360,360,0,240,120,120,480,480,0,0,240,480,360,120,480,0,0,480,600,480
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0,0,0,240,720,1200,1080,840,0,0,1080,1080,360,360 "Min:0;Max:1560")
aux dist_mgr = IF(Total_inventory<10380+Forecast_for_NE+SS,10380-
Total_inventory+Forecast_for_NE+SS,0)
aux Forecast_for_NE = FORECAST(demand,10,1)
aux proc mgr = IF(Forecast_for_NE+SS>RM,Forecast_for_NE+SS-RM,0)
aux prod mgr = IF(Forecast_for_NE+SS>Warehouse+Plant,Forecast_for_NE+SS-Warehouse-Plant,0)
aux Total_inventory = Distr_center+In_transit
const SS = 5000
```

**NOTES**


ABOUT THE AUTHORS

Octavio Carranza Torres (Ph.D. Universidad de Navarra, Spain) is a professor, researcher and consultant in Supply Chain Management. He is the founder of Vertebrar, a Supply Chain Management Consultancy (www.vertebrar.com) and works now primarily in consultancy in the Americas. He holds a doctorate in Industrial Engineering from Universidad de Navarra, Spain. He has been a professor at Universidad de San Andrés (Argentina), Universidad Panamericana (Mexico) and gives seminars and courses in Latin America. He has authored two books, Logistics Best Practices in Latin America and The Bullwhip Effect in Supply Chains, and has several publications (see www.octavioacarranzatorres.com). Two books of his authorship are to be published (“Operating from Mexico” and “Supply Chains: Measure and Performance, a roadmap to profitability”). He is the winner of the 2005 National Logistics award in México. His main research and consultancy interests are in supply chain performance measurement and logistics reengineering.

Arnold B. Maltz (Ph.D. The Ohio State University) is Associate Professor of Supply Chain Management at the W. P. Carey School of Business at Arizona State University. His Ph.D. is from The Ohio State University in Marketing and Logistics, where his initial work in outsourcing and third party logistics was honored by The Ohio State University, the Council of Logistics Management, and Accenture. After teaching at New Mexico State University, he moved to W. P. Carey where he teaches undergraduate and graduate courses in logistics, strategic cost management, and supply chain management. Dr. Maltz is currently researching how low cost countries and regions can fit into global supply chains. He has published in a number of logistics, operations, and marketing journals and spent twelve years in industry prior to joining the academic community.

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