International Journal of Management Science
Vol 16, No 3, November 2010

Numerical Studies on the Cost Impact of Incorrect Assumption and Information Delay in a Supply Chain

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(Received: May 29, 2009 / Revised: July 27, 2010 / Accepted: July 27, 2010)

ABSTRACT

In this paper, the impact of various system parameters such as the parameters of actual demand process, the review periods and the lead times, under each combination of inventory policies and information sharing, on the long run average inventory cost per period incurred at each participant in a supply chain, is considered. For this purpose, numerical studies are conducted, from which some valuable information as to how sensitive our long run average inventory cost per period are as the model parameters change is gleaned, from which, in turn, some managerial insights are gleaned in order for industry practitioners to perform better in supply chain management.

Keywords: Cost Impact, Inventory Policy, Information Delay, Supply Chain

1. Introduction

A variety of strategic partnerships in supply chain management, with the aim of simultaneously improving customer responsiveness and reducing the costs of excess inventory has been actively in place for the past years. Strategic partnerships are defined as a multi-faceted, goal oriented, long-term relationships between two companies in which both risks and rewards are shared. The famous examples of the strategic partnerships in supply chain management include Wal-Mart's Vendor Managed Inventory, the apparel industry's Quick Response initiative and the Efficient Consumer Response initiatives in the grocery industry. All of these efforts require some degree of information sharing, whether it is the sharing of customer demand data,

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current inventory level, or the form of the inventory policy (Cachon *et al*. [2]).

In spite of using recent advances in technology, such as point-of-sale scanners, bar-coding technology, electronic data interchange, and online inventory and control system, well explained in Buzzell and Ortmeyer [1], for information sharing, the manner that most industry practitioners use the shared information still does not appear to be optimal. For instance, although, according to Erkip *et al*. [3] and Lee *et al*. [7], serially correlated demands are a characteristic of most of today's consumer product industry, most industry practitioners, for their inventory control, tend to use commonly known inventory models developed on the assumption of i.i.d. due to a lack of knowledge regarding the form of the optimal policy or a desire to use a simple inventory policy. In addition, since the shared information, such as sales, inventory levels, and production schedules, is often sensitive, some industry practitioners seem to share somewhat delayed or outdated one instead. Therefore, the pitfalls resulting from these non-optimal practices, namely, incorrect assumptions on the demand process and information sharing, possibly with some delay, need to be quantified.

Recently, Kim [4], in order to quantify the cost impact of incorrect assumptions on the demand process, considers a supply chain in which there are two participants, a single retailer and a single manufacturer, and demand information by the retailer is shared instantaneously with the manufacturer. The demand process is an autocorrelated one and either the retailer or the manufacturer may not know the exact form of the demand process. The author develops a mathematical model that allows us to quantify the cost incurred at each participant in the supply chain, when they implement inventory policies based on correct or incorrect assumptions about the demand process. From this model, the author shows that shared demand information is beneficial to the manufacturer only when the manufacturer understands the true nature of demand process and uses the demand information accordingly.

More recently, Kim [5], in order to quantify the cost impact of information sharing, possibly with some delay, develops another mathematical model under the same supply chain setting as that of Kim [4]. From this model, the author shows that the shared demand information can be beneficial to the manufacturer if shared promptly; i.e., shared demand information reduces the manufacturer's long run average total inventory cost per period and that the more quickly information shared, the better; i.e., shorter delay helps reduce uncertainty associated with the perceived total demand over the effective lead time.

Very recently, Kim [6], in order to compare accurate inventory control with incorrect inventory one under correlated demand process, unlike Zinn *et al*. [9] and Urban [8] who use simulation models, develops a mathematical model that allows us to quantify the performance measures such as the amount of safety stock, the long run mean shortages and the long run mean excessive inventories under an individual firm setting. Using this model, the author conducts numerical studies to compare two approaches in terms of the amount of safety stock, the long run mean shortages, and the long run mean excessive inventories, from which the author identifies how consequential it becomes when the firm uses incorrect inventory control instead of accurate one under various situations.

This paper addresses similar issues to those of Kim [4] and Kim [5] and thus can be regarded as a sequel to Kim [4] and Kim [5]. Even though Kim [4] and Kim [5] conduct analytical studies for separate issues, which has some limit in them due to the complexity of mathematical formulas involved, the mathematical models developed by Kim [4] and Kim [5], if combined, can be used to study, under each combination of inventory policy and information sharing, the impact of various system parameters such as the parameters of actual demand process, the review period, and the lead time on the long run average inventory cost per period incurred at each participant in a supply chain. The results of these numerical studies will show how serious the pitfalls resulting from these non-optimal practices become under various situations.

This paper addresses similar issues as those of Kim [6]. However, this paper differs from Kim [6] in that we consider a supply chain setting instead of an individual firm setting and thus can account for the interaction among various participants in a supply chain.

The remainder of this paper is organized as follows: Section 2 reviews the models developed by Kim [4] and Kim [5]. Section 3 shows, from numerical studies, major findings about the impact of various system parameters on the long run average inventory cost per period. Final remarks are addressed in Section 4.

2. Model Review

As mentioned in Section 1, the models developed by Kim [4] and Kim [5] are combined and used for numerical studies in this paper. For the clear description of this paper, they are briefly reviewed in this section. For details on the materials presented in this section, see Kim [4] and Kim [5].

Model Structure: A supply chain consisting of a single retailer and a single manufacturer is considered where external demand follows an AR (1) process. If we let d_t be the demand faced by the retailer during period t, $t \in \{1,\ 2,\ 3, \cdots\}$, then we can write

$$d_t = \mu + \rho d_{t-1} + \varepsilon_t, \qquad (1)$$

where $\mu > 0$, $-1 < \rho < 1$, and $\varepsilon_t \sim N\left(0,\ \sigma^2\right)$.

The retailer, at the start of every review period t, $t \in \{1,\ 1+c,\ 1+2c, \cdots\}$, observes the inventory level and the previous demands, and calculates the order-up-to level $y_{j,t}$, $j = s, n$, from which the retailer determines the order quantity $q_{j,t}$, $j = s, n$, to place to the manufacturer, and the shipment of which the retailer receives at the start of period $t+l$, where l is a nonnegative integer multiple of c. Let $l' = c + l$ be the effective lead time for the retailer. Here the subscript 's', short for 'smart', refers to the retailer who is aware that the demand follows an AR (1) process and thus takes advantage of this knowledge to determine the order-up-to level and the subscript 'n', short for 'naïve', refers to the retailer who is not aware that the demand follows an AR (1) process and thus resort to an inventory model based on the assumption of i.i.d. demand to determine the order-up-to level.

The manufacturer, at the start of period t, $t \in \{1,\ 1+c,\ 1+2c,\ \cdots\}$, receives and ships the order quantity $q_{j,t}$, $j = s,\ n$, to the retailer. If the manufacturer does not have enough stock on hand to fill the order quantity, the manufacturer can always find an alternative source to borrow from and that the borrowed items are returned to the source when the next replenishment arrives. The manufacturer places an order at the start of period t, $t \in \{1,\ 1+C,\ 1+2C,\ \cdots\}$, where C is a positive integer multiple of c, that is, $C = mc$, $m \in \{1,\ 2, \cdots\}$, right before the retailer orders, based on the inventory level and the previous demands from the retailer or, in case of information sharing, the demand information shared by the retailer. The order arrives at the start of period $t+L$, where L is a positive integer multiple of C, that is, $L = MC$, $M \in \{1,\ 2,\ \cdots\}$. Let $L' = C + L = cm + MC = (m + mM)c$ be the effective lead time for the manufacturer. The supplier from which the manufacturer orders is assumed to have infinite capacity so that the manufacturer's order is always satisfied. As for the manufacturer, whether the retailer acts smart or naïve ($j = s,\ n$) determines the demand stream faced by the manufacturer. In addition, the effective lead time distribution perceived by the manufacturer may be different depending on whether the manufacturer itself acts smart or naïve ($J = S,\ N$) and on whether the demand information is shared or not ($K = IS_{\delta},\ NI$), where IS_{δ} denotes information sharing with δ, $\delta \in \{0,\ 1,\ 2,\ 3,\ \cdots\}$, periods of delay in the transmission of the demand information and NI denotes no information sharing. Therefore, we need to consider eight cases for the manufacturer ($j = s,\ n$; $J = S,\ N$; $K = IS_{\delta},\ NI$).

The Retailer: From Equation (1), the actual effective lead time demand for the retailer $d_t^{l'} \mid d_{t-1}$ can be written as

$$d_t^{l'} \mid d_{t-1} = \sum_{i=0}^{l'-1} d_{t+i} \mid d_{t-1} = \theta(d_{t-1}) + \psi(\varepsilon_t,\ \varepsilon_{t+1},\ \cdots,\ \varepsilon_{t+l'-1}), \tag{2}$$

where $\theta(d_{t-1})$ is a linear function of d_{t-1} and $\psi(\varepsilon_t,\ \varepsilon_{t+1},\ \cdots,\ \varepsilon_{t+l'-1})$ is a linear function of future unobserved error terms, $\varepsilon_t,\ \varepsilon_{t+1},\ \cdots,\ \varepsilon_{t+l'-1}$. Therefore, the actual effective lead time demand follows a normal distribution with mean

$$E\left[d_t^{l'} \mid d_{t-1}\right] = \theta(d_{t-1})$$

and variance

$$V\left(d_t^{l'} \mid d_{t-1}\right) = V\left(\psi\left(\varepsilon_t,\ \varepsilon_{t+1},\ \cdots,\ \varepsilon_{t+l'-1}\right)\right).$$

Next, the order-up-to level for period t, $y_{j,t}$, $j = s,\ n$, will be calculated as

$$y_{j,t} = E\left[d_{j,t}^{l'}\right] + z\sqrt{V\left(d_{j,t}^{l'}\right)},\ \ j = s,\ n, \tag{3}$$

where the perceived effective lead time demand $d_{j,t}^{l'}$, $j = s, n$, is used by the retailer to determine the order-up-to level and z is a constant chosen to meet a desired service level.

To calculate the long run average holding cost per period, if we denote the expected demand during the retailer's review period c, starting at $t+l$, given d_{t-1}, by $E\left[d_{t+l}^{c} \mid d_{t-1}\right]$, and the demand over the effective lead time, starting at $t+l$, given d_{t-1}, by $E\left[d_{t}^{l'} \mid d_{t-1}\right]$, then, for a periodic review inventory system with order-up-to level $y_{j,t}$, $j = s, n$, the average inventory level over the c periods between $t+l$ and $t+l'$, denoted by $inv_{j,t+l}^{c}$, $j = s, n$, can be written as

$$inv_{j,t+l}^{c} = y_{j,t} - E\left[d_{t}^{l'} \mid d_{t-1}\right] + \frac{E\left[d_{t+l}^{c} \mid d_{t-1}\right]}{2}, \quad j = s, n. \tag{4}$$

Therefore, the expected average inventory level per period can be represented as

$$inv_{j} = E\left[y_{j,t}\right] - E\left[d_{t}^{l'}\right] + \frac{E\left[d_{t+l}^{c}\right]}{2}, \quad j = s, n, \tag{5}$$

where $E\left[d_{t}^{l'}\right] = E\left[E\left[d_{t}^{l'} \mid d_{t-1}\right]\right]$ and $E\left[d_{t+l}^{c}\right] = E\left[E\left[d_{t+l}^{c} \mid d_{t-1}\right]\right]$.

Next, notice that the average number of stockouts between periods $t+l$ and $t+l'$ for a fixed value of $y_{j,t}$, $j = s, n$, can be written as

$$\int_{y_{j,t}}^{\infty} \left(d_{t}^{l'} \mid d_{t-1} - y_{j,t}\right) dF\left(d_{t}^{l'} \mid d_{t-1}\right), \quad j = s, n,$$

where $F\left(d_{t}^{l'} \mid d_{t-1}\right)$ is the cumulative distribution function of demand for the l' periods starting at period t, given d_{t-1}. Since $d_{t}^{l'} \mid d_{t-1}$ follows a normal distribution, the above formula can be simplified to

$$\sqrt{V\left(d_{t}^{l'} \mid d_{t-1}\right)} \int_{z_{j,t}}^{\infty} \left(x - z_{j,t}\right) \phi(x)\, dx = \sqrt{V\left(d_{t}^{l'} \mid d_{t-1}\right)} \left[\phi\left(z_{j,t}\right) - z_{j,t}\left(1 - \Phi\left(z_{j,t}\right)\right)\right], \quad j = s, n \tag{6}$$

where x is a standard normal random variable, $z_{j,t} = \frac{y_{j,t} - E\left[d_t^{l'} \mid d_{t-1}\right]}{\sqrt{V\left(d_t^{l'} \mid d_{t-1}\right)}}$, $j = s, n$, is the standardized value of the order-up-to level, $\phi(\cdot)$ is the probability distribution function for the standard normal random variable, and $\Phi(\cdot)$ is the cumulative distribution function for the standard normal random variable. Since $z_{j,t}$, $j = s, n$, is a random variable due to the dependence of $y_{j,t}$, $j = s, n$, on d_{t-1}, long run average amount of stockouts per period, which is the expectation of Equation (5) where the expectation is taken over $z_{j,t}$, $j = s, n$, divided by the review period c, can be written as

$$\frac{\sqrt{V\left(d_t^{l'} \mid d_{t-1}\right)}\left[h\left(\bar{z}_j\right)\left(1+\sigma_{z_j}^2\right) - \bar{z}_j\left(1 - H\left(\bar{z}_j\right)\right)\right]}{c}, \quad j = s, n, \tag{7}$$

where $\bar{z}_j = E\left[z_{j,t}\right]$, $j = s, n$, $\sigma_{z_j}^2 = V\left(z_{j,t}\right)$, $j = s, n$, $h(\cdot)$ is the probability distribution function for a normal random variable with mean 0 and variance $1+\sigma_{z_j}^2$, $j = s, n$, and $H(\cdot)$ is the cumulative distribution function for a normal random variable with mean 0 and variance $1+\sigma_{z_j}^2$, $j = s, n$.

Therefore, if we let h and p denote the holding cost per unit per unit time and the penalty cost per unit associated with backlogged demand, the long run average inventory cost per period g_j, $j = s, n$, can be written as

$$g_j = inv_j h + \frac{\sqrt{V\left(d_t^{l'} \mid d_{t-1}\right)}\left[h\left(\bar{z}_j\right)\left(1+\sigma_{z_j}^2\right) - \bar{z}_j\left(1 - H\left(\bar{z}_j\right)\right)\right]}{c} p, \quad j = s, n. \tag{8}$$

Finally, the retailer's order quantity for period t, which becomes the manufacturer's demand for that period, can be written as

$$q_{j,t} = y_{j,t} - y_{j,t-c} + \sum_{i=0}^{c-1} d_{t-c+i}, \quad j = s, n. \tag{9}$$

The Manufacturer: First, notice that the actual lead time demand faced by the manufacturer $D_{j,t}^{L'}$, $j = s, n$, can be shown as

$$D_{j,t}^{L'} = \sum_{i=0}^{m+mM-1} q_{j,t+ci} \mid d_{t-1},\ d_{t-2}, \cdots, \quad j = s, n\,.$$

Next, it is easy to show that $D_{j,t}^{L'}$, $j = s, n$, follows a normal distribution, and can be represented as a function of the known previous demand data and the future unknown error terms, which is

$$D_{j,t}^{L'} = \Theta_j\left(d_{t-1}, d_{t-2}, \cdots\right) + \Psi_j\left(\varepsilon_t, \varepsilon_{t+1}, \cdots, \varepsilon_{t+L'-c-1}\right), \quad j = s, n\,. \tag{10}$$

Therefore, the actual effective lead time demand has mean

$$E\left[D_{j,t}^{L'}\right] = \Theta_j\left(d_{t-1}, d_{t-2}, \cdots\right), \quad j = s, n\,,$$

and variance

$$V\left(D_{j,t}^{L'}\right) = V\left(\Psi_j\left(\varepsilon_t, \varepsilon_{t+1}, \cdots, \varepsilon_{t+L'-c-1}\right)\right), \quad j = s, n\,.$$

Next, the order-up-to level at the start of period t, $Y_{J,j,K,t}$, $J = S, N$, $j = s, n$, $K = IS_\delta, NI$, will be calculated as

$$Y_{J,j,K,t} = E\left[D_{J,j,K,t}^{L'}\right] + Z\sqrt{V\left(D_{J,j,K,t}^{L'}\right)}\,, \quad J = S, N, \quad j = s, n, \quad K = IS_\delta, NI, \tag{11}$$

where $D_{J,j,K,t}^{L'}$, $J = S, N$, $j = s, n$, $K = IS_\delta, NI$, is a random variable representing the effective lead time demand at the start of period t, as perceived by the manufacturer, and Z is a constant chosen to meet a desired service level.

As we did for the retailer, we can write the long run average inventory level per period, the long run average number of stockouts per period, and the long run average inventory cost per period, respectively, given $Y_{J,j,K,t}$, $J = S, N$, $j = s, n$, $K = IS_\delta, NI$, as

$$INV_{J,j,K} = E\left[Y_{J,j,K,t}\right] - E\left[D_{j,t}^{L'}\right] + \frac{E\left[D_{j,t+L}^{C}\right]}{2}, \tag{12}$$

$$\frac{\sqrt{V\left(D_{j,t}^{L'}\right)}\left[h\left(\bar{Z}_{J,j,K}\right)\left(1+\sigma_{Z_{J,j,K}}^{2}\right) - \bar{Z}_{J,j,K}\left(1-H\left(\bar{Z}_{J,j,K}\right)\right)\right]}{C}, \tag{13}$$

$$G_{J,j,K} = INV_{J,j,K}H + \frac{\sqrt{V\left(D_{j,t}^{L'}\right)}\left[h\left(\bar{Z}_{J,j,K}\right)\left(1+\sigma_{Z_{J,j,K}}^{2}\right) - \bar{Z}_{J,j,K}\left(1-H\left(\bar{Z}_{J,j,K}\right)\right)\right]}{C}P, \tag{14}$$

where $\bar{Z}_{J,j,K}$ and $\sigma_{Z_{J,j,K}}^{2}$ are the mean and the variance of the standardized value of the order-up-to level $Z_{J,j,K,t} = \dfrac{Y_{J,j,K,t} - E\left[D_{j,t}^{L'}\right]}{\sqrt{V\left(D_{j,t}^{L'}\right)}}$, and H and P denote the holding cost per unit per unit time and the penalty cost per unit associated with backlogged demand.

Now that we have briefly reviewed the models in Kim [4] and Kim [5] for calculating the long run average inventory cost per period incurred at each participant in the supply chain, we are now ready to conduct numerical studies, which is presented in Section 3.

3. Numerical Analysis

As mentioned in Section 1, the goals of this paper are to study, under each combination of inventory polices and information sharing, the impact of various system parameters such as the parameters of actual demand process, and review period and the lead time on the long run average inventory cost per period incurred at each participant in the supply chain.

We now present some results of numerical studies to show the impact of the various system parameters on the long run average costs per period incurred at each participant in a supply chain. In our numerical studies, we assume that z and Z are chosen in such a way that the long run average inventory cost per period under consideration for given parameter values when $j = s$ or $J = S$, namely, $z = \Phi^{-1}\left(\dfrac{p-ch}{p}\right)$

and $Z=\Phi^{-1}\left(\frac{P-CH}{P}\right)$. In addition, the demand process is specified by $\mu=100$, $\sigma=30$ while ρ is allowed to vary from -1 to 1. Unless otherwise stated, the parameters for the retailer are $c=1$, $l=0$ ($l'=1$), $h=2$, and $p=50$, and those for the manufacturer are $C=1$, $L=1$ ($L'=2$), $H=1$, $P=25$, and $K=IS_0$.

In Figure 1, the x-axis refers to the value of the correlation coefficient and the y-axis refers to the long run average inventory cost per period. The dotted line represents the long run average inventory cost per period for the naïve retailer and the solid line represents the long run average inventory cost per period for the smart retailer. From the figure, it is clear that being smart always benefits the retailer. Notice that when $\rho=0$, the long run average inventory cost per period for the naïve retailer is the same as that of the smart retailer since, in this case, $y_{n,t}$ (g_n) becomes the same as $y_{s,t}$ (g_s). In addition, as the correlation coefficient increases or decreases from 0, the difference between the long run average inventory costs per period for the smart retailer and the naïve retailer increases with an increasing rate. This is not only because the safety stock carried by the naïve retailer increases but also because the stockouts occur more frequently at the naïve retailer as the correlation coefficient increases or decreases from 0.

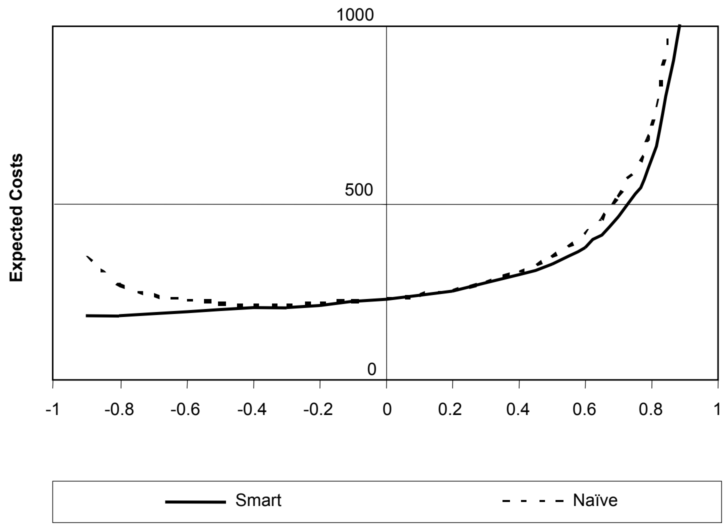


Figure 1. Smart vs. Naïve Retailer's Long Run Average Inventory Cost

In Figure 2, the x-axis refers to the value of the correlation coefficient and the y-axis refers to the ratio of the two variances $\frac{V\left(q_{s,t}\right)}{V\left(q_{n,t}\right)}$. The figure indicates that the variance ratio is greater than or equal to 1 when $\rho \le 0$. To further understand this figure, note that, in this case, $q_{s,t} = (1+\rho)d_{t-1} - \rho d_{t-2}$ and $q_{n,t} = d_{t-1}$. When ρ gets close to 1, we have $q_{s,t} \approx q_{n,t} + \mu$ since $d_{t-1} \approx \mu + d_{t-2}$. On the other hand, when ρ gets close to -1, we have $q_{s,t} \approx q_{n,t} - \mu$ since $d_{t-1} \approx \mu - d_{t-2}$.

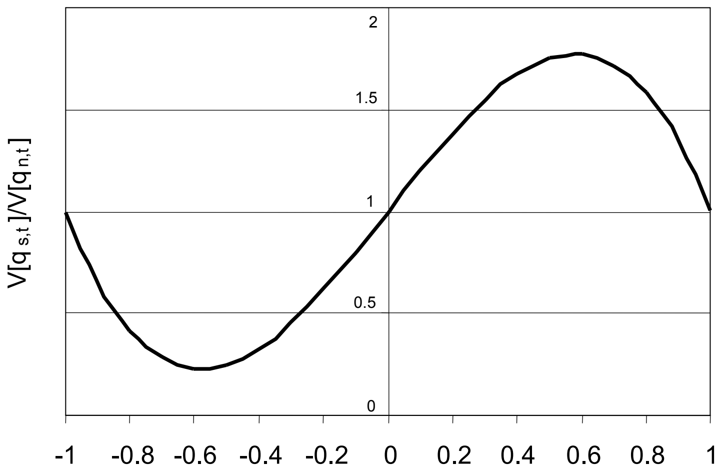


Figure 2. $\frac{V\left(q_{s,t}\right)}{V\left(q_{n,t}\right)}$

In Figure 3, the x-axis refers to the value of the correlation coefficient and the y-axis refers to the long run average supply chain cost per period, i.e., the sum of the retailer's long run average inventory cost per period and the manufacturer's long run average inventory cost per period. The dotted line represents the long run average supply chain cost per period when both the retailer and the manufacturer act smart, whereas the solid line represents long run average supply chain cost per period when the retailer is naïve and the manufacturer is smart. Notice that, from the figure, as ρ decreases from 0, the supply chain with the naïve retailer has higher long run average supply chain cost per period than the supply chain with smart retailer at an increasing rate. This is because, from Figure 1, as ρ decreases from 0, the smart retailer not only has lower long run average inventory cost per period but also, from Figure 2, causes less bullwhip effect to the manufacturer. It also can be seen that, when ρ is moderately positive, the supply chain with the naïve retailer has lower long run average inventory cost per period than the supply chain with the smart retailer and when ρ is close to 1, the supply chain with the smart retailer has lower long run average supply chain cost per period than the supply chain with the naïve retailer. This is because, as ρ increases from 0, the smart retailer has lower long run average inventory cost per period but, from Figure 2, causes more bullwhip effect to the manufacturer with a decreasing rate until it becomes the same as that of naïve retailer when $\rho = 1$.

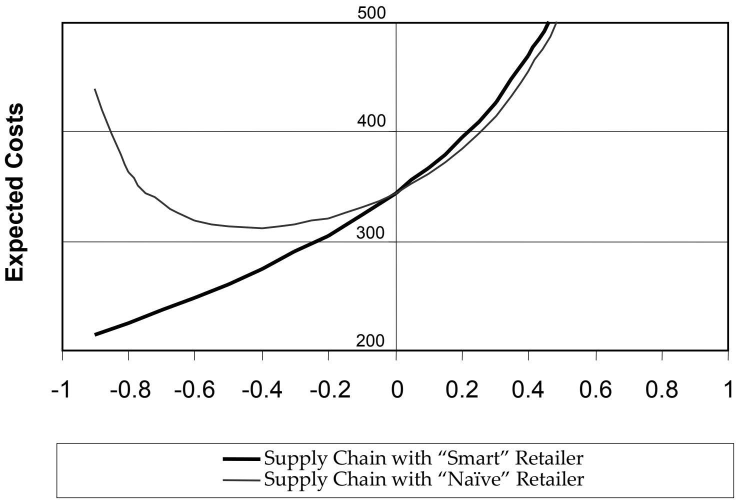


Figure 3. Long Run Average Supply Chain Cost Caused by Smart vs. Naïve Retailer

In Figure 4, the y-axis refers to the long run average inventory cost per period for the smart manufacturer when the retailer is smart, for various levels of information delay. Here, the dotted line represents the long run average inventory cost per period with no information sharing whereas the solid lines represent the long run average inventory cost per period with information delay $\delta = 0, 1, 2, 4$, respectively. From the figure, it is clear that, when $\delta \geq 1$, there is almost no value in information sharing. Also, in this case, having information sharing with a delay of 2 or more periods ($\delta \geq 2$) leads to higher costs at the manufacturer than having no information sharing.

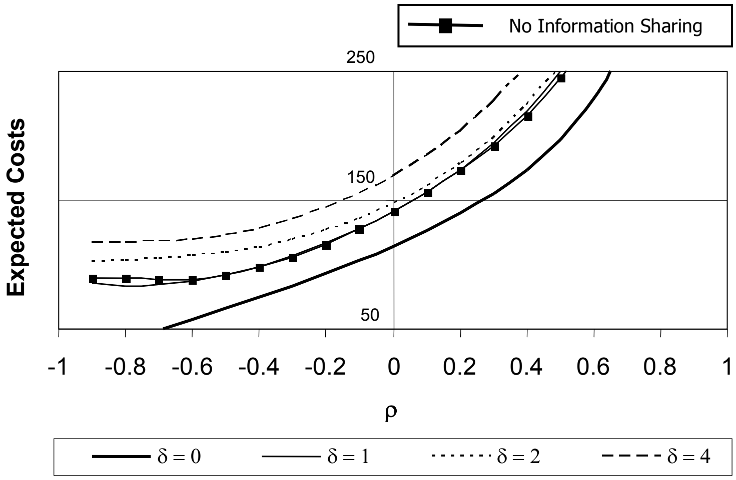
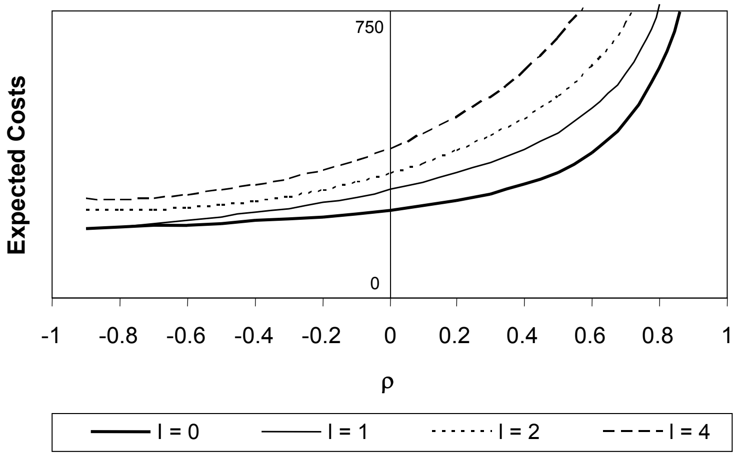


Figure 4. The Value of Delayed Information

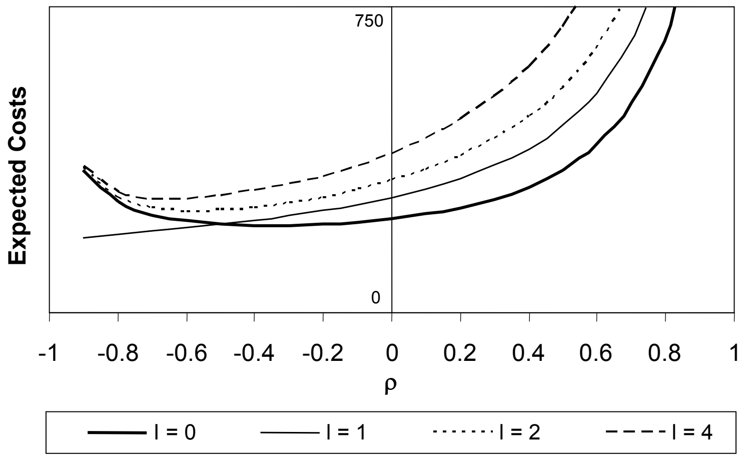
In Figure 5 (a), the lines represent the long run average inventory cost per period for the smart retailer with lead time of $l = 0, 1, 2, 4$ (from the bottom up). In addition, in Figure 5 (b), the lines represent the long run average inventory cost per period for the naïve retailer with lead time of $l = 0, 1, 2, 4$ (from the bottom up). For all of these results, we have taken $c = 1$. From the figure, it is clear that the long run inventory cost per period increases as the lead time increases and that, when the correlation coefficient approaches -1 and the lead time is even, i.e., the effective lead time is odd, being naïve can significantly hurt the retailer.[1] Notice also that, as the lead time increases, the difference between the long run average inventory costs per period for the smart and naïve retailer decreases. This result is due to the fact that as the effective lead time increases, the perceived effective lead time demand distribution for either type of retailer becomes similar to each other, in other words, $\sum_{i=0}^{l'-1} d_{t+i} \mid d_{t-1} \approx \sum_{i=0}^{l'-1} d_{t+i} \mid d_{t-1} \approx \sum_{i=0}^{l'-1} d_{t+i}$.[2]

[1] When the correlation coefficient approaches -1, the sum of two adjacent demands becomes less variable, i.e., $d_t + d_{t+1} \mid d_t \approx d_t + \mu - d_t + \varepsilon_{t+1} = \mu + \varepsilon_{t+1}$. Therefore, when the effective lead time is odd, the naïve model gives a poor demand forecast, and when the effective lead time is even, it gives a good forecast.

[2] Notice that, as i increases, the conditional distribution of d_{t+i}, given d_{t-1}, becomes very similar to the unconditional distribution of d_{t+i}.



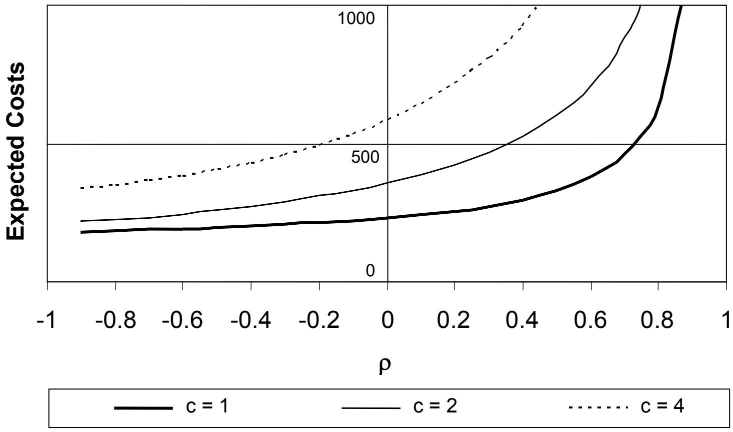
(a) Smart Retailer



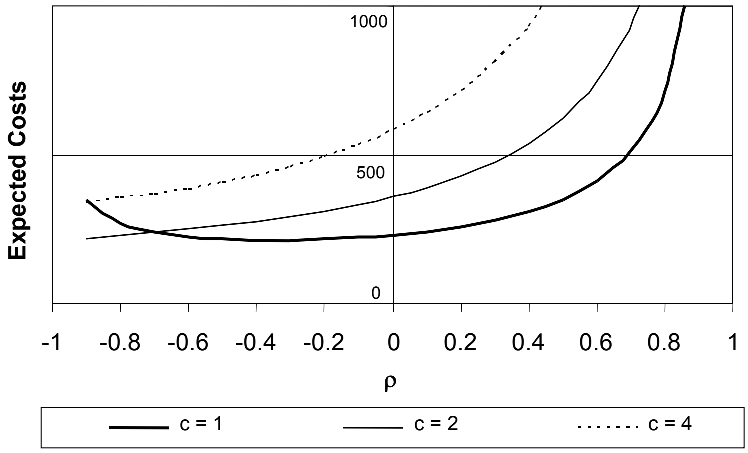
(b) Naïve Retailer

Figure 5. Retailer's Long Run Average Inventory Cost as a Function of Lead Time

In Figure 6 (a), the lines represent the long run average inventory cost per period for the smart retailer, with review periods $c = 1, 2, 4$ (from the bottom up). In addition, in Figure 6 (b), the lines represent the long run average inventory cost per period for the naïve retailer, with review periods $c = 1, 2, 4$ (from the bottom up). For all of these results, we have taken $l = 4$. From the figure, it is clear that the long run average inventory cost per period increases as the review period increases and that, as the review period increases, the difference between the long run average inventory costs per period for the smart and naïve retailer decreases. This result is due to the fact that as the effective lead time increases, the perceived effective lead time demand distribution for either type of retailer becomes similar to each other.



(a) Smart Retailer

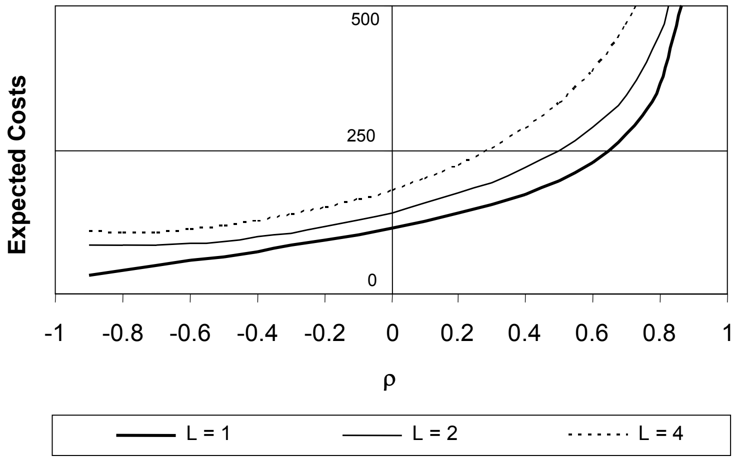


(b) Naïve Retailer

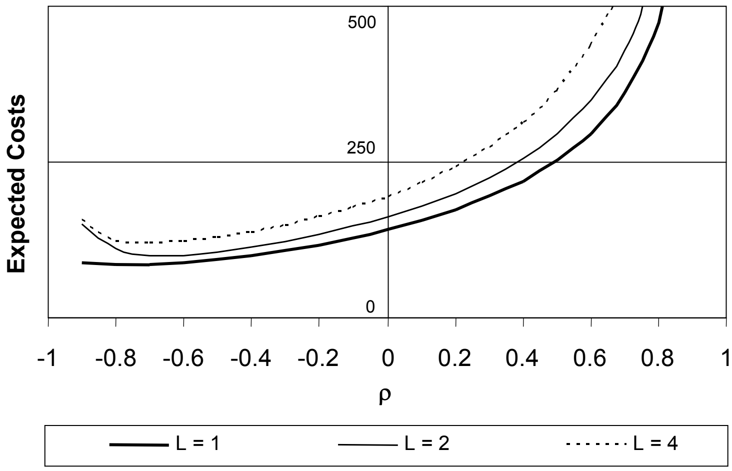
Figure 6. Retailer's Long Run Average Inventory Cost as a Function of Review Period

In Figure 7 (a), the lines represent the long run average inventory cost per period at a smart manufacturer who serves the smart retailer, with lead time $L = 1, 2, 4$, from the bottom up. In addition, in Figure 7 (b), the lines represent the long run average inventory cost per period of the naïve manufacturer serving the smart retailer, with lead time $L = 1, 2, 4$, from the bottom up. In each case, we have taken $C = 1$

and $\delta = 0$. From the figure, it is clear that the long run average inventory cost per period increases as the lead time increases and that the benefit of acting smart rather than naïve decreases as the lead time increases. This is due to the fact that, as more periods are included in the effective lead time, the effective lead time demand distribution for either type of retailer becomes similar to each other, in other words, $\sum_{i=0}^{l'-1} d_{t+i} \mid d_{t-1} \approx \sum_{i=0}^{l'-1} d_{t+i}$.

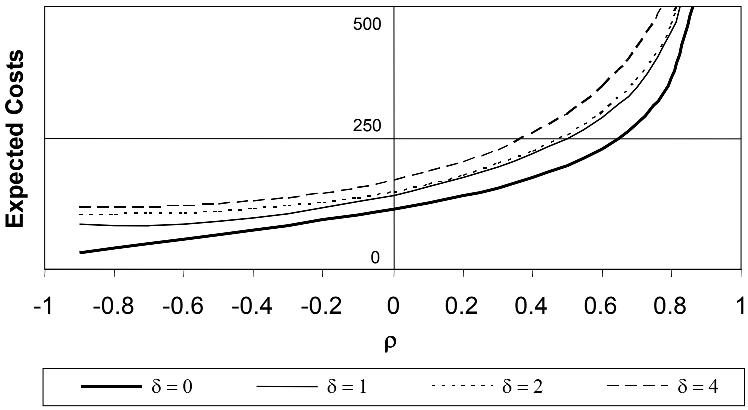


(a) Smart Manufacturer

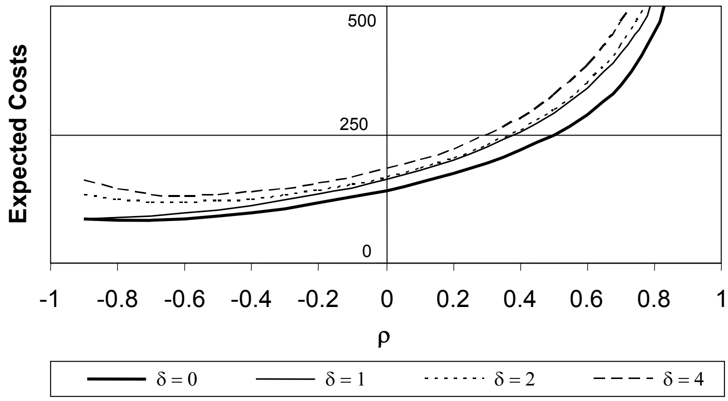


(b) Naïve Manufacturer

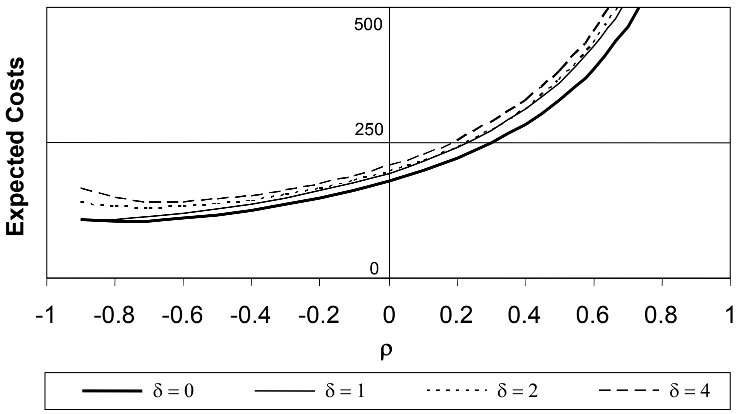
Figure 7. Manufacturer's Long Run Average Inventory Cost as a Function of Lead Time



(a) L = 1



(b) L = 2



(c) L = 4

Figure 8. Manufacturer's Long Run Average Inventory Cost as a Function of Information Delay

In Figure 8 (a)~Figure 8 (c), the y-axis refers to the long run average inventory cost per period for the manufacturer when the retailer is smart with various lead times, i.e., $L = 1, 2, 4$, respectively. Within each, the lines represent the long run average inventory cost per period for the smart manufacturer with information delay of $\delta = 0, 1, 2, 4$, from the bottom up. In each case, we have taken $C = 1$. From the figures, it is observed that the value of information sharing decreases as the lead time increases. Again, this is because, as more periods are included in the effective lead time, the effective lead time demand gets closer to an i.i.d. process. Although it is not shown here, the impact of the review period of the manufacturer on the long run average inventory cost per period at the manufacturer is found to be similar to that of lead time.

4. Final Remarks

In this paper, the models developed by Kim [4] and Kim [5] have been used to study the impact of various system parameters on the long run average inventory cost per period incurred at each participant of a supply chain. The question of how the long run average inventory costs per period depends on the choice of customer demand model and information sharing, possibly with some delay, is an important one not only from theoretical point of view but also from practical point of view. The numerical studies in this paper have proven to be useful to answer it.

We end this section with a brief summary of the key managerial insights obtained from Section 3. First, for the retailer:

- Acting smart always benefits the retailer.
- Acting smart may cause bullwhip effect, which has a negative effect on the next participant in the supply chain.
- As c or l increases, the value of acting smart decreases.
- As $|\rho|$ increases, the value of acting smart increases.

Next, for the manufacturer:

- Acting smart benefits the manufacturer.

- If information is shared with some delay, it may mislead even the manufacturer acting smart. Therefore, when information is somewhat delayed, the manufacturer may be better off using the retailer's order quantities $q_{j,t}$, $j = s, n$, to forecast demand instead.
- As c, l, C or L increases, the value of information sharing or acting smart decreases.

From the above observations, we can conclude that, in order for the retailer to minimize the long run average inventory cost per period, the retailer should reduce the review period and the lead time. Of course, the retailer also needs to act smart. The manufacturer should obtain the most recent demand data in addition to reducing the review period and the lead time. Again the manufacturer should act smart.

Finally, we can see that acting smart does not help the manufacturer reduce the long run average inventory cost per period when either the review period or the lead time is long. Similarly, acting smart does not help the manufacturer when there is some delay in information sharing.

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