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공급망 재고 관리에 대한 행동학적 연구
Supply-chain Inventory Management with Behavioral Consideration

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We develop inventory control strategies for a supplier who is selling a product to a group of newsvendors. Recent research in newsvendor experiments using human subjects revealed significant behavioral tendencies in the decision making processes for inventory management. If the supplier would incorporate these behavioral tendencies while managing her inventories, her costs would be significantly reduced. Using data from experiments, we estimate the possible reductions in supplier costs and determine the factors that significantly impact it. We observe a significant improvement in the supplier's inventory decision if she estimates the demand distribution with a model that captures the anchoring tendencies instead of assuming aggregate randomness. As the model selection relies much on the data, it is an important task to determine whether the retailers are mean-anchoring, demand-chasing, both, or neither. In addition, we observe that the information about retailers' behaviors is more beneficial for the supplier when the end-customer demands are more variable. It is certain that more precise information on the data will lead to a better inventory decision for suppliers. The information includes the retailers' behavioral tendencies, individual-specific order behaviors, and the variability of end-customer demands.

Keyword: supply chain management, inventory control, behavioral operations

Ⅰ. Introduction

We are living in a fast-changing business world where values of certain products diminish rapidly from the time they launch. The typical examples of such products include electronics that requires advanced technology and fashion apparels that can be only in style for a single selling season. The question about how much to prepare stock for these products with obsolescence is developed to a well-known newsvendor model in operations management research. The newsvendor model obtained its name from a newsvendor who has to decide how many newspapers should be ordered to

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maximize his profit, since too many orders end up with worthless leftovers and too few orders lead to foregone profits.

Newsvendor problems have been extensively studied with many extensions (Khouja, 1999). Most papers focus on the newsvendor problem only for retailers facing random demands rather than considering a supplier or a manufacturer who sells products to those retailers. This paper studies inventory control for a supplier or a manufacturer when her customers deal with newsvendor problems. For example, suppose a manufacturer produces fashion apparel items and sells them to local retail stores that manage a newsvendor problem for every selling season. These retail stores must place an order with the manufacturer well in advance because the lead time from order placement to receipt of products is usually long for apparel industry (Fisher and Raman, 1996). Considering that fashion products are time-sensitive, the manufacturer needs to prepare for stocks on hand to immediately meet the retailers' demands. Some apparel firms such as Nike place orders with original equipment manufacturers (OEMs) who must forecast the customer demand and produce the items before they receive orders.

Most newsvendor-type retailers in many industries including electronics, apparel, or food chain, etc. have suppliers. However, as mentioned earlier, there have not been many studies on the supply chain context. One of the reasons lies on an assumption of perfect rationality that retailers will always order an optimal quantity that is a well-known newsvendor solution, in which case there is no uncertainty in the supplier's stock decision.

However, recent experimental research in the newsvendor setting revealed that retailers do not make optimal inventory decisions. Experiments conducted by Schweitzer and Cachon (2000) covering thirty periods reported that there is a significant tendency of anchoring on the mean demand and that subjects choose a stocking level that is between the mean demand and the optimal quantity. They also found weak support for a chasing demand pattern. As follow-up papers, Bolton and Katok (2008) and Bostian et al. (2008) confirmed the experimental results of Schweitzer and Cachon (2000) and further studied the effect of learning. Benzion et al. (2008) showed that normal demand distribution generates the similar results to those under uniform demand distribution and that the order quantity is affected by previous-round results. While these non-optimal behavioral patterns are acknowledged to be robust, there has been no research that studies their impact on supply chain performance.

When retailers make non-optimal inventory decisions for a newsvendor situation, what should be the inventory control strategy of a supplier who sells the products to the retailers? Will understanding retailers' behaviors help the supplier manage inventories? This paper investigates whether a supplier could improve her inventory decision by incorporating the retailers' behaviors in the decision making processes.

We (i) develop mathematical models for the newsvendor decision maker; (ii) estimate the parameters using data from experiments with human subjects; (iii) determine the demand distribution the supplier faces; and ultimately (iv) observe the cost savings that the supplier achieves by incorporating these behavioral tendencies into her decision making.

Using the data from experiments, we estimate the possible reduction in supplier costs and determine the factors that significantly affect it. From the data showing an obvious demand-chasing pattern, we observe that a supplier can save considerable inventory costs by taking into account those retailers' behavioral tendencies. The amount of cost savings depends on the characteristics of the data, and it should be studied how we can determine the types of retailers' behaviors. We propose a model assuming that retailers are mean-anchoring with probability p demand-chasing with probability r, and random with probability ($1-p-r$). This assumption is based on the premise that retailer behaviors are explained by the tendencies of either mean-anchoring or demand-chasing. The sum of p and r cannot exceed 1.

We also propose a useful methodology for the supplier to estimate the demand distribution: Bayesian regression is an appropriate way of estimating model parameters when the sample size is small (Huff, 2010). A supplier can estimate the distribution of each retailer's order quantities and compute the potential inventory cost by Bayesian regression analysis.

In addition, by analyzing experimental results, we discovered that considering individual behaviors helps the supplier estimate the demand distribution better than considering aggregate random behaviors of retailers, which is expected intuitively as well. From the additional experiments, we obtained an insight about the effect of end-customer demands' variance: when the demand variance is larger, the supplier gets more benefit from the information about retailers' behaviors. Besides, we believe there are many more interesting and valuable research ideas regarding this subject.

The remainder of this paper is as follows. In section 2, we review some relevant literatures and point out the contribution of this paper. Section 3 describes a supply-chain setup and five models used in this research. In section 4, we analyze the possible cost savings from understanding retailers' behaviors with our own experimental data. Section 5 discusses several issues regarding the findings of this research. Section 6 concludes the paper and suggests future research directions.

Ⅱ. Literature Review

Behavioral operations management is a relatively new research field with significant potentials. Recently, researchers are paying increasing attentions to behavioral studies in operations management area, not only because they realize human factors should be considered to explain real-world phenomena but also because behavioral experimentation and mathematical modeling complement each other (Bendoly et al., 2006).

A group of behavioral papers are summarized in several review papers such as Boudreau et al. (2003), Loch and Wu (2005), and Bendoly et al. (2006). Further, Gino and Pisano (2008) guide some future research directions, and Bendoly et al. (2010) review related knowledge for research in behavioral operations. Particularly for supply chain management, some literatures emphasize the importance of behavioral research (Tokar, 2010; Bachrach and Bendoly, 2011; Knemeyer and Naylor, 2011), Siemsen (2011)). Recent review papers such as Schorsch et al. (2017), Fahimnia et al. (2019), Donohue et al. (2020) and Goudarzi et al. (2023) showed the popularity of behavioral study by introducing extensive amount of literatures on supply chain management in behavioral-operations approach. Many of them focus on several issues such as bullwhip effect (Croson and Donohue, 2006), sourcing (Xue et al. (2022)), contracting (Katok et al., 2008; Katok and Wu, 2009; Kalkanci et al., 2011; Castañeda et al., 2019; Johnsen et al.,2021; Schiffels and Voigt, 2021), pricing (Katok and Villa, 2022), or contracting and pricing (Wang et al., 2021). You may also recognize the recent tendency of behavioral research in inventory management field (Perera et al., 2020; Yamini, 2021; Davis et al., 2024). Still there has been no attempt to model the human aspect of decision makers for supply chain inventory management, which is the main purpose of this study in newsvendor setting.

For the topic of newsvendor problems, some researchers have discussed important issues about behavioral operations, though not in a supply chain context. Schweitzer and Cachon (2000) discover that human newsvendors do not make optimal inventory decisions and explained the behaviors by anchoring and insufficient adjustment heuristics. Castañeda and Gonçalves (2018) observe level and poor demand chasing behaviors in their newsvendor experiments. Gavirneni and Isen (2010) study behavioral aspects of newsvendor inventory decisions through verbal protocol analysis. Benzion et al. (2010) observe that human subjects do not make superior optimal newsvendor inventory decisions when they know demand distribution, compared to when they do not. Oberlaender and Dobhan (2014) analyze the case of hybrid organizations by considering behavioral aspects of multi-location newsvendors. We refer to Schweitzer and Cachon (2000) to use their heuristics as a way of explaining retailers' behavioral tendencies, but still the focus of our paper is on an entire supply chain: how the behavioral tendencies affect supply chain performance.

The methodology used in this paper is also relatively novel in operations management area, not to mention it is the most suitable way to analyze the experimental data. Azoury and Miyaoka (2009) state that a Bayesian approach to demand modeling is especially appropriate in an environment of high uncertainty with little historical data. By using Bayesian regression method when analyzing the experimental data, we were able to estimate the model parameters to determine the distribution of retailers' order quantities so that a supplier can predict her inventory cost. Interested readers may refer to Gelman et al. (2004) and Congdon (2007) for more details about Bayesian regression analysis. A recent study by Kirshner and Moritz (2021) suggested a regression method in order to measure demand chasing behavior in inventory management. They found that the regression approach outperforms a correlation method.

To sum up, the research contribution of this paper can be pointed out as follows. First, this paper contributes to supply-chain-management literatures by studying the effect of retailers' irrational inventory decisions. Second, this also contributes to the inventory-management literatures by considering behavioral aspects of newsvendor decisions in a supply chain context. Third, this paper uses Bayesian regression analysis which is an effective methodology to compute the possible cost savings as well as to propose a way to determine the individual decision-maker's behaviors or forecast demand distribution based on order history.

Ⅲ. Models

3.1 Setup

We consider a supplier selling a single product to N independent retailers at a unit wholesale price of W per unit. She procures the product of C per unit and if she can sell it to a retailer, makes a margin of $W-C$. On the other hand, if the unit is left over due to a low demand from the retailers, she foregoes the C dollars spent in acquiring it. Each retailer, in turn, faces random (uniformly distributed between 0 and U) demands from end-customers and must make a newsvendor decision about how much inventory to acquire. The retailers acquire the product at W per unit and sell it to the end-customers at P per unit. Unsatisfied demands at the retailers are assumed to be lost. Unsatisfied demand at the supplier is satisfied via expediting which costs the supplier C_e per unit. The retailers will always receive their whole order and thus in effect face uncapacitated replenishment. Any excess inventories at the retailers and the supplier are salvaged at no additional revenue at the end of the period. The sequence of events in each period is as follows:

1. The supplier decides her stocking level. The production capacity is infinite.
2. The retailers place their orders with the supplier and receive them from the supplier in full. If the supplier does not have enough inventory to meet all of the retailers' demands, she will use an expediting process to immediately acquire additional inventory and ships them to the retailer.
3. The retailers observe the end-customer demands and satisfy as much as possible from on-hand inventory. Unsatisfied end-customer demands at the retailers are lost.
4. Excess inventories at the supplier and the retailers are salvaged at no additional revenue.

The system is a repeated newsvendor problem with the retailers and the supplier making decisions that maximize their own expected profits.

3.2 Retailer and supplier behavior

The retailer's stocking level decision is one of a newsvendor with infinite capacity and thus the optimal solution is well known. The information needed to solve for a newsvendor problem consists of an overage cost (C_o) associated with every unit of unsold inventory, an underage cost (C_u) associated with every unit of demand lost due to lack of inventory, and demand distribution ($F(\cdot)$). Given this information, the optimal purchasing quantity can be computed as $F^{-1}\left(\frac{C_u}{C_o+C_u}\right)$. Under our setup, the underage cost is $P-W$ and the overage cost is W for retailers.

Let us first consider that all retailers behave optimally. The optimal order quantity is $\frac{P-W}{P}\times U$ and since the problem renews in every period, the order quantity would be the same in all periods. The total demand seen by the supplier in each period is $\frac{P-W}{P}\times NU$. Since there is no randomness in the demand seen by the supplier, her stocking level decision is trivial and her optimal profit is $(W-C)\times\frac{P-W}{P}\times NU$. There is no additional cost related to inventory decision of the supplier.

On the other hand, if retailers behave non-optimally, they do not make optimal decisions and demonstrate significant variability in their order quantities. This variability necessitates the supplier to make an appropriate newsvendor decision. The total demand seen by the supplier is equivalent to the sum of all retailers' order quantities. It is reasonable to assume that each retailer's order quantity is normally distributed because normal distribution is most commonly used for stochastic variables. Su (2008) found that the boundedly rational newsvendor's order quantity follows a truncated normal distribution for uniformly distributed end-customer demands.

The supplier's stock decision is affected by how she determines the distribution of the retailers' order quantities. We develop five models based on different assumptions on retailers' behaviors. For each model, we define the retailer decision making process at an individual level and characterize the resulting demand faced by the supplier. Human retailers will behave all differently, so it is natural to model the retailers' behaviors at an individual level rather than in aggregate. Following notations are used through all models:

Q_{it}: order quantity placed by retailer i at time t
Q^*: optimal order quantity for retailers (optimal newsvendor solution)
d_t: observed end-customer demand at time t

Model R: The supplier assumes that all retailers' order quantities are random.

Each retailer's order quantity can be modeled as:

$$Q_{it}^R = \beta^R Q^* + \varepsilon_{it}^R$$

where ε_{it}^R is the error term with distribution $\mathrm{N}(0,(\sigma_i^R)^2)$.

Then, the demand seen by the supplier is $\mathrm{N}\left(N\beta^R Q^*, \sum_{i=1}^{N}(\sigma_i^R)^2\right)$.

Model IR: The supplier assumes that each retailer's order quantity follows normal distribution with individual mean and variance.

Each retailer's order quantity can be modeled as:

$$Q_{it}^R = \beta_i^R Q^* + \varepsilon_{it}^{IR}$$

where ε_{it}^{IR} is the error term with distribution $\mathrm{N}(0,(\sigma_i^{IR})^2)$. Then, the demand seen by the supplier is $\mathrm{N}\left(\sum_{i=1}^{N}\beta_i^{IR} Q^*, \sum_{i=1}^{N}(\sigma_i^{IR})^2\right)$.

Model M: The supplier assumes that the retailers have mean-anchoring tendencies.

Retailers anchor on the mean demand ($\frac{U}{2}$) and insufficiently adjust towards the optimal order quantity (Q^*).This is one of the heuristics suggested by Schweitzer and Cachon (2000), and it explains well the pattern of order quantities between mean demand and optimal order quantity. We model this mean-anchoring behavior as follows:

$$Q_{it}{}^{M} = a_i{}^{M}\frac{U}{2} + \left(1 - a_i{}^{M}\right)Q^* + \varepsilon_{it}{}^{M}$$

where a_i^M is an individual-specific parameter representing the magnitude of the mean-anchoring tendencies, and ε_{it}^M is the error term with distribution $\mathrm{N}(0,(\sigma_i^M)^2)$.

In this case, the demand seen by the supplier is $\mathrm{N}\left(\sum_{i=1}^{N}\left\{a_i^M\frac{U}{2}+(1-a_i^M)Q^*\right\},\sum_{i=1}^{N}(\sigma_i^M)^2\right)$.

Model D: The supplier assumes that the retailers have a tendency to chase the previous demand.

Retailers anchor on a prior order quantity ($Q_{i,t-1}$) and adjust towards prior demand (d_{t-1}).This is another heuristic suggested by Schwetizer and Cachon (2000). We model this demand-chasing behavior as follows:

$$Q_{it}{}^{D} = b_i{}^{D} d_{t-1} + \left(1 - b_i{}^{D}\right)Q_{i,t-1}{}^{D} + \varepsilon_{it}{}^{D}$$

where b_i^D is an individual-specific parameter representing the magnitude of the demand-chasing tendencies, and ε_{it}^D is the error term with distribution $\mathrm{N}(0,(\sigma_i^D)^2)$. In this case, the demand seen by the supplier is

$\mathrm{N}\left(\sum_{i=1}^{N}\{b_i^D d_{t-1}+(1-b_i^D)Q_{i,t-1}^D\},\sum_{i=1}^{N}(\sigma_i^D)^2\right)$.

Model B: The supplier assumes that the retailers are both mean-anchoring and demand-chasing.

If each retailer has a mean-anchoring tendency with individual probability p_i and a demand-chasing tendency with individual probability r_i, we can model this behavior as follows:

$$Q_{it}{}^{B} = p_i{}^{B}\left\{a_i{}^{B}\frac{U}{2} + \left(1-a_i{}^{B}\right)Q^*\right\} + r_i{}^{B}\left\{b_i{}^{B} d_{t-1} + \left(1-b_i{}^{B}\right)Q_{i,t-1}\right\} + \left(1 - p_i^B - r_i^B\right)Q^* + \varepsilon_{it}{}^{B}.$$

where ε_{it}^B is the error term with distribution $\mathrm{N}(0,(\sigma_i^B)^2)$. Then, the demand seen by the supplier is $\mathrm{N}\left(\sum_{i=1}^{N}p_i^B\left\{a_i^B\frac{U}{2}+(1-a_i^B)Q^*\right\}+r_i^B\{b_i^B d_{t-1}+(1-b_i^B)Q_{i,t-1}\}+(1-p_i^B-r_i^B)Q^*,\sum_{i=1}^{N}(\sigma_i^B)^2\right)$.

Let S denote the supplier's stock level and D denote the demand faced by the supplier, i.e., sum of all the retailers' order quantities. Suppose this demand is normally distributed with mean μ and standard deviation σ. When the supplier's stock level (S) is greater than or equal to the retailers' demands (D), the supplier's profit would be

$$\pi = (W - C)D - D(S - D).$$

When the suppliers' stock level (S) is less than the retailers' demands (D), the supplier's profit would be

$$\pi(S) = (W - C)D - C_e(D - S).$$

Therefore, the supplier cost associated with inventory decision can be expressed as

$$C(S) = E[C(S - D)^+ + C_e(D - S)^+]$$

The optimal stock level S^* that minimizes this inventory cost is a well-known newsvendor solution,

$$\begin{aligned} S^* &= F^{-1}\left(\tfrac{C_e}{C+C_e}\right) \\ &= \mu + \sigma\Phi^{-1}\left(\tfrac{C_e}{C+C_e}\right) \end{aligned}$$

where $\Phi(\cdot)$ is the standard normal distribution.

Expected overage cost is computed as $C\int_{-\infty}^{S^*}(S^* - x)\emptyset(x)dx$. Let $Z_{CR} = \frac{S^*-\mu}{\sigma}$. Then the expected overage cost is $C\int_{-\infty}^{Z_{CR}}(S^* - (\mu + \sigma Z)\emptyset(Z)\sigma dZ = C\sigma\int_{-\infty}^{Z_{CR}}(Z_{CR} - Z)\emptyset(Z)dZ = C\sigma\emptyset(Z_{CR})$. We can compute the expected underage cost in the similar way.

Therefore, the resulting supplier cost is

$$C\left(S^*\right) = \sigma\left(C + C_e\right)\phi\left(\Phi^{-1}\left(\tfrac{C_e}{C+C_e}\right)\right)$$

where $\phi(\cdot)$ is the pdf of standard normal distribution.

As the standard deviation of demand indicates the uncertainty or "risk", it is notable and reasonable that the increase of sigma leads to the increase of the cost. We assume that the supplier is smart enough to solve the repeated newsvendor problem with perfect rationality. Thus, if the supplier is able to properly estimate the demand distribution, she can compute the supplier's inventory cost as it is determined by the standard deviation of her demand.

Ⅳ. Analysis

The key question for the supplier to solve her repeated newsvendor problem is how to estimate the distribution of retailers' order quantities given the retailers' order history. As a way to obtain the retailers' order history for our analysis, we conducted newsvendor experiments using human subjects. With the experimental data, we estimate the distribution of retailers' order quantities by models under different assumptions on retailers' behaviors, and observe how much a supplier can improve the decision making process by incorporating information about retailers' behaviors.

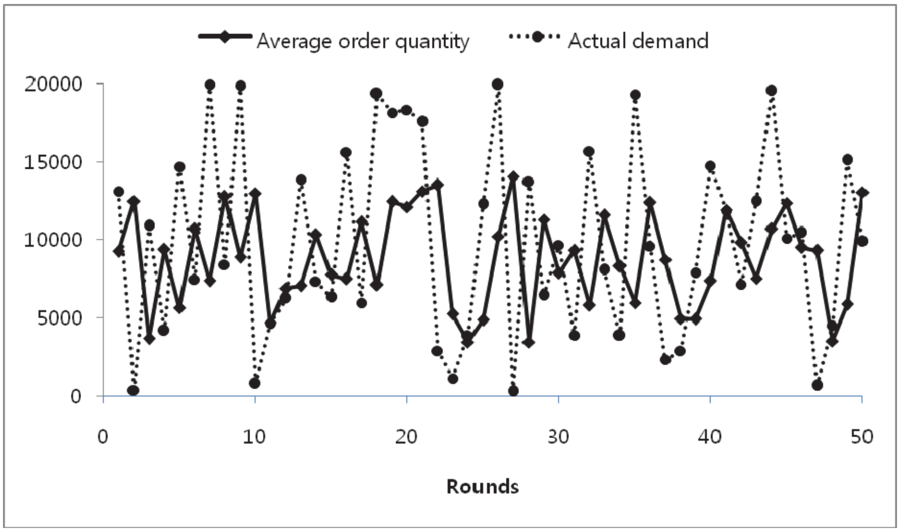
The two experiments reveal that a supplier can significantly reduce her inventory cost by considering retailers' behavioral tendencies. The second experiment not only validates the point but also examines the effect of end-customer demand variances.

4.1 Experiment 1

Experiment 1 was done by recruiting 68 undergraduate students at a state university in the U.S. The participants were requested to make the inventory decisions for extra credits. They were able to obtain 3 points for a required course only when they finished all the 50 rounds. Since the three-point credit could change the grade (e.g. from grade B to grade A), it is a strong incentive to students. Each subject was assigned a computer and asked to decide the order quantity for each round. Information about the retail price, the purchasing price, and the demand distribution was shown on the screen. Except for the first round, the subjects were informed of the actual demand of the previous round and the resulting profit/loss they made in each round. The retail price is $1000, the purchasing price is $300, and demand is discrete and uniformly distributed between 1 and 20000. Because of its simplicity, uniform distribution is frequently used in the newsvendor experiments (Schwetizer and Cachon, 2000; Bolton and Katok, 2008; Bostian et al., 2008). The results under normal demand distribution are usually not so different (Benzion et al., 2008). The newsvendor solution (optimal order quantity) of our experiment is 14000. However, similarly as shown in several experiments from other articles, the subjects did not order 14000 units most of the time. We used only 60 subjects' answers for analysis after excluding unreliable data. Figure 1 depicts the average order quantity across subjects along with the actual demand for each round.

Unlike other literatures, there is no "pull-to-center" effect in our data from Experiment 1, that is, the average order quantities do not always lie between mean demand (10000) and optimal order quantity (14000), only in 19 rounds out of 50 rounds (38%). Of all the decisions (3000 decisions), 31.23% of order quantities are between mean demand and optimal order quantity. However, clearly, we can see a very strong pattern of chasing demands. Of all the decisions excluding the first round (2940 decisions), 75.24% changed the order quantities across rounds in the direction of previous demand, 10.99% changed the order quantity away from previous demand, and 13.77% didn't change the order quantity.

We carried out a Bayesian regression analysis to estimate the model parameters described in section 3.2. Bayesian regression is widely used especially in marketing research due to its powerful ability to analyze experimental data even when the sample size is relatively small (Gelman et al., 2003). As we observe individual retailers' ordering behaviors, Bayesian regression would provide the best estimation for model parameters. Publicly



〈Figure 1〉 Experimental data - Experiment 1

〈Table 1〉 Parameter estimation - Experiment 1

	SD of demand	Average values					
		β	a	b	p	r	σ
Model R	39062.91	0.629					5043.00
Model IR	38127.00	0.628					4784.05
Model M	41109.61		0.890				5177.60
Model D	30117.76			0.601			3647.46
Model B	28927.66		0.703	0.676	0.241	0.691	3516.63

available Windows-based software WinBUGS (Windows Bayesian inference Using Gibbs Sampling) is used for Bayesian regression on our data. WinBUGS is developed for the Bayesian analysis of complex statistical models using Markov chain Monte Carlo methods. The results of Bayesian regression estimation are summarized in Table 1.

We provide average values of each parameter, but all the individual-specific parameters are available upon request. Also, we can provide the distribution of each individual-specific parameters, as Bayesian regression estimates parameters with probabilities unlike other regression methods.

Remember that the supplier's inventory cost is determined by the standard deviation of the demand the supplier sees. Therefore, we need to compare the standard deviation of the suppliers' demand by models, which is computed as follows.

$$\sigma = \sqrt{\sum_{i=1}^{N} \left(\sigma_i^m\right)^2}$$

where m indicates Model R, IR, M, D, and B, respectively, as far as each model estimates the demand distribution properly.

We define a performance measure for cost comparisons as:

Improvement of Model m (%) = 100 × (Estimated cost of Model R - Estimated cost of Model m) / Estimated cost of Model R

This measure implies how much the supplier' inventory cost is saved by estimating demand distribution with Model m, compared to assuming that retailers' orders are random in aggregate. Table 2 shows the Improvement of each model.

〈Table 2〉 Improvement - Experiment 1

	Improvement (%)
Model IR	2.396
Model M	-5.239
Model D	22.899
Model B	25.946

The highest Improvement, about 26%, is obtained when each retailer is assumed to be both mean-anchoring and demand-chasing with individual probabilities. The cost reduction when all retailers are assumed to be demand-chasing is considerable as well at 22.90%. However, assuming all retailers are mean-anchoring turns out to rather increase the supplier's inventory cost.

The plausible explanation is that our data from Experiment 1 presents obvious demand-chasing behaviors, but not clear mean-anchoring behaviors. In other words, if a model explains the data (order history) well, a supplier can save significant inventory cost by estimating her demand with the model; but otherwise, it leads to a worse outcome.

The fit of models to the data can be evaluated by a measure, DIC (Deviance Information Criterion) proposed by Spiegelhalter et al. (2002), provided in Table 3 for our data.

〈Table 3〉 DIC - Experiment 1

	DIC
Model R	59669.4
Model IR	59147.0
Model M	59680.8
Model D	56083.3
Model B	55894.8

The DIC is defined in analogy with the AIC (Akaike's Information Criterion). So, models with smaller DIC provide a better fit. It gives a measure for how well each model fits the data and penalizes for the number of parameters, similar to the AIC. Therefore, among the five models we developed, Model B provides the best fit for the data as well as generates the lowest inventory cost.

The important finding from the analysis is that a supplier can obtain significant cost savings if she incorporates the information about retailers' ordering behaviors (e.g. mean-anchoring, demand-chasing, or both) into the decision making processes. It is notable that inappropriate assumption on retailers' behaviors is of no use or leads to even worse performance.

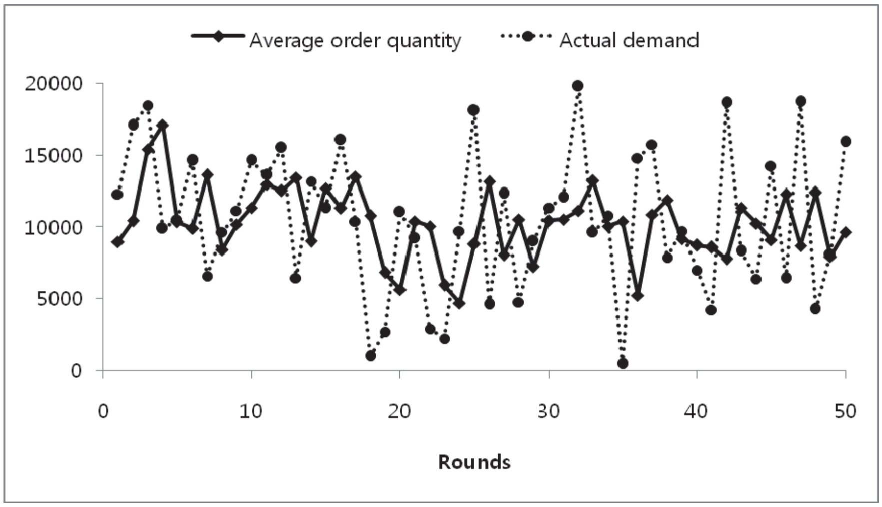
4.2 Experiment 2

Another experiment may enable more rigorous analysis as well as check whether our point applies to other data. 65 undergraduate students at the same university as before were recruited for this experiment. They were requested to make simultaneous inventory decisions for two products for 50 periods given the information about end-customer demands and cost parameters. This time we consider two products with different demand distributions, in order to observe the effect of demand variances. For product #1, the demand is discrete and uniformly distributed from 1 to 20000, and for product #2, the demand is discrete and uniformly distributed from 1 to 500. For both products, the selling price is $10 and the purchasing price is $3. These are also repeated newsvendor problems for each retailer. The optimal order quantity should be 14000 for product #1, and 350 for product #2. We had to select only 23 subjects' responses that are suitable for analysis for both products. The experimental results are shown in Figure 2 and Figure 3 by plotting the average order quantities across subjects in each period.

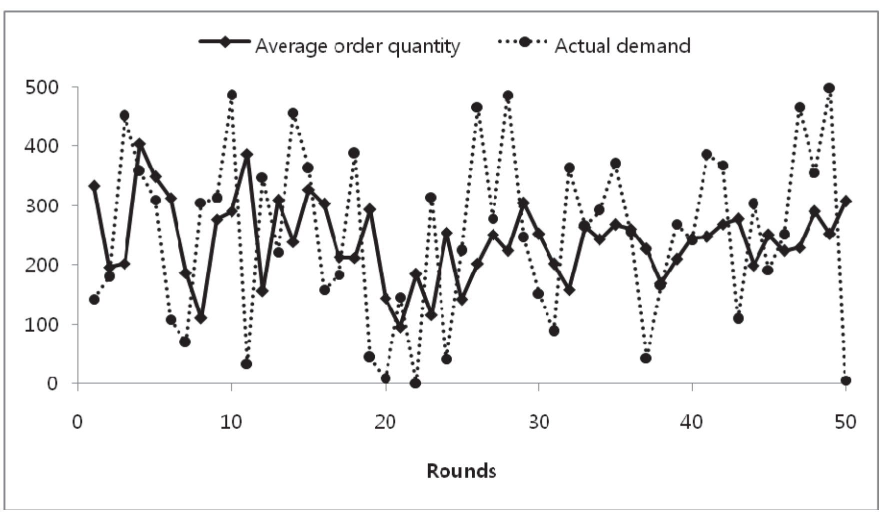
Similarly to Experiment 1, the order quantities vary, and show a demand chasing pattern, though not as strong as that of Experiment 1. For product #1, of 1127 decisions excluding first-round decisions, 65.48% changed the order quantities in the direction of the previous demands, 9.58% changed the order quantities away from the previous demands, and 24.93% didn't change the order amounts. For product #2, of 1127 decisions, 62.64% changed the order quantities in the direction of the previous demands, 9.49% changed the order quantities away from the previous demands, and 27.86% didn't change the order amounts. Of all the 1150 decisions, 47.22% of order quantities lie between the mean demand (10000) and the optimal order quantity (14000) for product #1, and 36.61% of order quantities lie between the mean demand (250) and the optimal order quantity (350) for product #2, providing some evidence to a little bit more mean-anchoring tendency than Experiment 1.

Again, we estimate the parameters of five models with the data by Bayesian regression, and the results are summarized in Table 4 and Table 5.

Table 6 and Table 7 provide the information about the cost improvement that can be achieved from estimating demand distribution



〈Figure 2〉 Experimental data - Experiment 2, product #1



〈Figure 3〉 Experimental data - Experiment 2, product #2

with each model instead of assuming aggregate randomness. For both products, the estimated supplier cost is the lowest when the supplier assumes that retailers are both mean-anchoring and demand-chasing with their own probabilities (Model B). The supplier can save the cost by about 44% for product #1 and about 33% for product #2 compared to when she assumes random distribution for retailer orders in aggregate (Model R).

〈Table 4〉 Parameter estimation and DIC - Experiment 2, product #1

Product #1	SD of demand	Average values						DIC
		β	a	b	p	r	σ	
Model R	22852.14	0.735					4765.00	22744.0
Model IR	19837.87	0.735					3943.83	22029.0
Model M	22296.74		0.724				4290.09	22331.4
Model D	13556.61			0.519			2507.67	19380.6
Model B	12880.20		0.602	0.598	0.200	0.691	2352.72	19233.9

〈Table 5〉 Parameter estimation and DIC - Expeirment 2, product #2

Product #2	SD of demand	Average values						DIC
		β	a	b	p	r	σ	
Model R	579.82	0.690					120.90	14292.7
Model IR	512.48	0.690					102.82	13643.3
Model M	564.63		0.831				113.09	14037.6
Model D	397.69			0.502			74.36	12417.5
Model B	386.15		0.689	0.545	0.225	0.707	72.02	12340.7

〈Table 6〉 Improvement - Experiment 2, product #1

	Improvement (%)
Model IR	13.190
Model M	2.430
Model D	40.677
Model B	43.637

〈Table 7〉 Improvement - Experiment 2, product #2

	Improvement (%)
Model IR	11.613
Model M	2.619
Model D	31.412
Model B	33.402

From the two experiments, we observe that a supplier can improve her inventory decision significantly by assuming that retailers have anchoring tendencies.

Ⅴ. Discussion

In this section, we go over several issues worth to discuss from the experimental results.

First, the decision making processes can be improved significantly by considering individual behaviors. In all cases, Model IR (assuming individual randomness) is superior to Model

R (assuming aggregate randomness), implying that more precise forecasting is possible by understanding individual behaviors instead of aggregate behaviors. Particularly, the supplier benefits most from assuming that retailers are both mean-anchoring and demand-chasing with their individual probabilities (Model B). For our data, the supplier can save the inventory cost by as much as about 26% at least. The magnitude of cost savings depends on the data, but it is certain that the information about retailers' behavioral tendencies helps the supplier's inventory decision. Model B provides the best fit to all data in terms of DIC, that is, considering both mean-anchoring and demand-chasing behavioral tendencies explains the given order history well.

Second, we need to precisely identify the retailers' behavioral tendencies. Our experimental results show that assuming only mean-anchoring retailers may lead to even worse performance for the supplier than assuming just random orders, when the data does not tell a clear sign of mean-anchoring tendencies. On the other hand, assuming only demand-chasing retailers improves the suppliers' inventory decision quite considerably, as the data shows a strong demand-chasing pattern. Therefore, we might say the retailers in our data are demand-chasing. It is not surprising that Model B generates the best outcome, as Model M and Model D are its trivial cases. Still, it is important to identify the retailer's behavioral tendencies because it will affect the usefulness of this approach.

We need to think of how we can determine whether the retailers are mean-anchoring, demand-chasing, or neither. For the mean-anchoring tendency, we may observe whether the average order quantities are usually between the mean demand and the optimal order quantity. In our data, out of 50 rounds, 19 average order quantities (38%) lie between the mean demand and the optimal order quantity for Experiment 1, 28 (56%) for product #1 in Experiment 2, and 21 (42%) for product #2 in Experiment 2. For the demand-chasing tendency, we may count how many times the average order quantity changes towards the previous demand instead of away from it. In our data, for 49 rounds excluding the first round, most average order quantities change toward the previous demand: 45 (91.8%) for Experiment 1, 46 (93.9%) for product #1 in Experiment 2, 41 (83.7%) for product #2 in Experiment 2. Another possible method to determine retailer's behaviors might be using the probability parameters of Model B. In all experiments, the sum of average parameters p and r is around 0.9, and that may be the reason why Model B improves the supplier's inventory decision so significantly. If retailers' behaviors are ambiguous in both mean-anchoring and demand-chasing, the sum of average probability parameters p and r might be relatively low and Model B might not improve the decision that much. In such case, we can still use the Model B as a tool to identify the retailer's behaviors.

Third, Experiment 2 was designed to observe the effect of demand variance as well as to check validity of the result of Experiment 1. To examine whether individual retailers have a consistent behavioral tendency on ordering two different products, we compared individual-specific model parameters through two-sample t test. As a result, we cannot find an evidence pointing that the set of model parameters are not different across two products with different demand variances. Although, it seems that the information about retailers' behavioral tendencies is more useful when the end-customer demands are more variable. It is probably because the random assumption makes more significant difference from anchoring-behavior assumption when the end-customer demands are more variable.

Fourth, it is notable that the experimental data of this paper shows a very strong demand-chasing behavioral tendency unlike those in other existing literatures. A plausible explanation might be that the subjects in our experiments are undergraduate students who have not been trained for newsvendor problems. Still, it does not cloud the fact that the information about retailers' behaviors improves the supplier's inventory decision, considering that neither the MBA who have learned the newsvendor model make optimal decisions nor the training improves the inventory decisions (Schweitzer and Cachon, 2000). What circumstances lead to retailers' demand-chasing tendencies can be an interesting topic for future research.

Lastly, the Bayesian regression analysis used to estimate model parameters in this paper can be a new methodology for forecasting demand given the historical data. There are many ways to forecast demands, including subjective methods such as Delphi method and computational methods such as linear regression. Bayesian regression is especially useful for individual-specific parameter estimation, even with small-size samples, and thus it would capture individual human behaviors effectively. As we only considered two behavioral tendencies (mean-anchoring and demand-chasing), there is still room for model improvement There may be a better model that explains human newsvendors' behaviors well than Model B and searching for such a model merits another future study.

Ⅵ. Conclusion

This paper investigates whether a supplier can improve inventory decisions by incorporating retailers' behavioral tendencies into the decision making processes when the retailers make non-optimal inventory decisions under a repeated newsvendor setting. By Bayesian regression analysis with experimental data, we were able to estimate the demand distribution a supplier faces and thereby compute the supplier's possible cost savings. As a result, we observe a significant improvement in the supplier's inventory decision if she estimates the demand distribution with a model that captures the anchoring tendencies instead of assuming aggregate randomness. As the model selection relies much on the data, it is an important task to determine whether the retailers are mean-anchoring, demand-chasing, both, or neither. In addition, we observe that the information about retailers' behaviors is more beneficial for the supplier when the end-customer demands are more variable. It is certain that more precise information on the data (order history) will lead to a better inventory decision for suppliers. The information includes the retailers' behavioral tendencies, individual-specific order behaviors, and the variability of end-customer demands, etc.

This study contributes to behavioral operations management literatures by focusing on the behavioral effect on supply chain performance in newsvendor inventory decisions. Further, it could be a first step towards future research with huge potentials. First, it is important to find the best model that describes retailers' behaviors. There may be other behavioral tendencies than mean-anchoring and demand-chasing. Also, we can think of a reverse situation for sourcing decision. That is, if suppliers are irrational and a retailer is rational, the retailer might enhance the sourcing decision by understanding suppliers' non-optimal behavioral tendencies. As mentioned earlier, Bayesian regression analysis may serve as a useful methodology for demand forecasting, with its powerful capability to explain individual-specific data. Finally, we might consider the behavioral effect on supply chain performance for other operational problems not limited to newsvendor settings. For example, retailers may have a tendency to use more marketing promotions in certain selling seasons and suppliers may figure out retailers' such behaviors to facilitate their inventory decisions. In all cases, the managerial implication would be that understanding supply-chain partner's behaviors will improve the decision-making processes and that it is important to find a way for better understanding.

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