Chapter 14
Pricing Decisions in a Heterogeneous Dual-Channel Supply Chain Under Lead Time-Sensitive Customer Demand

Sarin Raju, T. M. Rofin, and S. Pavan Kumar

Abstract Internet facilities helped retailers to sell through online channels, and as a result, e-tailers rose into prominence and started competing with retailers. But, the e-commerce industry always confronted the issue of lead delivery time, hindering the growth of many e-tailers. We observed scant literature that studies the impact of delivery lead time on a dual-channel supply chain consisting of retailer and e-tailer. This research paper uses game theory to verify the impact of delivery lead time on pricing decisions of a heterogeneous dual-channel supply chain consisting of the manufacturer, retailer, and e-tailer. We used the Stackelberg game to study the manufacturer's and downstream partners' interaction: retailers and e-tailers. A horizontal Nash game was used to model the interaction between the downstream partners. We had analytically modeled how the lead delivery time significantly affects the channel partner's optimal pricing, sales volume, and profitability. We also did sensitivity analysis to check the influence of the customers' channel preference coefficient toward a particular channel and its cross-effects on the pricing policies when the customer is also lead time-sensitive. The study revealed that irrespective of large delivery time or next day delivery time, customers' preference toward a particular channel didn't affect the manufacturer's profit, whereas it affected the profit of the retailer and e-tailer. On the other hand, the increase in lead time-sensitivity coefficient severely affected the profit of all the supply chain partners. By analyzing the pricing decisions, we found that both the customer preference and lead time-sensitivity coefficients affected the pricing decisions, but customers' channel preference coefficient failed to mitigate the effect of lead delivery time. The inputs from this study can be used by practicing managers to develop decision support systems and as an input in multi-agent systems for converting lead time-sensitive supply chains to robust and resilient ones.

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A. Gunasekaran et al. (eds.), *Applications of Operational Research in Business and Industries*, Lecture Notes in Operations Research,
https://doi.org/10.1007/978-981-19-8012-1_14

Keywords Dual-Channel supply chain · Delivery time · Game theory · Multi-agent systems · Resilient supply chain · e-tailer · Disruption

Introduction

With the advent of the Internet and rapid technological growth, people have become increasingly accustomed to purchasing goods online. Consequently, this period witnessed the rise of e-commerce firms [2, 3, 12, 35], which facilitates the e-tailer to successfully provide a large volume and variety of products, allowing the customers to order goods in home comfort. Many e-tailers like WS retail, Cloudtail, etc., have their logistics owned by their parent company, whereas many other e-tailers depend on third-party logistic firms like Delhivery, Blue Dart, FedEx, etc., for the end customer delivery support [26]. Though many choices are available, delivery lead time remains a core concern for the e-tailer when competing with the traditional retailer. Empirical researches prove that, like pricing, delivery service is also an equally important factor for delivery lead time conscious customers [6, 11, 30]. Many researchers claim that the customers are ready to pay more price for the quick delivery of their goods [15], and aligning with these researches, companies like Amazon have badged many customers 'Prime' and promised them fast delivery with extra prime membership. This paper, for the first time, analytically models the pricing decisions of a heterogeneous dual-channel supply chain (HDCSC) consisting of retailers and e-tailers for a delivery lead time conscious customer. This paper also checks the variation of sales volume and profitability of the customer with the change in delivery lead time.

For analysis, we assume an HDCSC [14, 33, 36] consisting of a manufacturer and two downstream channel partners, retailer, and e-tailer [26–28]. We employ the Stackelberg game (S Game) [8, 9, 13, 37] to study the interaction between the upstream channel and downstream partners with the manufacturer as the Stackelberg leader. We used the horizontal Nash (HN) game to check the game between the downstream channel partners [28]. With these assumptions, we are addressing the following overarching research questions:

1. What is the influence of the delivery lead time on pricing decisions of the product for the retailer and e-tailer?
2. How the delivery lead time significantly impacts the sales volume of the channel partners?
3. What is the effect of delivery lead time on the profit of the channel partners?
4. What is the impact of customer channel preference coefficient and lead time-sensitivity coefficient on pricing decisions?
5. Can the customers' preference toward the e-tailers mitigate the effects of the lead delivery time?

Based on the analysis of the above questions, we deduce the following academic and managerial contributions. The optimal decisions of all the channel partners, namely retailer, e-tailer, and manufacturer, were derived, and the impact of lead delivery time was shown. Using the optimal decisions and S and HN game analytics, the sales volume of the channel partners was derived and analyzed. Later, optimal profit of both the upstream and downstream channel partners was derived, and the impact of delivery lead time was analyzed. The study also examined the effect of customers' channel preference coefficient and lead time-sensitivity coefficients on the optimal decisions. We find that the pricing decisions are affected by the lead time-sensitivity coefficient irrespective of whether the e-tailer delivered the product in the next day or had a considerable delivery time, whereas the channel preference coefficient is indifferent toward the optimal profit of the manufacturer. We also find that the profit of both the upstream and downstream channel partners decreased with an increase in lead time-sensitivity coefficient, and the decrease is severe for the e-tailer. To our surprise, the optimal profit of the retailer also decreased with an increase in lead time-sensitivity coefficient. The study also revealed that the impact of lead time sensitivity for all the supply chain partners could be reduced if the e-tailer can ably deliver the product in the next day and customers' channel preference toward e-tailers cannot mitigate the effects of delivery lead time. The optimal decisions of the study can act as an input for decision support systems and multi-agent systems in making the HDCSC robust and resilient.

In the next section, we report a brief account of existing literature in the field.

Literature Review

The Internet reached every nook and corner by the twenty-first century, and as a result, the e-commerce industry came into prominence. Observing the benefits of the e-commerce industry, many manufacturers started opening their own online channel along with the traditional brick and mortar retailers, thereby maintaining two channels simultaneously. The presence of two channels, i.e., one company-owned online channel and the traditional brick and mortar retailer, gives rise to the dual-channel supply chain (DCSC) concept. After that, there were many studies in the field of DCSC which concentrated on pricing [16, 20], inventory policies [34, 38], channel coordination [5, 32], disruption [17, 24, 25], etc. Later, e-tailers were introduced to the DCSC studies by Rofin and Mahanty [28], thereby bringing heterogeneous dual-channel supply chains (HDCSC) to the game-theoretic studies. Later, the same researchers introduced channel power structures in HDCSC [29].

During COVID-19 disruptions, the e-commerce industry faced severe lead delivery time-related issues, and many researchers started studying the impact of delivery lead time and its mitigating strategies [1, 10, 15, 19, 23]. Delivery lead time-depended stochastic customer demand was analyzed by Modak and Kelle [23] in a DCSC consisting of the traditional retailer and retailer-owned online channel and derived analytical models with the objective of profit maximization. The impact of delivery lead time on channel selection and pricing was studied by Hu et al. [15] using a mixed DCSC of manufacturer and retailer. The study suggested using consumer delivery lead time preference in retailers' decision-making. Delivery time was used in a game-theoretical approach in green DCSC by Alizadeh-Basban and

Taleizadeh [1], and equilibrium conditions were derived using the manufacturer-S game, distributor-S game, and Nash game. Delivery phase failures in e-retailing were analyzed, and recovery measures were suggested by Jafarzadeh et al. [19]. The study provides insights into mitigating the effects on the criticality of situation and brand equity due to delivery phase failures. The delivery lead time competition between e-tailers was analyzed by Raju et al. [26], and pricing decisions were modeled using the Stackelberg game and horizontal Nash game when one e-tailer is delivering the product the next day and the second e-tailer takes taking long duration for the delivery.

Critical observation and analysis of the abovementioned studies, the researchers found that most of the studies are concentrating on DCSC consisting of the retailer and online channel owned by the manufacturer, and there is very scant literature in the field of HDCSC consisting of retailer and e-tailer as downstream partners (which is a different story and analytics), which concentrates on lead delivery time and its impact on the decision variables of channel partners. This study mainly focuses on this research gap.

In the next section, we elaborate on the planned research method.

Research Method and Propositions

The basic linear demand function, $D = a - \lambda p$ [25, 26], is employed to establish the relationship between the demand and price. Here, a denotes base market potential. We also assume that the demand of the product is sensitive to the price [18, 25] and is denoted by own-price elasticity, λ. It can be defined as the change in demand due to a unit change in price. We use θ as the customer's preference toward the e-tailer channel where $0 \leq \theta \leq 1$ and is known as the customers' channel preference coefficient. Empirical researches prove that, like pricing, delivery service is also an equally important factor for delivery lead time conscious customers [6, 11, 30]. So, we fixed delivery lead time and price as decision variables. With these assumptions, the following equations were derived.

$$\text{Demand for the retailer, } D_r = (1 - \theta)a - \lambda P_r + \gamma P_e + \beta L \tag{14.1}$$

$$\text{Demand for the e-tailer, } D_e = \theta a - \lambda P_e + \gamma P_r - \Omega L \tag{14.2}$$

Here, suffix r and e denote retailer channel and e-tailer channel, and γ represents cross-price elasticity. We also assume that $\lambda, \gamma > 0$ and $\lambda > \gamma$. In the study, we assume delivery lead time-sensitive customers, and L indicates the delivery lead time, and β and Ω represent the lead time-sensitivity coefficients of the demands of the retailer and e-tailer, respectively. It means that if L increases by one unit, Ω units of the customer will be lost by the e-tailer, and from that β units will be gained by the retailer. For mathematical and practical correctness, we have also assumed $\Omega > \beta$. The actual decision-making sequence starts with the manufacturer announcing the

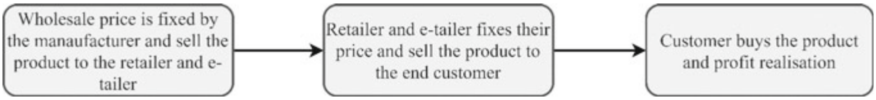

Fig. 14.1 Actual decision-making process

wholesale price, followed by the retailer and e-tailer fixing their price. The decision-making process ends with the customer buying the product and profit realization. The entire flow is shown in Fig. 14.1.

Here, we use two game theory analytics to study the interaction. An S game analytics is used to investigate the interaction between the upstream and downstream channel partners. Here, the manufacturer will have channel power over the other partners, and consequently, we assigned Stackelberg leadership to the manufacturer. We used second sub-game analytics to examine the downstream partners' interaction. Since the downstream channel partners have comparable channel powers, we used the HN game to derive the equilibrium conditions. The Stackelberg leader fixes the wholesale price, w, and the followers will use this price to derive their profit.

$$\begin{aligned}\text{Profit of the Retailer} &= \pi_r = (P_r - w)D_r \\ &= (P_r - w)\{(1-\theta)a - \lambda P_r + \gamma P_e + \beta L\}\end{aligned} \tag{14.3}$$

$$\begin{aligned}\text{Profit of the e-tailer} &= \pi_e = (P_e - w)D_e \\ &= (P_e - w)(\theta a - \lambda P_e + \gamma P_r - \Omega L)\end{aligned} \tag{14.4}$$

$$\text{Profit of the Manufacturer} = \pi_m = (w - s)(Q_r + Q_e) \tag{14.5}$$

Here, s denotes the unit production cost, and Q_r, Q_e are, respectively, the sales volumes of retailers and e-tailers. Wholesale price, w, can be derived using the principle of backward induction. The analytics of the backward induction is shown in Fig. 14.2.

After modeling the scenario, to get better managerial insights, we compare the pricing decisions and profitability of the channel partners when the e-tailer delivers the product the next day, and he took a higher delivery time.

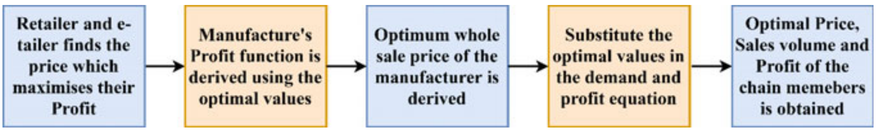

Fig. 14.2 Backward induction analytics

Propositions

For $\frac{\partial^2 \pi_r}{\partial P_r^2}$ and $\frac{\partial^2 \pi_e}{\partial P_e^2} < 0$, P_r and P_e can be obtained by taking first-order conditions (FOC) of π_r and π_e.

Propositions 1 *The optimal price of the retailer and e-tailer when the downstream channel partners are engaged in HN game is given by*

$$P_r = \frac{\gamma\theta a + 2a\lambda + 2L\beta\lambda + w\gamma\lambda - 2a\theta\lambda + 2w\lambda^2 - L\gamma\Omega}{4\lambda^2 - \gamma^2} \tag{14.6}$$

$$P_e = \frac{a\gamma\theta - a\gamma - L\beta\gamma - w\gamma\lambda - 2\theta a\lambda - 2w\lambda^2 + 2L\lambda\Omega}{4\lambda^2 - \gamma^2} \tag{14.7}$$

Substituting the values of P_r and P_e *in* (14.1) *and* (14.2)*, we will get the following corollary.*

Corollary 1 *The sales volume of the retailer and e-tailer when the downstream channel partners are engaged in HN game is given by*

$$Q_r = \frac{\lambda\left(2a(\theta-1)\lambda - w\left(\gamma^2 + \gamma\lambda - 2\lambda^2\right) - \gamma\theta a\right) + L\left(2\beta\lambda^2 + \gamma\lambda\Omega - \beta\gamma^2\right)}{\gamma^2 - 4\lambda^2} \tag{14.8}$$

$$Q_e = \frac{a\gamma(\theta-1)\lambda - 2\theta a\lambda^2 - w\lambda\left(\gamma^2 + \gamma\lambda - 2\lambda^2\right) + L\left(\gamma^2 - 2\lambda^2\right)\Omega - L\beta\gamma\lambda}{\gamma^2 - 4\lambda^2} \tag{14.9}$$

For $\frac{\partial^2 \pi_m}{\partial w^2} < 0$*, the optimal wholesale price of the manufacturer can be obtained by taking the FOC of* (14.5).

Proposition 2 *The upstream and downstream channel partners are assumed to be engaged in HN game. The optimal wholesale price obtained at the equilibrium point of the game is given by*

$$w = \frac{a - 2s\gamma - a\theta + \theta a + 2s\lambda}{4\lambda - 4\gamma} + \frac{L(-\beta + \Omega)}{4\lambda} \tag{14.10}$$

Substituting the respective optimal values of price, sales volume in (14.3), (14.4), *and* (14.5)*, we will get the optimal profit of both the downstream and upstream partners.*

Proposition 3 *The profit of the retailer, e-tailer, and manufacturer is given by*

$$\pi_r = \frac{\begin{array}{c}\left(2(a + L\beta - a\theta)\lambda + w\left(\gamma^2 + \gamma\lambda - 2\lambda^2\right) + \gamma(\theta a - L\Omega)\right) \\ \times\left(\lambda\left(\gamma\theta a - 2a(\theta - 1)\lambda + w\left(\gamma^2 + \gamma\lambda - 2\lambda^2\right)\right) + L\left(\beta\left(\gamma^2 - 2\lambda^2\right) - \gamma\lambda\Omega\right)\right)\end{array}}{\left(\gamma^2 - 4\lambda^2\right)^2} \tag{14.11}$$

$$\pi_e = \frac{\begin{array}{c}\left(L\beta\gamma + w\gamma^2 + a(\gamma - \gamma\theta) + w\gamma\lambda + 2\theta a\lambda - 2w\lambda^2 - 2L\lambda\Omega\right) \\ \times\left(-a\gamma(\theta - 1)\lambda + \lambda\left(2\theta a\lambda + w\left(\gamma^2 + \gamma\lambda - 2\lambda^2\right)\right) + L\left(\beta\gamma\lambda - \gamma^2\Omega + 2\lambda^2\Omega\right)\right)\end{array}}{\left(\gamma^2 - 4\lambda^2\right)^2} \tag{14.12}$$

$$\pi_m = \frac{(s - w)(\lambda(a + 2w\gamma - a\theta + \theta a - 2w\lambda) + L(\gamma - \lambda)(\beta - \Omega))}{\gamma - 2\lambda} \tag{14.13}$$

Numerical Analysis

In this section, we analyze the impact of delivery lead time using numerical analysis [7–9, 22, 31]. For numerical analysis, values were assigned based on previous research and underlying assumptions between various parameters [4, 21]. The base market potential, a is fixed as 150, and the unit product cost is assumed to be 5. The own-price elasticity (λ) and cross-price elasticity (γ) are assumed to be 1.5 and 1.3, respectively. The customer preference toward the online channel, θ, is assumed to be varied from 0.1 to 0.9. Ω is assumed to take the value 1.9.

Case 1: Same β and large delivery time

For case 1, we assumed that the lead time coefficient, β, remains the same, and delivery time is very large. For varying customers' channel preference coefficient, the change in optimal decisions and profits are shown in Table 14.1. We found that initially, the optimal price, sales volume, and profit of the e-tailer was very small owing to the large delivery time and very small customers channel preference coefficient. But, with an increase in customers' preference toward the online channel, the e-tailer could take the leverage irrespective of very large delivery time. As a result, the e-tailer's price successfully surpassed the retailer's price. A similar trend was observed for both the sales volume and profit. The customer preference toward the channel helped the e-tailer to overcome the demerit created by the very large delivery time. While analyzing the profit of the manufacturer, it is found that the profit is independent of the customer preference toward the channel.

Case 2: Same β and next day delivery time

Though we observed a similar trend during case 2 (see Table 14.2), much to our surprise, we found that if the e-tailer ably delivers the product in next day, it will help both the retailer and e-tailer to increase the price. The ability of the e-tailer to

Table 14.1 Performance of the HDCSC under the same β and large delivery time

θ	P_r	P_e	Q_r	Q_e	π_r	π_e	π_m
0.1	220	184	57	5	2200	15	10,964
0.3	213	191	47	15	1471	155	10,964
0.5	206	198	37	26	889	440	10,964
0.7	199	205	26	36	452	872	10,964
0.9	192	212	16	47	162	1449	10,964

Table 14.2 Performance of the HDCSC under the same β and next day delivery time

θ	P_r	P_e	Q_r	Q_e	π_r	π_e	π_m
0.1	225	196	54	11	1941	81	11,965
0.3	218	203	43	21	1261	308	11,965
0.5	211	210	33	32	727	681	11,965
0.7	204	217	23	42	340	1199	11,965
0.9	197	224	12	53	98	1864	11,965

provide the product in the next day benefitted both the downstream chain partners, and their profit significantly increased (See Tables 14.1 and 14.2). We also observed that the manufactures profit also improved when the delivery lead time was less.

Case 3: Varying β and large delivery time

For analyzing the impact of the lead time-sensitivity coefficient, we varied the β from 1.5 to 5 and reported the performance of the channel partners. We observed that the pricing decisions and sales volume of the e-tailers were severely affected by the lead time-sensitivity coefficient. Though the change in sales volume for the retailer was minimal, he couldn't take the leverage of the condition, and his optimal price also decreased with increase in β. Consequently, these pricing decisions affected the profit, and all the chain partners experienced smaller profit during high β.

Case 4: Varying β and next day delivery time

When the e-tailer ably delivers the product in next day, the lead time-sensitivity coefficient couldn't influence the decision variables much, as shown in Table 14.4.

Discussions and Results

The optimal price of the retailer is maximum when the e-tailer ably delivers the product in the next day. But, it is inferred that customers' channel preference coefficient failed to control the impact of delivery lead time significantly. Even though the optimal price decreased for the retailer and increased for the e-tailer with an increase in the customers' channel preference coefficient, the difference among the optimal price of the retailer and e-tailer remains constant when the e-tailer provided large delivery and next day delivery (Difference between the optimal price values of the retailer in Tables 14.1 and 14.2 remains constant with increase in customers' channel preference coefficient. A similar trend was observed for e-tailer also). Thus, it can be inferred that while considering lead delivery time, the optimal price of both the downstream partners increases with the decrease in the delivery lead time of the e-tailer but was independent of the customers' channel preference as it failed to overpower the effect of lead time significantly.

While analyzing the pricing decisions with the lead time-sensitivity coefficient (See Tables 14.3 and 14.4), we find that the optimal price of downstream partners decreased with the increase in the lead time-sensitivity coefficient, and thus the lead time-sensitivity coefficient can significantly disturb the pricing decisions of all the downstream channel partners in an HDCSC. This impact of lead time-sensitivity coefficient can be decreased if the e-tailer successfully delivers the product in the next day. Though the optimal price decreased with an increase in lead time-sensitivity coefficient during next day delivery, that decrease was trivial when compared with the large delivery time.

For better interpretation, we have compared the profit of the supply chain partners under different conditions and scenarios, and we find that if the e-tailer can deliver the product the next day, the optimal profit will increase for the e-tailer and manufacturer and will decrease for the retailer irrespective of the channel preference of the customer and lead time-sensitivity coefficients (See Tables 14.1, 14.2, 14.3 and 14.4). By analyzing the impact of customers' channel preference, we find that the optimal profit of the manufacturer is not impacted by the customers' channel preference.

Table 14.3 Performance of the HDCSC under varying β and large delivery time

β	P_r	P_e	Q_r	Q_e	π_r	π_e	π_m
1.5	211	204	37	27	898	496	11,595
2	204	197	36	25	886	427	10,809
3	192	182	36	21	864	304	9320
4	179	167	36	17	842	202	7941
5	166	151	35	13	820	121	6673

Table 14.4 Performance of the HDCSC under varying β and next day delivery time

β	P_r	P_e	Q_r	Q_e	π_r	π_e	π_m
1.5	212	211	33	32	728	687	12,030
2	211	210	33	32	727	679	11,949
3	210	209	33	32	725	662	11,787
4	208	207	33	31	723	646	11,627
5	207	206	33	31	721	629	11,467

As expected, the optimal profit of the retailer decreased and increased for the e-tailer, with the increase in customers' channel preference coefficient. But, the retailer could reduce this effect of customers' channel preference if the e-tailer could deliver the product the next day. While analyzing the impact of the lead time-sensitivity coefficient, we find that, with the increase in the lead time-sensitivity coefficient, the optimal profit of all the channel partners considerably decrease. This can only be reduced by controlling the delivery time, as this substantial diminution in the profit decreased when the e-tailer delivered the product in the next day.

Conclusion

A heterogeneous dual-channel supply chain comprising retailer and e-tailer as downstream partners is explored for studying the impact of delivery lead time. We assumed channel leadership for the manufacturer and employed the Stackelberg game to study the interaction between the manufacturer and downstream channel partners. We adopted second game-theoretic analytics in the form of horizontal Nash game to check the game within the downstream channel partners. We have modeled the interactions and later used numerical analysis to derive the influence of customers' channel preferences and delivery lead time coefficient. We have also numerically analyzed the impact of next day delivery and large delivery time and done sensitivity analysis to check the influence of the customers' channel preference coefficient toward a particular channel and its cross-effects on the pricing policies when the customer is also lead time sensitive.

The study revealed that irrespective of large delivery time or next day delivery time, customers' preference toward a particular channel didn't affect the upstream channel partner's profit, whereas it affected the profit of both the downstream partners. On the other hand, the increase in lead time-sensitivity coefficient severely affected the profit of all the supply chain partners. By analyzing the pricing decisions, we found that both the customer preference and lead time-sensitivity coefficients affected the pricing decisions, but customers' channel preference coefficient failed to mitigate the effect of lead delivery time.

Supply chain practitioners can apply the findings from the study in developing decision support systems and as an input to multi-agent systems. This will help the supply chains to predict the impact of lead time during the disruption period and thereby can help to build robust and resilient supply chains. Academicians can use this model as a base for future studies in heterogeneous dual-channel supply chain, which analyzes the impact of delivery time. The study is limited to the analytical modeling of the pricing decisions, sales volume, and optimal profit when the manufacturer is not discriminating the wholesale price. The study can be further expanded by analyzing the market condition of discriminatory wholesale prices for both the channel partners. The model developed in this study can be explored further in a more practical way if Python game theory software is used to create intelligent systems that can act as a multi-agent system. The model can be further validated by empirically checking the performance of the decision variables of both downstream and upstream channel partners. Future researchers can start from here.

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