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Supply chain hoarding and contingent sourcing strategies in anticipation of price hikes and product shortages

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ABSTRACT

In anticipation of price hikes and shortages caused by supplier disruptions and manufacturer production stops, customers might stockpile extra products. In the case of a supplier disruption, a manufacturer may decide to continue producing using a contingent source. Capturing the price dynamics in four disruption-related periods (i.e., responding, rising, recovering, and recovered), we derive optimal hoarding policies for customers. The results indicate that customer hoarding decisions fall into multiple patterns depending on the interactions between disruption events, market responses (quick and slow), and market recovery (instant, quick, slow, and never). We next present contingent sourcing tactics for manufacturers to mitigate disruptions with and without customer hoarding. We find that future price increases could induce contingent sourcing even if it is unprofitable to resume production during the price-responding phase. Our results offer recommendations regarding when and how to use hoarding and contingent sourcing accounting for uncertain disruption duration and asymmetric information along with disruption- and recovery-driven price dynamics. These recommendations can be of particular value for supply chain decision-making at times of growing inflation. We also demonstrate the impacts of customer hoarding and disruption information on the value of contingent sourcing.

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1. Introduction

Crises can lead to partial or full supply breakdowns, triggering ripple effects downstream in Supply Chains (SCs) (Shou *et al.*, 2013; Ivanov, 2022); one of these ripple consequences is rising prices. Consequently, persistent SC shortages frequently lead to price hikes and growing inflation, as seen in the 2022 semiconductor and energy crises that followed the COVID-19 pandemic disruptions. For example, the semiconductor industry production decline sent ripples downstream to the automobile industry. Through the global vehicle production networks, this shortage then quickly spread across the entire world, leading to significant price increases and product shortages (Lund *et al.*, 2020; Yahoo, 2022). Drops in product availability caused by supply failures can cause various patterns of price hikes in numerous goods categories (Carvalho *et al.*, 2021; Gupta *et al.*, 2021).

To deal with potential price increases, forward-looking customers may respond by hoarding large quantities of still-available products (or their substitutes) that exceed their current needs. Hoarding behavior is a common phenomenon during disruptive events that lead to deep uncertainty (Islam *et al.*, 2021; Sheu and Choi, 2021); it is caused by customers anticipating stock-outs and triggered by fear of significant price increases (Su, 2010). Sterman and Dogan (2015) and Sheffi (2021) emphasize that hoarding behavior is very common in cases of anticipated product shortages and price dynamics. LaBelle and Santacreu (2022) provide empirical evidence of the relationship between COVID-19-driven SC) disruptions and inflation.

During the COVID-19 pandemic, various hoarding behaviors have been observed worldwide. For example, residents hoard essential groceries such as canned food, and chipmakers (including TSMC and Intel) stockpile at least 24% more essential raw material inventory than ever before (Kim *et al.*, 2020; Klotz, 2021; New York Post, 2022). Individuals gambled on hoarding based on alerts in fall 2021 about COVID-19-driven disruptions at manufacturers in Asia, forcing many U.S. retailers to buy large quantities in advance (New York Times, 2022). Hoarding can also be inefficient during SC crises of uncertain duration and their associated price dynamics (Coles, 2022; Oliva *et al.*, 2022).

Numerous reactive and proactive strategies, such as inventory and sourcing policies from the supply side and customer compensation from the demand side, have been developed in the literature to hedge against supply failures and their cascading effects (Ivanov, 2020; Li et al. 2021). Ivanov *et al.* (2014) introduced the term "ripple effect" to describe the impact of disruption propagation on performance and other

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disruption-based changes in SCs. Subsequently, a series of studies appeared that elaborated on the ripple effect of establishing operation strategies for ordering, inventory control, and production planning (Queiroz *et al.*, 2022; Ivanov and Dolgui, 2021; Rozhkov *et al.*, 2022).

Nonetheless, few studies have considered the ripple effect of disruption- and recovery-driven prices and the impact of customer stockpiling considering price dynamics. Some recent marketing studies have begun to focus on consumer hoarding behavior in an attempt to understand how forward-looking consumers respond to price promotions (Ching and Osborne, 2020). However, to the best of our knowledge, the SC research is still in its infancy, particularly regarding: (i) disentangling the incentives and effects of customer hoarding driven by the ripple effect in both material flow and prices and (ii) establishing strategies to jointly optimize customer hoarding and contingent sourcing. We address these two questions in this study.

Our contribution to the literature is twofold. First, we derive optimal hoarding strategies to maximize customer utility, disentangling the following two questions: Should hoarding be realized and, if so, how? How do the disruption and post-disruption dynamics of material flow and prices interact to drive customer hoarding behavior? Second, optimal sourcing strategies to maximize manufacturers' profit are provided in closed form. They illustrate how to adjust contingent sourcing quantities following customer hoarding (or non-hoarding) behavior, disruption-driven price dynamics, and disruption length.

The remainder of this article is organized as follows. Section 2 presents the related literature, and Section 3 describes the problem. Section 4 proposes contingent sourcing strategies for manufacturers with customer non-hoarding. Section 5 discusses customer hoarding behavior and the corresponding contingent sourcing strategies for manufacturers when customers hoard. Section 6 highlights managerial insights, and Section 7 offers conclusions and opportunities for future research. All proofs not provided in the article can be found in the Appendix.

2. Literature analysis

Sourcing strategies used to hedge against SC disruptions include both proactive (e.g., supplier diversification) and reactive (e.g., contingent sourcing) aspects (Saghafian and Van Oyen, 2012; Sawik, 2019, 2021, 2022; Freeman *et al.*, 2020). Our work considers a contingent sourcing strategy under which the manufacturer/retailer places emergency orders with a backup supplier after its main supplier fails. The existing literature tends to focus on disentangling contingent sourcing time and/or quantity under various settings. For example, considering uncertain lead-times, Kouvelis and Li (2012) discuss the timing and size of ex-post emergency sourcing. Gupta *et al.* (2015) study the optimal order quantities to mitigate a SC supply failure with uncertain hitting time using two competing manufacturers. This is extended in Gupta *et al.* (2021) by considering the timing of disruptions and product substitution, as well as pricing decisions. A few studies acknowledge the importance of understanding customers' ex-post behavior before developing optimal sourcing decisions. Considering the learning effect facilitated among the same group of customers, He *et al.* (2020) explore contingent sourcing decisions by forecasting customers' ex-post reactions. Snyder *et al.* (2016) and Golmohammadi and Hassini (2020) provide comprehensive reviews for the first stream.

A growing body of literature examines how to manage the ripple effect (Ivanov *et al.*, 2014; Dolgui *et al.*, 2018; Hosseini *et al.*, 2019; Ivanov *et al.*, 2019; Pavlov *et al.*, 2022; Tucker *et al.*, 2020; Katsaliaki *et al.*, 2022). For instance, Li, Chen, Collignon, and Ivanov (2021) explore the effects of both forward and backward disruption propagation. Using a multi-portfolio approach and scenario-based stochastic programming models, Sheffi (2021) develops mitigation and recovery tactics that include pre-positioning inventory and ordering recovery supplies from backup suppliers. Ivanov and Dolgui (2021) review OR-methods to cope with the ripple effect in SCs.

Customer hoarding behavior is also well considered in similar terms, such as panic buying and buying frenzies (Allon and Bassamboo, 2011). First, a series of studies in marketing discusses how consumer hoarding impacts retailers' decisions and how customers strategically stockpile storable products when prices are low (Guo and Villas-Boas, 2007; Courty and Nasiry, 2016; Chen and Rao, 2020). For instance, modeling storage cost as a step function of inventory, Ching and Osborner (2020) investigate how forward-looking customers react to storable product price promotions. Second, in addition to changing sales prices, inspired by the emerging phenomena during the COVID-19 pandemic, Hall *et al.* (2020), Prentice *et al.* (2020), and Putri *et al.* (2021) analyze hoarding in response to potential future shortages. Billore and Anisimova (2021) present a systematic review of panic buying research. Third, a few studies develop strategies for mitigating supply disruptions in the presence of consumer hoarding. Using a rational expectations equilibrium analysis, Shou *et al.* (2013) discuss how retailers adjust inventory and quota policies in response to consumer panic buying. Considering consumer hoarding behavior in anticipation of a supply disruption in the next period, Yoon *et al.* (2018) investigate a retailer's sourcing strategy and find that hoarding becomes stronger if consumers have experienced similar past events. Since wholesalers tend to retain inventory prior to a supply disruption, Tsao *et al.* (2019) explore optimal ordering quantities and substitutions for wholesalers who purchase two brands of a product with different weights from two suppliers and sell to multiple differentiated retailers. By dividing customers in one period into two batches, Zheng *et al.* (2021) study retailers' optimal inventory ordering policy and discuss whether extra units should be stockpiled for future consumption.

Our study differs from the existing literature in three main dimensions. First, most studies evaluate panic situations over two fixed periods, whereas empirical survey studies (Pan *et al.*, 2020) indicate that characteristics such as the intensity of disruptive events play essential roles in driving

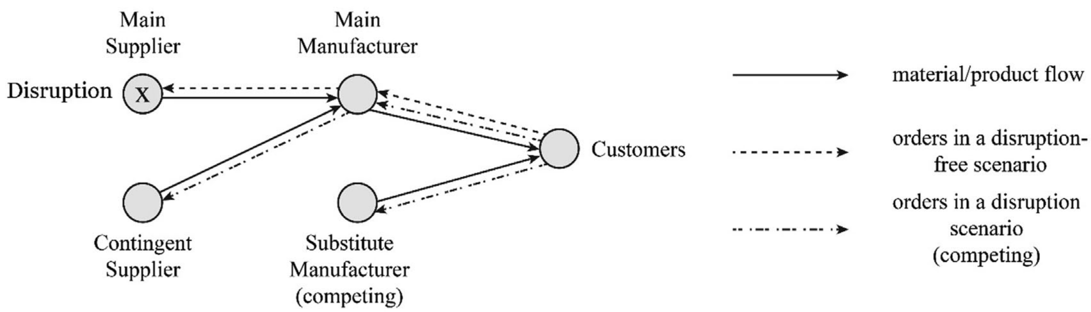

Figure 1. SC system in our model.

customer panic behavior. Thus, we incorporate both the disruption length and disruption recovery time to disentangle customer hoarding behavior. Second, despite recent discussions of the ripple effect, these studies have largely ignored two aspects: a disruption-driven price disturbance could cascade from raw materials down to the finished product market or could also propagate from the disruption to recovery and post-recovery periods. We fill this gap by incorporating multi-period cascading processes in our models. Third, we also consider the market's price response time to capture the essential time-based characteristics that have been shown to be important in industries (Carvalho *et* al., 2021).

3. Problem statement

We consider a system in which one manufacturer purchases from the main supplier (Li, He, and Minner, 2021), and there exists a substitute manufacturer and a contingent supplier (Figure 1).

Figure 1 illustrates the SC system and material and information flow logic. In the nominal (disruption-free) scenario, customers order from the main manufacturer, that in turn, places an order with the main supplier. When the main supplier experiences a disruption and stock-outs occur at the main manufacturer, customers can switch to substitutable products provided by a substitute manufacturer. The main manufacturer can react by switching to the contingent supplier. Figure 2 illustrates the decision-making logic and timeline in our analysis. Unexpected events trigger a main supplier failure of uncertain duration T, leading to production disruption at the main manufacturer, which does not maintain raw material or finished product inventories. Such settings are largely utilized in just-in-time production systems (Shen and Sun, 2021). Disturbed by the shortages that cascade from raw materials to finished products, the post-disruption price exhibits diversified dynamics in different phases (i.e., rising after the disruption and recovering after the disruption terminates). Anticipating future price hikes, customers may decide to stockpile products, buying more than they need and hoarding them for future consumption. Facing stock-outs at the main manufacturer, customers can purchase substitutable products with lower perceived value.

In anticipating customer hoarding behavior, the manufacturer can implement a contingent sourcing strategy; that is, the manufacturer can turn to the contingent supplier and purchase replenishments at a high price to resume partial or full production. We normalize the deterministic demand rate to one. Before the supply disruption occurs, production is realized at demand rate "1." Without loss of generality, we assume that a supply failure of random length T hits at time "0." As is commonly done in the literature (Paul *et al.*, 2023), we also assume that the disruption length follows a uniform random distribution with a mean value $E(T)$ and a density distribution function given as $f_T = 1/E(T)$. These assumptions correspond to the realities of decision-making in industry. Through collaboration and some preliminary information analysis, both the manufacturer and customers can roughly estimate an upper bound for the disruption length, denoted as 2μ and $2\mu_C$, respectively. However, no further information is available for them to make more precise predictions. This is consistent with reality, considering that most companies are still in the early stages of achieving a seamless flow of data/information (Lund *et al.*, 2020). Note that $\mu = \mu_C$ means they share the same information. Unlike the related literature that considers shortage-triggered price increases in a single fixed period (e.g., Yoon *et al.,* 2018), we capture the post-disruption price dynamics in four periods: *price-responding* $[0, t_0]$, *price-rising* $(t_0, T]$, *price-recovering* $(T, T + T_r]$, and *price-recovered* $(T + T_r, +\infty)$. Production stops immediately, resulting in a stock-out for customers and triggering a rise θ_1 in the finished product selling price, where $\theta_1 > 0$. However, as Carvalho *et al.* (2021) pointed out, the selling price could remain stable for a certain period before it starts to rise; therefore, we also consider a price response time of t_0. Once supply is restored, it is also likely to take recovery time T_r for the after-disruption price to return to normal (CBS News, 2021).

θ_2 stands for price changes during the price-recovery period, which could occur in two opposite situations in practice. If $\theta_2 > 0$, the price continues to grow after the supply disruption's end, but it cannot exceed the prior price increase (i.e., $\theta_2 \le \theta_1$). In other words, a postponed effect in the disruption-driven price-rise might exist, which is commonly observed due to disruption tails, such as delayed orders (Ivanov, 2019, 2021). If $\theta_2 < 0$, the price level in recovery becomes lower than the pre-disruption level. In reality, such phenomena could appear in markets where customers exhibit hoarding behavior. Driven by the surge in demand, competing manufacturers may sharply increase their production capacities, leading to short-term oversupply after the interruption ends (Austin, 2014). Consequently, the

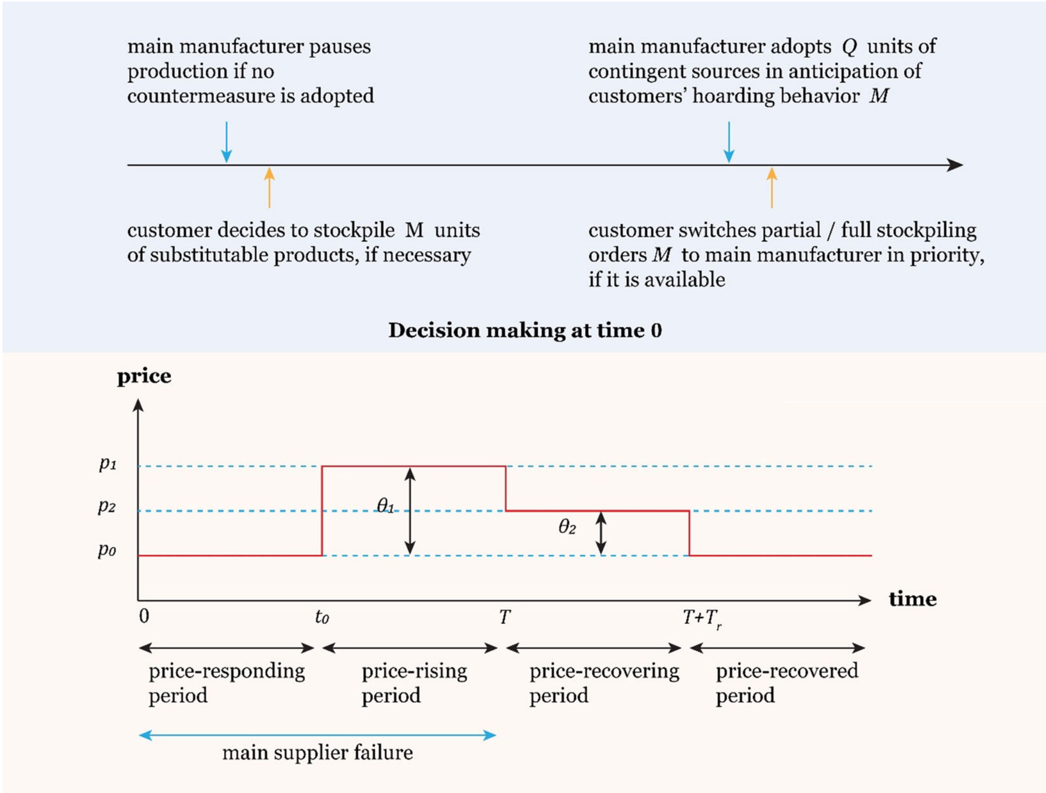

Figure 2. Decision-making logic and timeline.

price could experience a dramatic drop before it returns to normal.

$$p(t) = \begin{cases} p_0, & \text{if } 0 \le t \le t_0 \\ p_1 = p_0 + \theta_1, & \text{if } t_0 < t \le T \\ p_2 = p_0 + \theta_2, & \text{if } T < t \le T + T_r \\ p_0, & \text{if } t > T + T_r \end{cases}. \tag{1}$$

where p_0 represents the pre-disruption selling price. The ratio of the disruption length to the price recovery time describes the price recovery speed:

$$T/T_r = k. \tag{2}$$

Given the price recovery speed k, five market types are considered. If $k \to +\infty$ (i.e., $T_r \to 0$), the finished product after-disruption selling price instantly returns to the pre-disruption level when the main supplier resumes supplying raw materials. This market is referred to as "instant recovery (IR)." If $k \to 0$, the price can never recover because of the permanent impacts; thus, the market is referred to as "never recovery (NR)." Otherwise, if $0 < k < +\infty$, the "quick recovery (QR)" and "slow recovery (SR)" markets are defined, depending on whether k exceeds the thresholds. Similarly, the price response time t_0 also defines two types of markets: "quick response" and "slow response." Table 1 summarizes the market types derived from the characteristics of price-rising and price-recovering, where the thresholds are given in (20). The notations are shown in Table 2.

In summary, we model a three-stage SC with main and contingent suppliers and main and substitute manufacturers. The main supplier experiences a disruption of unknown duration, leading to a production stop at the main manufacturer. Customers can utilize a hoarding strategy to hedge against disruption-driven price hikes by purchasing unusually high quantities of a substitutable product from the substitute manufacturer. The main manufacturer can decide to use contingent sourcing to keep producing and the customer can hoard products at the main manufacturer. The price fluctuates across four disruption and recovery periods. Our objective is to determine the optimal hoarding strategy for customers and the optimal contingent sourcing strategy for the main manufacturer subject to the following assumptions:

1. Main and substitutable products are homogenous in terms of price but differ from each other with regard to value for customers.
2. The substitute manufacturer does not influence price dynamics; that is, it is considered a "passive" element in our model without any competition-based quantity or price reactions to panic buying or any influence on customer hoarding behavior.
3. Customers can stockpile either from the main or substitute manufacturer; a mixed policy with partial purchasing at the main and substitute manufacturers is now allowed.
4. The main manufacturer operates using a just-in-time policy and has no inventory on hand.
5. The disruption duration length is modeled via different uniform random distributions, under the different information of customers and the manufacturer.
6. We consider a once-off hoarding behavior; that is, the hoarding decision is made by the customer in anticipation of future price hikes due to a supply disruption at time $t = 0$.

Table 1. Market-type overview.

Condition			*Market type*	
$t_0 < \min\left\{\frac{2\mu_C}{1+\frac{1}{k}},\ \tau^{M_a^*}, \tau^{M_b^*}\right\}$		response	quick	
$t_0 > \min\left\{\frac{2\mu_C}{1+\frac{1}{k}},\ \tau^{M_a^*}, \tau^{M_b^*}\right\}$	$t_0 < \max\{0, \min\{\tau^{M_{2a}^*}, \tau^{M_{2b2}^*}\}\}$		slow	slightly
	$\max\{0, \min\{\tau^{M_{2a}^*}, \tau^{M_{2b2}^*}\}\} < t_0 < \tau^{M_{a0}^*}$			moderately
	$t_0 > \tau^{M_{a0}^*}$			considerably
$k \to +\infty$ (i.e., $\theta_2 \to 0$)		recovery	instant (IR)	
$k_{a0} < k < +\infty$	$k_{a0} < k < \max\{k_{aR}, 0\}$		quick (QR)	moderately
	$\max\{k_{aR}, 0\} < k < +\infty$			considerably
$0 < k < k_{a0}$	$\max\{k_{aR}, 0\} < k < k_{a0}$		slow (SR)	moderately
	$0 < k < \max\{k_{aR}, 0\}$			considerably
$k \to 0$			never (NR)	

Table 2. Notations used in this article.

	Notations	*Description*
Decisions	Q	manufacturer contingent sourcing quantity
	M	customer hoarding quantity
Parameters	T	length of disruption duration
	t_0	time when the during-disruption selling price starts to increase, referred to as "price response time"
	T_r	recovery time required for the selling price to return to the pre-disruption level
	k	after-disruption selling price recovery speed
	$\mu,\ \mu_C$	mean value of the random disruption length T, predicted by the manufacturer and customers
	$p(t)$	selling price per unit of product (substitutable and original products)
	p_0	pre-disruption selling price per unit of product
	θ_1	disruption-triggered price increase "during-disruption price rise"
	θ_2	price change during the disruption recovery, namely "after-disruption (recovering) price rise (or drop)"
	$v_0 + v_a$	consumer valuation of one unit of the original product, $v_a > 0$
	v_0	consumer valuation of one unit of a substitutable product
	$d(t)$	demand rate at time t after a disruption occurs
	c_s	unit mark-up cost for the contingent sourcing
	$c_h,\ c_H$	unit inventory holding cost per unit of time for the customers and manufacturer
	c_1	unit production cost per unit of product
	$C_M,\ C_N$	additional costs from contingent sourcing, with and without customer hoarding
	$R_M,\ R_N$	additional revenue from contingent sourcing, with and without customer hoarding
	$I_C(t)$	inventories held by customers
	$I_M(t),\ I_N(t)$	inventories held by the manufacturer, with and without customer hoarding
	$U,\quad U_N$	customer utility with and without hoarding

4. Contingent sourcing without customer hoarding

To establish a benchmark, we first analyze the problem without customer hoarding. Hence, demand is maintained at $d(t) = 1$. The manufacturer reroutes to a secondary source at the beginning of the disruption, purchasing Q units of raw material. This allows production to be gradually restored, thereby satisfying demand. Accordingly, the raw material inventory $I_N(t)$ drops at a constant rate of 1 until it reaches 0 at time Q. Then, the raw material replenishment could fall into two scenarios.

Remark: As we set the demand rate without hoarding (also the customers' consumption rate) to be "1," Q is also considered the time when Q units of contingent sources are used to meet demand. In this context, for example, the expression $Q - T$ means that there are $Q - T$ units of raw material that can be used to satisfy demand (without hoarding) in time period $[T, Q]$.

If the supply failure ends before inventory is fully depleted, that is, $T \leq Q$, the manufacturer can receive raw material from the primary supplier immediately after it runs out of inventory at time Q. In contrast, if $T > Q$, there is a short phase $(Q,\ T]$ during which the primary supplier remains unavailable. In this short phase, a passive acceptance strategy is adopted (Li *et al.*, 2017; Rozhkov *et al.*, 2022). The inventory during the disruption period $(0,\ T]$ can be described as

$$\begin{aligned} I_N(t) &= Q - t, \text{ if } t \in [0, Q]; \\ I_N(t) &= 0, \text{ if } t \in [Q, \max(Q,\ T)]. \end{aligned} \tag{3}$$

Compared with the passive acceptance strategy, the manufacturer faces both additional revenue R_N and additional costs C_N from contingent sourcing during the period $[0, Q]$ when Q units of raw materials are gradually depleted. Therefore, the manufacturer experiences a profit difference ΔP_N, referred to as the value of contingent sourcing:

$$\Delta P_N = R_N - C_N. \tag{4}$$

$$C_N = c_s Q + c_H \int_0^Q I_N(t)dt = c_s Q + \frac{1}{2} c_H Q^2. \tag{5}$$

The first term of C_N represents the contingent sourcing markup cost, and the second term measures the inventory holding cost following the inventory function presented in (3).

Additional revenue R_N is generated by satisfying demands at price $p(t)$ utilizing Q units of the contingent source materials during the disruption period $[0, T]$. Intuitively, $p(t)$ might have six patterns of dynamics based on the disruption length T, critical time Q when the manufacturer runs out of inventory, and time t_0 when the during-disruption price starts to rise. Let the random disruption length T vary within the range of $[0, 2\mu]$; these patterns can then be divided into two main scenarios: Scenario 1 where $Q \leq t_0$ and Scenario 2 where $Q > t_0$.

Table 3. Value of contingent sourcing without customer hoarding.

Scenario			*Revenue R_N*	*Value ΔP_N*
1	$Q \le t_0$	$T \le Q$	$R_N^{1a} = (p_0 - c_1)T$	$\Delta P_N^i = R_N^i - C_N,\ i = 1a, 1b, 2a, 2b, 2c.$
		$Q < T$	$R_N^{1b} = (p_0 - c_1)Q$	
2	$Q > t_0$	$T \le t_0$	$R_N^{2a} = (p_0 - c_1)T$	
		$t_0 < T \le Q$	$R_N^{2b} = (p_0 - c_1)T + \int_{t_0}^{T} \theta_1 dt$	
		$T > Q$	$R_N^{2c} = (p_0 - c_1)Q + \int_{t_0}^{Q} \theta_1 dt$	

1. $\boldsymbol{R_N}$ **in Scenario 1 where $\boldsymbol{Q \le t_0}$.** Under $Q \le t_0$, the manufacturer runs out of stock before the finished product selling price starts to rise. Contingent sourcing thus yields $R_N = (p_0 - c_1)\min(T,\ Q)$.
2. $\boldsymbol{R_N}$ **in Scenario 2 where $\boldsymbol{Q > t_0}$.** The manufacturer originally contingently purchases a relatively large amount of raw materials; thus, $Q - t_0$ units of inventory remain at time t_0. If the disruption lasts longer than t_0, the manufacturer earns additional revenue $R_N = (p_0 - c_1)\min\ (T,\ Q) + \int_{t_0}^{\min(T,\ Q)} \theta_1 dt$ from contingent sourcing due to the selling price increase during the interval $[t_0, \min(T,\ Q)]$. Conversely, if $T \le t_0$, no price rise occurs during the entire disruption, leading to $R_N = (p_0 - c_1)T$. From this discussion, the values of contingent sourcing are identified in scenarios of $T,\ Q,$ and t_0, as summarized in Table 3.

According to Table 3, when the manufacturer encounters a supply failure with random length T, it arrives at the expected value $E(\Delta P_N)$ of using contingent sources:

$$E(\Delta P_N) = \begin{cases} \int_0^Q \Delta P_N^{1a} f_T dT + \int_Q^{2\mu} \Delta P_N^{1b} f_T dT, & \text{if } Q \le t_0 \\ \int_0^{t_0} \Delta P_N^{2a} f_T dT + \int_{t_0}^{Q} \Delta P_N^{2b} f_T dT + \int_Q^{2\mu} \Delta P_N^{2c} f_T dT, & \text{if } Q > t_0 \end{cases}. \tag{6}$$

Therefore, we can propose Model 1 to formulate the manufacturer's contingent sourcing problem.

Model 1: Optimizing contingent sourcing without customer hoarding:

$$Q^* \in \mathit{argmax}\, E(\Delta P_N). \tag{7}$$

$$\text{Subject to } E(\Delta P_N) \ge 0, \tag{8}$$

$$0 \le Q \le 2\mu. \tag{9}$$

The objective function in (7) maximizes the manufacturer's expected value of contingent sourcing, (8) ensures that contingent sourcing is superior to a passive acceptance strategy, and (9) provides the sourcing quantity range. Note, 2μ describes the upper bound of the random disruption length; thus, absent customer hoarding behavior, the contingent sourcing quantity Q is limited to an amount below 2μ. Solving Model 1, the optimal sourcing quantity Q^* is determined as shown in Proposition 1.

Proposition 1. (Manufacturer's optimal sourcing without customer hoarding)

(i) *If $c_s \ge p_0 - c_1 + \theta_1$ (large): $Q^* = 0$.*

(ii) *If $p_0 - c_1 < c_s < p_0 - c_1 + \theta_1$ (medium): $Q^* = Q_b^*$ in relatively quick response markets where $t_0 < 2\mu\left(1 - \sqrt{1 - \frac{(B_2+1)^2}{B_1+1}}\right)$, and $Q^* = 0$ otherwise.*

(iii) *If $c_s < p_0 - c_1$ (small): $Q^* = Q_b^*$ in relatively quick response markets where $t_0 < 2\mu\left(1 - \sqrt{1 - \frac{(B_2+1)^2}{B_1+1} + \frac{B_2^2}{B_1}}\right)$, and $Q^* = Q_a^*$ otherwise.*

$$Q_b^* = 2\mu\frac{B_2 + 1}{B_1 + 1},\ Q_a^* = 2\mu\frac{B_2}{B_1},$$
$$B_1 = \frac{p_0 - c_1 + 2\mu c_H}{\theta_1},\ B_2 = \frac{p_0 - c_1 - c_s}{\theta_1}. \tag{10}$$

As indicated in Proposition 1, the manufacturer's optimal contingent sourcing decision could follow three strategies. Note, $Q_a^* < t_0 < Q_b^*$. Under $Q^* = Q_b^*$, the manufacturer emergently purchases a large amount of raw materials at the start of the supply disruption so that customers can still be served when the finished product price starts to rise after t_0. Under $Q^* = Q_a^*$, a small quantity is purchased; thus, the manufacturer runs out of raw materials prior to t_0. With high c_s, it is unprofitable for the manufacturer to resume production and sell products in the future price-rising period. Intuitively, non-sourcing is advantageous. With medium c_s, the manufacturer prefers to purchase Q_b^* contingent sources if t_0 is relatively short. The manufacturer suffers a loss of profit in the first post-disruption phase. Such loss of profit can be overcome by the additional profit gained from future price rises in the second post-disruption phase. In contrast, if t_0 is relatively long, leading to a short price-rising period, such loss of profit cannot be avoided. In this setting, no contingent sourcing is superior, that is, $Q^* = 0$. With small c_s, the manufacturer is profitable from the beginning. To amplify the profit difference, a large $Q^* = Q_b^*$ is suggested in markets with relatively short t_0, and $Q^* = Q_a^*$ is provided otherwise.

Corollary 1. *Q_b^* increases with θ_1, while Q_a^* is independent of θ_1.*

Corollary 1 confirms two advantages of utilizing contingent sourcing. First, in markets with relatively long t_0, the purpose of contingent sourcing Q_a^* is to reduce or even prevent lost sales. Thus, consistent with conventional knowledge (Kouvelis and Li, 2012), Q_a^* is independent of θ_1. Second, benefitting from a relatively short t_0, the manufacturer gains additional profits by satisfying demand during the relatively long price-rising period at price $\theta_1 + p_0$. Intuitively, the manufacturer increases the sourcing quantity Q_b^* in the presence of a higher during-disruption price rise.

We also find that larger Q_a^* and Q_b^* are required if the random disruption lasts longer.

5. Contingent sourcing with customer hoarding

This section explores optimal hoarding for the customer and the manufacturer's optimal sourcing quantity Q^* under customer hoarding.

5.1. Customer optimal hoarding behavior

In line with Shou *et al.* (2013) and Sheffi (2021), we consider once-off hoarding behavior. In anticipation of a future price rise due to supply disruption and an associated production stop at the main manufacturer, at time $t = 0$, customers purchase M units of a substitutable product at price p_0 for both current consumption 1 and future consumption $M - 1$ in the interval $(0,\ M]$. Thus, no purchases are needed during $(0,\ M]$. After the stock is used up at time M, customer behavior returns to normal. That is, customers purchase 1 unit of product at time t to fulfill their real-time demand and hold no inventory.

The demand dynamics and corresponding inventory can be described as

$$d(0) = M,\ d(t) = 0 \text{ if } t \in (0,\ M], \text{ and } d(t) = 1 \text{ if } t \geq M. \tag{11}$$

$$I_C(t) = M - t \text{ if } t \in [0, M], \text{ and } I_C(t) = 0 \text{ if } t \geq M. \tag{12}$$

where $M > t_0$. Note, if $M \leq t_0$, customers reserve a small amount of products so that the stock runs out before the selling price rises. Due to the inventory holding costs incurred, this is not profitable for customers. Thus, we limit our discussion to $M > t_0$. With hoarding behavior, customers receive customer utility U during the period $[0,\ M]$ (namely, the period impacted by hoarding):

$$U = M(v_0 - p_0) - c_h \int_0^M I_C(t)dt = U_0 - \frac{1}{2} c_h M^2, \tag{13}$$

where $U_0 = M(v_0 - p_0)$ gives the utility gained from hoarding when the disruption occurs. The second term represents the inventory holding cost incurred in the impacted period.

Compared with non-hoarding, customers experience the utility difference ΔU, referred to as the value of hoarding; accordingly, (14) becomes:

$$\Delta U = U - U_N. \tag{14}$$

Next, to further identify the value of hoarding, we consider utility U_N during the impacted period. Without hoarding, customers purchase 1 unit of products at time t at the real-time price $p(t)$. In view of the random disruption length T and corresponding recovery time T_r, the selling price $p(t)$ could fall into three main patterns.

In Pattern 1, where $\boldsymbol{T} < \boldsymbol{t}_0$, the supply failure is short and ends before the finished product market starts to respond with price increases. In other words, customers will not experience future price increases even if no stock is preserved. Further, by returning to the original manufacturer when it is available in the second phase $[T,\ M]$, they could reach customer utility $U_N^1 = U_0 + \int_T^M v_a dt$.

In Pattern 2, where $\boldsymbol{t}_0 < \boldsymbol{T} < \boldsymbol{M}$, the supply failure lasts longer, it triggers a rise in the finished product market price after time t_0 that ends before time M. As a consequence, customers will experience a price-rising phase and a subsequent price-recovering phase during the impacted period $[0,\ M]$. Thus, customer utility U_N^1 is reduced by the two parts $\int_{t_0}^T \theta_1 dt$ and $\int_T^{\min(T+T_r,\ M)} \theta_2 dt$, leading to U_N^{2a} and U_N^{2b} in the two sub-patterns of $T + T_r < M$ and $T + T_r > M$. That is:

$$\begin{aligned} &U_N^{2a} = U_N^{2b} - \int_M^{T_r+T} \theta_2 dt \text{ in Pattern 2A} \\ &\qquad \text{where } t_0 < T < t_1 = M/(1 + 1/k); \\ &U_N^{2b} = U_0 - \int_{t_0}^T \theta_1 dt - \int_T^M \theta_2 dt + \int_T^M v_a dt \text{ in Pattern 2B} \\ &\qquad \text{where } t_1 < T < M. \end{aligned} \tag{15}$$

In Pattern 3, where $\boldsymbol{T} > \boldsymbol{M}$, the supply failure lasts longer than M. Thus, during the entire impacted period, customers order from the competing manufacturer at price p_0 before time t_0 and at price $p_0 + \theta_1$ thereafter, arriving at customer utility of $U_N^3 = U_0 - \int_{t_0}^M \theta_1 dt$.

To summarize, there are four forms of U_N, that is, $\{U_N^1,\ U_N^{2a},\ U_N^{2b}, U_N^3\}$, depending on the duration of the random disruption and the length of the impacted period $[0,\ M]$. U_N^{2a} never happens if $M \leq (1 + 1/k)t_0$, and U_N^{2b} never happens if $M \geq (1 + 1/k)2\mu_C$ (see (15)). Therefore, under $M > t_0$ and $T \leq 2\mu_c$, the expected value $E(\Delta U)$ that customers could gain from different levels of hoarding to cope with a random supply failure falls into two scenarios, as shown in Table 4.

Given $E(\Delta U)$, we formulate Model 2 for customers to optimize their hoarding decisions.

Model 2: Optimization of customer hoarding:

$$M^* \in arg \max E(\Delta U). \tag{16}$$

$$\text{Subject to } E(\Delta U) \geq 0, \tag{17}$$

$$M > t_0. \tag{18}$$

The objective function, (16), maximizes the expected value of hoarding for strategic customers, (17) guarantees that the decision to hoard is superior to no hoarding, and (18) represents the range of the hoarding decision. Solving Model 2, the optimal hoarding decision M^* can be achieved as $= \{M_{2b}^*,\ M_c^*,\ M_b^*,\ M_a^*,\ 0,\ \lim_{\boldsymbol{k}\to\infty} M_b^*\}$.

$$\begin{aligned} &M_a^* = \frac{2\mu_C\theta_1 - t_0\theta_2}{A_1},\ M_b^* = \frac{2\mu_C\theta_1}{A_2}, \\ &M_c^* = \frac{2\mu_C(\theta_2 - v_a)}{2\mu_C c_h + \frac{k}{k+1}\theta_2},\ M_{2b}^* = \frac{2\mu_C(\theta_2 - v_a) - \theta_2 t_0}{2\mu_C c_h}, \\ &\lim_{\boldsymbol{k}\to\infty} M_b^* = \frac{2\mu_C\theta_1}{A_0 + \theta_1}. \end{aligned} \tag{19}$$

Table 4. Customer expected value of hoarding generated in the impacted period $[0,\ M]$.

Scenarios			*Customer utility* $\boldsymbol{E}(\Delta \boldsymbol{U})$
1a	$2\mu_C \geq \left(1+\frac{1}{k}\right)t_0$	$t_0 < M \leq \left(\frac{1}{k}+1\right)t_0$	$U - f_T[\int_0^{t_0} U_N^1 dT + \int_{t_0}^{M} U_N^{2b} dT + \int_M^{2\mu_C} U_N^3 dT]$
1b		$\left(\frac{1}{k}+1\right)t_0 \leq M \leq 2\mu_C$	$U - f_T[\int_0^{t_0} U_N^1 dT + \int_{t_0}^{t_1} U_N^{2a} dT + \int_{t_1}^{M} U_N^{2b} dT + \int_M^{2\mu_C} U_N^3 dT]$
1c		$2\mu_C \leq M \leq \left(\frac{1}{k}+1\right)2\mu_C$	$U - f_T[\int_0^{t_0} U_N^1 dT + \int_{t_0}^{t_1} U_N^{2a} dT + \int_{t_1}^{2\mu_C} U_N^{2b} dT]$
1d		$M \geq \left(\frac{1}{k}+1\right)2\mu_C$	$U - f_T[\int_0^{t_0} U_N^1 dT + \int_{t_0}^{2\mu_C} U_N^{2a} dT]$
2a	$2\mu_C \leq \left(1+\frac{1}{k}\right)t_0$	$t_0 \leq M \leq 2\mu_C$	same as Scenario 1a
2b		$M \geq 2\mu_C$	$U - f_T[\int_0^{t_0} U_N^1 dT + \int_{t_0}^{2\mu_C} U_N^{2b} dT]$

where $A_0 = 2\mu_C c_h + v_a$, $A_1 = A_0 + \theta_1 - \theta_2$, $A_2 = A_0 + \theta_1 - \frac{1}{1+k}\theta_2$. For convenience, $M^* = 0$ hereafter represents no hoarding.

As is visually depicted in Figure 3, the conditions for realizing M^* fall into four cases. Cases 1 and 4 represent two disruption events, that is, a disruption followed by a recovering price drop and a considerably short disruption followed by a high recovering price rise, respectively. Case 2 (Figure 3(b)) represents two events: (a) $2\mu_C > 0$ and $0 < \theta_2 < v_a$, that is, a disruption with a low recovering price rise, and (b) $2\mu_C > \theta_2 - v_a$ and $\theta_2 > v_a$, a long disruption with medium or high increases in the recovering price. Case 3 (Figure 3(c)) also includes two events: a short disruption followed by a medium recovering price rise and a moderately short disruption with a high recovering price rise. Table 5 summarizes these events. The economic interpretation behind $\theta_2 < v_a$ is as follows. If customer hoarding is not sufficient, customers will suffer a loss θ_2 of utility from each timely purchase during the recovery period. Nonetheless, the purchases are from the main manufacturer, which is available after the disruption terminates, bringing the value v_a. Therefore, if $\theta_2 < v_a$, there is no need to stock for future consumption in the recovery period.

In Figure 3, $\{\tau^{M_{a0}^*},\ \tau^{M_{2a}^*}, k_{aR}\}$ increases with θ_2, and k_{a0} decreases with it.

$$
\begin{aligned}
&k_{aR} = \frac{\theta_2}{A_0} - 1,\ k_{a0} = \sqrt{\frac{A_1}{A_0}},\ \tau^{M_{a0}^*} = \frac{2\mu_C\theta_1}{\theta_1 + A_0\left(1+\sqrt{\frac{A_1}{A_0}}\right)},\\
&\tau^{M_a^*} = \frac{2\mu_C\theta_1}{A_2\left(1+\frac{1}{k}\right)},\ \tau^{M_b^*} = \frac{2\mu_C\theta_1}{A_2 + \sqrt{A_2\left(A_0 + \frac{\theta_2}{k(1+k)}\right)}},\\
&\tau^{M_{2a}^*} = 2\mu_C\left(1 - \frac{A_0}{\theta_2}\right),\\
&\tau^{M_{2b2}^*} = 2\mu_C\left\{1 - \frac{v_a}{\theta_2}\frac{1}{1 - \sqrt{\left(1-\frac{v_a}{A_0}\right)\left[1 - v_a\frac{\theta_2+\theta_1}{\theta_2{}^2}\right]}}\right\},\\
&\lim_{k\to\infty}\tau^{M_b^*} = \frac{2\mu_C\theta_1}{\theta_1 + A_0\left(1+\sqrt{\frac{A_0+\theta_1}{A_0}}\right)},\\
&\tau^{M_c^*} = 2\mu_C\left\{\theta_1 - \sqrt{\theta_1\frac{\theta_2}{k} - \frac{(v_a-\theta_2)\left(A_0 - \frac{1}{k+1}\theta_2\right)}{\left(A_0 - \frac{1}{k+1}\theta_2\right) - (v_a - \theta_2)}\left(\theta_1 - \frac{\theta_2}{k}\right)}\right\}\Big/\left(\theta_1 - \frac{\theta_2}{k}\right).
\end{aligned}
\tag{20}
$$

Each subplot of Figure 3 gives the optimal hoarding decision for customers' hedging against the corresponding disruption events. We find that, in view of the market type defined by response time and recovery speed, customers might share the same pattern of optimal hoarding under distinguished disruption events. Proposition 2 provides guidance on how to adjust hoarding decisions when different disruption events under different markets are encountered.

Proposition 2. (Customer optimal hoarding behavior)

(i) *For* **QR** *markets, (a) in Cases 1-3, it is optimal to hoard M_b^* and 0 units of substitutable products if the price response is "quick" and "slow;" (b) in Case 4, M_b^* changes into M_c^* under moderately QR markets.*

(ii) *For SR markets, (a) in Cases 1-2, it is optimal to hoard M_b^*, M_a^*, and 0 units of substitutable products if the price response is "quick," "moderately slow," and "considerably slow;" (b) in Case 3, M^* follows the same pattern as moderately SR markets, and M_c^* and M_{2b}^* are required for "quick response" and "slightly slow response" under considerably slow SR markets; (c) in Case 4, M_a^* for "moderately slow response" changes to 0, and M_c^* is also required for $t_0 < \tau^{M_c^*}$ in "slow response."*

Note that as **IR** is the limit of **QR, NR** is the limit of **SR**. Thus, Proposition 2 also incorporates the hoarding decisions for these two rare markets. To be specific, M^* is given as $\left\{\lim_{k\to\infty} M_b^*,\ 0\right\}$ in the **IR** market. As for **NR** markets, M^* is given as $\{M_a^*,\ 0\}$ in Cases 1-2, $\{M_{2b}^*,\ M_a^*,\ 0\}$ in Case 3, and $\{M_{2b}^*,\ 0\}$ in Case 4.

The managerial insights from Proposition 2 are intuitive. In the **IR** market, the disruption impact only appears in the disruption-duration period; thus, the market response in this period determines customer hoarding behavior. If it is a "quick response" market resulting in a long period of during-disruption price rise, we suggest that customers hoard $\lim_{k\to\infty} M_b^*$ units of products to hedge against the future price rise. Otherwise, no hoarding is needed. Such an **IR** market sets a benchmark for general markets. In the **QR** markets, the results maintain the same pattern under general disruptions (Cases 1-3), in other words, hoarding M_b^* and 0 for quick and slow responses. Nonetheless, if a disruption of considerably short duration occurs leading to high prices even after the end of the disruption, a high hoarding level of M_c^* is preferable under moderately QR markets (Case 4).

As the recovery speed decreases, two main adjustments are indicated in each case. In Case 1 where $\theta_2 < 0$ (i.e., recovering price drop), markets where the hoarding strategy is used are reduced, as is the optimal hoarding quantity. To be specific, $\lim_{k\to\infty} M_b^*$ drops to M_b^*, then M_b^* continues decreasing until it reaches the minimum level M_a^* for **SR** markets (Corollary 2(ii)). The reason is intuitive. If the

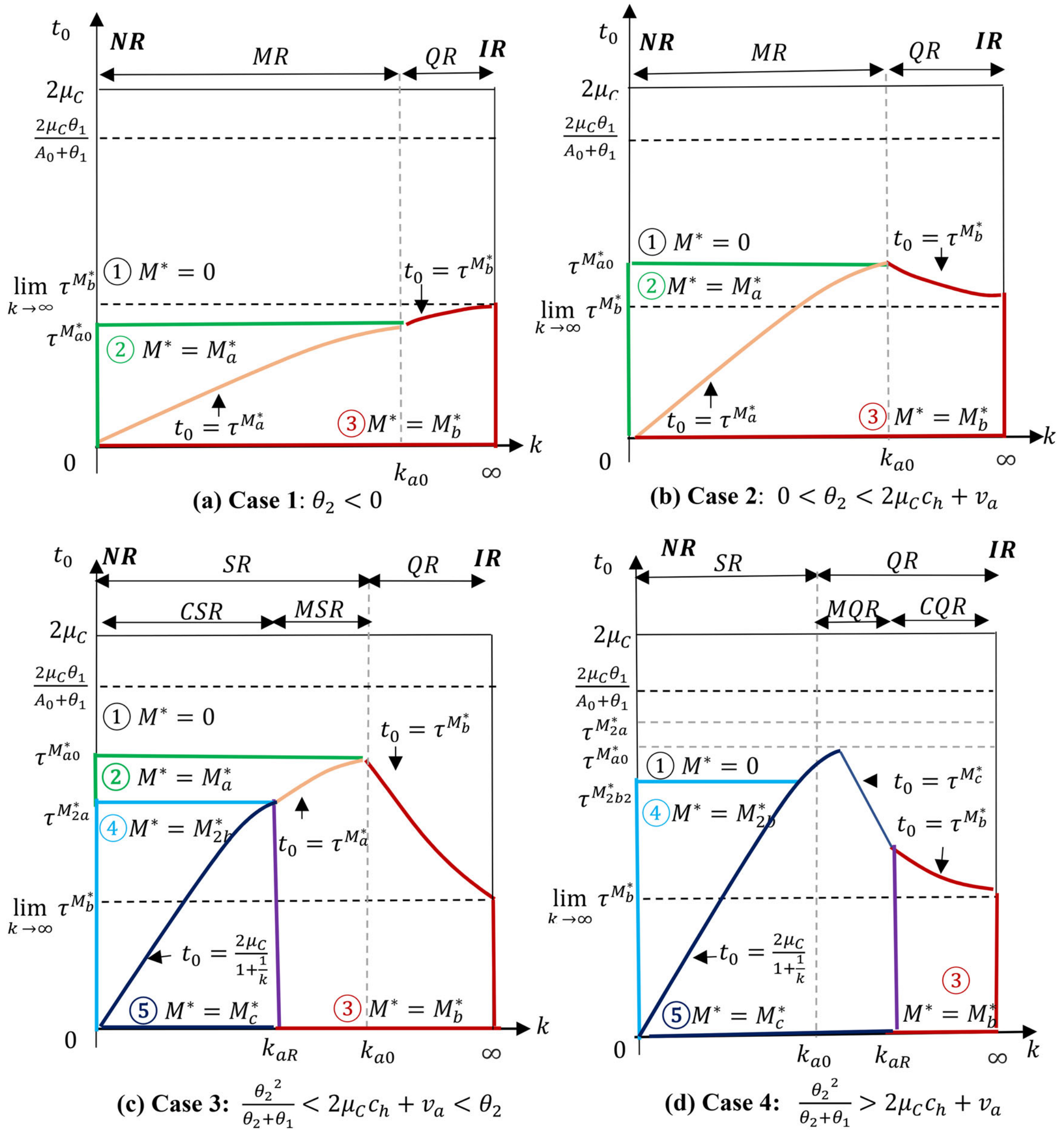

Figure 3. Customers' optimal hoarding decision M^*, under different types of markets and events.

Table 5. Disruption events in Figure 3.

Conditions		Events: recovering price		Events: disruption length		Case
$\theta_2 < 0$		drop				1
$0 < \theta_2 < v_a$		rise	low			2
$\frac{\theta_2{}^2}{\theta_2+\theta_1} < v_a < \theta_2$	$2\mu_C > (\theta_2 - v_a)/c_h$	rise	medium	long		2
	$2\mu_C < (\theta_2 - v_a)/c_h$	rise	medium	short		3
$\frac{\theta_2{}^2}{\theta_2+\theta_1} > v_a$	$2\mu_C > (\theta_2 - v_a)/c_h$	rise	high	long		2
	$\left(\frac{\theta_2{}^2}{\theta_2+\theta_1} - v_a\right)/c_h < 2\mu_C < (\theta_2 - v_a)/c_h$	rise	high	short	moderately	3
	$2\mu_C < \left(\frac{\theta_2{}^2}{\theta_2+\theta_1} - v_a\right)/c_h$	rise	high	short	considerably	4

termination of the disruption triggers a sharp price drop, customers can benefit from the drop by purchasing during the recovery period. Further, such benefit is magnified if the recovery period is prolonged. As a result, hoarding becomes less effective and less necessary.

Conversely, in Cases 2-4 where $\theta_2 > 0$, the "after-disruption price rise" derived from disruption-tailing effects continues to exacerbate customer loss of utility during the recovery period. To mitigate the deteriorating disruption impact, two opposite adjustments are suggested: hoarding is advisable in more markets, and the hoarding quantity increases (Corollary 2(i)). This trend reveals an important insight. In Cases 3-4, where the disruption is of short mean length and causes high or medium price fluctuations in recovery periods, it is advisable to hoard more than $2\mu_C$, that is, M_c^* and M_{2b}^*, if the price response is quick or slightly slow, and the subsequent recovery is considerably slow. In other words, regardless of how long the random disruption will last in the short time interval $[0,\ 2\mu_C]$, customers should stockpile more than $2\mu_C$. By doing this, there will be enough stock to be consumed in both the disruption-duration and disruption-recovery periods to hedge against the significant disruption-tailing effect.

Corollary 2. (Property of customer hoarding)

(i) *If $\theta_2 > 0$,* (a) *both M_b^* and M_c^* decrease with k, and M_a^* and M_{2b}^* decrease with t_0, and* (b) *for a given t_0, $M_a^* > M_b^* > \lim_{k\to\infty} M_b^*$ and $M_{2b}^* > M_c^* > 2\mu_C > M_b^* > \lim_{k\to\infty} M_b^*$.*

(ii) *If $\theta_2 < 0$, the results of M_a^* and M_b^* are opposite the results for the case of $\theta_2 > 0$.*

Further properties of M^* are observed in Corollary 2, indicating how the price response time t_0 plays a role in conjunction with the price recovery speed k. First, t_0 plays an essential role in determining whether hoarding should be implemented. Second, when t_0 is short enough (quick response), there is no need to adjust the hoarding quantity in accordance with t_0; therefore, the recovery speed k critically defines hoarding quantity, that is, M_b^* and M_c^*. However, in slow response markets, t_0 also defines the specific hoarding quantities M_a^* and M_{2b}^*.

Proposition 3. (Value of customer hoarding)

(i) *For a given t_0, $E(\Delta U)|_{M=M_b^*}$ decreases with k if $\theta_2 > 0$ and otherwise increases with it; $E(\Delta U)|_{M=M_c^*}$ decreases with k.*

(ii) *$E(\Delta U)|_{M^*>0}$ decreases with t_0.*

Proposition 3 indicates that, in contrast with conventional wisdom (Lund *et al.*, 2020), we find that "a late during-disruption price rise" could adversely harm customers who hoard products, as does "a quick after-disruption price recovery" in the event of a "recovering price rise." To be specific, if $\theta_2 > 0$, as the price recovery speed decreases, customers can conversely arrive at greater utility by increasing their hoarding quantity, such as from M_b^* to M_c^* (see Figure 3). Thus, in a market with a given response time, a long price recovery period where the price continues to rise after the end of the disruption enhances the value of hoarding and accordingly highlights its importance. In contrast, if $\theta_2 < 0$, the after-disruption price drop reduces the precautionary advantage of hoarding. This effect is diminished as the recovery period becomes shorter. Consequently, consistent with common sense, a quick recovery could help customers in this case. Similarly, given a recovery speed, customers could enjoy higher utility by adjusting their hoarding quantity to manage "an earlier during-disruption price rise."

5.2. Manufacturer's optimal contingent sourcing with customer hoarding

The contingent sourcing decision under non-hoarding (i.e., $M^* = 0$) is presented in Section 4. Next, we focus on $M^* > 0$ and explore the optimal contingent sourcing quantity Q^*. We start by identifying the value of contingent sourcing with customer hoarding behavior during the period $[0, Q]$ when Q units of contingent sources are depleted. Similar to Section 4, the value of contingent sourcing is defined by the profit difference ΔP_M and is composed of the extra revenue R_M and extra cost C_M :

$$\Delta P_M = R_M - C_M. \tag{21}$$

(i) Additional cost from contingent sourcing

C_M consists of the markup cost and inventory holding cost, that is

$$C_M = c_s Q + c_H \int_0^Q I_M(t)dt. \tag{22}$$

Given the demand dynamics under hoarding, there are two scenarios for the manufacturer's inventory:

$$I_M(t) = \begin{cases} Q - M^*, & \text{if } t \in [0, M^*] \\ Q - M^* - t, & \text{if } t \in [M^*,\ Q] \end{cases}, \ \text{if } Q > M^*;\ I_M(t) = 0,\ \text{if } Q \le M^*. \tag{23}$$

In Scenario 1, where $Q > M^*$, with massive emergency sourcing, the manufacturer meets the strategic customers' hoarding needs M^* at the initial time. Thus, during the next phase $(0, M^*)$, the inventory level remains at $Q - M^*$. Then, after customers use up their hoarded products at $t = M^*$, the manufacturer fulfills the real-time demand of 1 using the remaining inventory. This continues until the inventory is fully depleted at time Q. Given the inventory dynamics, the additional cost in (22) is specified as

$$\begin{aligned} C_M &= c_s Q + c_H\left[\frac{1}{2}(Q - M^*)^2 + (Q - M^*)M^*\right] \\ &= c_s Q + \frac{1}{2}c_H\left(Q^2 - M^{*2}\right). \end{aligned}$$

In Scenario 2, where $Q \le M^*$, the manufacturer chooses not to purchase contingent sources sufficient to satisfy all hoarding needs when the disruption occurs, allowing $M^* - Q$ of lost sales. That is, inventory remains $I_M(t) = 0$, resulting in $C_M = c_s Q$.

(ii) Additional revenue from contingent sourcing

The manufacturer's additional revenue R_M is derived from satisfying demand at the post-disruption dynamic price during disruption. To be consistent with the previous discussion about additional cost, we next examine R_M in the interval $[0, T]$ for Scenarios 1 and 2.

In Scenario 1, where $Q > M^*$, the instantaneous demand M^* is met at the initial time at price p_0. Then, real-time demand $d(t) = 1$ is met in the phase where $(M^*, \max\{M^*,\ \min\{Q,\ T\}\}]$ at price $p(t)$. Note, $M^* > t_0$ implies that there is an increase in the selling price; that is, $p(t) = p_1 = p_0 + \theta_1$ is determined after time M^*. By satisfying these two parts of demand, the manufacturer arrives at additional revenue:

$$R_M = (p_0 - c_1)M^* + \int_{M^*}^{\max\{M^*,\ \min\{Q,\ T\}\}} (p_0 - c_1 + \theta_1)dt. \tag{24}$$

The duration of the price-rising phase depends on the random disruption length. Given $T \sim U(0,\ 2\mu)$, R_M could exist

Table 6. Value of contingent sourcing under customer hoarding of $M^* < Q$.

Scenario				Revenue R_M	Cost C_M	Value ΔP_M
1	$Q > M^*$	$M^* < 2\mu$	$T \le M^*$	$R_M^{1a} = (p_0 - c_1)M^*$	$c_sQ + \frac{1}{2}c_H(Q^2 - M^{*2})$	ΔP_M^{1a}
			$M^* < T \le Q$	$R_M^{1b} = (p_0 - c_1)T + \int_{M^*}^{T} \theta_1 dt$		ΔP_M^{1b}
			$T > Q$	$R_M^{1c} = (p_0 - c_1)Q + \int_{M^*}^{Q} \theta_1 dt$		ΔP_M^{1c}
		$M^* \ge 2\mu$	$T \le M^*$	R_M^{1a}		ΔP_M^{1a}
2	$Q \le M^*$			$R_M^2 = (p_0 - c_1)Q$	c_sQ	ΔP_M^2

in three sub-scenarios: $T < M^*$, $M^* < T < Q$, and $T > Q$, if $M^* < 2\mu$ (see Table 6).

Note that if the customer hoarding quantity M^* exceeds 2μ, R_M always falls into the first sub-scenario.

In Scenario 2, where $Q \le M^*$, the manufacturer only satisfies Q of the M^* demand at the initial time. Thus, compared to doing nothing, revenue $R_M = (p_0 - c_1)Q$ is generated, independent of the random disruption length. Table 6 displays the additional revenue and cost that the manufacturer receives from contingent sourcing, as well as the corresponding value ΔP_M of contingent sourcing with hoarding.

According to Table 6, the manufacturer obtains the expected value $E(\Delta P_M)$ when using contingent sourcing to hedge against a supply failure with a random length of T, and hoarding behavior M^*.

$$E(\Delta P_M) = \begin{cases} \int_0^{M^*} \Delta P_M^{1a} f_T dT + \int_{M^*}^{Q} \Delta P_M^{1b} f_T dT + \int_Q^{2\mu} \Delta P_M^{1c} f_T dT, & \text{if } M^* < 2\mu \text{ and } Q > M^* \\ \Delta P_M^{1a}, & \text{if } M^* > 2\mu \text{ and } Q > M^* \cdot \\ \Delta P_M^2, & \text{if } \le M^* \end{cases} \quad (25)$$

The manufacturer's optimal sourcing Q^* can be formulated as in Model 3.

Model 3: Optimization of contingent sourcing with customer hoarding:

$$Q^* \in arg \max E(\Delta P_M). \quad (26)$$

$$\text{subject to } E(\Delta P_M) \ge 0 \text{ and } Q \ge 0. \quad (27)$$

In line with Model 1 (without customer hoarding), the objective ((26)) is to maximize the expected value of contingent sourcing. Nonetheless, unlike Model 1, in the presence of hoarding behavior M^*, the sourcing quantity constraint is extended into $Q \ge 0$. Solving Model 3, the optimal contingent sourcing decision could be achieved as $Q^* = \{Q_b^*, M^*, 0\}$, which primarily depends on customer hoarding behavior M^* and the contingent sourcing cost c_s, as summarized in Proposition 4:

$$Q_b^* = 2\mu \frac{B_2 + 1}{B_1 + 1}, \quad (28)$$

where B_1 and B_2 are given in (10), and M^* is in Figure 3. Note, $Q_b^* > 2\mu \frac{1 - \sqrt{1 - (B_2 + 1)^2}}{B_1 + 1}$.

Proposition 4. (Manufacturer's optimal contingent sourcing under customer hoarding)

(i) ***For $M^* \ge 2\mu$,*** *the manufacturer should purchase $Q^* = M^*$ units of contingent sources to meet customer demand when $c_s < p_0 - c_1$ (small); non-sourcing is used otherwise.*

(ii) ***For $M^* < 2\mu$,*** (a) *If $c_s \ge p_0 - c_1 + \theta_1$ (large): $Q^* = 0$;* (b) *If $p_0 - c_1 < c_s < p_0 - c_1 + \theta_1$ (medium): $Q^* = Q_b^*$ when customers hoard a small amount, that is, $M^* < 2\mu \frac{1 - \sqrt{1 - (B_2 + 1)^2}}{B_1 + 1}$, and $Q^* = 0$ otherwise; (c) If $c_s < p_0 - c_1$ (small): $Q^* = \max\{M^*, Q_b^*\}$.*

Proposition 4 reveals that the contingent sourcing decision falls into two customer hoarding-based patterns. First, when a supply failure occurs, if massive orders M^* are placed, that is, $M^* \ge 2\mu$, the contingent sourcing decision mainly relies on the current sourcing price. It is better for the manufacturer to satisfy all demand if c_s is small.

Then, in general cases when customers stockpile less than 2μ, no sourcing is preferable if c_s is large. Otherwise, in the sub-case of small c_s, the following suggestion is provided. In markets where customers stockpile less than Q_b^*, it is better to satisfy customers' stockpiling M^* at the initial time and then hoard a certain amount (i.e., $Q_b^* - M^*$) of emergency raw materials in anticipation of more profit from future production. Conversely, if customers stockpile more than Q_b^*, the current profit derived from meeting customers' stockpiling orders could exceed the expected profit that might be obtained from future price increases. Thus, it is better for the manufacturer to meet all the demand immediately and hoard no further inventory because of the uncertainty of price increases. In the sub-case of medium c_s, meeting the demand M^* adversely affects the manufacturer at the initial time $t = 0$. Nonetheless, if M^* is small enough, the current loss in profit can be made up by the gain from future price rises. Thus, it is still advantageous to use contingent sourcing, that is, to implement $Q^* = Q_b^*$.

5.3. Numerical analysis

A numerical analysis is conducted to gain further insights into the value of disruption information and contingent sourcing and how customer hoarding behavior affects the above values. We randomly establish a basic set as: $p_0 = 10$, $\theta_1 = 10$, $\theta_2 = 5$, $c_1 = 2$, $c_h = 0.5$, $c_H = 1$, $v_a = 10$, $k = 0.5$. By assuming that a time unit is a day, the basic setting indicates that before the disruption occurs, the manufacturer realizes a daily profit of $p_0 - c_1 = 8$ by meeting 1 demand. After the random disruption occurs, the manufacturer could gain other expected profit differences $E(\Delta P)$ by utilizing contingent sourcing tactics. Note that the sourcing and hoarding decisions are presented in closed form, and the numerical analysis is mainly for visual

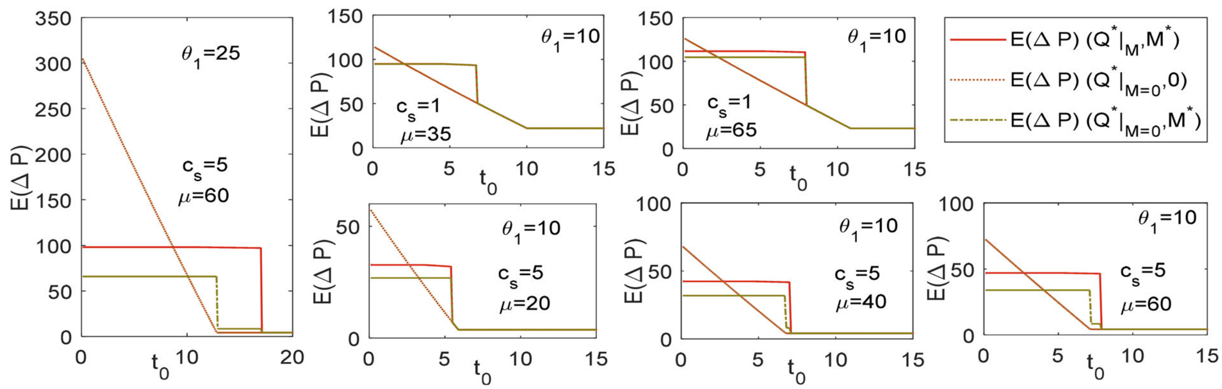

Figure 4. Manufacturer's expected profit differences between $(Q^*|_{M=M^*},\ M^*)$, $(Q^*|_{M=0},\ 0)$, and $(Q^*|_{M=0},\ M^*)$, under $\mu_C = \mu$.

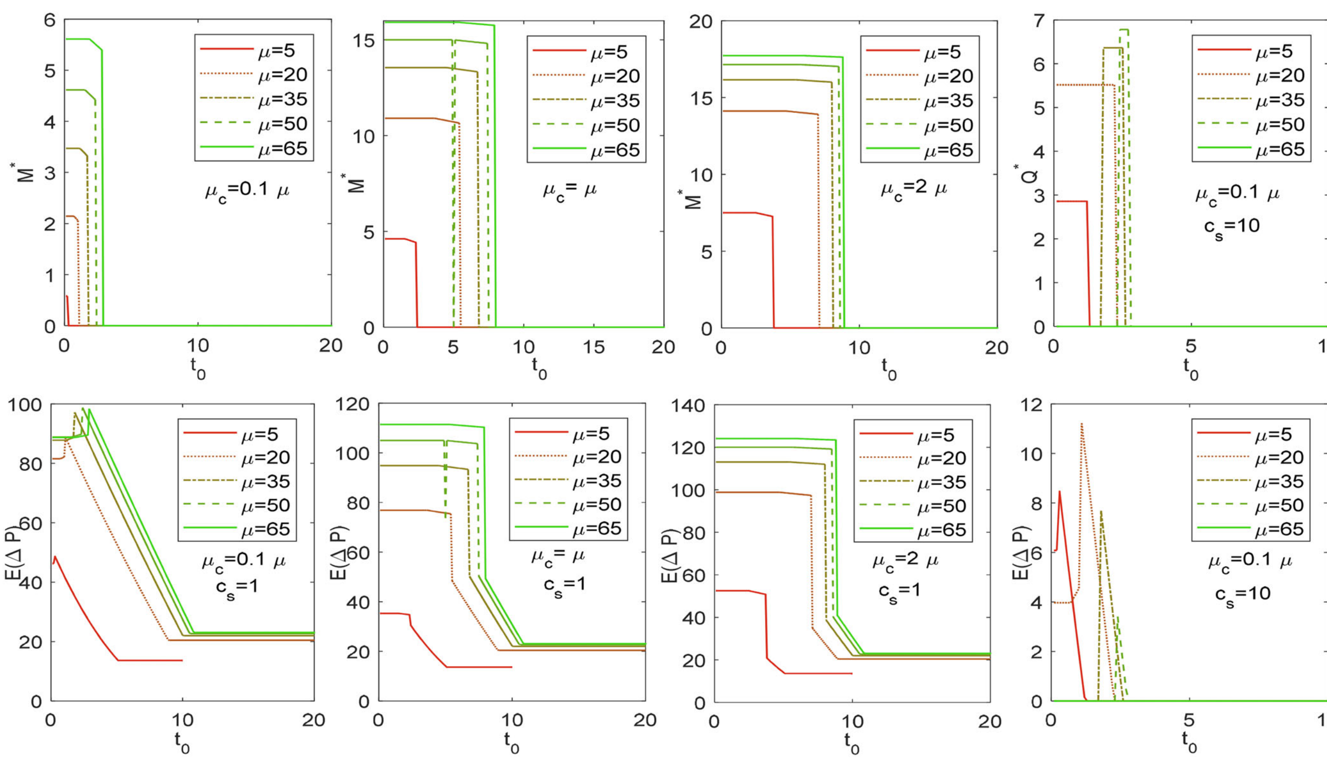

Figure 5. Manufacturer's expected profit differences with different $\{\mu_C,\ \mu\}$.

illustration. Further, sufficient numerical analysis has been conducted to confirm that the findings will not change under other settings.

In Figure 4, we compare the value $E(\Delta P)$ of contingent sourcing in three cases : $(Q^*|_{M=M^*},\ M^*)$, $(Q^*|_{M=0},\ 0)$, and $(Q^*|_{M=0},\ M^*)$. In the first two cases, the manufacturer employs optimal sourcing Q^* to mitigate disruption with and without customer hoarding, respectively. In the latter case, the manufacturer ignores customer hoarding and makes sourcing decisions by falsely assuming $M = 0$. Letting $\mu = \mu_C$, that is, assuming that customers and manufacturers share the same disruption information, the results indicate two findings regarding how customer hoarding behavior affects the value of contingent sourcing. First, customer hoarding behavior could dampen the contingent sourcing advantage under quick response markets (i.e., short t_0), and, conversely, enhance the contingent sourcing advantage under medium-response markets. We take the case $\theta_1 = 25$ for a specific explanation. As shown in Figure 4, if customers do not stockpile, the extra profit the manufacturer achieves by satisfying demand via contingent sourcing could reach 300 in an instantaneous-response market (i.e., $t_0 = 0$). However, if customers stockpile M^* quantity of goods, the manufacturer suffers a 66% loss in profit (i.e., profit drops from 300 to 100). A severe 77% loss in profit (i.e., profit drops to 70) occurs if the manufacturer ignores customer hoarding behavior. Nonetheless, the loss in profit generated from customer hoarding reduces as t_0 becomes longer. Furthermore, when t_0 exceeds a threshold, then hoarding behavior could conversely lead to profit growth even when the manufacturer deviates from the optimal sourcing quantity by ignoring hoarding. Second, the reinforcing effect of hoarding behavior on the advantage of the manufacturer's contingent sourcing becomes more prominent when hedging against long disruptions or when the post-disruption price rise is large. Letting c_s, μ, and θ_1 vary, these two findings always hold.

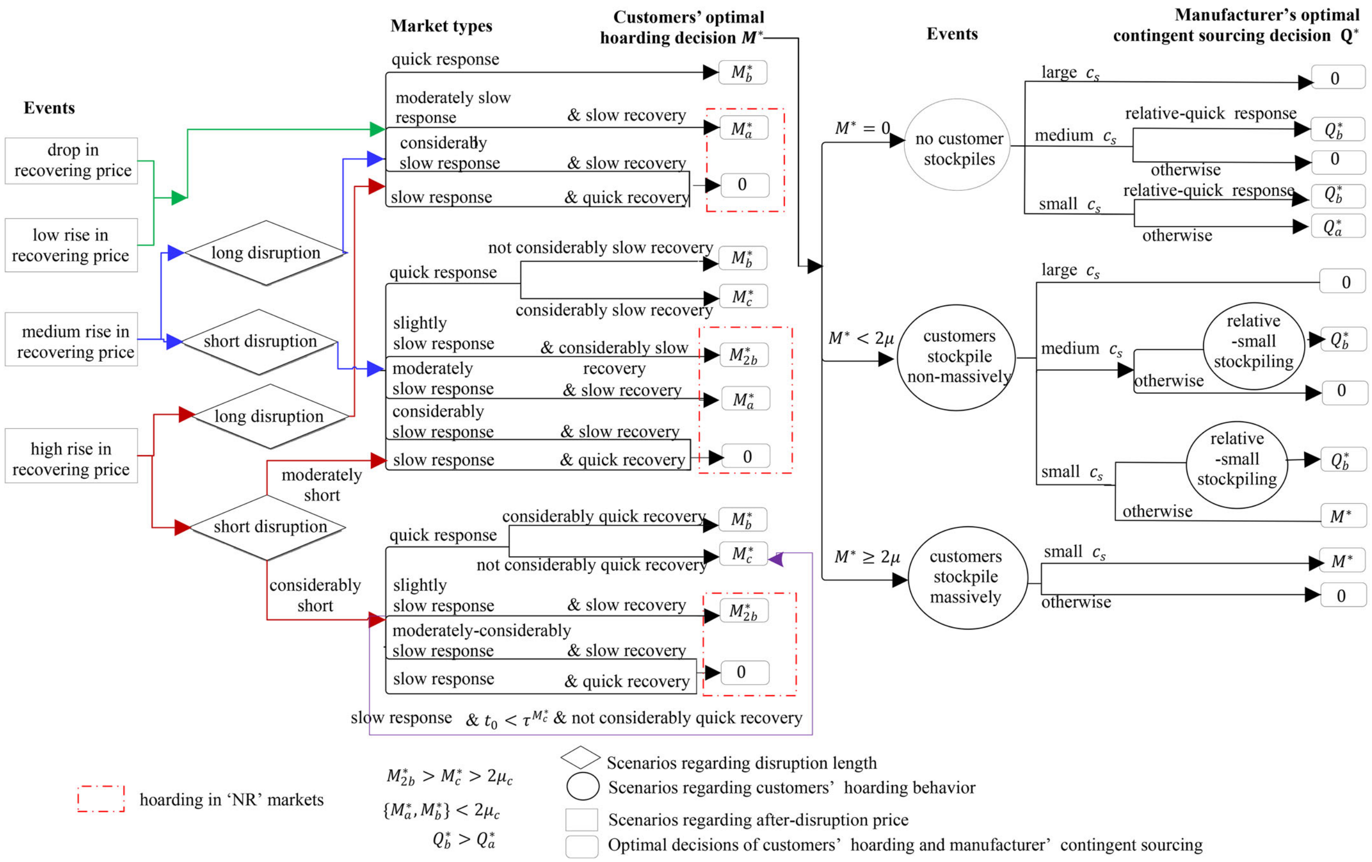

Figure 6. Optimal decisions of customer's hoarding and manufacturer's contingent sourcing.

In Figure 5, to observe the value of disruption information, we analyze customer hoarding and manufacturer contingent sourcing in three cases: $\mu_C = 0.1\mu$, $\mu_C = \mu$, $\mu_C = 2\mu$, that is, $(Q^*|_{M=M^*}, M^*)$, as well as the values $E(\Delta P)$ of contingent sourcing where customers underestimate the mean disruption length in the first case and overestimate it in the third case. Two important findings are indicated. First, overestimating the disruption length unsurprisingly facilitates customer panic, leading to unnecessary over-hoarding in two directions: hoarding to increase hoarding quantity and hoarding in some markets that might see only short-lived price increases. Second, both customer panic and over-optimism due to information asymmetry, which leads to over- and under-hoarding, might bring the manufacturer more profit, for instance, in the case of $\mu = 5$ and $c_s = 1$. It is worth noting that, when contingency sourcing cost is low, it is profitable for manufacturers to meet demand before prices increase. Thus, customer over-hoarding could enhance the value of contingent sourcing. On the contrary, when contingency sourcing cost is large so that it is not profitable to meet demand before prices increase (e.g., $c_s = 10$), customer under-hoarding could benefit the manufacturer. There might be a period where the manufacturer can serve customer demand at a high price after their consumption of stock.

6. Managerial implications

Figure 6 summarizes the customer optimal hoarding behaviors $M^* = \left\{M_{2b}^*, M_c^*,\ M_b^*,\ M_a^*,\ 0,\ \lim\limits_{k\to\infty} M_b^*\right\}$ and the manufacturer's corresponding optimal contingent sourcing decisions $Q^* = \{M^*, Q_a^*,\ Q_b^*,\ 0\}$ in non-instant recovery markets (i.e., slowly, quickly, and never recover) under different disruption events. Note that in the rare IR markets, M^* is given as $\lim\limits_{k\to\infty} M_b^*$ and zero for quick and slow responses, respectively. Following Figure 6, our results render the following insights for decision-makers.

For customers, optimal hoarding decisions fall into four cases when different disruption events are encountered under different markets. Non-hoarding is preferable if the market price response is slow enough. If the after-disruption price increases, customers should increase their hoarding quantity when the price recovery speed drops until it reaches the maximum value. Further, for the SR market, it is better for customers to increase their hoarding quantity as the market becomes more sensitive to the supply disruption and exhibits a during-disruption price rise earlier. If the after-disruption price decreases, the effectiveness of hoarding behavior is reduced. Specific hoarding quality adjustments are opposite those in the previous markets. Price responding and recovering jointly influence the customer value of hoarding in mitigating disruption. Unlike conventional wisdom, we find that market reactions to "a late during-disruption price increase" and "a quick after-disruption price recovery" could be disadvantageous for customers who hoard products to hedge against disruption-driven price hikes.

For manufacturers, in the absence of customer hoarding, three patterns of sourcing are provided, mainly depending on the sourcing cost and response time. It is worth noting that, unlike common sense, contingent sourcing is still advisable if the future price rises are attractive, even though the current high sourcing cost could reduce the manufacturer's profits in the first post-disruption phase, that is, the price-responding phase. In the presence of customer hoarding, if they stockpile extremely large amounts, it is always advantageous to source if the cost is small, irrespective of other factors such as future prices. Under general hoarding cases, three sourcing patterns are also provided, relying on the sourcing cost and customer hoarding quantity. Customer hoarding could dampen the sourcing value in quick response markets and, conversely, enhance the value in moderate response markets. Further, this reinforcing effect becomes more pronounced if long disruptions take place. Under disruption information asymmetry, both over- and under-hoarding facilitated by customer panic and over-optimism might bring the manufacturer more profit. This finding also provides evidence that a manufacturer might not be willing to share disruption information.

7. Conclusions

In this study, we examined a timely and novel setting in the SC resilience literature—ordering decisions under simultaneous material shortages and price hikes. This is a real-life setting encountered by many SCs in 2022 when inflation and material shortages followed the post-pandemic disruptions. Distinctively, we studied both customer hoarding and manufacturer contingent sourcing decisions to reduce the ripple effect in the SC and offer working methods for decision-makers in the novel setting of a shortage economy (Ivanov and Dolgui, 2022). In general, studies that consider correlated price and material flow dynamics and uncertainty are rare in the SC resilience literature; we contribute to this important and novel stream of adapting SC decision-making practices as a response to the "new post-COVID normal" (Rozhkov *et al.*, 2022; Babai *et al.*, 2023).

By capturing post-disruption price dynamics in four periods (i.e., responding, rising, recovering, and recovered), we first derived the manufacturer's contingent sourcing strategies that maximize post-disruption profit in the case of customer non-hoarding. Then, after disentangling the value of hoarding, we presented optimal hoarding strategies to maximize customer hoarding value. Last, we derived the manufacturer's contingent sourcing strategies considering hoarding behavior. The numerical analysis shed further light on the value of contingent sourcing under customer hoarding and asymmetric disruption information.

Our results can be instructive for managers making hoarding and contingent sourcing decisions in cases of different disruption and price dynamic expectations. We derived hoarding and contingent sourcing recommendations for different market responses and price recovery speeds, incorporating in our model uncertain disruption duration and asymmetric disruption information, simultaneous ripple effects in material flow and prices, and disruption- and recovery-driven price dynamics. For example, non-hoarding is preferable for customers if the market price reaction is slow enough. Late price increases during disruption and quick price recovery after disruption could reduce the benefit of hoarding goods. We also offer contingent sourcing tactics for manufacturers, indicating how to adjust sourcing quantities for production resumption with and without customer hoarding. We find that future price rises could induce contingent sourcing even if it is unprofitable to resume production during the responding phase.

As with any study, limitations exist and most are related to the assumptions made. First, we did not consider competition effects between the main and substitute manufacturers and assumed homogeneity of both prices and customer behaviors toward main and substitutable products. Second, the disruption length uncertainty is described via a uniform distribution. The study raises several opportunities for future research. First, post-disruption price dynamics can be extended by considering time-dependent characteristics in each phase. Second, competition effects can be extended in future studies. Another approach could consider general distributions or periodically adjust the numerical characteristics of distributions because uncertainty could be reduced based on updated disruption information.

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