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Inventory Policies and Supply Chain Coordination under Logistics Route Disruption Risks

Mao Zheng [1], Ningning Cui [1], Yibin Zhang [2], Fangfang Zhang [3,*] and Victor Shi [4]

1 School of Business Administration, Faculty of Business Administration, Southwestern University of Finance and Economics, Chengdu 610074, China; zhmao@swufe.edu.cn (M.Z.); 1161202z5003@smail.swufe.edu.cn (N.C.)
2 School of Business Administration, Shanghai Lixin University of Accounting and Finance, Shanghai 201620, China; zhangyb@lixin.edu.cn
3 School of Finance and Trade, Wenzhou Business College, Wenzhou 325035, China
4 Lazaridis School of Business and Economics, Wilfrid Laurier University, Waterloo, ON N2L 3C5, Canada; cshi@wlu.ca
* Correspondence: zhangff@wzbc.edu.cn

Abstract: Predictable logistics disruptions due to scheduled lockdowns for large-scale events such as the Olympic Games may not only reduce supply chain profits, but also increase carbon emissions. To help solve these problems, an emergency transit policy to be applied to the logistics path is an effective solution. However, optimal inventory control is needed. This paper proposes an optimization model to control ordering and inventory policies for decentralized and centralized supply chains. The model considers the logistics path damping coefficient, the logistics path acceleration coefficient, and the vehicle loading capacity ratio in emergency transit. Our major findings include the following. First, supply chain profits under centralization are confirmed to be higher than under decentralization. Second, a price discount mechanism can achieve supply chain coordination. Third, the manufacturers in a centralized supply chain are more inclined to choose a logistics path with a high acceleration coefficient in order to let their cargo arrive quickly and to reduce the impact of the lead time demand fluctuations. Finally, the implications of our research results for carbon emission reductions are discussed.

Keywords: logistics path damping coefficient; logistics path acceleration coefficient; optimal inventory control; supply chain coordination; carbon emission

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1. Introduction

In supply chains, logistics are a dominant source of carbon emissions worldwide. In particular, carbon emissions during logistics disruptions can increase by about 20% compared to normal operation conditions. Since the COVID-19 pandemic started in 2020, due to lockdowns and traffic regulations, there have been a number of logistics disruptions worldwide, and in many supply chains such as healthcare and food supply chains [1,2]. This led to shortages of high-demand products such as food, testing kits, masks, and medical gloves, and shutdowns of non-essential businesses worldwide [3,4]. A recovery and resiliency plan should be considered for supply-side disruptions to these supply chains' transportation and supply networks. Moreover, large-scale events such as the summer G20 and the Olympic Games also lead to planned disruption risks to logistics routes [5]. For all these predictable variabilities in demand and supply, it is critical to know how to mitigate operational disruption risks and coordinate the supply chain.

To deal with these predictable supply disruption risks, firms often modify or reconstruct their logistics routes. For example, they may set up an emergency transit facility on the outskirts of the affected city. Then, products are transported to the transit facility using large-tonnage vehicles without local plates, then further transported with local small-tonnage vehicles, which are permitted to travel via permissible logistics routes. In this way, the necessary products can be delivered on time. However, reconstructed logistics routes may still face the risk of congestion or even closure due to traffic control. This can lead to overstocking in the emergency transit facility, and can negatively affect the lead time of a manufacturer and its suppliers. To the best of our knowledge, the existing literature usually omits potential rerouting strategies for these predictable supply disruption risks, which are not uncommon in business practices. Our study fills this research gap.

To model these situations, we employ a damping coefficient of logistics routes to describe the possible adverse effects of route congestion or closure on the ordering lead time of a manufacturer and its suppliers' logistics decisions. On the other hand, as traffic control is an expected disruption risk, the government may simultaneously establish express logistics routes for authorized vehicles, for which a firm has to pay extra. Therefore, we also employ an expediting coefficient to describe these potential positive effects of traffic regulation.

When a manufacturer's ordering lead time changes, its ordering quantity and ordering point (i.e., the suppliers to order from) must be re-optimized to better satisfy customers' demands. On the other hand, when a supplier adopts the strategy of an emergency transit facility to deal with traffic control to reduce logistics costs, it needs to optimize the vehicle capacity ratio, i.e., the ratio between the tonnage capacity of the supplier's vehicle and that of the manufacturer's vehicle. Therefore, in this paper, we aim to answer the following main questions: in the presence of predictable logistics route disruption risk, what is the optimal ordering policy of the manufacturer in a supply chain? What is the optimal vehicle capacity ratio? How do supply chain centralization and decentralization affect these decisions? How should a centralized supply chain be coordinated to achieve optimal performance for the whole chain?

To answer the above questions, this study develops a mathematical model, considering logistics route disruption risks. An optimization model to control inventory policies, considering the logistics path choice (the logistics path damping coefficient and acceleration coefficient) and vehicle loading capacity ratio in the emergency transit options, is built to optimize inventory control for both decentralized and centralized supply chains. Using numerical examples, this study demonstrates how the model can optimize the recovery plan for tackling such supply disruptions. Furthermore, it shows how profits in a centralized supply chain are higher than in a decentralized one, and demonstrates the optimal price discount mechanism needed to coordinate the behavior of suppliers and buyers.

The main contributions of this study can be summarized as follows. First, we develop a mathematical model for logistics recovery, considering the impact of predictable logistics route disruptions from some major events such as the COVID-19 pandemic and the Olympic Games. Second, unlike earlier studies, the model considers the scenario in which supply could be disrupted due to logistics route congestion or closure. In the model, the logistics delivery lead time is variable, and is affected by the logistics route damping or expediting coefficient. Third, considering two scenarios of logistics route reconstruction under both decentralized and centralized supply chains, the optimal order quantity, reorder point, logistics route expediting coefficient, and vehicle capacity ratio at the emergency transit point are derived. Fourth, we focus on how to coordinate the supply chain to achieve optimal performance, analyze the model's properties, and provide managerial implications.

The remainder of this paper is organized as follows. Section 2 reviews the supply disruption literature focusing on production, inventory, and logistics issues. Section 3 describes the problem and presents models for both decentralized and centralized supply chains. The results of the model are exemplified using numerical examples in Section 4. The managerial implications for practitioners and the contributions of the study's findings are also discussed in Section 4. This paper is concluded by summarizing the main insights and outlining an agenda for future research in Section 5.

2. Literature Review

In this paper, our research focuses on redesigning logistics routes in the context of predictable disruptions due to scheduled large-scale events such as the summer Olympic Games. It also deals with production and inventory issues faced by manufacturers. Hence, in this literature review, we will first review studies on production and inventory issues related to disruptions, and then logistics route redesign issues.

2.1. Production and Inventory Issues

Supply chain (SC) risks are multifaceted, and can be classified into operational and disruption risks [6–15]. While operational risks are concerned with day-to-day disturbances in the SC operations, such as lead time and demand fluctuations, disruption risks belong to low-frequency, high-impact events [13,14]. To deal with disruption risks, many studies have been carried out on building and analyzing production recovery models. To date, employing mathematical programming tools, many studies have been carried out on production and inventory issues under disruptions in a variety of domains, such as supplier selection and order allocation [16], reverse supply chains [17], blood supply chains [18], and fashion supply chains [19,20]. Besides, some studies have developed production recovery models for managing transportation and scheduling disruptions [21,22]. For example, backorder, buffer inventory, or safety stock may be used [23–27].

2.2. Logistics Route Redesign Issues

In cargo logistics, transport risk (or delivery reliability) is an essential service performance measure, defined as the deviation of the actual arrival time from the planned arrival time [28]. Neither earliness nor tardiness is desirable for customers and freight forwarders. However, confronted with disruptive supply and congestion problems, there should be a recovery plan to make supply resilient within its logistics network. On issues related to transshipment and scheduling, most studies investigate multi-echelon inventory control models (R, nQ) [29,30]. They assume demand mostly follows a Poisson distribution in the scenarios of supply chain centralization and decentralization, and analyze how to implement pricing to coordinate ordering quantities and reordering points to improve customer service level. Lewis et al. [31] consider global supply chains facing port-of-entry disruption risks. They investigate the potential operational and economic impact of the temporary closure of ports of entry, focusing specifically on using supply chain inventory as a risk mitigation strategy for a one supplier, one customer system in which goods are transported through a port of entry subject to temporary closures. Closure likelihood and duration are modeled using a completely observed, exogenous Markov chain. Order lead times depend on the port of entry's status, including potential congestion backlogs of unprocessed work. An EOQ model with random disruption and partial order backlogs and how they relate to logistics disruptions are examined in [32].

A few studies have shown how demand disruption impacts logistics service supply chains [33,34]. They compare the decentralized decision-making, centralized decision-making, and centralized decision-making of the suppliers' alliance only. Three optimization models used to manage operations in intermodal logistics networks, from routine scheduling delays to recovery from major disruptions, are developed in [35]. Efficient transfer coordination in intermodal logistics networks can reduce the freight dwell time at transfer terminals where various routes interconnect, and reduce storage requirements at terminals. The first model coordinated vehicle schedules and cargo transfers at intermodal freight terminals, primarily by optimizing coordinated service frequencies and slack times. When delay perturbations propagated within a logistics network that used schedule coordination, a second model determined whether each ready outbound vehicle should have been dispatched immediately or held to wait for late incoming vehicles. Finally, a set of optimal resilient actions was considered using the proposed third model during the post-disruption phases, such as switching shipping modes and routes, renting other carriers' capacities, reallocating local trucks, and prioritizing the order of shipments because of limited capacities.

Several scenarios to recover from disruptions, so as to increase the system performance under supply and transportation disruptions, are considered in [36]. The simulation results show that the best alternatives were chosen by finding a compromise or tradeoff between the key performance indicators, specifically the service level and the cost of achieving the goals. A bilevel optimization problem for determining the most critical depots in a vehicle routing context is introduced in [37]. The problem is modeled as an attacker–defender game (or Stackelberg game) from the perspective of an adversary agent (the attacker) who aims to inflict maximum disruption on a routing network. They use the r-interdiction selective multi-depot vehicle routing problem to describe this problem and optimize the vehicle routes.

2.3. Knowledge Gap

Existing studies have made substantial contributions to managing severe disruptions specific to a particular firm or its supply chain from a strategic perspective. However, in the context of some predictable supply disruptions due to major events such as the COVID-19 pandemic and the Olympic Games, the existing literature has typically ignored rerouting strategies for these predictable risks. More specifically, time-to-recover, time-to-survive (e.g., out-of-service time, on-time delivery), the recovery level (e.g., service level, unfulfilled demand rate), and the profits lost during the recovery period have been extensively employed to quantify the impact of supply chain disruptions (e.g., [5]). However, these metrics are difficult to measure based on operational data. In practice, metrics such as the logistics path damping coefficient, acceleration coefficient, and vehicle loading capacity ratio in transit logistics are easier to measure for rerouting strategies for predictable supply disruptions. As a matter of fact, they are implemented extensively by companies such as Delphi (China) as a risk exposure index. To our knowledge, no studies have adopted these metrics from an operational perspective; our study fills this gap as well.

3. Models of Centralized and Decentralized Supply Chains

In this paper, we study a two-echelon supply chain consisting of a manufacturer and its raw material or part supplier, as illustrated in Figure 1. Generally, there are two potential logistic strategies for the supply chain when it faces a predictable supply disruption from large-scale events such as the Olympic Games. One strategy is the normal route, in which the supplier delivers products to the manufacturer's desired location, such as an assembly plant or a warehouse. This strategy often results in severe road congestion. Moreover, this strategy has been studied extensively in the literature to help minimize traffic congestion.

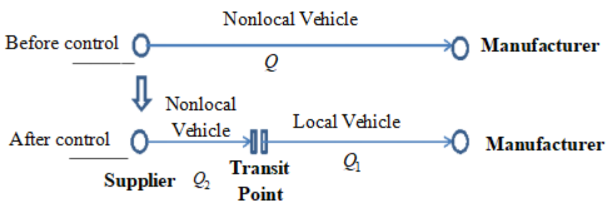

Figure 1. Reconfiguration of logistics routing under vehicle control.

The other strategy is to reroute the logistic channel by setting up a transit point near the boundary between urban and suburbs when confronted with a predictable disruption. The manufacturer in the city chooses the local vehicle (which may be licensed by government regulation) to transport the cargo from the transit point to its facility site, and keeps the nonlocal vehicle between the supplier and the transit point. This strategy is commonly adopted by governments all over the world. For example, in London, the municipal government only permits some licensed vehicles to enter the city, in order to protect the environment. In this study, we focus on this strategy, in which an emergency transit point is set up between the supplier and the manufacturer. In order to help firms minimize delivery delays during these predictable supply disruptions, governments sometimes set up special traffic routes (e.g., express logistic roadways) with major businesses to ensure municipal economic growth. Therefore, the manufacturer or the supplier should decide if setting up an emergency transit point can decrease their delivery delay, and how they should choose optimal express logistics. In the meantime, adding an emergency transit point means increasing supply chain costs (e.g., through warehouse setup costs and inventory costs). Moreover, express logistic roadways may not be free.

We set up our models and assumptions as follows.

(1) Suppose the manufacturer faces a demand rate of $\boldsymbol{X} \sim \boldsymbol{N}(\mu, \sigma^2)$ from its customers, and implements an order policy of (r, $\boldsymbol{Q_1}$). That is, when the inventory level drops below r, it places an order of $\boldsymbol{Q_1}$ to the supplier. Additionally, suppose $\boldsymbol{X}$ is Independent and Identically Distributed at different times.

(2) Suppose the manufacturer and the supplier choose a strategy to set up an emergency transit point at the boundary between an urban and suburban area, and change their transportation model and capacity. For example, the manufacturer is scheduled to pick up at the emergency transit point with a full truck load vehicle with a capacity $\boldsymbol{Q_1}$. The manufacturer must determine the optimal order policy (r, $\boldsymbol{Q_1}$) to minimize the supply chain cost, include the inventory cost and utilization cost of express logistic routes.

(3) Suppose the supplier chooses the capacity $Q_2 \geq \boldsymbol{Q_1}$ for a full truck load vehicle to ship the raw materials or products to the transit point.$Q_2 - \boldsymbol{Q_1}$ is the inventory at the transit point, which is managed by the supplier. When the supplier schedules its shipping, it should consider the relevant inventory cost and set up an appropriate ratio $\boldsymbol{n}$ to match its truck load capacity $\boldsymbol{Q_2}$ with the manufacturer's order $\boldsymbol{Q_1}$. We define this ratio $\boldsymbol{n}$ as the tonnage capacity ratio between the supplier's vehicle capacity in full truck load and the manufacturer's vehicle capacity in full truck load. Here, we have $\boldsymbol{Q_2} = \boldsymbol{n}\boldsymbol{Q_1}$. The supplier's question is to determine the optimal quantity $\boldsymbol{Q_2}$ to deliver to the emergency transit point or the optimal $\boldsymbol{n}$.

(4) In the meantime, the manufacturer should determine the proper lead time to satisfy its customer's requirements. A key factor is the time taken for materials or products to move from the emergency transit point to the manufacturer's site. We denote this $\boldsymbol{L}$. When considering traffic regulations of municipal governments, it may be modeled as $\boldsymbol{L} = (\boldsymbol{1} + \boldsymbol{\tau})\boldsymbol{L_0}/(\boldsymbol{1} + \boldsymbol{b\alpha})$, where $\boldsymbol{\tau}$ is the logistics route damping coefficient used to describe the degree of normal municipal congestion. If $\boldsymbol{\tau} = \boldsymbol{0}$, there is no municipal congestion; if $\boldsymbol{\tau} = \boldsymbol{1}$, there is full disruption. $\boldsymbol{L_0}$ is the regular time taken for materials or products to move from supplier to manufacturer with no traffic regulation. $\boldsymbol{b}$ is a constant. $\boldsymbol{\alpha}$ is the expediting coefficient, used to measure the degree of decongestion on express logistic roadways. When $\boldsymbol{\alpha} = \boldsymbol{0}$, the express logistic roadway has the same congestion as a normal route; when $\boldsymbol{\alpha} = \boldsymbol{1}$, the express logistic roadway has less congestion, and with the help of traffic regulation, the material flow time is restored to $\boldsymbol{L} = (\boldsymbol{1} + \boldsymbol{\tau})\boldsymbol{L_0}/(\boldsymbol{1} + \boldsymbol{b})$. However, to use the express routes, there is a cost of $w = (\boldsymbol{1} + \boldsymbol{\alpha})^{\boldsymbol{2}}w_{\boldsymbol{0}}$, where $w_{\boldsymbol{0}}$ is the normal transportation cost. A larger $\boldsymbol{\alpha}$ means stronger traffic control and a higher transportation cost. Obviously, the lead time $\boldsymbol{L}$ decreases in $\boldsymbol{\alpha}$. Thus, when the manufacturer determines the proper lead time, it can decide whether or not to use the express logistic roadways and their types (i.e., $\boldsymbol{\alpha}$).

(5) Assuming the customer's demand at the lead time is $X_L \sim \boldsymbol{N}(\mu_L, \sigma_L^{\boldsymbol{2}})$, we have $\mu_L = \mu\boldsymbol{L}$, $\sigma_L = \sqrt{\boldsymbol{L}}\sigma$. Suppose the standard distribution function for $\boldsymbol{X_L}$ is $\boldsymbol{F}(x)$, and $f(x)$ **is the** cumulative distribution function (CDF) and probability density function (PDF), with mean $\mu\boldsymbol{L}$. Thus, the reorder point $\boldsymbol{r} = \mu\boldsymbol{L} + \boldsymbol{SS} = \mu\boldsymbol{L} + k\sqrt{\boldsymbol{L}}\sigma$. Let $\boldsymbol{CSL}$ be the desired cycle service level for the manufacturer to service its customer; we can then denote the safety coefficient $k = \boldsymbol{F_S^{-1}}(\boldsymbol{CSL})$, where $\boldsymbol{F_S^{-1}}(\boldsymbol{CSL})$ is a standard inverse function of standard probability density function for $\boldsymbol{N}(\boldsymbol{0}, \boldsymbol{1})$ at $\boldsymbol{CSL}$. Thus, the safety inventory ss for the manufacturer is $ss = k\sqrt{\boldsymbol{L}}\sigma$.

(6) If there is a shortage, the expected shortage for every ordering cycle is $\boldsymbol{E}(\boldsymbol{X} - \boldsymbol{r})^{+} = \int_r^{\infty} (x - r)f(x)dx = \sigma\sqrt{\boldsymbol{L}}\boldsymbol{\Psi}(k).\boldsymbol{\Psi}(k) = \varphi(k) - k[\boldsymbol{1} - \boldsymbol{\Phi}(k)]$ represents the loss function for $k = (r - \mu L)/\sqrt{L}\sigma$. $\varphi(k)$ and $\boldsymbol{\Phi}(k)$ are the PDF and CDF of the standardized

normal distribution. Let $\boldsymbol{CSL}$ denote the desired cycle service level for the manufacturer to service its customer. We thus have the safety coefficient $\boldsymbol{k} = \boldsymbol{\Phi^{-1}}(\boldsymbol{CSL})$.

For clarity, Table 1 summarizes the notations used in this paper.

Table 1. Notation of parameters and decision variables.

Variables		Definitions
Parameters	μ	The expected value of demand rate from the manufacturer's customers
	σ	The standard deviation of the demand rate for the manufacturer's customers
	D	The cumulative demand over an observation period (e.g., one year or before disruption recovery)
	Q_1	The manufacturer's vehicle load capacity in full truck load.
	L_0	The normal time for materials or products to move from supplier to manufacturer with no traffic regulation
	b	A constant coefficient
	τ	The logistics route damping coefficient to describe the degree of normal municipal congestion
	w_0	The normal transportation cost from the transit point to the manufacturer
	w	The cost for the manufacturer to pay the government when using the express routes, $w = (1+\alpha)^2 w_0$
	s_b	The manufacturer's unit selling price
	s_c	The supplier's unit selling price
	p	The opportunity cost due to shortage
	CSL	The desired cycle service level for the manufacturer to service its customer
	A_b	The manufacturer's ordering cost
	h_b	The manufacturer's unit holding cost
	C_s	The supplier's unit production cost
	A_s	The supplier's ordering cost at the emergency transit facility
	h_s	Holding cost at the emergency transit facility
Decision Variables	r	The manufacturer's reorder point
	Q_1	The manufacturer's order quantity during the lead time
	n	The tonnage capacity ratio between the supplier's vehicle capacity in full truck load and the manufacturer's vehicle capacity in full truck load
	α	The type of the express logistic roadways

In summary, the manufacturer and supplier should determine the optimal order policies $\left(\boldsymbol{r}, \boldsymbol{Q_1^*}\right)$, the optimal number $\boldsymbol{n}^*$, and the optimal logistics routing type $\boldsymbol{\alpha}^*$. Their objectives are to minimize the supply chain costs, including the increasing inventory costs and utilization cost of express logistic routes, etc. Subsequently, they may obtain their optimal material flow time (or lead time) $\boldsymbol{L}^*$, safety stock $\boldsymbol{ss} = \boldsymbol{k}\sqrt{\boldsymbol{L}}\boldsymbol{\sigma}$, unit shipping cost $\boldsymbol{w}$ for using express, $\boldsymbol{w} = (\boldsymbol{1}+\boldsymbol{\alpha})^{\boldsymbol{2}}\boldsymbol{w_0}\Big)$ and the capacity (or quantity) $\boldsymbol{Q_2^*}$ of a full truck load vehicle for shipping the raw materials or products to the transit point. These decision variables are discussed in two decision-making structures (a decentralized scenario and centralized scenario).

3.1. Decentralized Supply Chain

With a decentralized supply chain, the supplier and the manufacturer aim to maximize their own profits. They decide on their own ordering, transportation, and inventory decisions. Specifically, they choose the optimal logistics route expediting coefficient α^*, ordering quantity Q_1^*, and vehicle capacity ratio n^* at the emergency transit facility.

3.1.1. The Manufacturer's Decisions

Without considering the express logistics route, the manufacturer's profit π_b under traffic regulation is

$$\pi_b = (s_b - s_c)D - A_b\frac{D}{Q_1} - h_b\left(\frac{Q_1}{2} + ss\right) - p\frac{D}{Q_1}E(X-r)^+ - \frac{Dw_0}{Q_1} \tag{1}$$

This consists of revenue $(s_b - s_c)D$ with demand D at an observation period, the manufacturer's fixed ordering cost, the inventory holding cost, the expected shortage cost, and the transportation cost.

To satisfy the customer's lead time requirement, the manufacturer should guarantee the material flow time $L = (1+\tau)L_0/(1+b\alpha)$ to meet the requirement, due to the logistics disruption. Setting up an emergency transit point is one effective solution to the supplier's delivery problem. In the meantime, utilizing an express logistics route or choosing the appropriate type α of express logistic roadway is another effective policy. However, this brings about the extra cost w compared with normal w_0. Where $w = (1+\alpha)^2 w_0$, $0 \le \alpha \le 1$ and $0 \le \tau \le 1$. Thus, the manufacturer's profit under traffic regulation is

$$\pi_b = (s_b - s_c)D - A_b\frac{D}{Q_1} - h_b\left(\frac{Q_1}{2} + ss\right) - p\frac{D}{Q_1}E(X-r)^+ - \frac{Dw}{Q_1} \tag{2}$$

In (2), Dw/Q_1 is the cost for the manufacturer to choose the express logistic roadways; ss and $E(X-r)^+$ are also changed, and related to the L or α. The other is familiar with (1). When $\alpha = 0$, $w = w_0$ and $L = (1+\tau)L_0$, the manufacturer chooses to transport using routes without vehicle regulations. The state in (2) returns to the state in (1). To describe these changes, we may rewrite the (2):

$$\pi_b = (s_b - s_c)D - A_b\frac{D}{Q_1} - h_b\left(\frac{Q_1}{2} + k\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha}}\right) - p\frac{D}{Q_1}\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha}}\Psi(k) - \frac{Dw_0}{Q_1}(1+\alpha)^2 \tag{3}$$

In (3), $\Psi(k) = \varphi(k) - k[1 - \Phi(k)]$ represents the loss function for $k = (r - \mu L)/\sqrt{L}\sigma$, $0 < \Psi(k) < 0.5$. To derive the optimal ordering policies $\left(r^*, Q_1^*\right)$ and the appropriate type α^*, the manufacturer should maximize the objective function on the decision variables Q_1, α and r. To this end, we have the first conditions, as follows:

$$\frac{\partial \pi_b}{\partial Q_1} = A_b\frac{D}{Q_1^2} - h_b\frac{Q_1}{2} + p\frac{D}{Q_1^2}\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha}}\Psi(k) + \frac{Dw_0}{Q_1^2}(1+\alpha)^2 \tag{4}$$

$$\frac{\partial \pi_b}{\partial \alpha} = \frac{b\sigma(h_b k + pD\Psi(k))\sqrt{(1+\tau)L_0}}{2(1+b\alpha)^{3/2}} - \frac{2Dw_0}{Q_1}(1+\alpha) \tag{5}$$

where $\Psi'(k) = \varphi'(k) + k\varphi(k) + \Phi(k) - 1$. Similarly, we also have $\frac{\partial^2 \pi_b}{\partial Q_1^2}$, $\frac{\partial^2 \pi_b}{\partial \alpha^2}$ and $\frac{\partial^2 \pi_b}{\partial k^2}$, as follows:

$$\frac{\partial^2 \pi_b}{\partial Q_1^2} = -D\left[(1+\alpha)^2 w_0 + A_b + p + \sigma\sqrt{\frac{(1+\tau)l_0}{1+b\alpha}}\Psi(k)\right]Q_1^{-3} \tag{6}$$

$$\frac{\partial^2 \pi_b}{\partial \alpha^2} = Q_1^{-1}\left[-3b^2\sigma\sqrt{(1+\tau)l_0}(Q_1 h_b k + Dp\Psi(k))(1+b\alpha)^{-\frac{5}{2}} - 2Dw_0\right] \tag{7}$$

For simplicity, suppose $k = \Phi^{-1}(CSL)$ is known. The manufacturer sets up an optimal CSL^* in advance, according to customers' requirements. Therefore, we have computed the value of k. We use Matlab to simulate the actual data, and find that $\frac{\partial^2 \pi_b}{\partial Q_1^2} < 0$ and $\frac{\partial^2 \pi_b}{\partial \alpha^2} < 0$. These results mean that π_b is a convex function in(Q_1, α). Setting the first conditions (4)–(6) equal to zero, we have the following proposition:

Proposition 1. *Under decentralization and logistics route reconstruction, the supplier's optimal order quantity, reorder point, and logistics route expediting coefficient maximize the following profit function:*

The optimal order quantity Q_1^* and reorder point r^* are

$$Q_1^* = \sqrt{\frac{1}{h_b}\left[2D\left[(1+\alpha)^2 w_0 + A_b + p\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha}}\Psi(k)\right]\right]} \tag{8}$$

$$r^* = \mu\frac{(1+\tau)L_0}{1+b\alpha} + k\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha^*}} \tag{9}$$

The optimal logistics route expediting coefficient can be obtained by solving

$$b\sigma\sqrt{1+\tau L_0}[Q_1 h_b k + Dp\psi(k)](1+b\alpha)^{-\frac{3}{2}} - 4D(1+\alpha)w_0 = 0 \tag{10}$$

Apparently, we still cannot obtain their closed-form solutions. Thus, we propose an iterative algorithm, as detailed below.

Step 1: Set $\alpha = 0$.

Step 2: Obtain Q_1 according to (9).

Step 3: Substitute Q_1 into (8) and obtain α, and ensure $0 \leq \alpha \leq 1$. If not, abort. If the optimal α is not obtained, increase the step size by 0.001 and repeat.

Step 4: Substitute the α obtained from Step 3 into (8), and obtain Q_1.

Step 5: If the two consecutive Q_1 obtained are similar, go to Step 6. If not, go back to Step 2.

Step 6: Use the Q_1 and α obtained to obtain the optimal inventory control strategy $\left(Q_1^*, r^*\right)$ and the corresponding maximal profit of the manufacturer.

3.1.2. The Supplier

After the manufacturer's inventory control decisions, the supplier will make decisions to maximize its own profit. At the emergency transit point, the supplier ships Q_2 inbound, but delivers the quantity Q_1 outbound. Hence, $Q_2 - Q_1$ is temporarily stored at the transit at lead time L_I. Therefore, the supplier's decision on Q_2 depends on the manufacturer's Q_1 and the tonnage capacity ratio n. That is $Q_2 = nQ_1$. In multi-echelon inventory control, when the upper echelon's quantity is an integer number of multiples of the lower echelon's, the upper echelon's inventory cost can be minimized. Hence, the supplier's total profit is

$$\pi_s = (s_c - c_s)D - A_s\frac{D}{nQ_1} - h_s\frac{(n-1)Q_1}{2} \tag{11}$$

where the first item represents the supplier's revenue over an observation period (e.g., one year, or before disruption recovery). The second is the supplier's order dealing cost, including the transportation cost during lead time L_I. The third is the inventory holding cost at the transit point. As (7) is a concave function of n, there exists an optimal n, which can be obtained by solving $\partial\pi_b/\partial Q_1 = 0$. The solution is

$$n^* = \sqrt{\frac{2DA_s}{h_s Q_1^2}} \tag{12}$$

Make n_0 an integer and [ ] the rounding operator. Then, n^* is between $[n_0]$ and $[n_0]+1$. Hence, the supply chain's total profit consists of the optimal profit of the manufacturer $\pi_b\left(Q_1^*, r^*\right)$ and the optimal profit of the supplier $\pi_s\left(n^*\right)$.

$$\pi_{b,s}\left(Q_1{}^*, \alpha^*, n^*\right) = \pi_b\left(Q_1^*, r^*\right) + \pi_s\left(n^*\right) \tag{13}$$

In a decentralized decision-making structure, the supply chain's profits comprise the optimal manufacturer and supplier profits. Due to objective conflict and information asymmetry, there is probably a double marginalization effect. Thus, we analyze the scenario of a centralized structure as a benchmark.

3.2. Centralized Supply Chain

Under a centralized supply chain, the manufacturer orders Q_I ($Q_2 = nQ_I$) and chooses the express logistics route with expediting coefficient α_I. Thus, that supply chain disruption risk can be reduced. The supplier's transportation cost is $w_I = (1+\alpha_I)^2 w_0$. Hence, the supplier's total profit is

$$\pi_I = (s_b - c_s)D - A_b\frac{D}{Q_I} - A_s\frac{D}{nQ_I} - h_b\left(\frac{Q_I}{2} + ss\right) - h_s\frac{(n_I-1)Q_I}{2} - p\frac{D}{Q_I}E(X-r_I)^+ - \frac{Dw_I}{Q_I} \tag{14}$$

where r_I is the reorder point of the supply chain for the centralized decision. $L_I = \frac{(1+\tau)L_0}{1+b\alpha_I}$ and $w_I = (1+\alpha_I)^2 w_0$ denote the lead time under the centralized supply chain and the manufacturer's transportation cost, respectively. w_0 is the same as in the decentralized scenario. The first item represents the revenue of the whole supply chain. The second is the manufacturer's fixed ordering cost. The third is the supplier's cost for transportation to the transit point and the related dealing cost, except for inventory costs. The fourth is the manufacturer's inventory holding cost. The fifth is the inventory holding cost at transit, taken by the supplier. The sixth is the expected shortage cost to the manufacturer. Finally, the last is the cost for the manufacturer to transport the material from the transit point to its site, and the extra cost of using the express logistics route of type α_I. Under these conditions, with $w_I = (1+\alpha_I)^2 w_0$, $L_I = (1+\tau)L_0/(1+b\alpha_I)$ and $ss = k\sigma\sqrt{L_I}$, we may rewrite (16) into the following supply chain profit function:

$$\begin{aligned}\pi_I = (s_b - c_s)D - \tfrac{D}{Q_I}\left[A_b + \tfrac{A_s}{n_I} + p\sigma\sqrt{\tfrac{(1+\tau)L_0}{1+b\alpha_I}}\Psi(k) + (1+\alpha_I)^2 w_0\right] - \tfrac{Q_I}{2}[h_b + (n_I-1)h_s] \\ -h_b k\sigma\sqrt{\tfrac{(1+\tau)L_0}{1+b\alpha_I}}\end{aligned} \tag{15}$$

Suppose the manufacturer implements the same safety stock; its safety stock is affected only by the L_I and the CSL does not change. Thus, $E(X-r)^+ = \int_r^\infty (x-r)f(x)dx = \sigma\sqrt{L_I}\Psi(k)$, where $\Psi(k) = \varphi(k) - k[1-\Phi(k)]$, $k = \Phi^{-1}(CSL)$, $k = (r_I - \mu L_I)/\sqrt{L_I}\sigma$, and $\Psi(k) > 0$. We have the following first condition for (17):

$$\frac{\partial\pi_I}{\partial Q_I} = \frac{D}{Q_I^2}\left[A_b + \frac{A_s}{n_I} + p\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha_I}}\Psi(k) + (1+\alpha_I)^2 w_0\right] - \frac{1}{2}[h_b + (n_I-1)h_s] \tag{16}$$

$$\frac{\partial \pi_I}{\partial \alpha} = \frac{b\sigma(pD\Psi(k) + h_b k Q_I)\sqrt{(1+\tau)L_0}}{2Q_I(1+b\alpha)^{3/2}} - \frac{2Dw_0}{Q_I}(1+\alpha) \tag{17}$$

$$\frac{\partial \pi_I}{\partial n_I} = \frac{A_s D}{Q_I n_I^2} - \frac{h_s Q_I}{2} \tag{18}$$

Similarly, we also have the second condition for the profit:

$$\frac{\partial^2 \pi_I}{\partial Q_I^2} = -\frac{D}{Q_I^3}\left[(1+\alpha_I)^2 w_0 + A_b + p + \sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha_I}}\Psi(k)\right] \tag{19}$$

$$\frac{\partial^2 \pi_I}{\partial \alpha_I^2} = -\frac{1}{4Q_I}\left[3b^2\sigma\sqrt{(1+\tau)l_0}(Q_I h_b k + Dp\Psi(k))(1+b\alpha_I)^{-\frac{5}{2}} + 2Dw_0\right] \tag{20}$$

$$\frac{\partial^2 \pi_I}{\partial n_I^2} = -\frac{2A_s D}{Q_I n_I^3} \tag{21}$$

Furthermore, $0 \le \alpha_I \le 1$, $0 \le \tau \le 1$, and $0 < \Psi(k) < 0.5$. We also confirm that $\frac{\partial^2 \pi_I}{\partial Q_I^2} < 0$, $\frac{\partial^2 \pi_I}{\partial n_I^2} < 0$, $\frac{\partial^2 \pi_I}{\partial Q_I \partial n_I} < 0$, $\frac{\partial^2 \pi_I}{\partial \alpha_I^2} < 0$. Hence, we can obtain the optimal solutions by setting the first derivatives to 0. Then, we have the following proposition.

Proposition 2. *Under centralization, the supplier chain's optimal order quantity Q_I^* and logistics route expediting coefficient are given as follows:*

$$Q_I^* = \sqrt{2D\left[n_I A_b + A_s + n_I p\sigma\sqrt{\frac{(1+\tau)L_0}{1+b\alpha_I}}\Psi(k) + n_I(1+\alpha_I)^2 w_0\right] / n_I[h_b + (n_I - 1)h_s]} \tag{22}$$

The optimal vehicle capacity ratio at the emergency transit point is

$$n_I^* = \sqrt{\frac{2DA_s}{h_s Q_I^2}} \tag{23}$$

The optimal logistics route expediting coefficient α_I^* solves the following equation:

$$b\sigma\sqrt{1+\tau L_0}[Q_I h_b k + Dp\Psi(k)]\left(1+b\alpha_I{}^*\right)^{-\frac{3}{2}} - 4D\left(1+\alpha_I{}^*\right)w_0 = 0 \tag{24}$$

where $0 \le \alpha_I \le 1$ and $0 < \Psi(k) < 0.5$. Then, (24) can be solved for the optimal α_I^*.

Furthermore, we can use the following iterative algorithm to obtain the optimal Q_I^*, $\alpha_I{}^*$, and n_I^*.

Step 1: Initialize n = 1.

Step 2: Using a similar iterative algorithm, obtain Q_I and α_I, and the supply chain's total profit based on (12).

Step 3: Calculate n_0 using the Q_I from Step 2. If $n_I < n_0 + 1$, make $n_I = n_I + 1$ and go to Step 2. Otherwise, go to Step 4.

Step 4: Given n_I, find the maximal supply chain profit and the associated optimal $\left(Q_I^*, \alpha_I^*, n_I^*\right)$, as well as the manufacturer's optimal inventory policy $\left(Q_I^*, r_I^*\right)$.

Under centralization, the supply chain's total profit is

$$\pi_I\left(Q_I^*,\ r_I^*,\ n_I^*\right) = \pi_b\left(Q_I^*, r_I^*\right) + \pi_s\left(n_I^*\right) \tag{25}$$

Comparing (13) and (25), we can see that the supply chain profit is higher under centralization than under decentralization. This is because decentralization leads the manufacturer and the supplier to maximize their own profits, which results in the double marginalization phenomenon.

3.3. Supply Chain Coordination

To achieve supply chain coordination, we propose a price discount contract. Specifically, the supplier will set the selling price to be $\delta_c s_c$, where δ_c is the price discount parameter, and $0 \leq \delta_c < 1$. This is to help to move the optimal decisions $\left(Q_1^*,\ \alpha^*\right)$ under decentralization to the optimal decisions $\left(Q_I^*,\ \alpha_I^*\right)$ under centralization. Hence, we have

$$s_c = \begin{cases} s_c & Q_1^* < Q_I^*,\ \alpha^* \neq \alpha_I^* \\ (1-\delta_c)s_c & Q_1^* \geq Q_I^*,\ \alpha^* = \alpha_I^* \end{cases} \tag{26}$$

Suppose Q_1 is adjusted by a coefficient δ_Q, and the logistics route expediting coefficient is adjusted by δ_α. To achieve the optimal profit level under the centralized case, we need to have $\delta_Q = Q_I^*/Q_1^*$ and $\delta_\alpha = \alpha_I^*/\alpha^*$. The manufacturer will accept the price discount contract only when

$$\pi_b\left(\delta_c s_c, \delta_Q Q_1^*,\ \delta_\alpha \alpha^*\right) \geq \pi_b\left(s_c,\ Q_1^*,\ \alpha^*\right) \tag{27}$$

Based on (2) and (27), the manufacturer's added profit due to the price discount contract is

$$\begin{aligned} \Delta\pi_b = \delta_{c1} s_c D + A_b \tfrac{D}{Q_1^*}\left(1 - \tfrac{1}{\delta_Q}\right) + h_b \tfrac{(1-\delta_Q)Q_1^*}{2} \\ + \tfrac{w_0 D}{Q_1^* \delta_Q}\left[\delta_Q(1+b\alpha)^2 - (1+b\alpha\delta_\alpha)^2\right] \\ + \tfrac{p\sigma\Psi(k)D}{Q_1^*\delta_Q}\left[\delta_Q\sqrt{\tfrac{(1+\tau)L_0}{1+b\alpha}} - \sqrt{\tfrac{(1+\tau)L_0}{1+\delta_\alpha b\alpha}}\right] \end{aligned} \tag{28}$$

Choosing the appropriate δ_{c1}, we can obtain $\Delta\pi_b \geq 0$. On the other hand, the supplier will accept the price discount contract only if

$$\pi_s\left(\delta_c s_c,\ \delta_n n^*\right) \geq \pi_s\left(s_c,\ n^*\right) \tag{29}$$

Based on (11) and (29), the supplier's additional profit from the price discount contract is

$$\begin{aligned} \Delta\pi_S = (\delta_{c2} - 1)s_c D + A_S \tfrac{D}{n^* Q_1^*}\left(1 - \tfrac{1}{\delta_Q \delta_n}\right) \\ + \tfrac{h_s Q_1^*\left[n^*(1-\delta_Q\delta_n) - (1-\delta_Q)\right]}{2} \end{aligned} \tag{30}$$

Similarly, we can obtain $\Delta\pi_s \geq 0$ by choosing an appropriate δ_{c2}. Based on our analysis so far, only when $\delta_{c2} \leq \delta_c \leq \delta_{c1}$ will both the manufacturer and the supplier be willing to adopt the price discount contract and maximize the total profit of the supply chain. Consequently, the manufacturer's order quantity changes from Q_1^* to Q_I^*, the logistics route expediting coefficient changes from α^* to α_I^*, and the supplier's selling price changes from s_c to $\delta_c s_c$. In general, a lower δ_c means a lower profit for the supplier, but a higher profit for the manufacturer. The final choice of δ_c will depend on the bargaining power of the two firms. Next, we conduct numerical examples to illustrate our analytical results and obtain more managerial insights.

4. Numerical Experiments

4.1. For the Decentralized Decision Structure

We set the parameters as follows: lead time demand $D = 2000$ units/week, μ = 4 units/week, σ = 3 units/week, k = 1, h_b = 2/unit, p = 10/unit, h_s = 1.2/unit, τ = 1, L_0 = 10 h, w_0 = 2/unit, A_b = 30/unit, A_s = 40/unit, S_b = 20/unit, ss = 10 unit, c_S = 5/unit, and b = 0.7.

We simulated all the above scenarios and input all parameters into the models above. All these simulations resulted in a sensitivity analysis, as follows.

4.1.1. The Impact of Inventory Holding Cost h_b

When changing the inventory holding cost h_b in the arrangement of $(1, 8)$, (take the proportion from **5%** to **40%** of the sales price, but fixing the other parameters) we have the results for the decision variables in the scenario of a decentralized supply chain, as shown in Table 2.

Table 2. The impact of h_b on $(Q_1^*,\ r^*)$, α^*, n^*, π_b and π_s.

h_b	Q_1^*	α^*	r^*	n^*	π_b	π_s
1	425	0.2	331	1	19,559	9811
1.5	347	0.22	326	1	19,456	9769
2	301	0.25	322	2	19,368	9687
2.5	269	0.27	319	2	19,289	9690
3	246	0.28	316	2	19,218	9689
3.5	228	0.3	312	2	19,151	9687
4	213	0.31	310	2	19,088	9684
5	191	0.34	306	2	18,973	9675
6	174	0.36	302	3	18,867	9637
7	161	0.38	299	3	18,769	9641
8	150	0.4	296	3	18,676	9642

We may find the optimal profits of the manufacturer and the supplier vary with the inventory holding cost h_b, but the variability is not high. On the contrary, the impacts of the inventory holding cost h_b on the manufacturer's optimal $\left(Q_1^*, r^*\right)$, the type of express roadway α^*, and the tonnage capacity ratio n^* are high, as shown in Figures 2 and 3.

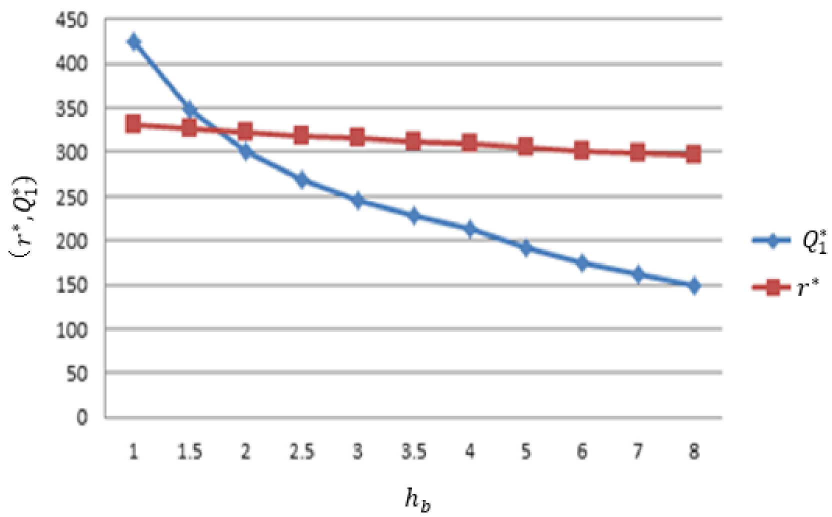

Figure 2. The impact of h_b on the optimal order policy $\left(Q_1^*, r^*\right)$.

In Figure 2, we may find that the manufacturer's optimal $\left(Q_1^*, r^*\right)$ decreases with its inventory holding cost. This shows that the manufacturer is reluctant to order more quantity, and holds too much safety inventory when faced with predictable supply chain disruptions.

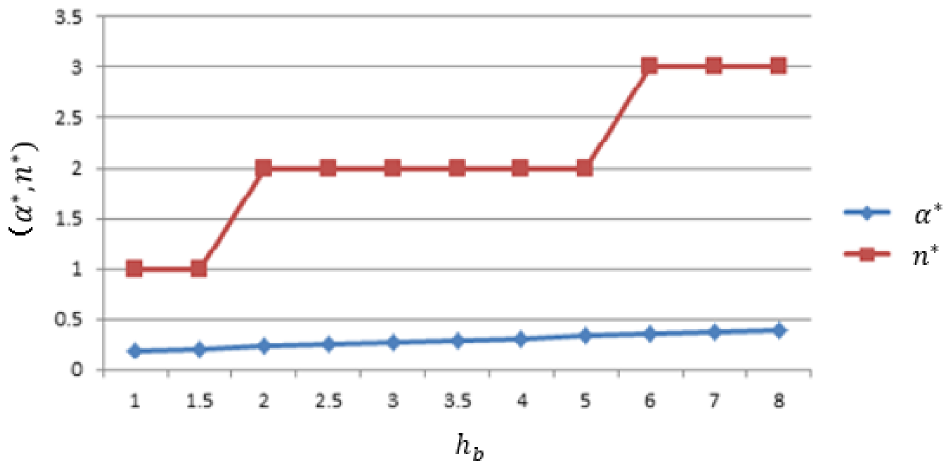

Figure 3. The impact of h_b on (α^*, n^*).

In Figure 3, the optimal tonnage capacity ratio n^* increases in intervals $(\mathbf{1.5}, \mathbf{2})$ and $(\mathbf{5}, \mathbf{6})$ of h_b. This means the supplier should avoid these ranges when choosing its n^* policy. The cost of the optimal type of express roadway α^* increases stably with h_b. All these results show that the manufacturer prefers to choose the express roadway to keep safety inventory in the presence of predictable logistics disruptions by decreasing the delivery lead time. The supplier prefers to optimize the tonnage capacity ratio to support the processes of one-time shipping and multiple deliveries to the transit point.

4.1.2. The Impacts of Delivery Cost A_s and Ordering Cost A_b

We also study the impact of delivery cost A_s (mainly the transportation cost) from the supplier, and the ordering cost A_b on the manufacturer. We find that A_b, but not A_s, impacts these decision variables significantly, as shown in Figures 4 and 5.

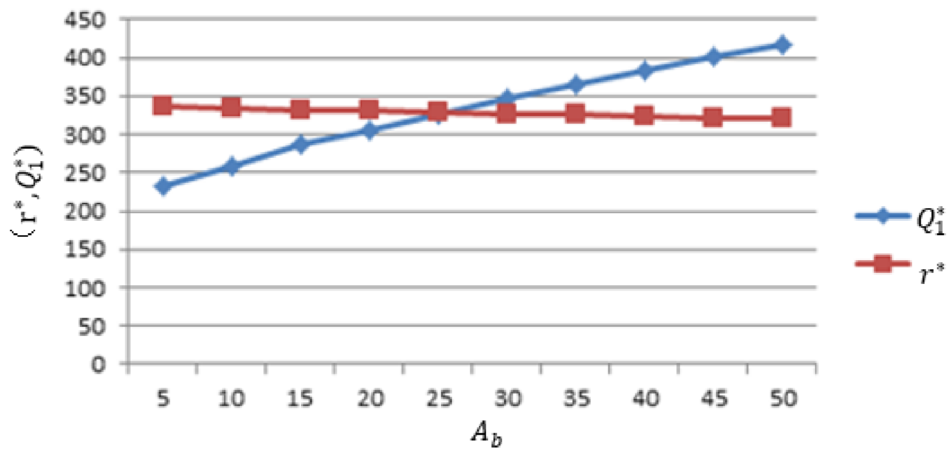

Figure 4. The impact of A_b on the optimal order policy $\left(Q_1^*, r^*\right)$.

In Figure 4, the optimal order policy Q_1^* increases with A_b, but r^* changes little. This is because the manufacturer wants to keep the ordering cost A_b unchanged by increasing the order quantity, when it should pay the extra fee for utilization of the express roadway. The reorder point r^* chiefly depends on the the desired cycle service level (CSL) or safety coefficient k.

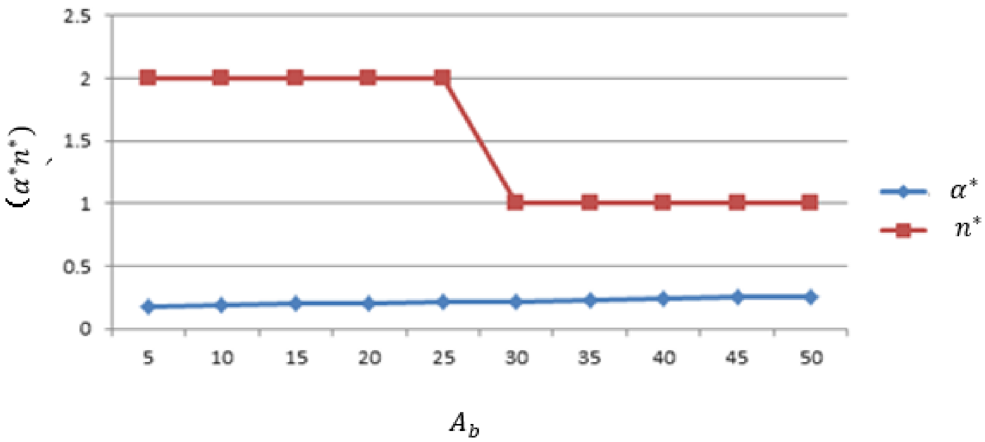

Figure 5. The impact of h_b on (a^*, n^*).

In Figure 5, α^* changes little with A_b. This is because the choice of α^* depends on the fees incurred by government traffic regulations. n^* varies in intervals of $(25, 35)$ with increasing A_b. That is to say, when A_b is more than 30, $Q_2 - Q_1$ decreases with A_b. The manufacturer is thus inclined to order more; this is consistent with Figure 4.

4.1.3. The Impact of Demand Uncertainty σ

When the demand uncertainty σ changes within the range of $(0, 8)$, we may produce the following table.

In Table 3, we can see that to deal with logistics disruption risk, as the standard deviation of the lead time demand increases, the manufacturer's optimal order quantity increases and the optimal logistics route expediting coefficient α^* increases, but the optimal reorder point r^* decreases. This indicates that in the presence of logistics disruption risk, the supply chain's optimal strategy is not to increase safety stock but to reduce the lead time by adopting express routes. Moreover, the optimal vehicle capacity ratio n^* becomes more insensitive as σ increases. Hence, the choice of vehicles depends on the ordering quantity and delivery quantity of the supplier and the manufacturer, but is more or less independent of the manufacturer's demand uncertainty.

Table 3. The impacts of σ on $\left(Q_1^*, r^*\right)$, α^*, n^*, π_b and π_s.

σ	Q_1^*	α^*	r^*	n^*	π_b	π_s
0	155	0	360	3	19,690	9641
1	181	0	365	2	19,627	9635
2	203	0	370	2	19,570	9681
3	224	0.2	330	2	19,520	9687
4	242	0.39	302	2	19,476	9689
5	259	0.55	283	2	19,436	9690
6	273	0.7	325	2	19,456	9769
7	286	0.83	258	2	19,365	9688
8	300	0.96	250	2	19,333	9686
9	310	1	250	2	19,303	9684

4.1.4. The Impact of Logistics Route Damping Coefficient τ

By changing the logistics route damping coefficient τ within the range of $(0, 1)$, we obtain the results in Table 4.

Table 4. The impacts of τ on $\left(Q_1^*, r^*\right)$, α^*, n^*, τ_b and τ_s.

τ	Q_1^*	α^*	r^*	n^*	π_b	π_s
0	197	0	129	2	19,585	9679
0.1	202	0	154	2	19,576	9680
0.2	205	0	179	2	19,567	9682
0.3	208	0.03	200	2	19,560	9683
0.4	211	0.06	220	2	19,553	9684
0.5	213	0.09	239	2	19,547	9685
0.6	216	0.11	258	2	19,541	9685
0.7	218	0.14	275	2	19,535	9685
0.8	220	0.16	295	2	19,530	9686
0.9	223	0.18	313	2	19,525	9687

In Table 4, the logistics route damping coefficient τ has a significant impact on the optimal order strategy $\left(r^*, Q_1^*\right)$, a smaller impact on α^*, π_b and π_s, and no impact on n^*. It also shows that the manufacturer's optimal order quantity and reorder point both increase in τ. To alleviate the logistics disruption risk, the manufacturer will order more to increase the safety stock. This is because of the relationship between τ and L: $L = (1+\tau)L_0/(1+b\alpha)$.

In Table 4, the greater τ is, the greater the degree of traffic congestion is, and the longer the logistics time L is. This suggests that the manufacturer should choose the express roadway to decrease the possible long lead time and maintain the same customer service level (CSL). However, it costs more to use these express roadways.

4.2. For the Centralized Decision Structure

4.2.1. The Impact of Demand Uncertainty σ

When changing the demand uncertainty σ within the range of $(1, 5)$ (taking the proportion from 5% to 25% of the demand rate, but fixing the other parameters to be the same as those in the decentralized structure), we may find the results of the decision variables in the scenario of a decentralized supply chain, as shown in Table 5.

Table 5. The impact of σ on $\left(Q_1^*, r^*\right)$, α^*, n^*, τ_b and τ_s.

σ	Q_I^*	α_I^*	r_I^*	n_I^*	π_b^I	π_s^I
0	245	0	360	2	19,657	9689
1	286	0	365	1	19,588	9733
2	323	0.04	362	1	19,526	9752
3	356	0.28	317	1	19,472	9775
4	373	0.47	290	1	19,430	9785
5	384	0.63	272	1	19,395	9791

In Table 5, π_b^I and π_s^I are the profit for the manufacturer and the supplier, respectively, under a centralized supply chain. The total profit is $\pi_I^* = \pi_b^I + \pi_s^I$. The impact of σ on π_I^* and the total profit π_D^* for a decentralized structure are shown in Figure 6. To better understand the comparison between centralized and decentralized supply chains, we also assess how σ impacts the optimal solutions of $\left(Q_1^*, Q_I^*\right)$, (α^*, α_I^*), (n^*, n_I^*), and (π_D^*, π_I^*), as shown in Figures 6–9.

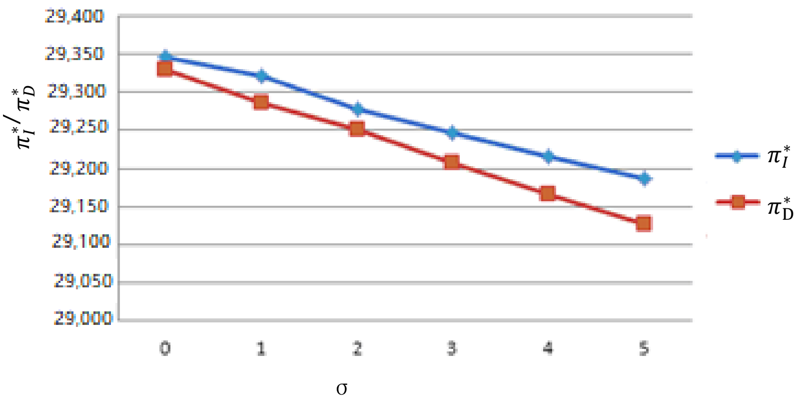

Figure 6. The curves between the optimal profits $\left(\pi_D^*, \pi_I^*\right)$ and **σ**.

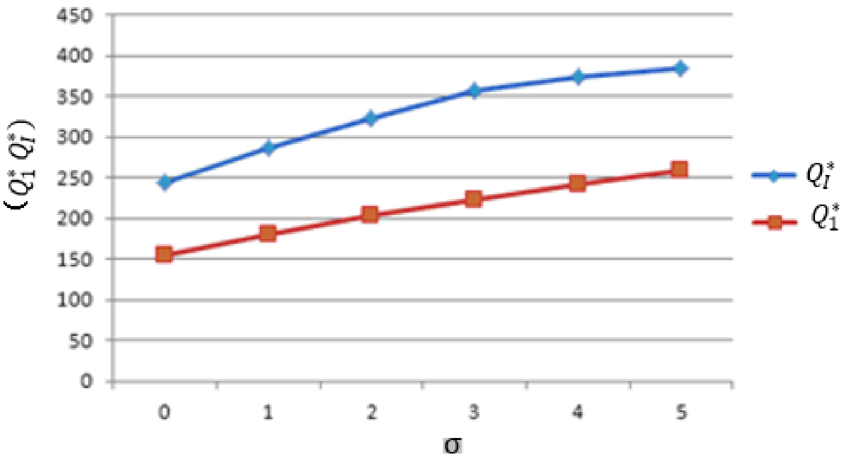

Figure 7. The curves between $(Q_1^*,\ Q_I^*)$ and **σ**.

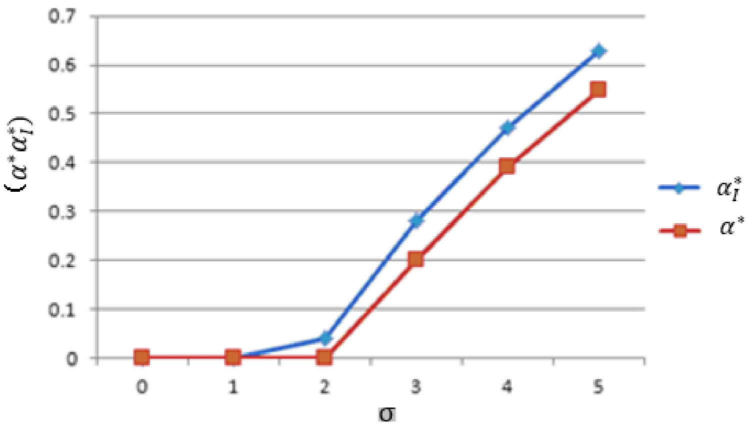

Figure 8. The curves between the logistics route expediting coefficients $(\alpha^*,\ \alpha_I^*)$ and **σ**.

Figure 6 shows that the supply chain profits under both centralization and decentralization $\left(\pi_D^*, \pi_I^*\right)$ decrease in σ. Additionally, centralization leads to higher supply chain profits.

Figure 7 shows that the optimal order quantity Q_I^* is larger under centralization than decentralization. Moreover, Q_I^* increases in σ. Therefore, supply chain decentralization can reduce the order quantity.

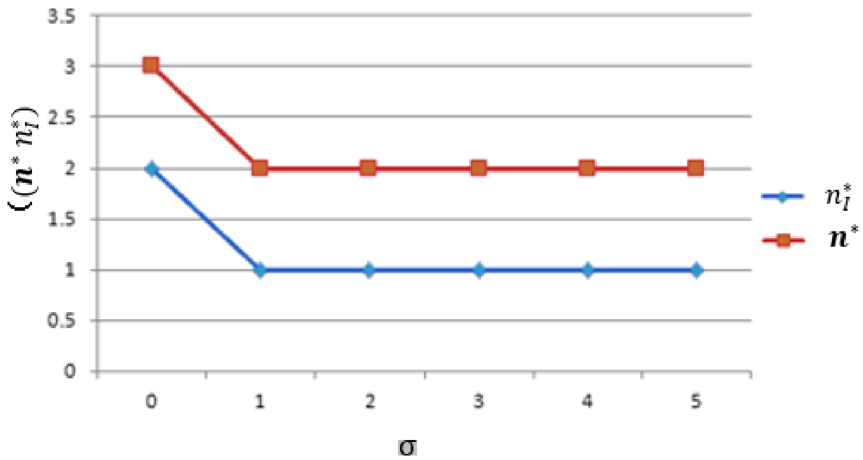

Figure 9. The curves between the optimal vehicle capacity ratios (n^*, n_I^*) and σ.

From Figure 8, we can see that when σ is below 1.5, supply chain centralization or decentralization has little impact on the logistics route expediting coefficient $\left(\alpha^* \alpha_I^*\right)$. However, this impact becomes more significant as σ reaches 2 or more. Furthermore, centralization and decentralization results in $\left(\alpha^*, \alpha_I^*\right)$. Thus, as demand uncertainty increases, the centralized supply chain tends to choose a higher logistics route expediting coefficient to deal with disruption risk.

From Figure 9, we can see that the centralized supply chain leads to a larger optimal vehicle capacity ratio, i.e., $n_I^* > n^*$. However, these ratios will be unchanged after σ reaches a certain threshold. Hence, we can conclude that the optimal vehicle capacity ratio is insensitive to the manufacturer's demand uncertainty.

4.2.2. The Impact of the Type of the Express Logistic Roadways α

When changing the type of the express logistic roadways α within the range of $(1, 0)$ (meaning the extent to which congestion is relieved as a result of traffic regulation), and using $w_0 = 10$/unit (but fixing the other parameters to be the same as in the decentralized structure), we may obtain results for the decision variables of two scenarios, as shown in Figures 10 and 11.

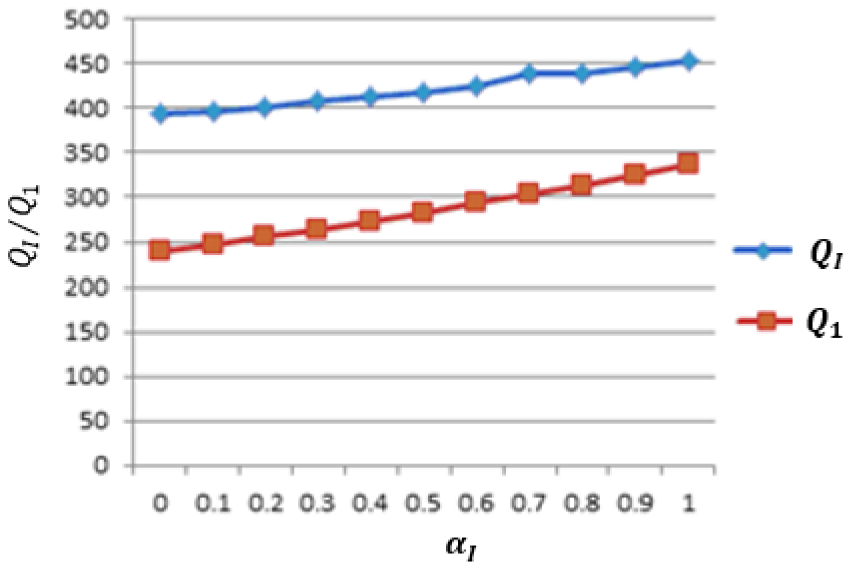

Figure 10. The curves between the order quantities Q_I/Q_1 and α_I.

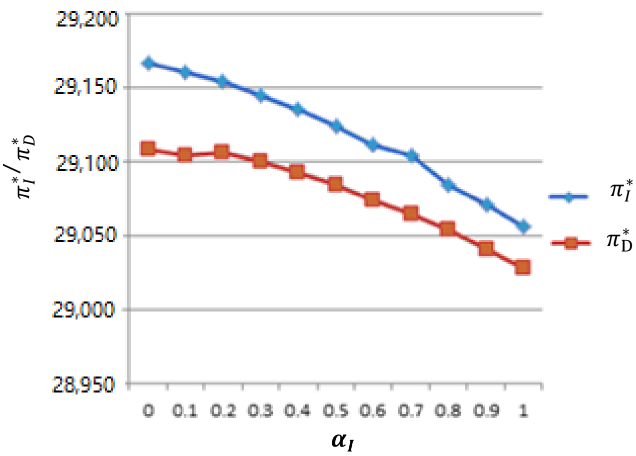

Figure 11. The curves between profits π_I/π_D and α_I.

From Figures 10 and 11, it can be seen that if the government adopts more strict traffic control, α_I increases. This will then increase the manufacturer's order quantity Q_1. Furthermore, the difference between Q_I and Q_1 will decrease in α_I. In terms of profit, an increased α_I will hurt the total profit of the supply chain. Moreover, the profit difference between centralization and decentralization will decrease in α_I. This means that if the government's traffic control policy becomes stricter, it is more beneficial to adopt supply chain centralization. When α_I is smaller, the supplier prefers the strategy of using an emergency transit facility. Finally, we have performed an analysis that shows that when the supplier adopts a price discount contract, the supplier and the manufacturer can achieve supply chain coordination. This will lead to the optimal order quantity and logistics route expediting coefficient, which maximizes supply chain profits.

5. Conclusions

Predictable logistics disruption due to large-scale events such as the COVID-19 pandemic lockdown and the Olympic Games can significantly reduce supply chain profits. In this paper, we proposed a supply chain logistics model to optimize logistics routes in terms of the route damping coefficient, route expediting coefficient, and vehicle tonnage capacity ratio at the emergency transit facility. We also studied the manufacturer's optimal order quantity and the supplier's optimal transshipment strategy under supply chain centralization and decentralization. Our analysis and results show that a decentralized supply chain leads to a lower order quantity as demand uncertainty increases. Our results also confirm that centralization leads to higher supply chain profits. Therefore, we propose using a price discount contract to improve supply chain profits.

Furthermore, our results show that in the presence of logistics disruption risks, the optimal strategy of the supply chain is not to increase safety stock, but to shorten the lead time using express logistics routes. This means the manufacturer should choose logistics routes with a higher expediting coefficient in order to transport products quickly and reduce lead time demand uncertainty. Moreover, a centralized supply chain can better deal with disruption risk. Finally, the choice of transportation vehicle should depend on the ordering quantity and delivery quantity of the supplier and the manufacturer, not on the manufacturer's demand uncertainty.

There are several limitations of this paper; hence, multiple future research directions can be pursued. First, in this paper, we mainly focus on the economic objectives of the supply chain and its members. Logistics disruptions have been shown to worsen environmental pollution significantly [38]. On the one hand, our research analysis and results on minimizing the negative impacts of logistics disruptions may help to lessen carbon emissions. On the other hand, future researchers can look to explicitly incorporate the objective of carbon emission reduction in their modeling and analyses. Second, although we propose a price discount contract, there are many existing alternative business practices.

Thus, more research may be carried out to coordinate the supply chain with the dual objectives of profit maximization and carbon emission minimization [39]. This may also be achieved by considering consumers' low-carbon purchase intentions [40]. Last but not least, this paper omits the use of big data to address supply chain disruptions. Therefore, big data analytics can be examined to see how logistics disruptions and carbon emissions can best be minimized [41].

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