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Policies Adoption for Supply Disruption Mitigation Based on Customer Segmentation

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ABSTRACT Supply chain disruptions resulted from various disasters may cause awesome loss; therefore, corresponding operational policies should be designed to mitigate the negative effect. In industrial goods supply chain, customers are segmented and have different contributions and significances to manufacturers, which have to be considered when adopting mitigation policies. From the customer heterogeneity perspective, the models of a three-stage supply chain with a single supplier and two suppliers are established, and sensitivity analysis is carried out to investigate scenario parameters' impact on optimal mitigation policies. The numerical experiments find that safety stocks are suitable for low disruption probability situation. Meanwhile, strategic reserves with lower holding cost are attractive and efficient to handle a fairly highly disruptive situation or high key customer loss. The results also indicate backup supplier should be adopted if there is a low disruption probability or the backup supplier's price is not significantly higher. This paper extends the supply disruption research and leads some managerial implications and insights that might be useful for disruption mitigation in industrial goods supply chain.

INDEX TERMS Supply disruption, mitigation policies, customer segmentation, strategic reserves, backup supplier.

I. INTRODUCTION

In the past 30 years, although the global expansion of supply chain raises more opportunities to enterprises, it also makes the supply chain more vulnerable. Disasters at any stage may affect or even halt the normal operation of the whole supply chain. The examples of disaster's may include natural disaster [1]–[3], facility suspending [4], IT system failure [5], [6], transportation infrastructure shutdown [7], [8], strike [3], [9] Cascading crises [10], etc. These disasters have a low occurrence probability, but if it happened, there would be a significant and long-term impact on the operation of enterprises. The Japan earthquake and tsunami in 2011 gives a vivid example, the automobile part shortage hits almost all auto makers on the earth [11]. And researchers point out the loss by disruption are keeping increasing [12].

Effective mitigation policies in business operation could not only minimize the disruption loss, but even acquire

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an increase. In 2001, a Philips Semiconductor plant in United States was cease by fire. Nokia, one of its downstream buyer, accomplished the quick response to disruption, found substitute supply and got a 15 percent increase in its market share at the expense of its competitor Ericsson, who failed to adopt proper mitigation policies [13].

Realizing the increasing losses of supply chain disruption by disasters, both supply chain managers and researchers show more interest in disruption management. While the design of reliable, resilient supply chain is a matter of fact, the mitigating and contingency policies are another important issue worthy of study. Researchers have explored various optimal policies in different disruption scenarios and supply chain situations.

The research problem of this article was inspired by Schmit's research [14]. Although most studies suppose a fixed percentage of sales will be lost in case of disruption, Schmitt models the customer behavior as a stochastic mixture of backordering and lost sales. This model better approximates to the individual behavior of consumer goods in the end market, which raises our question: "what would be the

customer behavior in industrial purchasing in case of disruption resulted from disaster?"

After interviewing several operation managers, we find that customer importance and purchasing repetitiveness in industrial goods industry is obviously different from ones in consumer goods industry, which would have great impact on the preparation of disruption mitigation.

Consumer goods are sold to final users by retailers in the end market, so the manufacturers or brand owners do not know whether a specific customer will buy or not in the next round. The variation of customers' demand volume is slight and we can suppose that all customers are equal individuals.

In contrast, customers in industrial purchasing may have huge difference in demand volume and contribution to manufacturers. Many companies' customers obey the Pareto law which means a few key customers contribute a great share of total sale. While the manufacturer directly contacts with customers, it knows which customer have kept purchasing for years. The manufacturer would like to maintain the long lasting supply relationship since there may be a high cost to find a new customer. The manufacturer may value some customers more because they are willing to pay higher price, or the manufacturer may be the only supplier of these customers and the monopolizing position would ensure its future sale.

In short, in industrial goods industry, customers are heterogeneous and have different significance to the manufacturer. In case of disruption, the manufacturer will try its best to ensure the supply of key customers and may give up to meet the demand of ordinary customers.

On the customer side, customers for industrial goods often purchasing repetitively and concerns more about supply continuity. In industrial purchasing, the changing of supplier is costly in terms of money and time. Supply disruptions may cause purchaser' operation ceased since they could not find substitute immediately, which is just the case of auto parts shortage in Japan earthquake and tsunami [11]. Therefore, supply continuity is an important determining factor of the steady supply relationship and future sale. If the manufacturer suffering disruptive events succeeded to supply to its key customers, it would greatly increase the loyalty of key customers and ensure its future sale. On the other hand, any purchaser suffering the main supplier disruption would try to find new suppliers or transfer some orders to other suppliers to reduce it risk, which is exactly what Nokia did [13]. Even if the supplier recovered, its sale share at the company had been snatched by other suppliers.

The unmet demand of key customers would not only cause a sale loss at disruption time, but may lead to sale decrease in future. In contrast, the unmet demand of ordinary customers, whose demand volume are small with a high ordering cost, may only cause a little loss. So we can suppose the different significance of customers means different lost sale cost.

The customer heterogeneity in industrial goods supply chain has great impact on the adoption of disruption mitigation policies. Actually, investigated operation managers admitted that their first goal in disruption management would

be to meet the basic needs of key customers to guarantee their loyalty and future sale share even if the cost was higher than the selling price. It is clear that the customer heterogeneity in industrial goods industry would cause different optimal disruption policy from consumer goods industry.

However, there are numerous previous studies based on the assumption of customer homogeneity and suppose all customers would choose the same behavior, while almost no research on mitigation policies is based on customer heterogeneity assumption.

Based on the findings above, the authors think how to choose appropriate policies to mitigate supply disruption in industrial goods industry is a question worth of study. In practice, different companies are in different situation and faced policies adoption problem with different scenario parameters, and also the scenario parameters may change overtime, this research will not aim at find optimal solution for a certain situation. Instead, this research will investigate the impact of scenario parameters on the optimal mitigation policy and hope to find some managerial insights to guide the decision making of supply managers.

In practice, some companies may choose to have only one supplier for one item while others may have two or more suppliers. This research establishes single supplier and two suppliers model to investigate two cases respectively.

The reminder of this article is organized as follows. Section 2 reviews literatures on disruption mitigation in inventory model and supply chain research while customer segmentation is also introduced. Section 3 studies a three stage supply chain with only one unreliable supplier, and the impact of different scenario parameters on optimal mitigation policies was tested. Section 4 accomplishes the similar work for supply chain with one unreliable supplier and one backup supplier. Finally section 5 summarizes our findings and managerial insights.

II. LITERATURE REVIEW

The research on supply disruption can be thought as a branch of supply chain risk management (SCRM), which contains many research topics and plenty of results. However, recent years have seen the booming of research on supply chain disruption management, which can be categorized into two stream, demand-side disruption and supply-side disruption. This section will focus on the mitigation policies to supply side disruption.

A. MITIGATING SUPPLY DISRUPTION

Before the supply chain disruption gained wide attention, some researchers in inventory management had discussed what would be the optimal order quantity and/or interval if suppliers were not reliable and/or the lead time were unfixed. This research stream aims to solve the frequent supply uncertainty in long run with the help of better ordering policy, such as optimal order quantity and/or interval. Parlar and Berkin's research studied the optimal order quantity in an inventory system with random supply disruption

by exponentially distributed on-off periods [15]. There are also other similar studies in different settings, such as the Parlar and Perry's study in multiple supply sources [16]. Yan *et al.* [17] discussed the multi-instant decision making problem under supply disruption, which aimed to find optimal purchasing amount when suppliers had different reliability and supply price at different instant. Mohammadzadeh and Zegordi [18] studied the optimal ordering quantity and pricing and production capacity in one-buyer-three-supplier system with main supplier disruption.

Researchers in inventory management had deliberated sophisticated inventory model, which is enlightening for the research of disruption mitigation. The focus of this research stream is the supply uncertainty and the supplier may be supposed still being able to deliver part of the purchase. While this may simulate the supplier's capacity changing by its own reasons, there are still many cases that the supplier had totally disrupted by external reasons. Some researches only consider the purchasing behaviors as potential measures for disruption, which may be unnecessary constraints for supply managers.

If the disruption or uncertainty is caused by supplier's own reasons, it maybe appear again and again and the aim of studies in inventory management is to find solutions in long run. However, if the disruption is caused by external reasons which have a low probability, we can suppose it will not appear again. Therefore, researchers in supply chain domain aims to solve the accidental supply disruption with the enactment of one-off policies, such as safety stocks (which may be called inventory in some literature) and/or back-up system. Tomlin [19] is one of the earlier researchers who studied the optimal mitigation policies in supply chain situation. In his article of 2006, he studied the impact of scenario parameters on the optimal mitigation policy. Tomlin considered three policies: inventory, sourcing from backup supplier and contingent rerouting.

Schmitt had published three articles on mitigation policies to protect the service level. In her first article, the disruption mitigating problem in a three stage supply chain was considered. By contrasting traditional inventory arrangement at different stage of supply chain with back-up capacity, Schmitt [14] found the only effective mitigation policy for a long-term disruption is back-up capacity. In her second article, downstream buyer's optimal ordering and stocking policies in infinite-horizon were studied in the single supplier and two suppliers model [20]. In her third research, a simulation model was set up according to a real world three stage supply chain and effective mitigation policies for given service level in different scenario parameters were studied [21].

Son and Orchard [22] put forward a new kind of mitigation policy: strategic reserves, which is common in humanitarian relief operations and less considered by private sector. Strategic reserves may be held at another physical location, which makes they have a lower holding cost and an extra fixed access cost. Son and Orchard's research showed that strategic reserves can reduce the expected costs.

Hou and Zhao [23] designed a buy-back mechanism with penalty between buyers and their backup suppliers, who would be invoked when the main supplier disrupted. Lewis *et al.* [24] considered the impact of port closure on supply chain and use Markov chain to model the closure time and probability. Three mitigation policies' impact on performance were investigated, which are inventory, contingency plan and process capability (similar to back-up capability of Schmitt). Hekimoğlu *et al.* [25] stressed the dynamic nature of disruption probability and established Markov model for an auto parts supply chain. According to their research disruption can be mitigated by timely changing safety stocks. Li *et al.* [26] studied the optimal mitigation policies when the disruption duration is unknown. Ang *et al.* [27] established a supply chain model for two tiers supplier and proved penalty-contract may help the manufacture alleviate the disruption of tier 2 supplier disruption. Table 1 summarized the extant mitigation policies.

TABLE 1. Extant research and mitigation policies.

| Mitigation policies | References |
|-------------------------|--------------------------|
| Optimal order quantity | [15],[16],[17],[18],[20] |
| Inventory/safety stocks | [19],[20],[21],[25] |
| Backup supplier | [19] |
| Backup capacity | [14],[24],[26] |
| Contingency rerouting | [19],[24],[26] |
| Strategic reserves | [22] |

There are already many studies on the optimal mitigation policies based on different disruption situation. However, almost all existing studies assume that all customers are the same and the unmet demand incurred same lost sale costs. This article intends to study the optimal policies adoption problem with customer heterogeneity and different lost sale costs.

Paul *et al.* [28] thought that policies for supply disruption should be categorized into three groups: mitigation policies, recovery policies and passive acceptance. Mitigation policies may include safety stocks, multiple sourcing, back-up capacity. Back-up supplier can be thought as recovery policies which would be invoked only after disruptions. Although it is not considered by current researches, doing nothing is still widely adopted by many companies, which may not be a very bad policy in some scenarios.

B. CUSTOMER SEGMENTATION

In 1956, when Smith [29] brought forward the concept of market segmentation, he pointed that all markets should be viewed as heterogeneous markets. Marketing research thinks that enterprises could find better way to meet specific customer demand only after the heterogeneous demand was categorized and studied respectively. Therefore, customer segmentation is thought as the first step of marketing and the

basic approach to understand customer demand and choose target market.

Early marketing research focus more behavior-based customer segmentation. Geography factors, demography factors, psychology factors, social culture factors, product usage, usage context are used as the ground of customer segmentation.

However, customer value-based segmentation gets more attention since it connects more directly with enterprise income. It allows enterprises to focus limited resources on desired customer group, which would improve their satisfaction and loyalty. In 1994, Hughes [30] brought forward RFM model, which use the Recency, Frequency and Monetary to measure customer value. Verhoef and Donkers [31] put forward customer value segmentation matrix, which evaluate customer according to the realized and potential value. Reinartz and Kumar [32] thought that customer should be categorized according to loyalty and profitability.

In the light of customer segmentation, disruption to different customer group would have different impact on customer satisfaction, loyalty and future, which can be modeled as different lost sale costs. Supply managers have to consider this difference and then can make better decision.

III. SINGLE SUPPLIER MODEL

In this section, we consider a three-stage supply chain, which contains only one unreliable supplier, one manufacturer and final customers. The only unreliable supplier may be disrupted with a certain probability. The manufacturer has two policies to mitigate the supplier disruption: safety stocks and strategic reserves.

To simplify the problem, we suppose customers can be categorized into two groups, key customers and ordinary customers. They would incur different lost sale costs.

A. ASSUMPTIONS

We suppose the disruption was a total disruption and the only supplier could not deliver any goods in current order cycle. We also suppose the supplier would recover in the next order cycle, so only the demand and cost of current order cycle would be considered.

The final customers' demand was deterministic. Customers can be categorized into two groups: key customers and ordinary customers. The unmet customer demand would cause a lost sale cost, which the key customers' is higher than ordinary customers'. Certainly, the manufacturer would try to meet the key customers' demand first. If there were more goods available, ordinary customers had a chance to obtain their merchandise.

If there were safety stocks, the manufacturer would pay the holding cost no matter there was disruption or not. After disruption, safety stocks would be consumed and the manufacturer needs to pay the purchasing cost to rebuild. If strategic reserves were adopted, the manufacturer would pay a lower holding cost and the same rebuilding cost. However, comparing to safety stocks, the manufacturer also need to

pay an extra access cost to invoke the strategic reserves. Moreover, the manufacturer would have to pay the normal purchasing cost and fixed ordering cost for its purchasing from the unreliable supplier if there was no disruption.

B. MODEL DESCRIPTION

Notations to be used in this paper as follows:

Parameters:

| | |
|--------------|---|
| D | total demand of final customers |
| α | proportion of key customers to all customers |
| $1 - \alpha$ | proportion of ordinary customers to all customers |
| C_l^k | lost sale cost of key customers |
| C_l^o | lost sale cost of ordinary customers |
| p | disruption probability of the unreliable supplier |
| C_p^u | unit purchasing cost from the unreliable supplier |
| C_h^{ss} | unit holding cost of safety stocks |
| C_h^{sr} | unit holding cost of strategic reserves |
| C_a^{sr} | fixed access cost of strategic reserves |
| C_o^u | fixed ordering cost of the unreliable supplier |

Intermediate Variables:

| | |
|-------|-------------------------------------|
| N^k | unmet demand of key customers. |
| N^o | unmet demand of ordinary customers. |

Decision Variables:

| | |
|----------|---|
| V^{ss} | volume of the manufacturer's safety stocks |
| V^{sr} | volume of the manufacturer's strategic reserves |

If there was no disruption, the manufacturer would pay the normal purchasing cost, fixed ordering cost and holding cost for safety stocks and strategic reserves:

$$D * C_p^u + C_o^u + V^{ss} * C_h^{ss} + V^{sr} * C_h^{sr} \quad (1)$$

If the disruption happened, the manufacturer would not pay the normal purchasing cost and ordering cost. The manufacturer would use safety stocks and strategic reserves, which would be rebuilt in the next normal order cycle and should be thought as disruption response cost. The manufacturer also should pay holding cost for safety stocks and strategic reserves, the access cost for strategic reserves and lost sale cost from key customers and ordinary customers

$$(V^{ss} + V^{sr}) * C_p^u + V^{ss} * C_h^{ss} + V^{sr} * C_h^{sr} + \text{sgn}(V^{ss}) * C_a^{sr} + C_l^k * N^k + C_l^o * N^o \quad (2)$$

Sgn is the sign function and return 1 if $V^{ss} \neq 0$ and 0 if $V^{ss} = 0$.

The aim of the manufacturer is to minimize the ETC (Expected Total Cost). The model of single supplier problem would be as follows:

$$\begin{aligned} \text{MIN ETC} = & (1 - p) * (D * C_p^u + C_o^u + V^{ss} * C_h^{ss} + V^{sr} * C_h^{sr}) \\ & + p * [(V^{ss} + V^{sr}) * C_p^u + V^{ss} * C_h^{ss} \\ & + V^{sr} * C_h^{sr} + \text{sgn}(V^{ss}) * C_a^{sr} \\ & + C_l^k * N^k + C_l^o * N^o] \end{aligned} \quad (3)$$

$$\text{Subject to } V^{SS} \geq 0 \tag{4}$$

$$V^{SR} \geq 0 \tag{5}$$

$$V^{SS} + V^{SR} \leq D \tag{6}$$

According to the assumptions, the unmet demand can be determined as follows:

$$N^k = 0, \quad N^o = D - V^{SS} - V^{SR} \tag{7}$$

$$N^k = \alpha * D - V^{SS} - V^{SR}, \quad N^o = (1 - \alpha) * D \tag{8}$$

C. NUMERICAL EXPERIMENTS AND MANAGERIAL INSIGHTS

The aim of this study is to investigate the influence of different scenario parameters on the optimal disruption mitigation policy. To this end, parameters was changed to simulate different disruption scenario in the numerical experiments. Based on the integer linear programming model in above subsections, LINGO is employed and branch and bound method is used to find the optimal solution. According to the suggestions of operation managers, a set of initial parameters was specified to simulate a real world company.

In order to find meaningful managerial insights, the authors focused on the changing of optimal policies. After extensive tests of scenario parameters, only a few significant parameter combinations leading to change of optimal policy are pick out and expect to find what policy can further lower the total cost in different scenarios and general guidelines on disruption mitigation.

Computational results show that optimal mitigation policies are clustered. The manufacturer will not choose an arbitrary amount of safety stocks or strategic reserves and all its choices belonged to the five kinds of policies in Table 2. Even a slight change of one parameter may incur a leap of the optimal policy from one kind to another.

This result is shaped by our customer segmentation assumption. In case that the holding cost of safety stocks was less than its potential benefit from ordinary customers, the optimal policy would be holding safety stocks for all customers. However, if the holding cost of safety stocks surpassed the benefit from ordinary customers but still was less than the benefit from key customers, the optimal policy would be holding safety stocks for key customers only. Also because of our access cost of strategic reserves, the manufacturer would not adopt a combination of safety stocks and strategic reserves.

Since the changing of scenario parameters will cause changing of the optimal policy, we assign the five kinds of policies values of number which would enable graph expression of relationship among changing of parameters and optimal policies. In the experiments, some policies have never been adopted and grey color is used to denote that.

To better illustrate the changing pattern, two parameters are changed simultaneously to investigate their mutual influence

TABLE 2. Five kind of disruption mitigation policies adopted by the manufacturer.

| Policies Abbr. | Policies Detail | Value of Decision Variable |
|------------------|---|---------------------------------|
| Bear Loss | Preparing nothing for disruption, all customer demand would be unmet if disruption happened | $V^{SS}=0$ $V^{SR}=0$ |
| Ss-key | Safety stocks are just to meet the demand of KEY customers, but the demand of ordinary customers would be unmet. No strategic reserves. | $V^{SS}=\alpha*D$ $V^{SR}=0$ |
| Ss-all | Safety stocks are just for ALL customers. No strategic reserves. | $V^{SS}=D$ $V^{SR}=0$ |
| Sr-key | Strategic Reserves are just to meet the demand of KEY customers, but the demand of ordinary customers would be unmet. No safety stocks. | $V^{SS}=0$ $V^{SR}=\alpha*D$ |
| Sr-all | Strategic Reserve are just for ALL customers. No safety stocks. | $V^{SS}=0$ $V^{SR}=D$ |

on optimal policy, which enables to compare more scenarios. The related and comparable parameters were chosen as parameter pairs, which would help to reveal the changing pattern in related scenarios. So the two environment parameters α and p , two lost sale cost C_l^k and C_l^o , two holding cost C_h^{SS} and C_h^{SR} , two cost of strategic reserves C_h^{SR} and C_a^{SR} , and setup and access cost of strategic reserves, C_p^u and C_a^{SR} are set as investigated parameter pairs.

1) THE MUTUAL INFLUENCE OF α AND p

Our first experiment is to reveal the impact of key customer proportion and disruption probability on optimal policies. Experiment results was shown in Fig. 1.

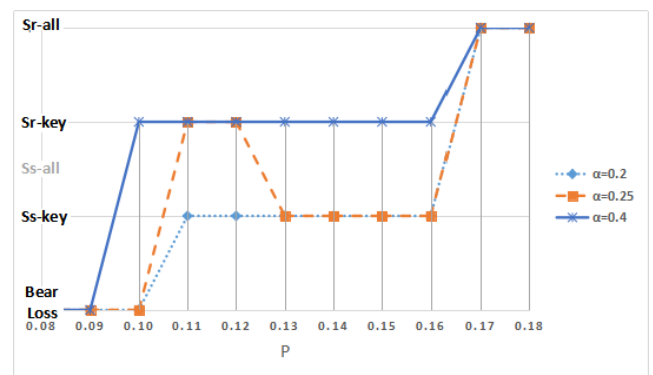


FIGURE 1. Influence of α and p on optimal policy (other parameters: $D = 1000, C_l^k = 33, C_l^o = 27, C_p^u = 19, C_h^{SS} = 1.5, C_h^{SR} = 1.3, C_a^{SR} = 400, C_o^o = 200$).

In Fig. 1, experiment results in the same disruption probability are connected to show the changing pattern of optimal policies. Other disruption probability, such as $\alpha = 0.3$, is omitted because its changing pattern is very similar to existing parameters.

From Fig. 1 we can see that the optimal policy would be Bear Loss when p was quite low. As p increased, transitions to others optimal policy happened much earlier when the proportion of key customers were higher. That indicates a reliable supplier (lower p) should be preferred when the company relied more on key customers (which means a high α).

If the company lived in a highly unstable environment (which means a high p), establishing strategic reserves could reduce its potential loss. When the supplier was highly subject to disruption, the company should establish strategic reserves for all customers. When the disruption probability was not so high and the key customer proportion were high, establishing strategic reserves only for key customers would be a wise choice.

If we contrast different broken lines of α , we can see that strategic reserves were more preferred as the increasing of α . That implies the manufacturer should establish strategic reserves if it had more key customers. It also means, if the manufacturer had established the strategic reserves, it could try to sell more to key customers and increase α , which would not incur more cost. If the manufacturer did not establish strategic reserves yet, it should try to sell more to ordinary customers and lower α , which could be rescued by safety stocks.

2) THE MUTUAL INFLUENCE OF C_l^k AND C_l^o

Fig. 2 shows optimal policies in different lost sale cost of key customers (C_l^k) and ordinary customers (C_l^o). It was revealed that the optimal policy would be Bear Loss or Sr-all if C_l^o was higher (the line $C_l^o = 28.5$) or C_l^k was lower, which means the difference between key customers and ordinary customers

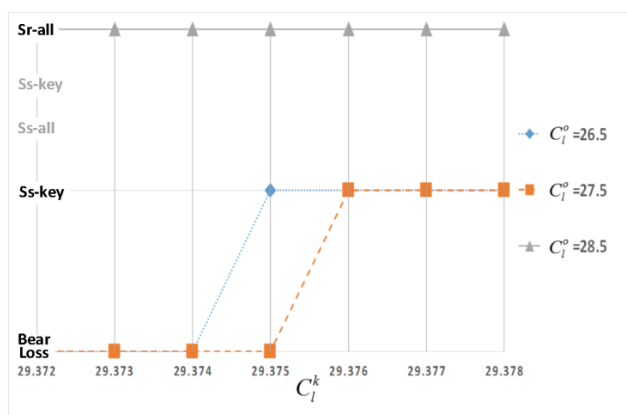


FIGURE 2. The mutual influence of C_l^k and C_l^o (other parameters: $D = 1000, \alpha = 0.3, p = 0.16, C_p^u = 19, C_h^{ss} = 1.5, C_h^{sr} = 1.3, C_a^{sr} = 400, C_o^u = 200$).

is little. When the difference is noticeable, the optimal policy would be safety stocks to meet key customers' demand..

3) THE MUTUAL INFLUENCE OF C_h^{ss} AND C_h^{sr}

This experiment contrasted the optimal policies under different holding costs. From Fig. 3 we can see that the best solution is Sr-all when the holding cost of strategic reserves is quite low and holding cost of safety stocks is high either in relative or absolute term. If both of them were high in absolute term, keeping strategic reserve only for key customers is a wise choice. If C_h^{ss} , the holding cost of safety stocks, is low, we'd better use safety stocks for only key customers. Considering that the holding cost of strategic reserves is notably lower than the holding cost in practice, this experiment indicates that strategic reserves would be a competitive policy in many scenarios.

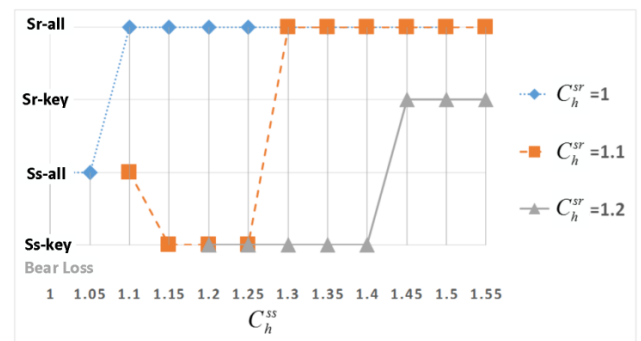


FIGURE 3. The mutual influence of C_h^{ss} and C_h^{sr} (other parameters: $D = 1000, \alpha = 0.3, p = 0.16, C_l^k = 33, C_l^o = 27, C_p^u = 20, C_a^{sr} = 400, C_o^u = 200$).

4) THE MUTUAL INFLUENCE OF C_h^{sr} AND C_a^{sr}

The holding cost C_h^{sr} and access cost C_a^{sr} are all costs of strategic reserves. This experiment proved that the holding cost C_h^{sr} and access cost C_a^{sr} has complementary influence on the excellence of strategic reserves. If C_a^{sr} was low enough, strategic reserves would be preferred even if we suffered a relative high C_h^{sr} . Similarly, a low C_h^{sr} would ensure us using strategic reserves while C_a^{sr} was relative high. It should be noticed that if we had a low access cost C_a^{sr} , we would have a wide range of C_h^{sr} to allow us choosing the Sr-key policy.

5) THE MUTUAL INFLUENCE OF C_a^{sr} AND C_p^u

In our model, unit purchasing cost C_p^u determined the set-up cost of strategic reserves. From Fig. 5 we can see that strategic reserves would be the optimal policy if both C_a^{sr} and C_p^u were low. However, as the increase of C_a^{sr} and C_p^u , the cost of safety stocks and BearLoss policy was relative decreased and became better choices. If we contrast different broken line of C_o^u , it is obvious that the optimal policies changed quickly as the changing of C_p^u and slowly as the changing of C_a^{sr} . It proved that strategic reserves are more sensitive to C_p^u and

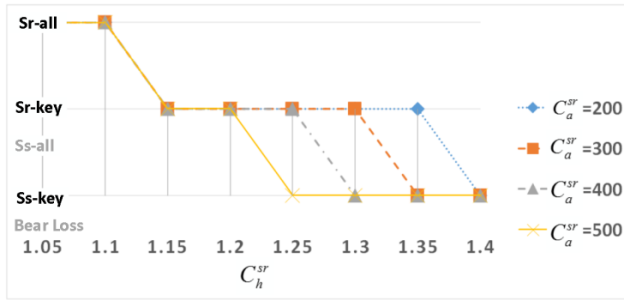


FIGURE 4. The mutual influence of C_h^{sr} and C_a^{sr} (other parameters: $D = 1000$, $\alpha = 0.3$, $p = 0.16$, $C_l^k = 33$, $C_l^o = 27$, $C_h^{ss} = 1.5$, $C_p^u = 20$, $C_o^u = 200$).

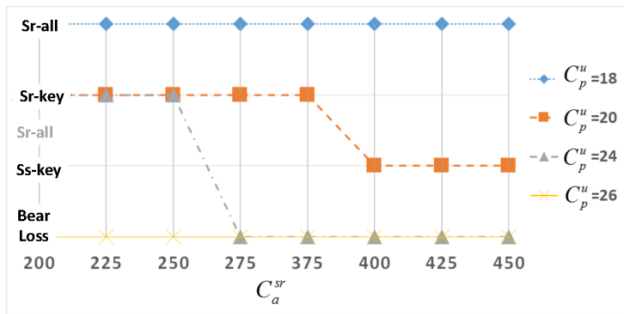


FIGURE 5. Mutual influence of C_a^{sr} and C_p^u (other parameters: $D = 1000$, $\alpha = 0.3$, $p = 0.16$, $C_l^k = 33$, $C_l^o = 27$, $C_h^{ss} = 1.5$, $C_h^{sr} = 1.3$, $C_o^u = 200$).

hence suitable for low value items or should be established when market price is low.

IV. TWO SUPPLIERS MODEL

In this section, we suppose the manufacturer have two suppliers, one unreliable supplier and one backup supplier. The manufacturer now has three policies to mitigate the supplier disruption: safety stocks, strategic reserves and backup supplier.

A. ASSUMPTIONS

Besides the assumptions in single supplier model, we also suppose the unreliable supplier offered lower price and was preferred, which is the same in other research, such as [33]–[35]. The backup supplier, who was suppose charging a higher price, would not suffer disruption and be invoked only at disruption. If the manufacturer invoked the backup supplier, there would be a fixed ordering cost.

Although some companies have more than two suppliers, their role could be thought as preferred supplier in normal time and backup supplier in disruption. So we think that the single supplier model and two suppliers model can represent a great variety of situations.

B. MODEL DESCRIPTION

Besides notations in the single supplier model, we also use the following notations.

Parameters:

- C_p^b unit purchasing cost of the backup supplier
- C_o^b fixed ordering cost of the backup supplier

Decision variables

- V^b volume purchased from the backup supplier

If there is no disruption, the manufacturer’s cost would be the same as in formula (1). When the disruption happened, the manufacturer would not only pay the holding costs of safety stocks and strategic reserves and lost sale cost, but also may pay costs for the purchasing from the backup supplier in current order cycle. The rebuilding of strategic reserves and safety stocks from the unreliable supplier in next order cycle should also be seen as disruption response cost. So the total cost at the disruption would be:

$$(V^{ss} + V^{sr}) * C_p^u + V^{ss} * C_h^{ss} + V^{sr} * C_h^{sr} + \text{sgn}(V^{ss}) * C_a^{sr} + \text{sgn}(V^b) * C_o^b + V^b * C_p^b + C_l^k * N^k + C_l^o * N^o \quad (9)$$

The aim of the manufacturer is to minimize the ETC (Expected Total Cost). The model of two suppliers problem would be as follows:

$$\begin{aligned} \text{MIN ETC} &= (1 - p) * (D * C_p^u + C_o^u + V^{ss} * C_h^{ss} + V^{sr} * C_h^{sr}) \\ &+ p * [(V^{ss} + V^{sr}) * C_p^u + V^{ss} * C_h^{ss} \\ &+ V^{sr} * C_h^{sr} + \text{sgn}(V^{ss}) * C_a^{sr} + \text{sgn}(V^b) * C_o^b \\ &+ V^b * C_p^b + C_l^k * N^k + C_l^o * N^o] \quad (10) \\ \text{Subject to } V^{ss} &\geq 0 \quad (11) \\ V^{sr} &\geq 0 \quad (12) \\ V^b &\geq 0 \quad (13) \\ V^{ss} + V^{sr} + V^b &\leq D \quad (14) \end{aligned}$$

According to the assumptions, the unmet demand can be determined as follows:

$$\begin{aligned} N^k &= 0, N^o = D - V^{ss} - V^{sr} - V^b, \\ &\text{if } V^{sr} + V^{sr} + V^b \geq \alpha * D \quad (15) \\ N^k &= \alpha * D - V^{ss} - V^{sr} - V^b, N^o = (1 - \alpha) * D, \\ &\text{if } V^{sr} + V^{sr} + V^b < \alpha * D \quad (16) \end{aligned}$$

C. NUMERICAL EXPERIMENTS AND MANAGERIAL INSIGHTS

To compare the effectiveness of backup supplier to safety stocks and strategic reserves in different disruption scenarios, similar experiment settings were adopted. To address the difference brought by the backup supplier, we compared the influence of environment parameter α and p , purchasing price of unreliable supplier and backup supplier, the access cost of strategic reserves and ordering cost of reliable supplier.

In two suppliers model, besides policies in Table 2, the manufacturer has two more policies:

In the two suppliers model, we focus on scenarios in which backup supplier is invoked instead of similar experiments in

TABLE 3. Two extra policies adopted by the manufacturer.

| Policies Abbr. | Policies Detail | Value of Decision Variable |
|----------------|--|--|
| Bs-key | Purchasing from the backup supplier to meet the demand of KEY customers, but the demand of ordinary customers would be unmet. No safety stocks and strategic reserves. | $V^{ss}=0$ $V^{sr}=0$ $V^b=\alpha*D$ |
| Bs-all | Purchasing from the backup supplier to meet the demand of ALL customers. No safety stocks and strategic reserves. | $V^{ss}=0$ $V^{sr}=0$ $V^b=D$ |

single supplier model. In fact, comparing similar situations with different optimal policies will help us gain interesting findings.

1) MUTUAL INFLUENCE OF α AND p

The impact of α and p on the optimal policy was firstly tested in the two suppliers model. We choose the same parameters as the experiment in single supplier model to probe the difference introduced by the extra backup supplier. Experiment results was shown in Fig. 6.

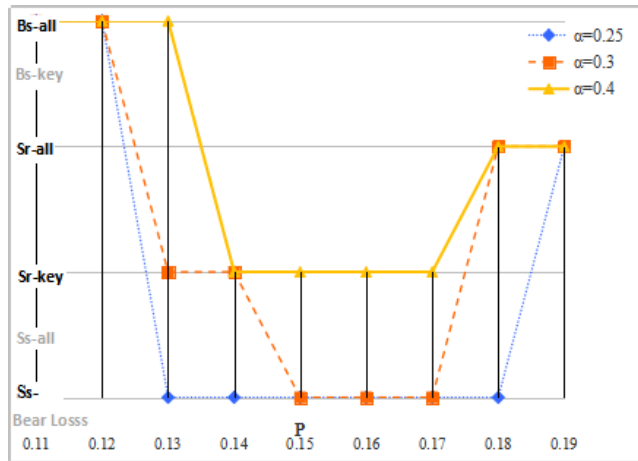


FIGURE 6. Mutual influence of α and p on optimal policy (other parameters: $D = 1000, C_f^k = 33, C_f^o = 27, C_p^u = 19, C_p^b = 29, C_h^{ss} = 1.5, C_h^{sr} = 1.3, C_a^{sr} = 400, C_o^u = 200, C_o^b = 500$).

The notable difference is the optimal policy in two suppliers model is Bs-all is employed when p is quite low. In contrast, it is Bear Loss in single supplier model (see Fig. 1). The change proved the employment of backup supplier can reduce the total cost in relatively stable circumstance. Since in real world the supplier finding cost is insignificant compared with the ordering cost and purchasing cost, it would be beneficial to establish potential supply relationship with the backup supplier.

When the p is high, the optimal policy are still Sr-all. It further proved that strategic reserves are more effective in high uncertainty circumstance.

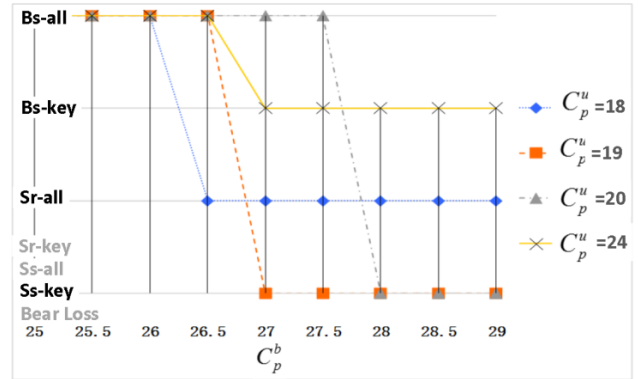


FIGURE 7. Mutual influence of C_p^u and C_p^b on optimal policy (other parameters: $D = 1000, \alpha = 0.3, p = 0.16, C_f^k = 33, C_f^o = 27, C_h^{ss} = 1.5, C_h^{sr} = 1.3, C_a^{sr} = 400, C_o^u = 200, C_o^b = 500$).

2) MUTUAL INFLUENCE OF C_p^u AND C_p^b

Fig. 7 revealed the mutual influence of C_p^u and C_p^b . We can see that the optimal policies at difference C_p^b are often the same. In contrast, they are more likely change following the change of C_p^u . It implies the unit purchasing cost of unreliable supplier C_p^u has bigger impact on the total cost than the backup cost. Therefore, the manufacturer should choose the cheapest supplier as the preferred, and the most reliable supplier as the backup.

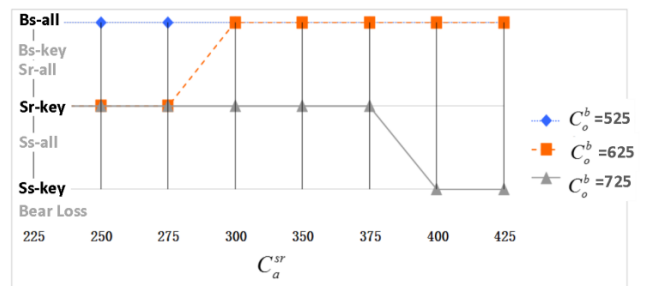


FIGURE 8. Mutual influence of C_a^{sr} and C_o^b on optimal policy (other parameters: $D = 1000, \alpha = 0.3, p = 0.16, C_f^k = 33, C_f^o = 27, C_h^{ss} = 1.5, C_h^{sr} = 1.3, C_a^{sr} = 400, C_o^u = 200, C_o^b = 500$).

3) MUTUAL INFLUENCE OF C_a^{sr} AND C_o^b

Under the same perspective, we can know from Fig. 8 that the optimal policy and total cost are more sensitive to C_o^b . Therefore, the manufacturer should try to lower the fixed ordering cost of backup supplier while bearing a high access cost of strategic reserves.

V. CONCLUSIONS

This research considered policies adoption in mitigating supply disruption from the customer heterogeneity perspective.

Many previous studies in supply disruption management suppose customers were similar in purchasing attributes and opportunity cost. This article emphasizes the customer heterogeneity in industrial goods industry which would cause different lost sale cost and had impacts on optimal mitigation policies. Based on the heterogeneous customer assumption, we established the single supplier and two suppliers model and the sensitivity analysis of optimal policies to different scenario parameters was carried.

Based on our experiments results in different scenarios, safety stocks are still desirable when the proportion of key customers are low. The work also proved that strategic reserves and backup supplier could reduce the total cost especially when there is a high proportion of key customers. It suggests enterprises with high customer concentration should employ strategic reserves or backup supplier.

Strategic reserves are more effective when the disruption probability is low, or the holding cost of strategic reserves is considerably lower than safety stock, or key customers may cause higher loss, or purchasing price from the unreliable supplier is low.

If the disruption probability is low and unreliable suppliers are less possible to be disrupted, or the backup supplier's price is not very higher than the unreliable supplier's, it would be better for the purchaser to find a backup supplier.

By the customer heterogeneity perspective, our work may enrich the research of supply disruption mitigation. The particular customer behaviors in industrial purchasing are revealed while simulations for optimal policies in different scenarios are performed. The findings may be useful to guide supply disruptions in industrial goods industry.

Findings would be more contributory and applicable if assumptions were closer to reality. Although our heterogeneous customer assumption is a step further, it still has some limitations. Key customers may explore new suppliers and reduce dependence on the current supplier after its disruption, which means the loss of the manufacturer may be caused not only in the current order cycle but also in future order cycles. This time-lagged customer behavior is worth further research.

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