Exploring the Effects of Sharing Information on Expected Cost under the VMI Model

Huei-Mei Liang, Chan-Fu Chuang, Chiu-Miao Chen

Abstract

This paper was to discuss the effects of information sharing between the vendors and the retailers. Assuming the underlying demand process was followed by auto-regressive moving average ARMA(1,2) in vendor managed inventory (VMI). Considering different information-sharing levels, such as no information sharing, partial information sharing, and full information sharing, with the factors of the lead time, the correlation coefficient between demand prediction and current demand, and the correlation coefficient between prediction error terms and demand, this research was to find the importance of single and multiple effects on the vendors’ delivery variance, delivery-up-to level, and expected cost. Through the sensitivity analysis, the effects from the single and multiple factors at different information-sharing levels could be observed. Moreover, the numerical simulation examined the findings as follows. (1) Information sharing stabilized delivery variance and delivery-up-to level as well as reduced expected cost. (2) At any information sharing level, all factors influenced the vendor’s delivery variance, delivery-up-to level, and expected costs. (3) At any information sharing, the factors of a smaller lead time and a larger coefficient between demand prediction and current demand had more significant effects on minimizing inventory and cost.

Key Words: Information Sharing, ARMA, VMI

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1. Introduction

Vendor-managed inventory (VMI) is a form of automated replenishment of supply chain collaboration that the vendor takes responsibility for managing the retailers’ inventory. In VMI collaboration, the vendor to create more efficient inventory management and consumer satisfaction has to be able to gain necessary information. Information sharing is a supply chain mechanism and highly related to inventory and cost (Lee et al., 1997). However, in the collaboration demand uncertainty could cause the bullwhip effect (Cooper et al., 1997; Fisher, 1997). Once the members of VMI face demand uncertainty, the vendor would experience unstable delivery-up-to and inventory level for its replenishment.
Demand uncertain reflects incompletely or inaccurately information sharing between the members which might bring about supply chain inventory and cost added up to a higher level (Lee et al., 2000). For this reason, Gavirneni et al.’s (1999) emphasized demand information sharing could reduce considerable percentage of inventory level and network cost. In any supply chain collaboration, using demand information including previous demand information and prediction errors to reduce inventory and cost is an effective alternative. Yet, how to identify different demand information sharing including previous demand information or historical demand prediction errors for the vendor accomplishing replenishment at minimized delivery deviation and cost requires needed more discussion.

Therefore, this research attempted to explain (1) what effects of different information sharing, including no information sharing, partial information sharing, and full information sharing, influence on inventory level and expected cost; and (2) how importance of the related factors affects the vendor’s delivery and cost at different information sharing. For the process of information sharing, we assumed the underlying demand process followed by ARMA (1,2) which was conditioned by previous demand information and demand prediction errors to determine the replenishment level and expected cost. Under two-level supply chain of VMI collaboration, the research comprising the factors of lead time \((l)\), the correlation coefficient \((\rho)\) between previous demand and current demand, and the correlation coefficient \((\theta)\) between demand prediction errors and current demand was to evaluate different effects of the vendor’s delivery variance, delivery-up-to level, and expected costs. In light of sensitivity analysis with the related factors at different information sharing, the single and interactive effects on the vendor’s delivery-up-to level and expected costs could be proposed. Further, associating the numerical simulation is to verify the proposals from the sensitivity analysis.

2. Literature Review

In supply chain collaboration, uncertainties are mainly divided into three categories which are manufacturing uncertainty, supply uncertainty, and demand uncertainty. Of these, demand uncertainty is the most unpredictable factor (Cachon and Fisher, 2000; Lin, 2010; Lin et al., 2002; Fisher, 1997) that supply chain members could experience unstable delivery resulted in higher delivery variance. More worse, demand fluctuation or delivery variance propagating upward over the supply chain could cause the bullwhip effect. This
bullwhip effect leads the supply chain members have to bear more excessive inventory and unnecessary cost (Lee et al., 1997). To avoid the bullwhip effect, demand and delivery variance have to be effectively controlled through coordinated mechanism where the necessary information sharing is considered an important object for the supply chain to reduce inventory variance and operation cost (Cachon and Fisher, 2000; Ramayah and Omar, 2010).

In recent, the value of demand information sharing has been widely recognized that information could affect supply chain performance. Many researches attempt to build quantitative models to explain information sharing benefits in supply chain collaboration. Lee et al. (1997) found that sharing real demand information across supply chain members could reduce the bullwhip effect. Lee et al. (2000) assumed the underlying demand process followed by autoregressive policy by the retailer revealing information sharing. Demand information between supply chain members was importantly relative to their inventory levels and cost. Especially, from the supplier’s standpoint to observe the effects of information sharing, Raghunathan (2001) indicated the supplier gaining historical demand information can effectively reduce the variation on demand forecasting when studied LST (Lee, So, and Tang; LST) model. Thonemann (2002) found the supplier’s average demand delivery and standard deviation can be improved through information sharing in supply chain. Cachon and Fisher’s (2000) (R, nQ) models involved one supplier and n customers to observe replenishment policy. Gavirneni et al. (1999) adopted (s, S) model to analysis information flow between the supplier and the retailer in a two-level supply-chain capacity and inventory. All these researches showed analytically how the supplier benefits from less inventory level and cost by gaining retailer’s demand information (Cachon and Fisher, 2000). Information sharing involving previous demand information resulted in the substantial benefits on the supplier side was significant. However, researches discussed how various effects of different information sharing, such as no information sharing and full demand information sharing were lack of explanation. More discussion on demand information effects with the related factors is necessary to identify different impacts.

For the fundamental perspective of demand information and the effect on the vendor side, Simchi-Levi et al. (2000) quantified information sharing with lead time factor in a two-level supply chain and Lee et al. (2000) used AR(1) model discussed the importance of information sharing after taking into account previous demand error and lead time in a two-level supply chain. In the model of Chen et al. (2001), it pointed out that demand error caused real stock in VMI so that the vendor had to bear the additional cost. Hence,
inventory level or demand errors not shared with other partners can be regarded as incomplete information exchange. Then, the supplier’s replenishment was only used previous demand prediction error to make an adjustment. Demand error, causing inventory variance, was information that needs to be shared and critical to further demand prediction. Hence, different information sharing can be based on how many previous demand errors shared. Information sharing can be classified into such as the supplier gaining all previous demand errors was full information sharing, the supplier gaining previous one-term demand information was seemed as partial information sharing, and the supplier without any previous demand error was no information sharing. For this viewpoint, Kulp’s (2002) and Kulp et al. (2004) involved the factors of information sharing and transmission reliability in mathematic model to discuss how VMI benefits the supply chain as a whole. However, these complex models about information sharing, determining different information sharing with previous demand errors were still more quantitative modeling and simulation analysis to demonstrate the results. Especially, discussing single and interactive effects from the related factors of lead time, historical prediction error, and demand information at different information sharing were needed more classifying the priorities for the vendor replenishment.

Therefore, this research is to construct three models of information sharing including no information sharing, partial information sharing, and full information sharing. By using the factors of lead-time $l$, correlation coefficient $\rho$ between previous two consecutive demands, the correlation coefficient $\theta$ between demand prediction error terms and demand, the sensitive analysis is to observe the importance of the vendor’s delivery variance, optimal delivery-up-to level, and expected cost at three levels of information sharing. Finally, numerical simulation is conducted to verify the findings from the sensitivity analysis.

3. Models

The model of optimal delivery-up-to level and expected cost for the vendor

To construct the mathematical models, this research proposals delivery variance, optimal delivery-up-to level, and expected costs as the components of inventory and expected costs for the vendor. In VMI, there are basic assumptions and notations as the follows.
3.1 Basic assumptions

(1) In VMI, optimal order-up-to level for the retailer has to be replaced by optimal delivery-up-to level for the vendor.

(2) In VMI, the vendor bears the holding cost and loss cost.

(3) In any circumstance, the vendor has to satisfy the retailer’s requirement.

(4) In VMI, single product and facility is the premise.

3.2 Notations

At time $t$, the notations for optimal delivery-up-to level at different information sharing are shown:

$T_0$: optimal delivery-up-to level at no information sharing
$T_1$: optimal delivery-up-to level at partial information sharing
$T_2$: optimal delivery-up-to level at full information sharing

At time $t$, the vendor’s expected costs including holding cost and loss cost at three levels of information sharing are shown:

$C_0$: holding cost and loss cost at no demand information sharing
$C_1$: holding cost and loss cost at partial information sharing
$C_2$: holding cost and loss cost at full information sharing

$l$: the vendor’s lead time of replenishment
$P$: per unit time of loss cost for the vendor
$H$: per unit time of holding cost for the vendor

Besides, in VMI if we assume the retailer’s demand process followed by ARMA (1,2) which represents the error terms of previous demand prediction relating to future demand, then the retailer’s demand at time $t$ can be described as follows.

$$D_t = d + \rho D_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2}$$

(3.1)

(1) $d$ is a fixed demand number and greater than zero.

(2) $\rho$ represents the correlation coefficients between previous demand and current demand. It is assumed $0<\rho<1$.

(3) $\varepsilon_t$ represents error terms which are the unpredictable factors affecting future demand. The error terms at certain time (t) are assumed $\varepsilon_t \sim N(0,\sigma^2)$.

(4) $\theta$ represents the correlation coefficients between previous unpredictable error
terms and demand. The unpredictable factors have less influence with time decreasing. That is $0 \leq \theta_i \leq \theta_t \leq 1$.

Before discussing total demand ($D_t$) of the retailer, the factor of lead time on replenishment has to be explained. At time $t$, the vendor schedules replenishment and finishes at time $t+1+l$. Within this time frame, total demands for the retailer can be described as follow. Notice that the time series model of the customer demand in Lee et al. (2000) that assumes AR(1) is a special case of this model.

$$
\beta_t = \sum_{j=1}^{i+l} D_{t+j} = \frac{1}{1-\rho} \left\{ \rho \sum_{j=1}^{i+l} (1-\rho^j) + \rho (1-\rho^{i+l}) D_t \right\} + \varepsilon_{i+l+1} + (1+\rho+\theta_t) \varepsilon_{i+l} \\
+ \cdots + \left[ \frac{\theta_1 (1-\rho^j)}{1-\rho} + \frac{\theta_2 (1-\rho^j)}{1-\rho} \right] \varepsilon_i + \left[ \frac{\theta_3 (1-\rho^j)}{1-\rho} \right] \varepsilon_{i-1}
$$

(3.2)

Obtaining total demand of the retailer at the given lead time, the vendor could determine the optimal delivery-up-to level which could minimize its expected cost. This optimal delivery-up-to level can be evaluated by the conditional expectation and variance in this lead time interval because the optimal delivery-up-to level is highly affected by information sharing. In our model, demand information of ARMA (1,2) indicates that the unpredictable factors ($\varepsilon_{i-\cdot}$) disclosed by the retailer at different information sharing levels. Three constructed models are explained as the follows.

Model 0: In this model, it represents no information sharing that the vendor doesn’t have $\varepsilon_{i-\cdot}$ and $\varepsilon_{i}$ information.

Model 1: In this model, it represents partial information sharing that the vendor owns $\varepsilon_{i-\cdot}$ information.

Model 2: In this model, it represents full information sharing that the vendor has $\varepsilon_i$ and $\varepsilon_{i-\cdot}$ information.

Above these models, the optimal delivery-up-to level has same structure with this description.

$$
T_i = M_i + K \sqrt{v_i} \sigma \quad i=0, 1, 2
$$

($K = \Phi^{-1}[\frac{P}{P+H}]$ and $\Phi$ is a function of cumulative normal distribution) (3.3)

At any information sharing, the vendor’s delivery can be according to the equation (3.2) in which timeframe is $t$ to $t+1+l$. And, delivery has a normal distribution with mean
of $M_i$ and variance of $V_i$. The means and variances at different information sharing are illustrated as follows.

### 3.2.1 Model 0: No information sharing

In this model, the vendor only knows demand at time $t$ ($D_t$). To determine optimal delivery-up-to level at time $t$, the demand error terms of $\epsilon_t$ and $\epsilon_{t-1}$ unknown but they would influence replenishment decision. In another word, at time $t$ the vendor has no information about previous error terms but it has to make demand prediction for further replenishment. At this situation, the vendor could follow equation (3.2) ignoring previous demand-prediction error terms to evaluate time $t+l+1$ demand which is still assumed is a normal distribution with mean $M_0$ and variance $V_0$. The mean and variance in the model can be described as follows.

\[
M_0 = E(\sum_{i=1}^{l+1} D_{ti} | D_t) = \frac{1}{1-\rho} \left\{ d \sum_{i=1}^{l+1} (1-\rho^i) + \rho(1-\rho^{l+1})D_t \right\} 
\]

\[
V_0 = Var(\sum_{i=1}^{l+1} D_{ti} | D_t) = \nu_0 \sigma^2
\]

\[
\nu_0 = 1 + (1 + \rho + \theta_1)^2 + \sum_{k=1}^{l+1} \left[ \frac{(1-\rho^{k+1})}{1-\rho} + \frac{\theta_1(1-\rho^{k+1})}{1-\rho} + \frac{\theta_2(1-\rho^{k+1})}{1-\rho} \right]^2 + 
\left[ \frac{\theta_1(1-\rho^{l+1})}{1-\rho} + \frac{\theta_2(1-\rho^{l+1})}{1-\rho} \right]^2 + \left[ \frac{\theta_2(1-\rho^{l+1})}{1-\rho} \right]^2
\]

### 3.2.2 Model 1: Partial information sharing

In this model, at time $t$ the vendor has information about the retailer’s demand ($D_t$) and previous demand error terms ($\epsilon_t$) but doesn’t know the unpredicted factor $\epsilon_{t-1}$. From time $t$ to time $t+l+1$, total demand for the vendor can be described by the equation (3.2) while demand is a normal distribution with mean $M_0$ and variance $V_0$. The expected mean and variance in this model can be displayed as follows.

\[
M_i = E(\sum_{i=1}^{l+1} D_{ti} | D_t, \epsilon_{t-1}) = M_0 + \left[ \frac{\theta_2(1-\rho^{l+1})}{1-\rho} \right] \epsilon_{t-1}
\]

\[
V_i = Var(\sum_{i=1}^{l+1} D_{ti} | D_t, \epsilon_{t-1}) = \nu_0 - \left[ \frac{\theta_2(1-\rho^{l+1})}{1-\rho} \right]^2 \sigma^2 = \nu_i \sigma^2
\]
Notice that \( v_1 = v_0 - \left( \frac{\theta_1(1-\rho^{i+1})}{1-\rho} \right)^2 \)

### 3.2.3 Model 2: Full information sharing

In this model, at time \( t \) the vendor knows demand \( (D_t) \) and the previous demand error terms of \( \varepsilon_t \) and \( \varepsilon_{t-1} \). From time \( t+1 \) to time \( t+l+1 \), total demand is assumed by a normal distribution with mean \( (M_2) \) and variance \( (V_2) \) which are displayed as follows.

\[
M_2 = E(\sum_{1}^{t+l} D_{t+i} | D_t, \varepsilon_{t-1}, \varepsilon_t) = M_1 + \left[ \frac{\theta_2(1-\rho^{i+1})}{1-\rho} \right] \varepsilon_{t-1} + \left[ \frac{\theta_1(1-\rho^{i+1})}{1-\rho} \right] \varepsilon_t
\]

\[
V_2 = Var(\sum_{1}^{t+l} D_{t+i} | D_t, \varepsilon_{t-1}, \varepsilon_t) = v_2 \sigma^2
\]

where \( v_2 = v_0 - \left( \frac{\theta_1(1-\rho^{i+1})}{1-\rho} \right)^2 - \left[ \frac{\theta_1(1-\rho^{i+1})}{1-\rho} \right]^2 \)  \( \cdot \left[ \frac{\theta_2(1-\rho^{i+1})}{1-\rho} \right]^2 \)  \( \cdot \left[ \frac{\theta_2(1-\rho^{i+1})}{1-\rho} \right]^2 \)  \( \cdot \left[ \frac{\theta_1(1-\rho^{i+1})}{1-\rho} \right]^2 \)  \( \cdot \left[ \frac{\theta_1(1-\rho^{i+1})}{1-\rho} \right]^2 \)

### 3.3 Information sharing affecting delivery variance and optimal delivery-up-to level

Based on above models, delivery variance or optimal delivery-up-to level would be affected by different information sharing in these indications: (1) The more information sharing is, the more stable delivery has. (2) The level of Optimal delivery-up-to can be decreased when more information sharing is. In addition, the levels of information sharing and optimal delivery-up-to are important to the expected costs. These indications focus on delivery based on a specific level of information sharing is described as follows.

Here, a conditional expectation of the delivery amount \( (E_i(M_i), i=0, 1, 2) \) is assumed various levels of information sharing which are conditioned on how much error terms known. And, different delivery amount are expressed by:

\[
E_0(M_0) = E(M_0) \quad E_1(M_1) = E_{i-1}(M_1) \quad E_2(M_2) = E_{i-1, i-1}(M_2)
\]

\( E_i(T_i) \) can be defined the optimal delivery-up-to level as similar as the delivery. The structure of \( T_i \) will be used in deriving the expected costs, it will be shown more detail in next section.

(1) Theorem 1

As the mean of the delivery amount will not be affected by any level of information sharing, it can be shown by \( E_0(M_0) = E_1(M_1) = E_2(M_2) \).
(2) Theorem 2
(a) By increasing the level of information sharing, the vendor’s delivery variance will be decreased. It can be demonstrated by $0 < V_2 < V_1 < V_0$
(b) A decreasing delivery variance would consistent with an increasing level of information sharing. The decreasing range is larger than the increasing that it can be demonstrated by $0 < (V_0 - V_1) < (V_1 - V_2)$.

(3) Theorem 3
(a) With more information sharing is, optimal delivery-up-to level decreased that it can be shown $E_q(T_2)<E_q(T_1)<E_q(T_0)$. It indicates more revealing information to the vendor who has more visible inventory on inventory management. And, the vendor can accurately determine the optimal delivery-up-to level.
(b) Decreasing the optimal delivery-up-to level is faster than increasing the level of information sharing. It can be demonstrated by $(E_q(T_0) - E_q(T_1))< (E_q(T_1) - E_q(T_2))$.

3.4 The model of expected cost
Next, to explore information sharing affecting the vendor’s expected cost, the holding cost and the loss cost are necessary involved in expected cost because of the vendor charging replenishment decision. This situation for the expected cost has to be defined as a cumulative standard normal distribution function and $x$ would be a given inventory which is a right loss function (Lee et al., 2000). Then, the expected loss function $L(x)$ could be described as the follows.

$$L(x) = \int_{x}^{\infty} (z-x) d\Phi(z) ;$$

where $\Phi(z)$ is a function of cumulative standard normal distribution. Thus, the expected inventory, given the inventory $x$, is $S(x) = \int_{-\infty}^{x} (x-z) d\Phi(z) .

To further observe the vendor’s expected cost, this research follows the property of the loss functions that $H$ and $P$ are represented per unit holding cost ($H$) and loss cost ($P$).

It can be known that $K = \Phi^{-1}\left[\frac{P}{P+H}\right]$

There are definitions are described as:
(1) $L(x)$ is a decreasing and convex function of $x$.
(2) $(H + P)L(x) + Hx \geq (H + P)L(K) + HK \ \forall x \geq K$

Above the Lemma, we can proof as the follows.
The first statement follows directly from the first and the second derivatives of \( L(x) \).

\[
L'(x) = -\int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \, dz < 0, \tag{3.12}
\]

\[
L''(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} > 0. \tag{3.13}
\]

\[(H + P)L(x) + Hx = (H + P)[L(x) + \alpha x] \; \text{where} \quad \alpha = \frac{H}{P + H} = 1 - \Phi(K)\]

We have \((H + P)L(K) + HK = (H + P)[L(K) + \alpha K]\)

Now, let \( F(x) = L(x) + \alpha x \cdot \forall x \geq K \)

It could follow that

\[
F'(x) = L'(x) + \alpha \\
= -(1 - \Phi(x)) + 1 - \Phi(K) \\
= \Phi(x) - \Phi(K) \geq 0 \tag{3.14}
\]

Having these properties of the function of \( L(x) \), then we will discuss the relationship between various information sharing levels and the expected costs.

### 3.4.1 Expected cost at full information sharing

When VMI is at full information sharing, the vendor gains demand errors \( \epsilon_{t-1} \) and \( \epsilon_t \) that it can predict total demand with the complete information during the lead time \((\beta_t, F_{t-1}, \epsilon_t)\). Based on this point, optimal delivery-up-to level \((T_2 = M_2 + K\sqrt{v_2}\sigma)\) could minimize expected cost at the retailer’s warehouse. However, when the replenishment reaches the retailer, the inventory incurred the holding cost of excessiveness or the loss cost of shortage will add on the vendor. The expected cost \( C_2 \) at full information sharing can be described as follows while the lead time has the attribution of a normal distribution.

\[
C_2 = E_{\epsilon_{t-1}, \epsilon_t} \left\{ P \int_{T_2}^{\infty} (x - T_2) dF_2(x) + H \int_{-\infty}^{T_2} (T_2 - x) dF_2(x) \right\} \\
= E_{\epsilon_{t-1}, \epsilon_t} \left\{ P \cdot \sigma \sqrt{v_2} \int_{K}^{\infty} (z - K) d\Phi(z) + H \cdot \sigma \sqrt{v_2} \int_{-\infty}^{K} (K - z) d\Phi(z) \right\} \\
= \sigma \sqrt{v_2} \left\{ P \int_{K}^{\infty} (z - K) d\Phi(z) + H \int_{-\infty}^{K} (K - z) d\Phi(z) \right\} \tag{3.15}
\]

\[
= \sigma \sqrt{v_2} \left[ P \cdot L(K) + HK + H \cdot (-L(K)) \right] \\
= \sigma \sqrt{v_2} (H + P)L(K) + HK
\]
3.4.2 Expected cost at partial information sharing

In this case, the vendor gains previous error term \( \varepsilon_{t-2} \). During the lead time \( (\beta_t|\varepsilon_{t-1}) \), the vendor’s demand prediction on replenishment is less precise so as to the delivery becomes more unstable due to unpredictable term \( \varepsilon_{t-1} \) influencing demand calculation at time \( t \). At partial information sharing, optimal delivery-up-to level can be expressed by

\[
T_1 = M_t + K_1 \sqrt{\frac{\varepsilon_t}{\sigma}}
\]

(3.11)

where \( K_1 = \frac{M_t - M_2}{\sigma \sqrt{v_2}} + K \frac{\sqrt{\varepsilon_t}}{\sqrt{v_2}} \). And, the expected cost with mean \( \bar{M}_t \) and variance \( \bar{V}_t \) can be displayed as this equation.

\[
C_t = \mathbb{E}_t \left\{ P \int_{-\infty}^{\bar{M}_t} (x - T_1) dF_2(x) + H \int_{-\infty}^{\bar{M}_t} (T_1 - x) dF_2(x) \right\}
\]

\[
= \mathbb{E}_t \left\{ \sigma \sqrt{v_2} [(H + P) L(K_t) + HK_t] \right\}
\]

(3.16)

3.4.3 Expected cost at no information sharing

In this case, the retailer discloses no information at time \( t \). Without knowing \( \varepsilon_{t-1} \) and \( \varepsilon_t \), the vendor cannot predict total demand during the lead time \( (\beta_t) \). Then, the optimal delivery-up-to level of \( T_0 \) can be rearranged as:

\[
T_0 = M_0 + K_0 \sqrt{\frac{\varepsilon_0}{\sigma}}
\]

(3.12)

where \( K_0 = \frac{M_0 - M_2}{\sigma \sqrt{v_2}} + K \frac{\sqrt{\varepsilon_0}}{\sqrt{v_2}} \).

Similarly, total demand is assumed a normal distribution with the mean \( M_0 \) and variance \( V_0 \). The expected cost at no information sharing can be described in this equation.

\[
C_0 = \mathbb{E}_{t, \varepsilon_{t-1}} \left\{ P \int_{-\infty}^{M_0} (x - T_0) dF_2(x) + H \int_{-\infty}^{M_0} (T_0 - x) dF_2(x) \right\}
\]

\[
= \mathbb{E}_{t, \varepsilon_{t-1}} \left\{ \sigma \sqrt{v_2} [(H + P) L(K_0) + HK_0] \right\}
\]

(3.17)

In sum, the relationship between the expected costs at different levels of information sharing can follow these indications:

\[
(1) \quad C_0 = \mathbb{E}_{t, \varepsilon_{t-1}} \left\{ \sigma \sqrt{v_2} [(H + P) L(K_0) + HK_0] \right\}
\]

\[
C_t = \mathbb{E}_t \left\{ \sigma \sqrt{v_2} [(H + P) L(K_t) + HK_t] \right\}
\]

\[
C_1 = \sigma \sqrt{v_2} [(H + P) L(K_t) + HK_t]
\]

(3.18)

\[
(2) \quad 0 \leq C_2 \leq C_1 \leq C_0
\]

(3.19)
Based on above, more information disclosed will make both demand prediction and optimal delivery-up-to level stable. After all, more information sharing would bring about less expected cost. How to prove these indications the research will use the sensitivity analysis to compare various influences at different information sharing with the related factors.

4. Sensitivity Analysis

To compare the importance of the factors at different levels of information sharing, the sensitivity analysis introduced is to measure the effects. As mention before, more information sharing brings, more accurate demand prediction and hence it can eventually reduce optimal delivery-up-to level as well as expected cost. The effects of delivery variance \( (V_i) \), optimal delivery-up-to level \( E_i(T) \), and expected cost \( C_i \) are explained as below.

4.1 The sensitivity analysis on the delivery variance

Recall the variances of demand prediction, three levels of information sharing included no information sharing, partial information sharing, and full information sharing, represented by \( V_0 \), \( V_1 \), and \( V_2 \), respectively. Next, the sensitivity analysis with lead time \( l \), the correlation coefficient \( \rho \), and the correlation coefficient \( \theta_1 \) and \( \theta_2 \) will discuss the effects.

4.1.1 The sensitivity analysis of the related factors

For the sake of consistency in notations, first we replace the discrete notation of lead time \( l \) with the notation of continuum, \( \frac{\partial V_i}{\partial T} \equiv V'_i(l+1) - V'_i(l) \). The summarized results shown on Table 1 and the factors \( l \), \( \rho \), \( \theta_1 \), and \( \theta_2 \) relating to demand prediction are concluded.

1. All of these factors have positive impact.
2. All of these factors will increase impacts as more information sharing incurred.
   The correlation coefficient \( \theta_1 \) has a particular important role on improving delivery variance while VMI is full information sharing.
3. Among three levels of information sharing, the correlation coefficient \( \theta_1 \) has more influence than \( \theta_2 \).
### Table 1  Sensitivity analysis of the factors to the variance of demand prediction

<table>
<thead>
<tr>
<th>The factors</th>
<th>Property/Implication</th>
</tr>
</thead>
<tbody>
<tr>
<td>The lead time $l$</td>
<td>Prop. 1: (1) $0 \leq \frac{\partial V}{\partial l} \leq \frac{\partial V}{\partial l}$ \leq \frac{\partial V}{\partial l}$; (2) $0 \leq \frac{\partial V}{\partial l} - \frac{\partial V}{\partial l}$ \leq \frac{\partial V}{\partial l} - \frac{\partial V}{\partial l}$; At any information sharing level, longer lead time 1 makes demand prediction less accuracy. With information sharing, the accuracy increases at a speed faster than the level of information sharing.</td>
</tr>
<tr>
<td>The correlation coefficient $\rho$</td>
<td>Prop. 2: (1) $0 \leq \frac{\partial V}{\partial \rho} \leq \frac{\partial V}{\partial \rho}$; (2) $0 \leq \frac{\partial V}{\partial \rho} - \frac{\partial V}{\partial \rho}$ \leq \frac{\partial V}{\partial \rho} - \frac{\partial V}{\partial \rho}$; At any level of information sharing, when the correlation $\rho$ between demands in two consecutive terms is higher, the demand prediction becomes less accurate; and the situation is even worse when less information is shared.</td>
</tr>
<tr>
<td>The error term $\theta_1$</td>
<td>Prop. 3: (1) $0 \leq \frac{\partial V}{\partial \theta_1} \leq \frac{\partial V}{\partial \theta_1}$; (2) $0 \leq \frac{\partial V}{\partial \theta_1} - \frac{\partial V}{\partial \theta_1}$ \leq \frac{\partial V}{\partial \theta_1} - \frac{\partial V}{\partial \theta_1}$; (3) $0 \leq \frac{\partial^2 V}{\partial \theta_1^2} \leq \frac{\partial^2 V}{\partial \theta_1^2}$; (4) $0 \leq \frac{\partial^2 V}{\partial \theta_1^2} - \frac{\partial^2 V}{\partial \theta_1^2}$ \leq \frac{\partial^2 V}{\partial \theta_1^2} - \frac{\partial^2 V}{\partial \theta_1^2}$; The demand accuracy will be affected by the error in the previous term in the way that the more influential the previous error is to the demand, the less accurate the prediction will be. This is true at any level of information sharing. However, the influences could be lessened by information sharing in a speed faster than linear.</td>
</tr>
<tr>
<td>The error term $\theta_2$</td>
<td>Prop. 4: (1) $0 \leq \frac{\partial V}{\partial \theta_2} \leq \frac{\partial V}{\partial \theta_2}$; (2) $0 \leq \frac{\partial V}{\partial \theta_2} - \frac{\partial V}{\partial \theta_2}$ \leq \frac{\partial V}{\partial \theta_2} - \frac{\partial V}{\partial \theta_2}$; (3) $0 \leq \frac{\partial^2 V}{\partial \theta_2^2} \leq \frac{\partial^2 V}{\partial \theta_2^2}$; (4) $0 \leq \frac{\partial^2 V}{\partial \theta_2^2} - \frac{\partial^2 V}{\partial \theta_2^2}$ \leq \frac{\partial^2 V}{\partial \theta_2^2} - \frac{\partial^2 V}{\partial \theta_2^2}$; The results are similar to property 3. But, less influence $\theta_2$, on delivery is between partial and full information sharing.</td>
</tr>
<tr>
<td>The error terms $\theta_1$ and $\theta_2$</td>
<td>Prop. 5: (1) $0 \leq \frac{\partial V}{\partial \theta_1} \leq \frac{\partial V}{\partial \theta_1}$; (2) $0 \leq \frac{\partial^2 V}{\partial \theta_1^2} \leq \frac{\partial^2 V}{\partial \theta_1^2}$ \leq \frac{\partial^2 V}{\partial \theta_1^2}$; At any information sharing level, the importance of $\theta_1$ on delivery is larger than $\theta_2$.</td>
</tr>
<tr>
<td>The importance of $l$ and $\rho$</td>
<td>Prop. 6: (1) The lead time $l$ has more impact than the correlation coefficient $\rho$ between two consecutive demands as it is short. On the contrast, the correlation coefficient $\rho$ becomes more important as longer lead time. (1) When the lead time is relatively short, the vendor to improve delivery-up-to level is suggested to use the lead time as the instrument. (2) While the lead time is relatively long, the vendor to improve delivery-up-to level is suggested to use the factor of correlation coefficient $\rho$ between two consecutive demands.</td>
</tr>
<tr>
<td>The importance among the factors $\rho$, $\theta_1$, and $\theta_2$</td>
<td>Prop. 7 (1) $0 \leq \frac{\partial V}{\partial \rho} \leq \frac{\partial V}{\partial \rho}$; (2) $0 \leq \frac{\partial^2 V}{\partial \rho^2} \leq \frac{\partial^2 V}{\partial \rho^2}$ \leq \frac{\partial^2 V}{\partial \rho^2}$; At full information sharing, demand prediction could be improved by $\rho$, $\theta_1$, and $\theta_2$ in sequence.</td>
</tr>
</tbody>
</table>
To promote demand prediction accuracy, the vendor is suggested to improve lead time \( l \) as the priority as well as the correlation coefficient \( \rho \). In addition, to reduce delivery variance in partial or full information sharing, the vendor still depends on the factors of \( l, \rho, \theta_1, \) and \( \theta_2 \). Of these, the correlation coefficient \( \theta_1 \) generate much impact at full information sharing.

### 4.1.2 The interactive sensitive analysis

Due to these factors having positive effects on vendor’s delivery variance, they could generate more interactive effects on reducing the vendor’s delivery variance. The research proposals the factors at different information sharing have interactive or multiple effects on delivery variance (\( V_i \)). This interactive analysis conditions one of the factors is fixed and observes the rest of factors influencing the vendor’s delivery variance (\( V_i \)). From the observations, there are concluded as follows: (1) All factors have positive effects on \( V_i \). (2) More information sharing is helpful to reduce \( V_i \). Further, the interactive influences among \( l, \rho, \theta_1, \) and \( \theta_2 \) on vendor’s delivery variance are discussed as follows (Table 2).

<table>
<thead>
<tr>
<th>Table 2</th>
<th>The interactive analysis on the vendor’s delivery variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interactive analysis</td>
<td>Property/Implication</td>
</tr>
<tr>
<td>The interactive influences of ( l ) and ( \rho ) to delivery variance</td>
<td>Prop. 8 : (1) ( 0 \leq \frac{\partial^2 V_i}{\partial \rho \partial l} \leq \frac{\partial^2 V_i}{\partial l \partial \rho} \leq \frac{\partial^2 V_i}{\partial l^2} ); (2) ( 0 \leq \frac{\partial^2 V_i}{\partial \theta_1 \partial \rho} - \frac{\partial^2 V_i}{\partial \rho \partial \theta_1} \leq \frac{\partial^2 V_i}{\partial l \partial \theta_1} - \frac{\partial^2 V_i}{\partial l \partial \theta_1} )</td>
</tr>
<tr>
<td>At any level of information sharing, the interactive effect combines a longer ( l ) and larger ( \rho ) causing less stable on delivery. Through more information, the vendor can stabilize delivery variance.</td>
<td></td>
</tr>
</tbody>
</table>

| The interactive influence of \( l \) and \( \theta_1 \) to delivery variance | Prop. 9: (1) \( 0 \leq \frac{\partial^2 V_i}{\partial \theta_1 \partial l} \leq \frac{\partial^2 V_i}{\partial l \partial \theta_1} = \frac{\partial^2 V_i}{\partial l \partial \theta_1} \); (2) \( 0 = \frac{\partial^2 V_i}{\partial \theta_1 \partial l} - \frac{\partial^2 V_i}{\partial \theta_1 \partial l} \leq \frac{\partial^2 V_i}{\partial l \partial \theta_1} - \frac{\partial^2 V_i}{\partial l \partial \theta_1} \) |
| At any level of information sharing, the interactive effect combines a longer \( l \) and \( \theta_1 \) causing less stable delivery. Through more information sharing, the vendor can stabilize delivery variance. |

| The interactive influence of \( l \) and \( \theta_2 \) to delivery variance | Prop. 10: (1) \( 0 \leq \frac{\partial^2 V_i}{\partial \theta_2 \partial l} \leq \frac{\partial^2 V_i}{\partial l \partial \theta_2} \leq \frac{\partial^2 V_i}{\partial l^2} \); (2) \( 0 \leq \frac{\partial^2 V_i}{\partial \theta_2 \partial \theta_1} - \frac{\partial^2 V_i}{\partial \theta_2 \partial \theta_1} \leq \frac{\partial^2 V_i}{\partial l \partial \theta_2} - \frac{\partial^2 V_i}{\partial l \partial \theta_2} \) |
| At any level of information sharing, the interactive effect of a longer \( l \) and \( \theta_2 \) causes the vendor’s delivery less stable. Though information sharing, the vendor can stabilize delivery. This improvement by more information sharing is at a nonlinear fashion. |
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Prop. 11: (1) \( 0 \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1} \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1} = \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1}; \)

(2) \( 0 \leq \left( \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1} - \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1} \right) \leq \left( \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1} - \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1} \right) \)

At any level of information sharing, the interactive effect combines a larger \( \rho \) and \( \theta_1 \) causing less stable on delivery. Through information sharing, the vendor can make delivery variance stable.

Prop. 12: (1) \( 0 \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2} \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2} \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2}; \)

(2) \( 0 \leq \left( \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2} - \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2} \right) \leq \left( \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2} - \frac{\partial^2 Y_p}{\partial \rho \partial \theta_2} \right) \)

At any level of information sharing, the interactive effect combines larger \( \rho \) and \( \theta_2 \) causing delivery less stable. Through information sharing, the vendor can make delivery stable.

Prop. 13: (1) \( 0 \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2} \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2} = \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2}; \)

(2) \( 0 \leq \left( \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2} - \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2} \right) \leq \left( \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2} - \frac{\partial^2 Y_p}{\partial \theta_1 \partial \theta_2} \right) \)

At any level of information sharing, a larger influence of demand prediction error terms causes the vendor’s delivery less stable. Through information sharing, the vendor can improve its delivery stable.

Prop. 14: \( 0 \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \rho \partial \theta_1} \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \rho \partial \theta_1} \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \rho \partial \theta_1}; \)

At any level of information sharing, the interactive from a longer \( l \), \( \rho \), and \( \theta_1 \) will cause less stable delivery. Through information sharing, the delivery variance can be stabilized.

Prop. 15: \( 0 \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \rho \partial \theta_1} \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \rho \partial \theta_1} \leq \frac{\partial^2 Y_p}{\partial \theta_1 \partial \rho \partial \theta_1}; \)

At any level of information sharing, the interactive effect combines a longer lead time \( l \), \( \theta_1 \), and \( \theta_2 \) causing delivery less stable. Through full information sharing the vendor can stabilize the delivery.

Prop. 16: \( 0 \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1 \partial \theta_2} \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1 \partial \theta_2} \leq \frac{\partial^2 Y_p}{\partial \rho \partial \theta_1 \partial \theta_2}; \)

At any level of information sharing, the interactive effect from a larger \( \rho \), \( \theta_1 \), and \( \theta_2 \) will cause delivery unstable. Through information sharing, the vendor can benefit from stable delivery.
4.2 Sensitivity analysis of the optimal delivery-up-to level

From above indications, more information sharing would stabilize delivery and reduce delivery variance. In a long run, the vendor may consider a stable optimal delivery-up-to level as the mechanism. Here, focusing on unpredictable factors of $\theta_1$ and $\theta_2$, the following analysis is to explore how they affect optimal delivery-up-to level (Table 3).

<table>
<thead>
<tr>
<th>Table 3</th>
<th>The sensitivity analysis of the optimal delivery-up-to level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitive analysis</td>
<td>Property/Implication</td>
</tr>
<tr>
<td>The influence of the factors from $\theta_1$ and $\theta_2$ to optimal delivery-up-to level ($E_{i,n-1}(T_i)$)</td>
<td>Prop. 17: (1) $0 \leq \frac{\partial E(T_i)}{\partial \theta_1} \leq \frac{\partial E_{i,n-1}(T_i)}{\partial \theta_1}$; (2) $0 \leq \frac{\partial E(T_i)}{\partial \theta_2} \leq \frac{\partial E_{i,n-1}(T_i)}{\partial \theta_2}$, $i = 0, 1, 2$</td>
</tr>
</tbody>
</table>

1. At no and partial information sharing, a larger influence from previous error terms would make the vendor’s optimal-delivery-up-to level unstable.

2. At any information sharing, a larger influence from previous error $\epsilon_{t-1}$ and last previous error $\epsilon_{t-2}$ to demand prediction that means a larger $\theta_1$ and $\theta_2$ will make the vendor’s delivery-up-to level unstable. In addition, the impact of $\theta_1$ is more significant than $\theta_2$. (This result is got by the assumption of $\theta_2 \leq \theta_1$.)

4.3 Sensitive analysis on the vendor’s expected cost

Due to the complexity of the expected cost functions, we are unable to derive analytically the sensitivity analysis directly with respect to the various factors. We could only presume that if vendor’s delivery variance can be decreased, the vendor does not have excessive inventory so as to it could engage in reducing holding costs, loss costs, and expected costs. In next section, the numerical simulation is to demonstrate these points.

5. Numerical Simulation

This numerical simulation includes the factors of lead time $l$, $\rho$, $\theta_1$, and $\theta_2$ to observe the differences of delivery variances ($V_i$), optimal delivery-up-to level ($E(T_i)$), and expected cost ($C_i$) at different information sharing levels. As the demand process has assumed ARMA(1,2) in our model, demand can be illustrated by $D_i = d + \rho D_{i-1} + \epsilon_i + \theta_1 \epsilon_{i-1} + \theta_2 \epsilon_{i-2}$.

The following numerical simulations with various numbers are posited:

1. $d = 100$
2. $\sigma = 50$ (where $\sigma$ is the standard deviation of $\epsilon_i$)
3. The holding cost $H = 1$ (without loss of generality)
(4) The back order cost $P = 25$. $K = \Phi^{-1}\left(\frac{P}{P+H}\right) = 1.77$ (\(\Phi\) is the cumulative standard normal distribution).

(5) $D_r = 200$

(6) The lead times $l$ are assumed to be 2, 3, 5, and 6 days

(7) $0.1 \leq \rho \leq 0.9$ (while $0.1 \leq \theta_2 \leq \theta_1 \leq 0.9$).

Since the research studies how the related factors at different information sharing affect delivery variance, optimal up-to level, and expected cost, and one leads to the other in this sequence. We will bring with the effects on delivery variance. The simulations are shown by shown by $V_i$, $i=0, 1, 2$, as three different levels of information sharing, respectively.

Figures 1 and 2 verify our early propositions that lead time $l$ and the demand correlation coefficients $\rho$ significantly effects delivery variances. At any information sharing, indeed shorter lead time $l$ has significant influence on reducing delivery variance at a non-linearly fashion; the effect is more significant at large value of the correlation coefficient $\rho$.

![Figure 1](image-url)  
\(\Delta\) Figure 1  Given $l = 2$ and 3, $\theta_1 = 0.8$, $\theta_2 = 0.7$, the influence of $l$ and $\rho$ on $V_i$
5.1 The numerical simulation on the expected cost

Now we consider directly the impacts of these factors on expected cost.

5.1.1 The influences of the lead time $l$ and the correlation coefficient $\rho$ on expected costs

We process the simulation with two factors of given $\theta_1=0.8$ and $\theta_2=0.7$ when $\rho$ is ranged from 0.1 to 0.9 and lead times are set from two to six days. The Figures 3 and 4 showed different effects on expected cost at three information sharing ($C_0$, $C_1$, and $C_2$). It is worth to notice the figures of the lead time $l$ is shortened within two days, the lead time $l$ will still offset the influence of $\rho$. In other words, when the lead time is shorter, the effect of information sharing and the other factors become less critical. On the other hand, the lead time is longer that the vendor could increase the level of information sharing or decrease the correlation coefficient $\rho$ while it was at a larger index.
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Figure 3 Given \( l = 2, 3 \), \( q_1 = 0.8 \), \( q_2 = 0.7 \), the effect of \( l \) and \( \rho \) on \( C_0, C_1, \) and \( C_2 \)

Note: \( c(l, 0.8, 0.7) \) indicates \( l = 3 \), \( q_1 = 0.8 \), and \( q_2 = 0.7 \), respectively.

Figure 4 Given \( l = 5, 6 \), \( q_1 = 0.8 \), \( q_2 = 0.7 \), the effect of \( l \) and \( \rho \) on \( C_0, C_1, \) and \( C_2 \)
5.1.2 The influence of $\theta_1$ and $\theta_2$ on expected cost

Focus on the correlation coefficients $\theta_1$ and $\theta_2$ to expected costs, the simulation shows the speculation about $\theta_1$ which has more impact on expected costs than $\theta_2$. At the same time, a larger $\theta_1$ and $\theta_2$ would have more impact on expected cost. On the other hand, increasing $\theta_1$ and $\theta_2$ have the opposite effect with a higher level of information sharing. This speculation can be verified by in Figures 5 and 6.

![Figure 5](image1.png)  
**Figure 5** The effect of $\theta_1$ on expected cost  
Note: $C_0(5, 0.8, 0.6)$ represents the value of $C_0$ at $l = 5$, $\theta_1 = 0.8$, $\theta_2 = 0.6$  
Note: $C_0(5, 0.7 \rightarrow 0.8, 0.6)$ represents the increase of $\theta_1$ from 0.7 to 0.8 and $\theta_2$ is limited on 0.6.

As the impact of $\theta_1$ whose value ranges from 0.7 to 0.8. Not surprisingly, the expected costs between full information sharing and partial information sharing didn’t affect by the increased value of $\theta_1$. But, if we increase the value of $\theta_1$, it has significant effect on the expected cost between partial information and no information. For this particular set of parameters, different information sharing levels also influence on the expected costs. In the sense that more information sharing will ease the increase, as shown in Figures 5 and 6, where the increase on expected costs at each level is shown.

Similarity, the simulation is to show the effect of $\theta_2$ on expected costs at different
information sharing by increasing its value. The result, shown in Figures 7 and 8, demonstrates \( \theta_2 \) have a similar pattern with \( \theta_1 \) on expected cost but it has less significant influence. In another word, we compare the importance of two factors of \( \theta_1 \) and \( \theta_2 \) on expected costs that \( \theta_1 \) has more influential on expected costs than \( \theta_2 \). The influence will be amplified by the increase in the correlation \( \rho \) in the demands of two consecutive terms. On the other hand, increasing more information sharing level might be resulted in more effect on expected costs.

Note: \( C_0(5, 0.7, 0.6) \) is \( C_0 \) at \( l = 5 \), \( \theta_1 = 0.7 \), and \( \theta_2 = 0.6 \).

Note: \( C_0(5, 0.7, 0.6 \rightarrow 0.7) \) is increased in \( C_0 \) at \( l = 5 \), and \( \theta_1 = 0.7 \), while \( \theta_2 \) ranges from 0.6 to 0.7.

### 5.2 Summary of the simulations

In sum, the factors of \( l \) and \( \rho \) have more significant influences and \( \theta_1 \) and \( \theta_2 \) are the less two (see Figure 1-8). The vendor to reduce delivery variance and expected cost can either shorten lead time and the correlation coefficient \( \rho \) or increase information sharing as a effective mechanism. When the vendor could effectively narrow the lead time at very short status, the vendor can gain the most significant benefit on small delivery variance and expected cost on. This linear reduction from information sharing is obvious (see Figure 1,
3). On the contrast, if the lead time turns into large, alternatively the vendor could either reduce the correlation coefficient $\rho$ or increase more information sharing as a response (see Figure 2, 4). But, in this situation of the long lead time, the effects of reducing $\rho$ at linear change are commonly more effective than increasing information sharing at a non-linear change. Except, information sharing was affected by the $\theta_2$ increased that full information could has the most effect on cost reduction (see Figure 8). Moreover, the interactive effects combining shortening lead time and the correlation coefficient $\rho$ with a full information can yield more reduction on delivery variance and expected cost.

### 6. Conclusions and Discussion

In VMI, we study how different levels of information sharing on demand can affect the vendor’s expected cost via delivery variance and optimal delivery-up-to level, by assuming the demand process followed by ARMA (1,2). We show that more information sharing will reduce the delivery variance and optimal delivery-up-to level analytically; and hence expected cost supposedly. These findings are further verified by numerical analysis. In addition, we also find that lead time $l$ and the correlation coefficient $\rho$ between two consecutive demands also plays critical roles in terms of improving the performance.

Based on these findings, there have standpoints discussed as the follows. First, more information sharing has most significant effect on stabilizing delivery variance and reducing expected cost in the end. The improvement from more information sharing shown a faster than non-linear speed is more significant than a linear change from the related factors. Therefore, in VMI if the vendor wants to minimize delivery variance and expected cost, information sharing as much as possible is suggested. Secondary, the improvement can also be done by shorten the lead time $l$ and (or) the correlation coefficient $\rho$ between two consecutive demands at any given information sharing level. Shortening these two factors combined with full information sharing would generate synergy effect on reducing delivery and expected cost; and the effect is the most significant. However, if information sharing is too costly or unlikely, reducing the lead time $l$ or reducing the correlation coefficient $\rho$ (if possible) also help. Specially, quick lead time $l$ (ie. the vendor can respond to the uncertain demand at less time) can offset the cost that the less information sharing brings.
Exploring the Effects of Sharing Information on Expected Cost under the VMI Model

Reference


