Impacts of Manufacturer Overconfidence on Supply Chain Performance with Demand Forecasting

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ABSTRACT

In this paper, we construct a dyadic supply chain consisting of a single manufacturer with overconfidence and a rational retailer under the MTO strategy. The manufacturer and the retailer play a Bayesian Stackelberg game in our model. We consider that the manufacturer may underestimate the variability in his forecast precision (PR bias). We derive the optimal decisions for two supply chain scenarios: one dominated by manufacturers (MS) and one dominated by retailers (RS). Our results suggest that both the manufacturer and the retailer can achieve profit growth under PR bias, but the forecasts made by each side must meet certain conditions. Further, the impacts of each type of overconfidence on SC performance are similar under the MS and RS models, and the manufacturer is always more likely to benefit from his confidence under the RS model than under the MS model. In addition, the influences of the overconfidence on retailers’ profits require additional judgment with effort costs.

KEYWORDS

Overconfidence, Bayesian game, Demand forecasting.

INTRODUCTION

Driven by the increasingly active business environment and the rapid development of information technology, demand forecasting has attracted increasing attention from practitioners in recent years. Many companies spend considerable amounts of money each year on, for example, forecasting technology, equipment updates and direct purchases of data to obtain more complete information about the consumer market. From the perspective of supply chain management, accurate market forecasts not only allow enterprises to increase their profits but also improve the overall competitiveness of the entire supply chain and facilitate stable, cooperative relations[1].

At the same time, streamlined manufacturing processes and a higher level of customization have enabled many manufacturers in the supply chain to sell their products downstream in a make-to-order (MTO) fashion. In particular, when sufficient demand maintains the economy of mass production, MTO is a common supply chain strategy[2] because it significantly reduces inventory costs for manufacturers and alleviates the impact of demand uncertainty. Nevertheless, this does not mean that demand forecasts lack a role in MTO systems. In contrast, they...
are considered on high-level decision-making levels[3] and enable firms to evaluate their decisions more precisely in terms of the impact of decision elasticity.

The impacts of forecasting in MTO scenarios have been widely studied in the supply chain management literature. This literature typically focuses on price decisions and considers competition in a supply chain using different forecasts of market demand. Vives identifies conditions under which the sharing of private information between competitors is profitable[4]. Yue and Mishra set up optimal models with demand forecasting under dual-channel and single-channel supply chains dominated by the manufacturer[5, 6]. Both of these articles derive the Bayesian equilibrium pricing strategy under information sharing/no information sharing cases and conclude that information sharing always brings more profits to manufacturers and the entire supply chain. Generally, these articles on supply chain demand forecasting under MTO focus on information sharing in the process of demand forecasting.

Especially when a priori knowledge exists, people generally overestimate the precision of their estimates and predictions[7-10]. According to a social survey conducted by Bao, more than 80% of managers have a certain level of overconfidence due to their prior knowledge in dealing with problems[11]. Many other studies have also confirmed the prevalence of overconfidence among business managers[12, 13]. This makes it impossible to avoid a practical problem that is caused by overconfidence in the forecasting process of demand, especially when supply chain managers have a priori but imperfect market information. How does such bias affect the final performance of the supply chain?

In recent years, many scholars have attempted to study operation management problems from the perspective of overconfidence. Lu X et al[14] study the impacts of supplier hubris on inventory decisions under RMI and VMI models. They point out that supplier overconfidence prompts the supplier to exert more efforts and enhances the profits of the retailer and of the entire supply chain. Ren Y and Croson R perform two experiments to verify that individuals are overprecise in their estimation of order variation, and they find that overprecision significantly correlates with order bias[15]. Zhang C study the decision making of overconfident retailers in a situation where stochastic market demand is influenced by the sales effort of retailers based on the model proposed by Ren Y and Croson R[16]. The results show that overconfidence can make retailers’ decision close to the decision in the rational scenario in low-profit or high-profit conditions. In general, research examining the impact of overconfidence is almost entirely focused on the inventory bias of newsvendors and ignores uncertain elastic bias under the MTO strategy.

This paper studies a Bayesian Stackelberg game model composed of a single manufacturer (he) and a single retailer (she) under an MTO scenario. The manufacturer decides on the added effort level and provides the original wholesale price, while the retailer is responsible for the market retail price. Market demand is a linear function of retail price and effort level, and the elasticity coefficient of effort level is a stochastic factor in our assumption. We consider the retailer to be a rational decision maker, and we address one type of manufacturer overconfidence: precision-biased overconfidence (PR). A manufacturer with PR underestimates the variability (the variance of forecasting error) of the effort elasticity coefficient. We develop optimal models for each of the two scenarios—a manufacturers (MS) game model and a retailers (RS) game model—which represent the different dominators of the supply chain. We
conduct extensive comparative studies to highlight the impacts of manufacturer overconfidence on supply chain performance.

**MODEL FRAMEWORK**

**DEMAND AND PROFIT FUNCTION**

This paper considers a standard dyadic channel consisting of a single manufacturer with overconfidence characteristics and a single retailer with rationality. The manufacturer produces a product at unit manufacturing cost $c$ and wholesales the product to the retailer at wholesale price $w$, who in turn retails it to customers at retail price $p$ over a single selling season. Moreover, given that the manufacturer often exerts additional levels of effort $e$—which may include product design, the improvement of production technology, product promotion and so on—to meet diversified market needs, we define market demand as a normal function of retail price $p$ and manufacturer effort level $e$, i.e.,

$$D(p,e) = a - p + \gamma e,$$

where $a$ is the base market size, and it is common information with $a > p$. $\gamma$ measures the effort elasticity. We assume that the marketing effort exerted by manufacturers costs $\frac{K}{2}e^2$, and $K$ represents the cost coefficient of efforts, depicting the difficulty of exerting effort.

The profits of the manufacturer and the retailer are, respectively, expressed as

$$\pi_m = (w - c)(a - p + \gamma e) - \frac{K}{2}e^2$$

and

$$\pi_r = (p - w)(a - p + \gamma e).$$

**INFORMATION STRUCTURE**

Generally, the impact of effort level on demand, which is different from retail price $p$, is difficult for both retailers and manufacturers to accurately perceive or evaluate[17]. Therefore, we assume that the elasticity of effort level $\gamma$ is an uncertainty variable of market demand, which can only be inferred by manufacturers and retailers according to their own experience. With this in mind, we use the Bayesian Nash equilibrium theory to derive the optimal strategy of each decision maker, a pair of strategies and conjectures whereby (a) each firm’s strategy is a best response to his conjecture about the behavior of his rival, and (b) the conjectures are right in the equilibrium.

Assume that the effort elasticity is a random variable and $\gamma = \gamma + \zeta$, where $\zeta$ is normally distributed with a mean of zero and a variance of $\sigma_0^2$. We assume that $\gamma$ is a fixed constant and is large relative to $\sigma_0^2$, so the probability of negative demand is negligible. We assume that each player obtains a forecast of primary elasticity $\gamma_i$. We denote the retailer’s and the manufacturer’s forecasts of $\gamma$ as $\gamma_1$ and $\gamma_2$, respectively. We assume that $\gamma_i = \gamma + \varepsilon_i$ ($i = 1,2$), where $\varepsilon_i$ is the forecast error to $\gamma$, and $\varepsilon_i \sim N(0,\sigma_i^2)$. A higher (lower) variance implies a less (more) precise forecast. Furthermore, there is a certain correlation between $\varepsilon_i$. We define the correlation between forecast error $\varepsilon_i$ as $\rho$. Then, the covariance matrix of forecast errors is represented by

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix}.$$

To ensure the reliability of the prediction knowledge of both parties, we assume that the covariance is lower than
variance $\sigma_i^2$, i.e., $\rho\sigma_1\sigma_2 \leq \sigma_i^2$. All parameters of the model, except the forecasts, are common knowledge to the manufacturer and the retailer.

**OVERCONFIDENCE SETTING**

According to Don Moore, the overconfidence of decision makers can be overprecision\[18\]. We assume that overprecision leads to the manufacturer’s PR, which indicates that the manufacturer underestimates the variance of his forecasting error. Thus, the manufacturer’s forecasting of $\gamma$ with PR is denoted as $\gamma_i$. Then, we assume that $\gamma_i = \gamma + \eta \varepsilon_i$, where $0 < \eta < 1$, with a smaller $\eta$ indicating more overconfidence, and $\gamma_i \sim N(\bar{\gamma}, \sigma_0^2 + \eta^2 \sigma_2^2)$.

**OVERCONFIDENCE SETTING**

Suppose retailers, as rational decision makers, cannot observe whether manufacturers are overconfident. Thus, the conditional expectation of $\gamma$ and $\gamma_i$ under condition $\gamma_1$ is $E(\gamma_1 | \gamma_i) = (1 - t_i) \bar{\gamma} + t_i \gamma_1$ and $E(\gamma_2 | \gamma_i) = (1 - m_i) \bar{\gamma} + m_i \gamma_i$, where $t_i = \frac{\sigma_i^2}{\sigma_i^2 + \sigma_0^2}$, $m_i = \frac{\sigma_i^2 + \rho \sigma_1 \sigma_2}{\sigma_i^2 + \sigma_0^2}$.

Manufacturers believe that conservative retailers’ forecasts still obey the prior common knowledge that $\gamma_i = \gamma + \varepsilon + \epsilon_i$ with PR bias, the conditional expectation of $\gamma$ and $\gamma_i$ under condition $\gamma_i \sim N(\bar{\gamma}, \sigma_0^2 + \eta^2 \sigma_2^2)$, where $t_i = \frac{\sigma_0^2}{\sigma_0^2 + \eta^2 \sigma_2^2}$, $m_i = \frac{\sigma_0^2 + \eta \rho \sigma_1 \sigma_2}{\sigma_0^2 + \eta^2 \sigma_2^2}$.

**MS GAME MODEL**

Under the MS game model, manufacturers are the dominant players in the supply chain, while retailers are the followers. The sequence of games is summarized as follows: (1) the manufacturer first determines unit wholesale price $w$ and corresponding effort level $e$, and (2) the retailer sets retail price $p$ and the order quantity according to the manufacturer’s decision. Thus, the MS model can be formulated as follows:

$$\max_{w, e} E[\pi^M(w, e, p^* M) | \gamma_2]$$

subject to $w > c, e > 0$

$$p^*_M = \arg \max E(\pi^M | \gamma_i)$$

$$\max E[\pi^M(p) | \gamma_i]$$

$$p > w$$

(1)

According to Bayesian Nash equilibrium theory, it is easy to derive the optimal retail price of retailers $p^*_M = \frac{a + w + \gamma_i}{2}$ by substituting $p^*_M$ into the
manufacturer’s profit function. The optimal wholesale price and effort level can be given as

\[
(w^*_M, e^*_M) = \left( \frac{2K(a-c)}{4K-(2\gamma_m-\gamma_r)^2} + c, \frac{(a-c)(2\gamma_m-\gamma_r)}{4K-(2\gamma_m-\gamma_r)^2} \right)
\]

(2)

where

\[
\gamma_r = E(\gamma | \gamma_1), \quad \gamma_m = E(\gamma | \gamma_2), \quad \text{and} \quad \gamma_r = E(\gamma | \gamma_2).
\]

For the optimal decision, the expected profits of manufacturers and retailers are, respectively,

\[
\pi^*_m = \frac{(a-c)^2}{2} \frac{K-(2\gamma_m-\gamma_r) \cdot (6\gamma_m-2\gamma_r-3\gamma_r)}{(4K-(2\gamma_m-\gamma_r)^2)^2}
\]

(3)

\[
\pi^*_r = \frac{(a-c)^2}{4} \frac{2K-(2\gamma_m-\gamma_r) \cdot (2\gamma_m-\gamma_r-\gamma_r)}{4K-(2\gamma_m-\gamma_r)^2}
\]

(4)

Three constraints are proposed to make all the results and discussions meaningful: (a) \(4K > (2\gamma_m-\gamma_r)^2\) guarantees that \(\pi^*_m\) is jointly concave in \(w^*\) and \(e^*\), (b) \(2\gamma_m-\gamma_r \geq 0\) ensures that the effort is non-negative, and (c) \(K > (2\gamma_m-\gamma_r) \cdot (6\gamma_m-2\gamma_r-3\gamma_r)\) ensures that the manufacturer’s profits \(\pi^*_m\) are non-negative.

When the manufacturer has PR bias, his forecasting is \(\gamma^*_r\). Then, we have \(\gamma_m = E(\gamma | \gamma^*_r) = (1-t)^\gamma + t\gamma^*_r\), \(\gamma_m = (1-t)^\gamma + t\gamma^*_r\) and \(E(\gamma | \gamma^*_r) = (1-m)^\gamma + m\gamma^*_r\). Let \(\gamma^*_r = \gamma + \sqrt{\sigma^2 + \eta^2 \gamma^*_r}\) and \(\gamma^*_r \sim N(0,1)\). After analyzing the influence of the manufacturer’s PR bias on channel performance under the MS model, we reach the following conclusions.

**Proposition 1.** PR bias affects various supply chain decisions under the MS model, as shown in Table I.

| \(\eta\) | \(\gamma^*_r < \gamma_1\) | \(\gamma^*_r < \gamma_2\) | \(\gamma^*_r < 0\) | \(\gamma^*_r > 0\) |
|---|---|---|---|---|
| \(K < K^*_{MS}\) | \(K \geq K^*_{MS}\) | \(K^*_{MS}\) | \(K^*_{MS}\) |
| \(w^*_M\) | - | - | - | + |
| \(e^*_M\) | + | + | + | - |
| \(p^*_M\) | + | - | - | + |

Note:
\[ y_1 = -\frac{\sqrt{\sigma_0^2 + \eta' \sigma_2^2}}{\sigma_0^2 + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2} \{ \sigma_0^2(y + \gamma_1) + 2 \sigma_1^2 \gamma_1 \}, \]

\[ y_2 = -\frac{\sqrt{\sigma_0^2 + \eta' \sigma_2^2}}{\sigma_0^2 + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2} \{ \sigma_0^2(y + \gamma_2) + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2 \} \gamma_2, \quad \text{and} \]

\[ K_{MS}^* = -\frac{\{ \sigma_0^2(y + \gamma_1) + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2 \} \gamma_1}{4 \{ \sigma_0^2 + \eta' \sigma_2^2 \} \{ \sigma_0^2 + \sigma_1^2 \} \gamma_1(y - y_1)}. \]

**Proof:**

We plug \( y_2 = \hat{y} + \sqrt{\sigma_0^2 + \eta' \sigma_2^2} \gamma_2 \), and the corresponding conditional expectations into \( w_{m'}^*, e_{m'}^* \) and \( p_{m'}^* \):

\[ \frac{\partial y}{\partial \eta} = -\frac{1}{4} \frac{K(a-c)(\sigma_0^2 + \sigma_1^2) \gamma_1(y - y_2) \sigma_0^2 \sigma_2}. \]

Where

\[ Y = \frac{\{ \eta \sigma_0 + \rho \sigma_1 \} \sigma_0^2 + 2 \eta \rho \sigma_1 \sigma_2 \} \{ \sigma_0^2 + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2 \} \gamma_2}{(\sigma_0^2 + \sigma_1^2) \gamma_1 \sigma_0^2 \sigma_2}. \]

Since \( y_2 = -\frac{\sqrt{\sigma_0^2 + \eta' \sigma_2^2}}{\sigma_0^2 + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2} \{ \sigma_0^2 + \sigma_1^2 \} \gamma_2 < 0 \), then

\[ \frac{\partial y}{\partial \eta} > 0 \quad \text{if} \quad y_2 < \gamma_2 < 0 \]

\[ \frac{\partial y}{\partial \eta} < 0 \quad \text{if} \quad \text{otherwise}. \]

Similarly, \( \frac{\partial e^*}{\partial \eta} = -\frac{1}{4} \frac{(a-c)(\sigma_0^2 + \sigma_1^2) \gamma_1 \{ \eta \sigma_0 + \rho \sigma_1 \} \sigma_0^2 + 2 \eta \rho \sigma_1 \sigma_2 \} \gamma_2}{(\sigma_0^2 + \sigma_1^2) \gamma_1 \sigma_0^2 \sigma_2} \]

and

\[ \frac{\partial e^*}{\partial \eta} > 0 \quad \text{if} \quad \gamma_2 < 0 \]

\[ \frac{\partial e^*}{\partial \eta} < 0 \quad \text{if} \quad \text{otherwise}. \]

Where

\[ Y = \frac{\{ \sigma_0^2 + \sigma_1^2 \} \{ \sigma_0^2 + \eta' \sigma_2^2 \} \gamma_1 \{ \eta \sigma_0 + \rho \sigma_1 \} \sigma_0^2 + 2 \eta \rho \sigma_1 \sigma_2 \} \{ \sigma_0^2 + 2 \sigma_1^2 - \eta \rho \sigma_1 \sigma_2 \} \gamma_2}{(\sigma_0^2 + \sigma_1^2) \gamma_1 \{ \sigma_0^2 + \sigma_1^2 \} \gamma_1 \sigma_0^2 \sigma_2}. \]

Similarly,

\[ \frac{\partial y_2}{\partial \eta} = -\frac{1}{4} \frac{(a-c)(\sigma_0^2 + \sigma_1^2) \gamma_1 \{ \eta \sigma_0 + \rho \sigma_1 \} \sigma_0^2 + 2 \eta \rho \sigma_1 \sigma_2 \} \gamma_2}{(\sigma_0^2 + \sigma_1^2) \gamma_1 \{ \sigma_0^2 + \sigma_1^2 \} \gamma_1 \sigma_0^2 \sigma_2} \]

where

\[ f = \frac{1}{2} \{ \sigma_0^2 + \sigma_1^2 \} \gamma_1 \{ \sigma_0^2 + \eta' \sigma_2^2 \} \gamma_1 \{ \sigma_0^2 + \sigma_1^2 \} \gamma_1 \gamma_1 \sigma_0^2 \sigma_2 \]

\[ \gamma_1 \{ \sigma_0^2 + \sigma_1^2 \} \gamma_1 \sigma_0^2 \sigma_2 \]. \]

Hence,

\[ \frac{\partial p_{m'}^*}{\partial \eta} > 0 \quad \text{if} \quad \{ \gamma_2 < y_1 \} \cap \{ K < K_{MS}^* \} \mathrm{or} \{ \gamma_2 > 0 \} \]

\[ \frac{\partial p_{m'}^*}{\partial \eta} < 0 \quad \text{if} \quad \text{otherwise}. \]

The conclusion of proposition 1 indicates that when the manufacturer is optimistic \( \gamma_2 > 0 \), all optimal decisions in the supply chain are negatively associated with parameter \( \eta \); i.e., the more PR bias the manufacturer has, the
higher the price and effort level. Interestingly, when the manufacturer's forecasting is in a pessimistic state \( \gamma_\varphi < 0 \), the supply chain decisions will show various changes according to the value of \( \gamma_\varphi \). In the range \( y_i < \gamma_\varphi < 0 \), all decisions are positively associated with \( \eta \), while \( \eta \) has the exact opposite effect on wholesale price \( w_\mu^* \) and effort level \( e_\mu^* \) within interval \( \gamma_\varphi < y_2 \). In addition, the impacts of \( \eta \) on retail prices is similar to \( w_\mu^* \), except for the case \( \gamma_\varphi < y_i \) and \( K < K_{MS}^n \).

**Proposition 2.** Manufacturers can benefit from PR-biased confidence, where \( \pi_m^U \) decreases as \( \eta \) increases under the MS model if members’ forecasting and the other parameters meet the following condition (and manufacturers’ profits will increase with \( \eta \) if otherwise):

\[
\left\{ \begin{array}{l}
\left| \gamma_\varphi (y_i - \hat{\gamma}) \right| > 0
\end{array} \right) \cap \left( \gamma_\varphi (y_i - \hat{\gamma}) > 0 \right).
\]

**Proof:**

With PR overconfidence, \( \frac{\partial \pi_m^U}{\partial \eta} = \frac{\{(a-c)^2 \sigma_0^2 + \sigma_0^2 \}(\sigma_0^2 + \sigma_i^2)\left[(\eta \sigma_\varphi + \rho \sigma_i) \sigma_0^2 + 2 \eta \sigma, \sigma_i^2 \right]}{(\sigma_0^2 + \sigma_i^2 - \eta \rho \sigma_i \sigma_2)^2} \),

where \( H = 4(\sigma_0^2 + \sigma_i^2)^2(\sigma_0^2 + \eta \sigma_i^2)(\sigma_0^2 + \sigma_i^2 - \eta \rho \sigma_i \sigma_2)^2(y_\varphi - y_i)^2 > 0 \).

Since \( \gamma_i = \frac{\sqrt{\eta^2 \sigma_0^2 + \sigma_0^2}}{2 \sigma_i^2 + \sigma_0^2 - \eta \rho \sigma_i \sigma_2}(y_i - \hat{\gamma}) \), then:

\[
\left\{ \begin{array}{l}
y_i > 0 \text{ if } \gamma_i > \hat{\gamma} \\
y_i < 0 \text{ if } \gamma_i < \hat{\gamma}
\end{array} \right.
\]

Consequently,

\[
\left\{ \begin{array}{l}
\frac{\partial \pi_m^U}{\partial \eta} < 0 \text{ if } y_i < \gamma_\varphi < 0 \text{ and } \gamma_i > \hat{\gamma} \\
0 < y_\varphi < y_i \text{ and } \gamma_i < \hat{\gamma}
\end{array} \right.
\]

We can further classify the above results into proposition 3.

**Proposition 3.** The actual profits of retailer \( \pi_m^U \) under the MS model decrease with PR-biased coefficient \( \eta \) if

(1) \( 0 < \gamma_\varphi < \frac{\sqrt{\eta^2 \sigma_0^2 + \sigma_0^2}}{2 \sigma_i^2 + \sigma_0^2 - \eta \rho \sigma_i \sigma_2}(y_i - \hat{\gamma}) \)

(II) \( \frac{\sqrt{\eta^2 \sigma_0^2 + \sigma_0^2}}{2 \sigma_i^2 + \sigma_0^2 - \eta \rho \sigma_i \sigma_2}(y_i - \hat{\gamma}) < \gamma_\varphi < 0 \text{ and } K > K_{MS}^n \)

(III) \( \gamma_\varphi > \max \left\{ \frac{\sqrt{\eta^2 \sigma_0^2 + \sigma_0^2}}{2 \sigma_i^2 + \sigma_0^2 - \eta \rho \sigma_i \sigma_2}(y_i - \hat{\gamma}), 0 \right\} \text{ and } K < K_{MS}^n \)

where \( K_{MS}^n = \frac{\sigma_i^2(\sigma_0^2 + \sigma_i^2 - \eta \rho \sigma_i \sigma_2)(\sigma_i^2 \gamma_i + \sigma_0^2 \gamma_i^2)(y_\varphi - y_i)^2}{4(\sigma_0^2 + \eta \sigma_i^2)(\sigma_0^2 + \sigma_i^2)^2(y_\varphi - y_i)^2} \),

\[ y_3 = \frac{\sqrt{\eta^2 \sigma_0^2 + \sigma_0^2}}{2 \sigma_i^2 + \sigma_0^2 - \eta \rho \sigma_i \sigma_2}(y_i - \hat{\gamma}) \).

**Proof:**

\[ \frac{\partial \pi_m^U}{\partial \eta} = \frac{(a-c)^2 \sigma_0^2 + \sigma_0^2}{8(\sigma_0^2 + \eta \sigma_i^2)[(\sigma_0^2 + \sigma_i^2)(\sigma_0^2 + \eta \sigma_i^2)K - \sigma_0^2(\sigma_0^2 + \sigma_i^2 - \eta \rho \sigma_i \sigma_2)^2(y_\varphi - y_i)^2]} \]

where
The conclusion of propositions 3-4 is that both manufacturers and retailers can benefit from PR-biased overconfidence. In the precondition whereby the manufacturer's profit decreases as \( \eta \) increases, the forecasting of both parties should be on the same side of the mean, which is expressed as \( \gamma_o (y_1 - \hat{y}) > 0 \). This also shows that with PR bias, the direction of the manufacturer’s forecasting must be consistent with that of the retailer. On this basis, the closer the manufacturer's forecast is to the mean, the more likely the manufacturer is to benefit from PR bias.

The location relationship between \( \gamma_o \) and 0 determines whether retailers have an advantage with PR bias because the manufacturer will enhance (reduce) the effort exerted if his forecast is \( \gamma_o > 0 \) (\( \gamma_o < 0 \)). As proposed by proposition 4, the retailer may still benefit from \( \eta \) when \( \gamma_o (y_1 - \hat{y}) > 0 \) does not hold if \( K < K^1_{\text{MS}} \) and \( \gamma_o > 0 \), but once the manufacturer is not optimistic about the effort elasticity, i.e., \( \gamma_o < 0 \), the retailer may be at a disadvantage because of additional conditions \( K > K^1_{\text{MS}} \).

**RS GAME MODEL**

The second decentralized scenario arises in markets where the retailer has more bargaining power. The retailer is the leader and the manufacturer the follower. In this case, we can formulate the two-echelon RS model as follows:
\[ \begin{align*}
\max_{\pi^m} E(\pi^m | \gamma_1) &= (p - w^*) \cdot E[D(p, e^*) | \gamma_1] \\
\text{s.t.} \ p > w^*, D(p, e^*) > 0 \\
(w^*, e^*) &= \arg \max \ E(\pi^m | \gamma_2) \\
\max_{w, e} E(\pi^m | \gamma_1) &= (w - c) E[D(p, e) | \gamma_1] - \frac{K}{2} e^2 \\
\text{s.t.} \ w \geq c
\end{align*} \]  
(5)

Assuming that \( t = p - w \), the optimal decisions for the manufacturer are

\[ (w, e) = \left( \frac{K(a + c - t) - c \cdot \gamma_m^2}{2K - \gamma_m^2}, \frac{\gamma_m \cdot (a - c - t)}{2(2K - \gamma_m^2)} \right) \]  
(6)

By substituting (2) into the retailer's profit function, the optimal marginal profit can be derived as \( \hat{t}_m = \frac{a - c}{2} \). Obviously, the marginal profit set by the retailer is independent of her own forecasting, and it is always a fixed value. This indicates that the optimal decision of the retailer is completely dependent on the decision of the manufacturer.

Then, the manufacturer's actual strategy corresponding to \( \hat{t}_m = \frac{a - c}{2} \) can be given as

\[ (w^*, e^*) = \left( \frac{K(a - c)}{2(2K - \gamma_m^2)} + c, \frac{\gamma_m \cdot (a - c)}{2(2K - \gamma_m^2)} \right) \]  
(7)

For the optimal decision, the expected profits of manufacturers and retailers are, respectively,

\[ \pi^m = \frac{K(a - c)^2}{4(2K - \gamma_m^2)} (K - \frac{3}{2} \gamma_m^2 + \gamma_m \gamma_r) \]  
(8)

\[ \pi^r = \frac{(a - c)^2}{4(2K - \gamma_m^2)} (K - \gamma_m^2 + \gamma_m \gamma_r) \]  
(9)

Note that (a) \( \pi^m \) is jointly concave in \( w^* \) and \( e^* \) if \( 2K > \gamma_m^2 \), and (b) \( K - \frac{3}{2} \gamma_m^2 + \gamma_m \gamma_r \), should hold to guarantee that \( \pi^m > 0 \) and \( \pi^r > 0 \).

The manufacturer's forecasting with PR bias under RS is \( \gamma_m^0 \). As in section 3, let \( \gamma_m^0 = \hat{\gamma} + \sqrt{\sigma^0_\eta} \gamma_\phi \); then, \( \gamma_m = E(\gamma | \gamma_m^0) = (1 - \hat{t}_m^0) \hat{\gamma} + t_m^0 \gamma_m^0 \), and \( \gamma_r = E(\gamma | \gamma_r) = (1 - t_r) \hat{\gamma} + t_r \gamma_r \). By substituting \( \gamma_m^0 \) into (3)-(5), we can draw the following conclusions.

**Proposition 4.** When \( \eta > 0 \), each decision in the supply chain increases monotonously with \( \eta \), and decreases if \( \eta < 0 \).

The conclusion of proposition 6 indicates that the effect of \( \eta \) on each decision variable is completely based on the manufacturer's basic judgment on market effort elasticity \( \gamma \). This is because the manufacturer does not have to make any
conjectures about the retailer’s forecasts $\gamma_i$ under the RS model, and the retail price is always set as the wholesale price plus a fixed value. Therefore, all decisions of the supply chain are affected only by the manufacturer’s forecast $\gamma_o$.

**Proposition 5.** Manufacturers can benefit from PR confidence, which means that $\pi^m$ decreases with $\eta$ under the RS model if members’ forecasting and the parameters meet the following conditions (and manufacturers’ profits increase with $\eta$ otherwise):

$$\{\gamma_o < \frac{\sqrt{\sigma^2_0 + \eta^2 \sigma^2_1}}{\sigma^2_0 + \sigma^2_1} (\gamma_1 - \hat{\gamma}) \} \cap \{\gamma_o (\gamma_1 - \hat{\gamma}) > 0\}.$$  

**Proposition 6.** The actual profits of retailer $\pi^r$ under the MS model decrease with the PR bias coefficient $\eta$ if

(I) $0 < \gamma_o < \frac{\sqrt{\sigma^2_0 + \eta^2 \sigma^2_1}}{\sigma^2_0 + \sigma^2_1} (\gamma_1 - \hat{\gamma}), \quad \gamma_1 > \hat{\gamma}$

(II) $\frac{\sqrt{\sigma^2_0 + \eta^2 \sigma^2_1}}{\sigma^2_0 + \sigma^2_1} (\gamma_1 - \hat{\gamma}) < \gamma_o < 0, \quad \gamma_1 < \hat{\gamma}$ and $K > K^o_{RS}$

(III) $\gamma_o > \max \left\{ \frac{\sqrt{\sigma^2_0 + \eta^2 \sigma^2_1}}{\sigma^2_0 + \sigma^2_1} (\gamma_1 - \hat{\gamma}), 0 \right\}, \quad K < K^o_{RS}$

where

$$K^o_{RS} = \frac{\sigma^2_0 (\sigma^2_1 \gamma_i + \sigma^2_o (\gamma_o - z_1))^2}{2 \sqrt{\sigma^2_0 + \eta^2 \sigma^2_1} (\sigma^2_0 + \sigma^2_1) (\gamma_o - z_2)} = \frac{\sqrt{\sigma^2_0 + \eta^2 \sigma^2_1}}{\sigma^2_0 + \sigma^2_1} (\gamma_1 - \hat{\gamma}).$$

Combined with propositions 3-4, the influence of PR confidence on the profit of supply chain members under the two models has some common characteristics; i.e., the preconditions that the manufacturer can benefit from PR bias are $\gamma_o (\gamma_1 - \hat{\gamma}) > 0$, and forecasting $\gamma_o$ should not deviate too much from the mean, 0, while the retailer has more available opportunities to increase profit if $\gamma_o > 0$ than if $\gamma_o < 0$.

Some differences can also be found. According to assumption $\sigma^2_1 > \rho \sigma_0 \sigma_2$, it is easy to find that $|y_i| < |z_2|$ is constant for the same $\gamma_1$, which means the range of $\gamma_o$ that allows $\pi^m$ to benefit from $\eta$ is larger under the RS than under the MS. Second, $K^o_{RS} > K^o_{MS}$ can be derived based on the relation $z_1 < y_2 < 0$; this result shows that the retailer has more advantages (disadvantages) under the RS than under the MS if $\gamma_o > 0$ ($\gamma_o < 0$).

**NUMERICAL STUDIES**

In this section, by conducting numerical experiments, we illustrate some of the analytical findings in the previous sections to gain more insight. We compare the performances of the SC in the MS and RS with different types of manufacturer bias.

The input parameters of the example are $a=200$, $c=50$, $\hat{\gamma}=0.5$, $K=0.75$, $\sigma_0=0.4$, $\sigma_1=\sigma_2=0.5$, $\rho=0.6$, $\gamma_i \sim N(\hat{\gamma}, \sigma^2_0 + \sigma^2_1)$, and $\gamma_o \sim N(0,1)$.

The effect of PR bias on supply chain performance is complex and depends primarily on the location relationship between both members’ forecasts and their
corresponding forecast means. Considering that \( \eta \) only affects the deviation of the manufacturer's forecast and cannot determine whether the manufacturer's forecast \( \gamma_\phi \) is greater than or less than the mean 0, we discuss one typical case in which the values of \( \gamma_\phi \) and \( \gamma_1 \) are fixed.

We discuss the case where \( \gamma_\phi > 0 \) and \( \gamma_1 = 0.75 > \hat{\gamma} \) so that both forecasts are greater than their mean. Then, the impacts of \( \eta \) on another factor \( y_3 (z_2) \) influence the profit of members under the MS (RS) model in this case, as shown in Fig 1. We observe that \( y_1 \) and \( z_2 \) increase with \( \eta \) and \( z_2 > y_1 \) if \( \gamma_1 > \hat{\gamma} \). To further discuss the impact of \( \eta \) on the manufacturer's profit, we set \( \gamma_\phi = 0.4 \) so that \( \gamma_\phi \) intersects with both \( z_2 \) and \( y_3 \).

![Figure 1. The characteristics of \( y_3 \) and \( z_2 \).](image1)

Figure 2 shows the effect of \( \eta \) on manufacturers' profits. \( \pi_m^R \) and \( \pi_m^M \) reach the maximum at \( \gamma_\phi = z_2 \) and \( \gamma_\phi = y_3 \), respectively, and the profit functions on both sides of their maximum point are asymmetric. Additionally, PR bias seems to have a weak impact on the change in the manufacturers' profits, which is in a very small range compared with AB bias. Possible explanations are as follows: (a) \( \eta \) does not affect the forecast means, and thus, its impact on forecasts is significantly less than that of \( \lambda \), and (b) the value of \( \gamma_\phi \), that we set is too close to \( z_2 \) and \( y_3 \); the profits \( \pi_m^R \) and \( \pi_m^M \) will affected by \( \eta \) distinctly if \( \gamma_\phi \) is larger or smaller than \( z_2 \) and \( y_3 \).

![Figure 2. The impacts of \( \lambda \) on \( \pi_m^R \) and \( \pi_m^M \) with PR bias.](image2)
As shown in Figure 3, the retailer's profits $\pi_r^k$ and $\pi_r^m$ in this case are both decreasing monotonously with $\eta$. This is because the value of $K$ is constantly less than that of $K_{MS}^r$ and $K_{MS}^r$ (see proposition 4 (III), 8 (III)), and thus, the more confident the manufacturer is, the more profits the retailer can achieve in this case.

![Figure 3. The impacts of on $\pi_r^k$ and $\pi_r^m$ with PR bias.](image)

**SUMMARY**

The majority of previous research on channel strategies considering overconfidence have the following characteristics: (a) the analysis on overconfidence are always based on the situation of information symmetry, which may lack enough realistic evidence; (b) the behavior of overconfidence is previously studied only in the newsboy model, but not in the supply chain with MTO mode. In order to further enrich the research in this field, this paper studies how manufacturer overconfidence affects supply chain performance under the MTO strategy. By developing models under two scenarios (MS and RS) with overconfidence (PR), we derive the equilibrium strategy in the supply chain and discuss the impacts of PR overconfidence on supply chain performance under each scenario. Then, we conduct numerical studies to provide some comparisons and validate the proposed conclusions.

Our results suggest that both manufacturers and retailers can benefit from PR bias, but each side's forecasts must meet certain conditions. Our results provide useful policy guidelines for management. For example, by observing the manufacturer’s efforts cost elasticity, the retailer can reasonably choose to share her forecast direction with manufacturers or guide manufacturers toward an optimistic judgment on effort elasticity if the manufacturers have PR bias.

This paper attempt to determine the influence of overconfidence on supply chain management from a micro-level perspective that focuses on decision elasticity. However, our discussion did not go further to put forward some effective improvement contracts to motivate SC coordination. Second, the inventory should be considered in an imperfect information game, which is omitted in our model; i.e., the order quantity offered by retailers may be not equal to the actual market demand. Future research can make up for these shortcomings in our model with a more comprehensive perspective. Additionally, overconfidence may lead to more interesting conclusions when multiple parameters are unknown. Its impacts on SC performance with different types of SC structures and parameter distributions are worth exploring.
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