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THE EFFECT OF CUSTOMER SEGMENTATION ON AN INVENTORY SYSTEM IN THE PRESENCE OF SUPPLY DISRUPTIONS

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ABSTRACT

Customer segmentation is an important marketing tool. Effective customer segmentation helps the enterprises increase profits and improve customer service level. On the other hand, due to possible detrimental consequences, supply disruptions have been receiving more and more attention. This paper aims to investigate the effect of customer segmentation on a single-product inventory system in the presence of supply disruptions. The concerned inventory system involves an unreliable supplier, a retailer, and customers. The retailer adopts a continuous-review (s,S) inventory policy. Partial backordering is considered when stockouts occur. This inventory system is simulated. Based on different customer backorder proportions, the effect of customer segmentation on the inventory system is studied under different scenarios about supply disruption severity. The experimental results show that supply disruption duration is an important factor in influencing the effect of customer segmentation on the inventory system. Some managerial insights are also derived from the results.

1 INTRODUCTION

Customer segmentation, also referred to as market segmentation, is the practice of segmenting customers into groups of individuals with common characteristics. By gaining an overall understanding of customers and then grouping them into categories, companies are able to better optimize marketing programs, satisfy customers and increase profits. Customer segmentation is very common in real life. For instance, many business entities differentiate their customers by members and non-members. Also, many enterprises provide different service levels for different classes of customers. Take order shipment methods for example. The customers are divided into a couple of classes. The customers who pay more expensive shipping fee receive orders quicker than those who pay less expensive shipping fee. For more examples about customer segmentation, the readers may refer to Duran et al. (2007).

Effective customer segmentation helps enterprises increase profits and improve customer service level. Dragoon (2005) provides RBC Royal Bank as an example of implementing effective customer segmentation. The bank identified medical school and dental school students and interns as a group with a high potential to turn into wealthy and profitable customers. The bank put together a program to address the financial needs of credit-strapped young medical professionals, including help with student loans, loans for medical equipment for new practices and initial mortgages for their first offices. Within a year, RBCs market share among customers in this subsegment has shot up from 2 percent to 18 percent, and the revenue per client is now 3.7 times that of the average customer. This example well illustrates the importance of effective customer segmentation. In general, there are two kinds of customer segmentation approaches (Goecart.com 2005). The first approach, traditional segmentation, organizes customers by key variables such as demographics. The second approach, value-based segmentation, looks at customer needs as well as the costs of establishing and maintaining customer relationships.

On the other hand, supply disruptions have been receiving more and more attentions. The causes of supply disruptions are various, including natural disasters, equipment breakdowns, labor strikes, political instability, traffic interruptions, terrorism, and so forth (Chopra and Sodhi 2004). Supply disruptions may result in severe consequences, for example, huge economic loss. Take the 2000 lightning incident in Albuquerque, New Mexico as an example (Eglin 2003). This incident catastrophically destroyed a Royal Phillips Electronics semiconductor plant, which was Ericsson's single then-supplier. As a result, when the plant had to shut down after the fire, Ericsson had no other sources of microchips and ultimately lost $400 million in sales.

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The 1999 Taiwan earthquake is another representative example that reflects one of tremendous impacts of supply disruptions. Taiwan was the third largest supplier of computer accessories in the world at that time. The earthquake caused a two-week global semiconductor shortage, and thereby undermined countless companies all over the world. The readers may refer to Hopp and Yin (2007) and Kleindorfer and Saad (2005) for more examples about the destruction supply disruptions may bring about. In view of huge negative consequences, supply disruptions have been incorporated into the study of inventory control for decades (Chao 1987, Parlar and Berkin 1991, Song and Zipkin 1996, Lewis 2005).

The literature of inventory control with supply disruptions can be divided into continuous-review based and periodic-review based. The continuous-review setting is taken into account in most of the previous work (Gupta 1996, Parlar 1997, Gürler and Parlar 1997, Arreola-Risa and DeCroix 1998, Mohebbi 2003, Mohebbi 2004). Gupta (1996) studies a continuous-review inventory problem with an unreliable supplier. The author considers two situations where exact expressions of average cost are derived. The necessity of paying attention to supply uncertainty is acknowledged. Parlar (1997) considers a continuous-review stochastic inventory problem with random demand and random lead-time in the situation where supply may be disrupted. The concerned inventory policy is a (r, Q) policy. The average cost function is derived by using the renewal reward theorem. Gürler and Parlar (1997) make further research contribution by considering an additional randomly available supplier in the problem that Parlar (1997) addresses. Arreola-Risa and DeCroix (1998) study inventory management under random supply disruptions and partial backorders, with an (s, S) policy being considered. The optimal policy parameters are yielded under a specific scenario. Mohebbi (2003) and Mohebbi (2004) consider two continuous-review lost-sales inventory systems with compound Poisson demand, with one system having Erlang distributed lead time and the other having hyperexponentially distributed lead time. The literature on the continuous-review setting is vast. However, due to intricate nature, little work has been conducted on the periodic-review setting. The references to this aspect include (Parlar, Wang, and Gerchak 1995, Özekici and Parlar 1999). Parlar et al. (1995) analyze a finite-horizon periodic-review inventory model with backlogging. Under their specific settings, the optimal inventory policy is proven to be of an (s, S) type. Özekici and Parlar (1999) consider infinite-horizon periodic-review inventory models with unreliable suppliers. They show that an environment-dependent order-up-to level policy is optimal when the order cost is linear in order quantity.

This paper aims to investigate the effect of customer segmentation on an inventory system, based on different scenarios of supply disruption severity. The remainder of the paper is organized as follows. Section 2 describes the considered problem and introduces the adopted inventory policy and relevant notation. Section 3 demonstrates the simulation model for the concerned inventory system. In Section 4, an experiment is conducted and the effect of customer segmentation on the inventory system is examined in the presence of supply disruptions. Section 5 concludes the paper.

2 PROBLEM DESCRIPTION

This paper is to study the effect of customer segmentation on a single-product inventory system with supply disruptions. The components of the concerned inventory system include a retailer, a supplier, and customers. The retailer sells products to customers and replenishes its stock from the supplier. The supplier is unreliable and is subject to random supply disruptions that might result from material shortages, equipment breakdowns, insufficient labor, and the like. When a supply disruption occurs, the supplier can not immediately fulfill the orders of the retailer received during that time. Only when the disruption issue is resolved can the orders be processed. In other words, order processing is delayed due to the unavailability of the supplier. We define the time period during which the supplier is available (or under normal condition) as its *on* period, and the time period during which the supplier is not available (or under disruption condition) as its *off* period. To be realistic, we consider stochastic replenishment lead time instead of constant or zero lead time.

2.1 Inventory Policy

The retailer adopts a continuous-review inventory policy (s, S), where s is reorder point and S is order-up-to level. This policy has been proven optimal under many situations in the previous literature. The (s, S) policy means that, the retailer monitors its product inventory position continuously, and once inventory position is at or below reorder point s, an order is immediately placed to the supplier. The order quantity is determined in such a way that the retailer's inventory position is increased to the order-up-to level S. Figure 1 shows a standard (s, S) inventory policy with discrete customer demands that does not consider supply disruptions. Time points t_1 and t_3 are the moments when inventory position just reaches or passes reorder point s. At each of these moments an order of appropriate quantity is placed to the supplier such that inventory position is increased to S. t_2 and t_4 are time points when the ordered products are received by the retailer. Time periods $t_2 - t_1$ and $t_4 - t_3$ are two realizations of stochastic replenishment lead time L. In Figure 1, the solid line represents inventory level, whose value may be positive or negative. When it is positive, the retailer incurs holding cost that is proportional to holding duration and the quantity of held products. When it is negative, its absolute value is actually the quantity of backordered products, and the retailer is subject to backorder cost which is proportional to the backorder quantity and the time period during which the backorders are not fulfilled. The dotted line and the solid line above reorder point s represent inventory position, which by definition is equal to the corresponding inventory level plus the quantity of the currently outstanding orders (Hopp and Spearman 2008). Outstanding orders stand for the orders that have been placed to the supplier but have not yet been received by the retailer.

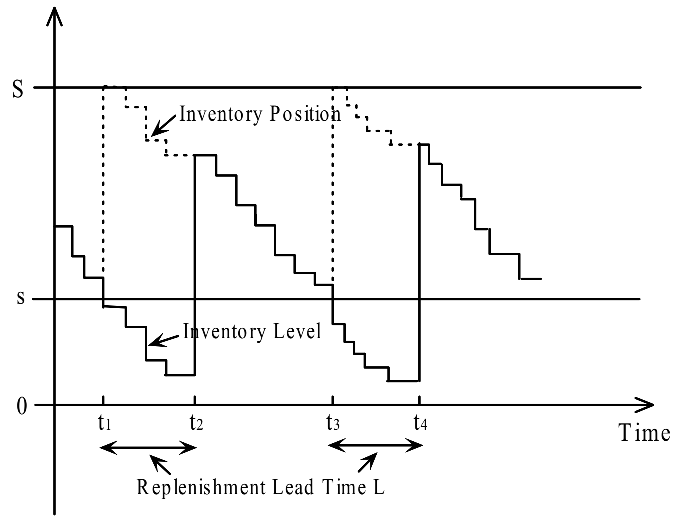

Figure 1: A standard (s,S) policy with discrete customer demands

Figure 2 shows an (s,S) inventory policy where supply disruptions are taken into account. In this figure, the red line segments on ‘Time’ axes represent *off* periods of the supplier, and other line segments on the axes represent *on* periods. Similar to those in Figure 1, time points t_1 and t_3 are the moments when inventory position is at or below s. At each moment, an order is triggered. However, the orders placed at these time points receive different treatments. At time point t_1, the supplier is in an *on* period. The order is processed and shipped out immediately. The retailer receives the order at time point t_2. However, at time point t_3 the supplier is in an *off* period, so the order can not be processed until the supplier restores to its normal status. That is, the order is processed and shipped out after the *off* period ends which occurs at time point t_5. The retailer finally receives the order at time point t_4'. Time periods $t_2 - t_1$ and $t_4' - t_3$ are two realizations of stochastic replenishment lead time L. Comparing Figure 2 with Figure 1, it is evident that supply disruptions delay order replenishment.

2.2 The Considered Problem

In this paper we consider partial backordering in the stockout situations. When the retailer is out of stock, a customer may choose to backorder the products he/she needs or to leave for other sellers (*i.e.*, lost sale). The retailer incurs backorder cost or lost-sale cost accordingly. In general, backorder cost is less than lost-sale cost, since the retailer may obtain profits from selling backordered products.

The retailer segments its customers into two classes. The difference between these two classes is that one class has higher priority to receive backorders. According to SurveyMethods.com (2007), Brent R. Grover of Evergreen Consulting, LLC states that in most situations, customer segmentation can be as simple as identifying as few as two customer groups. This statement justifies the retailer’s customer segmentation from a coarse perspective. The reasons for such segmentation may be several. One possible reason is that high-priority customers are the retailer’s best patrons. They often purchase products from the retailer. The retailer desires to acknowledge them by providing high priority to these customers. High priority may not only keep these customers, but also make them purchase products from the retailer more frequently. This is a win-win situation. Another potential reason is that some customers pay premium to obtain high priority, so that they don’t have to wait for a longer time. Hereafter, we represent high-priority customers as customer class 1 and low-priority customers as customer class 2.

Assuming that a number of customers place backorders to the retailer, high-priority customers will receive products prior to low-priority ones when the backordered products become available. High-priority customers are more important to the

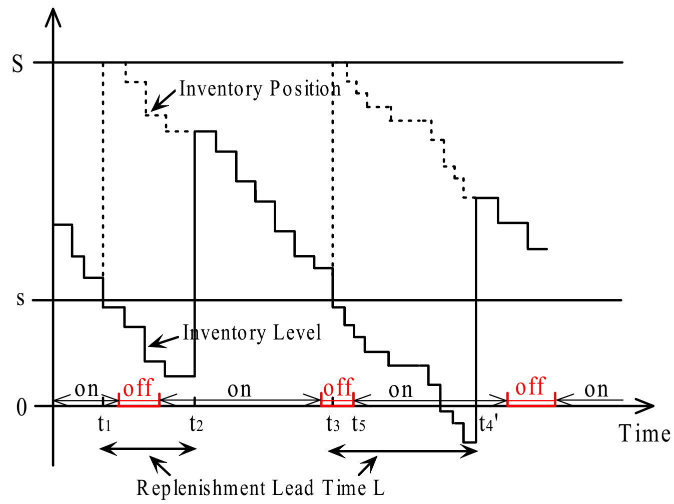

Figure 2: An (s,S) policy with supply disruptions and discrete customer demands

retailer than low-priority customers. Losing a high-priority customer costs the retailer more than losing a low-priority one, so the retailer is more eager to exhibit goodwill to high-priority customers. When a high-priority customer places a backorder, the retailer must expedite the fulfillment of the backorder. This results in relatively high backorder cost, as backorder cost may include costs of expediting, loss of customer goodwill and loss of sales revenues. Therefore, unit backorder cost per unit time resulted from high-priority customers is generally larger than that from low-priority customers. In addition, when a stockout occurs and lost sale is chosen, for the same reason the retailer is subject to higher unit lost-sale cost from customer class 1 than that from customer class 2.

As mentioned before, an unreliable supplier has *on* and *off* periods. *On* periods represent the frequency of supply disruptions and *off* periods represent the duration of supply disruptions. In other words, *on* and *off* periods reflect the disruption severity of an unreliable supplier. The longer the *on* periods, the less frequent the disruptions and the slighter the disruptions. On the contrary, the longer the *off* periods, the longer the disruption duration and the more severe the disruptions. In this paper, we use different combinations of mean values of *on* and *off* periods to represent different supply disruption scenarios. Under these scenarios, the effect of customer segmentation on the inventory system is investigated based on different customer backorder proportions. The effect of customer segmentation on the inventory system is measured by the annual total cost the retailer incurs.

2.3 Notation and Formulas

The to-be-used notation is as follows:

D: stochastic demand size of a customer
d: the mean product quantity that customers demand per unit time
λ: the mean inter-arrival time of customers
L: the replenishment lead time
T: time length of the simulation (a year herein)
IL_0: initial inventory level of the retailer
$IL(t)$: the inventory level of the retailer at time point t
IP_0: initial inventory position of the retailer
$IP(t)$: the inventory position of the retailer at time point t
u: the mean duration of *on* periods
v: the mean duration of *off* periods
A: ordering cost for each order placement
h: unit holding cost per unit time
b_i: unit backorder cost per unit time from customer class i, $i = 1,2$

l_i: unit lost-sale cost from customer class i, $i = 1,2$
N: the number of order placements in one year
OQ_k: the order quantity at the k-th order placement, $k = 1,2,\ldots,N$
$BoQ_i(t)$: the backorder quantity from customer class i at time point t, $i = 1,2$
NL_i: the number of lost sales from customer class i, $i = 1,2$
p: customer backorder proportion
q: the proportion of customer class 1 (*i.e.*, high-priority class)
AOC: annual ordering cost
AHC: annual holding cost
ABC: annual backorder cost
ALC: annual lost-sale cost
ATC: annual total cost

The calculation of annual ordering cost, annual holding cost, annual backorder cost, and annual lost-sale cost are as follows:

$$AOC = A \times N\,, \tag{1}$$

$$AHC = \int_0^T h \times \max(I(t),0)dt\,, \tag{2}$$

$$ABC = \sum_{i=1}^{2} \int_0^T b_i \times BoQ_i(t)dt\,, \tag{3}$$

$$ALC = \sum_{i=1}^{2} l_i \times NL_i\,. \tag{4}$$

Therefore, the annual total cost of the retailer is:

$$ATC = AOC + AHC + ABC + ALC. \tag{5}$$

3 THE SIMULATION OF THE INVENTORY SYSTEM

Previous work of inventory management usually sets limitations to the addressed inventory systems. For example, limit the number of outstanding orders not to be more than one at any time, assume that unmet customer demands are either completely lost or completely backordered, and so on. In this paper, we will discard these limitations. In addition, we incorporate customer segmentation, which has not been addressed before, into the study of inventory management. Based on these consideration, it is difficult to study the problem using an analytical method. Therefore, we simulate the concerned inventory system, which is composed of two processes: customer demand process and inventory replenishment process.

The following is customer demand process. When a customer arrives, the retailer checks its inventory level. There exist three situations based on the retailer's inventory level. The first situation is that the inventory level is positive and is enough to satisfy the demand of the customer. That is, $Inv \geq D$, where Inv and D denote the current inventory level and the customer's demand size, respectively. Under this situation, the customer purchases the products with satisfaction. The retailer updates its inventory level and inventory position accordingly. The second situation is that the inventory level is positive but is not enough for the customer's demand. That is, $0 < Inv < D$. Under this situation, the customer takes all available products and then decides whether to backorder the unfulfilled products or not. The third situation is that there are no products available at all, *i.e.*, $Inv \leq 0$. Under this situation, the customer can choose either to backorder the unfulfilled products or to leave without ordering. In the second and third situations, we assume that $p\%$ of the customers choose to backorder the products and the remaining choose not to. We also assume that $q\%$ of the customers belong to class 1 (*i.e.*, the class with high priority). If a customer chooses to backorder, the inventory level and inventory position of the retailer decrease by the demand size of the customer, in either of the second and third situations. In addition, the backorder quantity of the corresponding customer class is equal to minus inventory level if it is the second situation, or increases by the demand size of the customer if it is the third situation. If the customer chooses not to backorder, part of the sale is lost when it is the second situation or all of the sale is lost when it is the third situation. The resulting lost-sale cost is calculated according to what class the customer belongs to. If it is the second situation, the inventory position decreases by the current inventory level, which is the quantity of all products in the stock. The inventory level is subsequently set to be zero, since the customer takes all available products. The inventory level and inventory position remain untouched in the third situation.

Inventory replenishment process is depicted as below. The continuous-review (s,S) inventory policy requires the retailer to review its inventory position at all time. However in operational level, owing to discrete customer demands, the retailer only needs to review inventory position each time a customer demand arrives. At every review point, if inventory position after customer demand is above reorder point s, no replenishment is needed; otherwise, an order placed to the supplier is triggered. When an order is placed, the availability of the supplier needs to be checked. If the supplier is in its normal condition, it processes the order immediately. If the supplier encounters a disruption at that time, the order has to wait for being processed until the supplier restores to its normal status. After being processed, the order is shipped out. Going through the transportation process, the order arrives at the retailer and the inventory level is increased correspondingly. Then, if there exist unfulfilled backorders, the retailer needs to fulfill them. Three situations need to be addressed. The first situation is that the stock is enough for all backorders to be fulfilled. In mathematical words, that is, $OQ \geq BoQ_1 + BoQ_2$, where OQ and $BoQ_i (i = 1,2)$ represent the arriving order quantity and the current backorder quantity from customer class i, respectively. Under this situation, all customers' backorders are satisfied. So the backorder quantity of each customer class becomes zero. The second situation is that the backorders from customer class 1 can be satisfied but only part of the backorders from customer class 2 can be satisfied. That is, $BoQ_1 \leq OQ < BoQ_1 + BoQ_2$. The reason why customer class 1 is served first is that these customers have high priority of receiving backorders. Under this situation, the backorder quantity of each customer class is adjusted appropriately. The third situation is that the arriving products even cannot satisfy the backorders of customer class 1 (*i.e.*, $OQ < BoQ_1$). In this case, only the backorder quantity of customer class 1 is adjusted.

4 EXPERIMENT IMPLEMENTATION AND RESULTS

4.1 Input Parameters for the Experiment

In the experiment, customer demands are assumed to follow a compound Poisson distribution, where customer inter-arrival time follows an exponential distribution with a mean of $\lambda = 0.2$ days, and each customer's demand size has a probability distribution as shown in Table 1, where j and f_j denote the possible demand size of a customer and the corresponding probability. Further, without loss of reasonability, the following assumptions are made. The ordering cost for each order placement is $A = \$10$; the unit holding cost per unit time is $h = \$0.2$; the unit backorder costs per unit time from customer classes 1 and 2 are $b_1 = \$0.6$ and $b_2 = \$0.4$, respectively; the unit lost-sale cost from customer classes 1 and 2 are $l_1 = \$1.5$ and $l_2 = \$1.2$, respectively. The supplier's *on* and *off* periods are supposed to follow exponential distributions with means being u days and v days, respectively. As mentioned before, u and v are combined to represent the severity of supply disruptions. The order processing at the supplier is assumed to be instantaneous and the transportation duration of an order is assumed to follow a normal distribution with a mean of $\mu = 3$ days and a standard deviation of $\sigma = 0.1$.

Table 1: The probability distribution of each customer's demand size

Demand Size (j)	1	2	3	4	5
Probability (f_j)	0.1	0.25	0.3	0.25	0.1

Assume that the retailer measures its customer service level by the probability of no stockout per order cycle. Then given a customer service level, the optimal reorder point s can be derived (Axsäter 2006). First the safety factor k can be obtained by the formula $CSL = \Phi(k)$, where CSL denotes customer service level and $\Phi(\cdot)$ denotes the cumulative density function of a standard normal distribution. Then the reorder point s is computed by $s = Ld + k\sigma_d\sqrt{L}$, where L is replenishment lead time, d and σ_d are the mean value and standard deviation of customer demand per unit time. Here we approximate L by μ (*i.e.*, $L = 3$), and by computation we get $d = \lambda^{-1}\sum_{j=1}^{5} jf_j = 15$ and $\sigma_d = (\lambda^{-1}\sum_{j=1}^{5} j^2 f_j)^{1/2} = 7.18$. Assume that the retailer desires a 90% customer service level, then we derive that safety factor $k = 1.29$ and $s = 61$. In addition, Rossetti et al. (2008) and Silver et al. (1998) provide a simple heuristic to obtain order-up-to level S. By the heuristic, S is equal to the sum of reorder point s and the order quantity estimated using the EOQ formula. That is, $S = s + Q$, where $Q = \sqrt{\frac{2Ad}{h}}$. Through the computation, $Q = 39$ and $S = 100$.

The initial inventory level and inventory position of the retailer are set to be the same as order-up-to level, *i.e.*, $IL_0 = IP_0 = S = 100$. This setting prevents the initial inventory status from being unrealistically "empty and idle". Further, the adopted initialization represents an inventory system that begins as if it has just received replenishment. Later we will warm up the simulation model to remove the influences that the initial settings bring about.

4.2 Experimental Design and Simulation Settings

We use the mean durations of *on* and *off* periods u and v to represent the severity of supply disruptions, and design six supply disruption scenarios as shown in Table 2. u takes three possible values: 5, 20, and 50, representing the fast, moderate, and slow frequency of supply disruptions, respectively. v takes two possible values: 0.5 and 2, representing the short and long duration of supply disruptions, respectively. Each disruption scenario is a combination of u and v. Among six scenarios, scenario 2 represents the most severe supply disruption, scenario 5 represents the least severe supply disruption, and other scenarios represent supply disruptions, the severity of which is in between. In addition, we consider three possible customer backorder proportions, $p = 20\%, 50\%$, and 80%. For each p, the effect of customer segmentation is studied on the annual total cost of the retailer, regarding six supply disruption scenarios. q denotes the proportion of high-priority customers, and we set its values from 10% to 90%, with an increment of 20%. Therefore, the combinations of u and v, p values and q values make up totally 90 scenarios in this experiment.

Table 2: The experimental scenarios of supply disruption

Scenario	$u(day)$	$v(day)$
1	5	0.5
2	5	2
3	20	0.5
4	20	2
5	50	0.5
6	50	2

Warm up period for the simulation is determined by observing the moment when the average of time-persistent inventory level begins to stabilize. In this experiment, it is obtained to be 30 days. For each of 90 scenarios, we run $n = 50$ replications. The choice of the number of replications is based on the formula (Kelton et al. 2007): $n \cong n_0 h_0^2/h^2$, where n_0, h_0 are the starting number of replications and the corresponding half width of a 95% confidence interval, and h is the desired half width which is set to be 50 in this experiment. For each replication, the experimental length is set to be a year plus warm up period. For each of 90 scenarios, the average annual total cost of the retailer is derived based on 50 replications.

4.3 Result Analyses

The experimental results are illustrated in Figure 3. At first sight, the three subfigures in Figure 3 do not have big differences. They have the same mode, which indicates that the influence of p value is small on the effect of customer segmentation on the inventory system regarding different supply disruption scenarios. However, after careful observation we find that given a disruption scenario and a q value (*i.e.*, a proportion of high-priority customers), the average annual total cost of the retailer decreases with the increase of p value. This reflects that, when other experimental parameters are fixed, the more the customers who choose to backorder in stockout situations, the less the annual total cost of the retailer. This can be easily understood, since backorder cost is usually less than lost-sale cost.

Now we observe the common mode appearing in three subfigures. First, regardless of what supply disruption scenario, the average annual total cost of the retailer increases with q. This implies that, the more the high-priority customers, the more the cost of the retailer. This point is not surprising because the retailer pays more attention to this customer class, and incurs more unit backorder cost per unit time and more unit lost-sale cost from this customer class than those from low-priority customers. The managerial suggestion from this point is that, the retailer should control the proportion of high-priority customers such that the cost it incurs does not exceed the benefit that customer segmentation brings about.

Second, it is obvious that the increase magnitude of the average annual total cost with q is related to the specific disruption scenario. The increase magnitude of scenario 2 is the biggest, scenario 4 the second biggest, and scenario 6 the third biggest. For the remaining scenarios, the increase magnitudes are almost the same. We observe that the common trait for scenarios 2, 4, and 6 is that $v = 2$. Among these three scenarios, the increase magnitude decreases in u, which indicates that the more frequent the disruptions (*i.e.*, the smaller the u), the bigger the increase magnitude. All these observations demonstrate that the disruption duration indicator v plays an more important role than the disruption frequency indicator u,

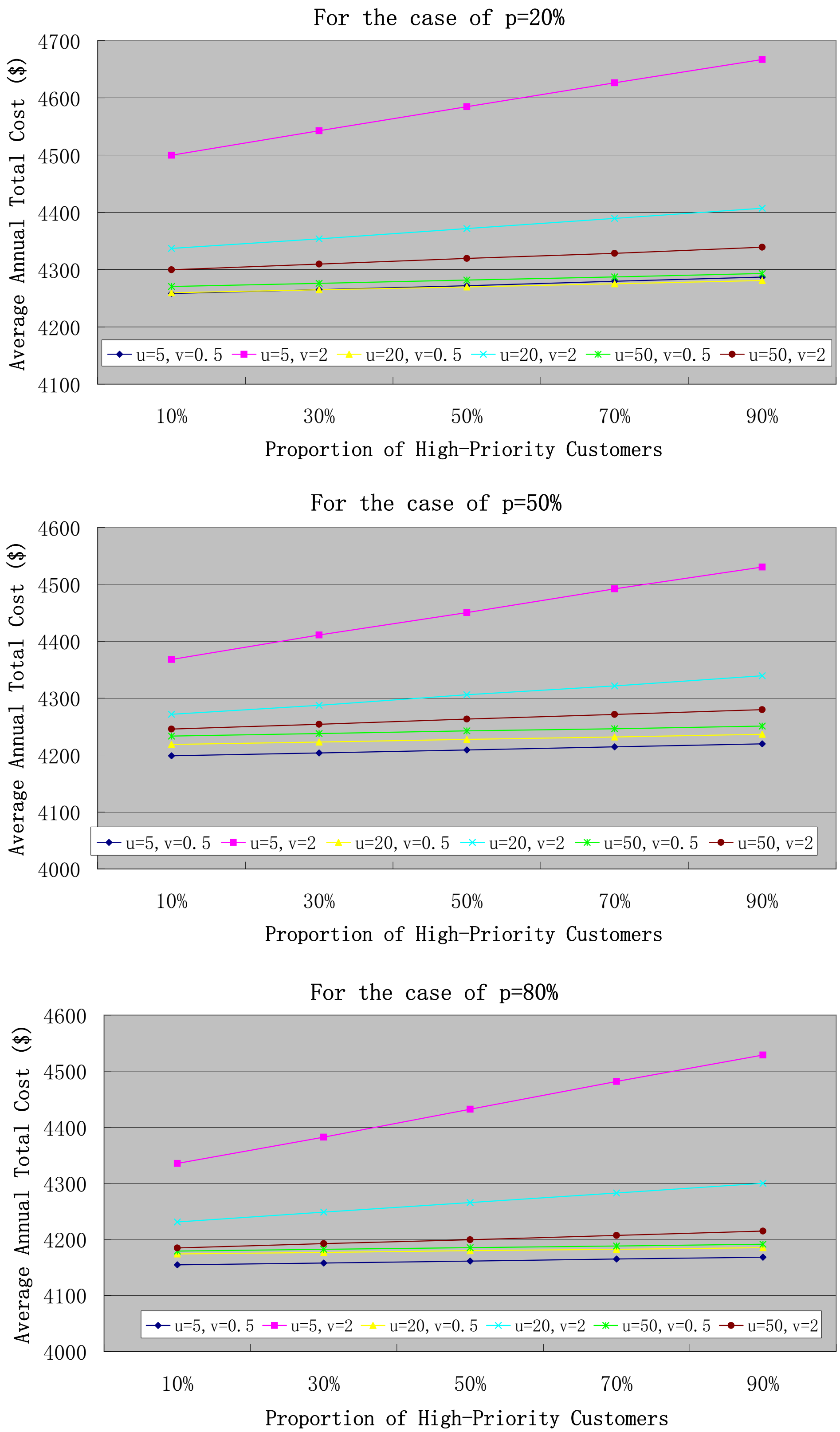

Figure 3: The effect of customer segmentation on average ATC based on supply disruption severity with different p values

regarding the influence on the effect of customer segmentation on the average annual total cost of the retailer. In addition, the performance of u when $v = 2$ is much better than that when $v = 0.5$, as far as its indication of supply disruption frequency is concerned.

Third, we find that for a given q, the average annual total cost in scenario 2 is the biggest, scenario 4 the second biggest, and scenario 6 the third biggest. This fashion is consistent with the above. These scenarios have a common v of 2. Among these three scenarios, the average ATC of the retailer decreases in u given a q value. This implies that, when $v = 2$ and q is fixed, the more frequent the disruptions, the larger the average ATC. However, for $v = 0.5$, the case is contrary. When $v = 0.5$, given a q value, the average ATC increases in u. This indicates that less frequent disruptions (*i.e.*, bigger u) lead to larger average ATC. The explanation may be the following. The designated high customer service level (90%) leads to a vast amount of stock and thereby large holding cost. Appropriate supply disruptions may reduce holding cost and further the total cost. In some sense, under the situations of $v = 0.5$ (*i.e.*, relatively short disruption duration), less frequent disruptions may be insufficient to cut down holding cost. Therefore, the total cost is large. However, this is not the case for the scenarios of $v = 2$. $v = 2$ in the experiment represents long enough disruption duration, which has a large enough impact on the retailer's inventory replenishment. Under the situations of $v = 2$, the inventory replenishment is severely delayed. Holding cost is therefore reduced, however, the shortage cost (*i.e.*, the sum of backorder cost and lost-sale cost) increases dramatically. Thus, the total cost increases. More frequent disruptions will further enlarge the increase of the total cost. This also implies that the influence of v is bigger than that of u.

5 CONCLUSION

In this paper, we consider a single-product inventory system that involves a retailer, an unreliable supplier, and customers. The supplier provides products to the retailer and is subject to random disruptions. The retailer sells products to customers and adopts a continuous-review (s,S) inventory policy. Partial backordering is allowed, which means that when a stockout occurs, customers can choose to backorder products or not. In addition, customers are segmented into two classes. One class has high priority to receive backorders, and the other class has low priority. Unit backorder cost per unit time and unit lost-sale cost from high-priority customers are larger than those from low-priority customers. We simulate the concerned inventory system, and investigate the effect of customer segmentation on the inventory system regarding different scenarios of supply disruption severity, given three customer backorder proportions. The supply disruption severity is represented by the combined disruption frequency and disruption duration, which are denoted by the mean durations of the supplier's *on* periods and *off* periods, respectively. The effect of customer segmentation on the inventory system is measured by the annual total cost of the retailer.

The experimental results illustrate that supply disruption duration plays a more important role than supply disruption frequency in influencing the effect of customer segmentation on the inventory system. The performance of supply disruption frequency is more active when supply disruptions last longer. The results also show that the bigger the customer backorder proportion, the less the annual total cost of the retailer, and that the bigger the high-priority customer proportion, the more the annual total cost of the retailer. These results provide some managerial insights for the retailer, including choosing the supplier whose disruption duration is short, persuading the customers to backorder in the stockout situations, and controlling the number of high-priority customers.

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