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Optimal pricing and pricing policy selection for a B2C car-sharing platform during peak and off-peak hours

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ABSTRACT

This study examines the optimal pricing and pricing policy selection for a business-to-consumer (B2C) car-sharing platform during peak and off-peak hours, where two pricing policies are evaluated, that is, fixed pricing policy and dynamic pricing policy. First, we construct the B2C car-sharing market demand function and the sharing platform's profit maximization model under each pricing policy, and obtain optimal outcomes by solving the model, including service price, market demand, platform's profit, consumer surplus, and social welfare. Then, through analysis, we reveal the effects of the pricing policy selection on the optimal outcomes. The results show that compared with the fixed pricing policy, implementing a dynamic pricing policy can increase the sharing platform's profit, but decrease the consumer surplus and social welfare. Additionally, implementing a dynamic pricing policy can also increase the demand during off-peak hours and decrease the demand during peak hours.

1. Introduction

In recent years, business-to-consumer (B2C) car-sharing service, as an emerging business model, has developed rapidly, and some well-known B2C car-sharing platform enterprises have emerged, such as Zipcar in the U.S. [1], SHARENOW in Germany [2], and GoFun in China [3]. Zipcar has launched the car-sharing service in seven countries, including the U.S., the UK, and Canada[1]. SHARENOW has launched this service in eight countries, including Germany, France, and Italy[2]. GoFun has provided this service for consumers in more than 80 cities in China[3]. In terms of the number of shared-car users, Zipcar has more than one million users[4], and the number of users in China was 12.597 million by June 2020[5]. Global Market Insights Inc. highlighted that the size of the global car-sharing market exceeded two billion USD in 2020 and was expected to grow at an annual growth rate of more than 20% in the next five years[6]. The data show that an increasing number of consumers are beginning to use B2C shared-cars, and the number of users is increasing year by year.

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1 https://www.zipcar.com/.
2 https://www.share-now.com/.
3 https://www.shouqiev.com/index.html.
4 https://www.zipcar.com/press/overview.
5 https://www.mob.com/mobdata/report/103.
6 https://www.gminsights.com/industry-analysis/carsharing-market.

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B2C car-sharing service differs from consumer-to-consumer (C2C) car-sharing service. The difference between these two services lies in the ownership of shared-cars. Specifically, in the C2C car-sharing service, the ownership of the shared-cars belongs to the drivers who provide the services, whereas, in the B2C car-sharing service, the ownership of the shared-cars belongs to the sharing platform. Additionally, for the B2C car-sharing service, consumers can perceive inconvenience costs in using shared-cars. Inconvenience cost refers to the negative utility a consumer perceives when he/she goes to a designated parking place to pick up or return a shared-car each time[7]. In other words, the inconvenience cost consists of two consumer inconveniences. One is the inconvenience perceived by the consumer who usually needs to walk some distance to a designated parking place to pick up the car. The other is the inconvenience perceived by the consumer who usually needs to return the car to a designated parking place, that is, there is usually a certain distance between the consumer's travel destination and the location of returning the car. Therefore, the inconvenience cost can decrease the utility of the consumer who accepts the B2C car-sharing service [4]. However, for the C2C car-sharing service, a consumer accepts the service by calling cars on his/her mobile phone, and there is no inconvenience cost. Therefore, it is necessary to focus on the role of the inconvenience cost in the operation of the B2C car-sharing service.

In recent years, due to the rapid growth of the number of car ownership and car use, there have been peak hours in cities in many countries [5]. During peak hours, the consumers' demand for car travel increases significantly, and traffic congestion may occur. For example, in Boston of the U.S., 7:00–9:00 a.m. and 4:00–6:00 p.m. are the peak hours [6]. In Singapore, 7:30–9:30 a.m. and 5:30–7:30 p.m. are the peak hours [7]. In Beijing of China, the peak hours occur from 7:00–9:00 a.m. and 5:00–7:00 p.m. [8]. The peak hours in Hong Kong occur from 7:00–10:00 a.m. and 4:00–7:00 p.m.[8]. Obviously, peak hours can also occur in the B2C car-sharing market. The data provided by CBNData show that the consumers' demand for shared-cars during peak hours increases significantly in more than 20 cities in China, including Shanghai, Guangzhou, and Nanjing[9].

In reality, most B2C car-sharing platforms adopt a fixed pricing policy, that is, the service price remains unchanged regardless of peak or off-peak hours, such as GoFun and EVCARD. However, during peak hours, many C2C car-sharing platforms have implemented a dynamic pricing policy, that is, a consumer pays a lower service price during off-peak hours and a higher service price during peak hours [9], such as Uber and DiDi Chuxing. Moreover, some scholars have found that the C2C car-sharing platforms can benefit from implementing the dynamic pricing policy [10]. However, B2C car-sharing service is different from C2C car-sharing service. As consumers can usually perceive inconvenience costs when using B2C shared-cars, it is unclear whether adopting the dynamic pricing policy is beneficial to the B2C car-sharing platform. Additionally, whether the B2C car-sharing platforms should adopt a fixed or a dynamic pricing policy is also worthy of attention. Implementing the dynamic pricing policy may help to increase the platforms' profits, but it may also harm the interests of consumers. Adopting the fixed pricing policy may help to protect the consumers' interests, but it may also weaken the platforms' profitability. Additionally, some factors may affect the pricing policy selection of the B2C car-sharing platforms [3,11], such as the proportion of peak hours to one day, the inconvenience costs perceived by consumers, and the consumers' sensitivity to service prices, but it is unclear how these factors affect the pricing policy selection. In summary, this study focuses on several key problems as follows.

1) During peak and off-peak hours, how does the sharing platform make the optimal pricing? Which pricing policy is beneficial to the platform?
2) What factors can affect the pricing policy selection of the B2C car-sharing platform?
3) What are the effects of the pricing policy selection on consumer surplus and social welfare?

This study aims to investigate the optimal decision of a B2C car-sharing platform on the pricing policy during peak and off-peak hours. Driven by the practice of the B2C car-sharing service industry, this study considers that the B2C car-sharing platform can choose the fixed pricing policy or the dynamic pricing policy. First, we develop the market demand function and the platform's profit maximization model under each pricing policy and obtain optimal outcomes, including service price, market demand, platform's profit, consumer surplus, and social welfare. Then, by comparing the optimal outcomes under the two pricing policies, we analyze the pricing policy selection of the sharing platform and the effects of the pricing policy selection on the optimal outcomes. We also conduct an extended study where the B2C car-sharing platform pursues social welfare maximization. Finally, we present a case study.

The main contributions of this study are as follows. First, this study investigates the B2C car-sharing platform's optimal decision on the pricing policy during peak and off-peak hours. As far as we know, there is little research on this aspect. Thus, this study fills this research gap. Second, this study reveals the changes that the pricing policy selection brings to the service price, market demand, platform's profit, consumer surplus, and social welfare, which can support the decision of the B2C car-sharing platform. Third, in view of the existing research, we obtain several new findings, for example, implementing the dynamic pricing policy can decrease social welfare. An increase in the inconvenience cost can reduce demand and harm the platform's profit, regardless of peak or off-peak hours.

The originality of this study follows from the fact that (i) we present the optimal pricing and pricing policy selection strategy for a B2C car-sharing platform during peak and off-peak hours, which has not been mentioned in previous studies, and

[7] https://www.zipcar.com/how-it-works.
[8] https://www.td.gov.hk/en/publications_and_press_releases/publications/free_publications/the_annual_traffic_census_2019.
[9] https://www.cbndata.com/report/393/detail?isReading=report&page=1.

(ii) for the setting of the optimization models, we introduce the inconvenience costs perceived by consumers in B2C car-sharing services for the first time.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the model setting and optimal outcomes. Section 4 gives related analysis and discussion. Section 5 presents the extended study. Section 6 presents a case study. Section 7 summarizes the main findings and managerial implications and provides the future research directions. All proofs are provided in the Appendix.

2. Literature review

This study examines the pricing policy selection of the B2C car-sharing platform during peak and off-peak hours. The literature related to this study mainly involves the following aspects.

The first stream of the literature examines the influencing factors of B2C car-sharing services. Some related studies have been conducted in recent years. For example, Kim et al. [12] highlighted that consumers' social and economic perspectives are the main factors affecting their attitudes toward shared electric vehicles. Kim et al. [13] found that the satisfaction degree of consumers significantly affected their choice of using shared-cars, and the availability of shared-cars would affect the consumers who accept B2C car-sharing services. For firms that provide car-sharing and car sale services, Yu et al. [14] studied the optimal pricing of car-sharing and car sale services. The results indicated that the difference in car grades significantly affects a firm's potential profitability. Li and Kamargianni [15] adopted integrated choice and latent variable models to study the effect of the advocacy of car-sharing services on the choice of car-sharing services. They found that consumers' preference for car-sharing services was positively correlated with the advocacy of the car-sharing service. Wen and Siqin [16] adopted the mean–variance theory to analyze the B2C sharing service platform's optimal decisions on average quality levels and prices, and discussed the effects of product quality uncertainty and risk sensitivity on the platform's decisions. The results showed that an increase in the degree of risk aversion can decrease the average quality levels of products and induce the platform to set lower prices. Dowling et al. [11] used data from a European car-sharing company to study consumers' choices between pay-per-use and flat-rate pricing modes. They found that factors such as weather and home location would affect the choice of the pay-per-use mode. Huang and Qian [3] employed an empirical analysis method to study the psychological factors that prompt consumers to adopt electric vehicles in different business models. They found that the need for uniqueness can increase the consumers' willingness to use B2C shared electric vehicles. Thurner et al. [17] studied Russians' willingness to use three new types of vehicles, including electric, shared, and autonomous driving vehicles. The results showed that the younger the participants, the higher their willingness to participate. The literature discussed mainly examined some influencing factors of B2C car-sharing services. However, these studies do not focus on the effects of the inconvenience costs perceived by consumers on the B2C car-sharing service and the pricing policy selection. In this study, we focus on the effect of consumers' inconvenience costs on the pricing policy selection of the B2C car-sharing platform, which enriches existing research.

The second stream of the literature studies the B2C car-sharing service pricing. In recent years, some scholars have researched this aspect. Bellos et al. [1] studied the optimal pricing strategies of an original equipment manufacturer that launched both car sale and car-sharing service businesses. The results showed that launching a car-sharing service business is not always beneficial to the environment. Perboli et al. [18] designed a service-pricing scheme for a B2C car-sharing platform to optimize car-sharing service systems according to the different mobility demands of consumers and the traffic congestion in urban areas. The results showed that the key to the success of car-sharing services is to design effective service pricing schemes. Ke et al. [4] studied the impact of introducing a car-sharing service on automobile markets and investigated the optimal pricing strategies of an automaker and a retailer. They found that offering car-sharing services could cannibalize the demand for retail channels and decrease retail prices. To solve the problem of the imbalanced distribution of electric vehicles, Ren et al. [19] proposed a dynamic pricing scheme for a large-scale electric vehicle sharing network and proved the effectiveness of the scheme through two case studies. Xie et al. [20] determined the optimal pricing of one-way electric vehicle sharing systems by constructing a mixed-integer programming model. The results showed that some consumers might choose public transportation instead of shared-cars during rush hours due to higher car-sharing service prices. Huarng and Yu [21] used the fuzzy set and qualitative comparative analysis method to study the passengers' satisfaction with surge pricing. The results showed that loyal passengers are more tolerant of surge pricing than non-loyal passengers. Li et al. [22] studied the cooperation between an original equipment manufacturer and a peer-to-peer sharing platform and investigated its optimal pricing strategies. They found that the perceived value factor and marginal cost are the crucial factors that affect the cooperation between the original equipment manufacturer and the peer-to-peer sharing platform. Moreover, consumer surplus would change with the platform's pricing. Pei et al. [23] studied the service pricing of an entrant enterprise that conducted B2C or C2C sharing businesses. They found that external B2C and C2C sharing may lead to higher rental prices than internal sharing when the product cost is relatively high. Nguyen et al. [24] found that making appropriate adjustments to the B2C car-sharing service, such as adjusting the service price or fleet size, can encourage some consumers of the B2C car-sharing service to use public transport. The literature reviewed the pricing strategies of the B2C car-sharing service under different cases, but did not explore the pricing policy selection of the B2C car-sharing platform during peak and off-peak hours. Notably, a B2C car-sharing service differs from a C2C car-sharing service. The main difference is that consumers can perceive inconvenience costs when using B2C shared-cars, that is, there is usually a certain distance between the consumer's travel destination and the location of returning the car. While some scholars studied the choice of the pricing policy of C2C car-sharing platforms during peak and off-peak hours [10,25], this study focuses on whether the existing findings are appropriate for B2C car-sharing platforms; thus, filling the research gap.

The objective of this study is different from that of the existing studies. First, the existing literature studied pricing policies for the C2C car-sharing service, such as Cachon et al. [10] and Lin and Zhou [25], but hardly focused on the pricing policies for a B2C car-sharing service. This study aims to examine optimal pricing and pricing policy selection for a B2C car-sharing platform during peak and off-peak hours, which has not been researched in the previous studies. In reality, the B2C car-sharing service is different from the C2C car-sharing service, that is, consumers can suffer inconvenience costs when accepting B2C car-sharing services. Therefore, this study can provide a decision-making basis for B2C car-sharing platforms. Additionally, although previous studies have examined some influencing factors of the B2C car-sharing service [3,11–17], few studies investigated the effects of the inconvenience cost on the pricing decision and pricing policy selection of the B2C car-sharing platform. Therefore, this study focuses on the shortcomings or limitations of existing studies, which can fill the research gap.

3. Model

This section provides definitions of the notations used and the problem description and then presents the model setting and optimal outcomes.

The notations used in this paper are shown in Table 1, where n and h denote off-peak and peak hours, respectively, and $i = \mathrm{F}$ and $i = \mathrm{S}$ denote the fixed pricing policy and the dynamic pricing policy, respectively.

This study considers a car-sharing market consisting of a B2C car-sharing platform (or platform thereafter) and consumers. There are peak and off-peak hours in the market, and the potential market demand during peak hours is usually higher than that during off-peak hours [26,27], thus, we assume $a_h > a_n$ [10]. A full day includes off-peak hours and peak hours, therefore, $\theta_n + \theta_h = 1$ [10]. As the consumer demand for shared-cars is relatively high during peak hours, that is, the available cars during peak hours are less than those during off-peak hours, the average inconvenience cost for consumers who look for and return cars (or inconvenience cost thereafter) during peak hours is relatively high, thus, we posit that $\beta_h > \beta_n$. In this section, we provide an example to illustrate this assumption. For example, because it is difficult to balance the number of incoming and outgoing cars, consumers may not be able to find idle cars during peak hours in Boston [28]. Hence, the consumers need to spend more time and effort looking for cars than during off-peak hours. The number of potential consumers in the market is fixed for a certain period, but a part of them may switch between shared-cars, taxis, buses, and other means of transportation when traveling. Thus, the consumer demand for shared-cars is uncertain. We use γ to characterize the uncertainty of the car-sharing market demand. γ is a random variable defined in interval $[A, B]$ with mean value μ and variance σ^2, and its probability density function and cumulative distribution function are $f(\cdot)$ and $F(\cdot)$, respectively. The platform can choose either a fixed or dynamic pricing policy. The fixed pricing policy means that the platform adopts the same service price p during peak and off-peak hours. The dynamic pricing policy means that the platform adopts a higher service price p_h during peak hours and a lower service price p_n during off-peak hours.

3.1. Fixed pricing policy

According to Cachon et al. [10], Wang et al. [29], and Huang et al. [30], the demand in the car-sharing market under a fixed pricing policy can be expressed as.

$$d_j^{\mathrm{F}} = a_j - bp - \beta_j + \gamma, \tag{1}$$

where $j = n$ and $j = h$ represent the off-peak and peak hours, respectively. Referring to Huang et al. [30] and Chen et al. [31], we adopt the linear demand function to describe consumers' demand for shared-cars, which is consistent with reality and helpful to analyze the results. We take the off-peak hour ($j = n$) as an example to specify the demand function. The demand function during off-peak hours is $d_n^{\mathrm{F}} = a_n - bp - \beta_n + \gamma$, where a_n denotes the size of the potential market during off-peak hours and b denotes the demand sensitivity to the service price (i.e., the degree of consumers' sensitivity to the service price). We assume that a_n is sufficiently large to ensure the platform's profit is positive [32].

When the platform adopts the fixed pricing policy, the profit function of the platform can be expressed as

$$\Pi^{\mathrm{F}} = (p - c)\theta_n d_n^{\mathrm{F}} + (p - c)\theta_h d_h^{\mathrm{F}}. \tag{2}$$

In Eq. (2), the first and second terms denote the profit earned by the platform during off-peak and peak hours, respectively. Referring to Niu et al. [32], Chiu et al. [33], and Hosseini-Motlagh et al. [34], we develop the expected profit function of the platform, that is, $E(\Pi^{\mathrm{F}}) = (p - c)[\theta_n(a_n - bp - \beta_n + \mu) + \theta_h(a_h - bp - \beta_h + \mu)]$. Further, we can construct the profit maximization model of the platform under the fixed pricing policy as

$$\max_p \; E(\Pi^{\mathrm{F}}) = (p - c)[\theta_n(a_n - bp - \beta_n + \mu) + \theta_h(a_h - bp - \beta_h + \mu)] \tag{3}$$

By solving Eq. (3), we obtain the following proposition.

Table 1
Summary of notations.

Notations	definitions
p	The service price under the fixed pricing policy (decision variable).
p_n	The service price during off-peak hours under the dynamic pricing policy (decision variable).
p_h	The service price during peak hours under the dynamic pricing policy (decision variable).
a_n	The size of the potential market during off-peak hours.
a_h	The size of the potential market during peak hours.
β_n	The average inconvenience cost for consumers who look for and return cars during off-peak hours.
β_h	The average inconvenience cost for consumers who look for and return cars during peak hours.
θ_n	The proportion of off-peak hours to one day.
θ_h	The proportion of peak hours to one day.
b	The demand sensitivity to service price, $b > 0$.
c	Operating cost per car, including fuel fees, maintenance fees, etc.
γ	The random variable characterizing the uncertainty of the car-sharing market demand, with mean value μ and variance σ^2.
d_n^i	Market demand during off-peak hours.
d_h^i	Market demand during peak hours.
Π^i	The profit of the B2C car-sharing platform.
CS^i	Consumer surplus.
SW^i	Social welfare.

Proposition 1. *When the platform adopts the fixed pricing policy, the optimal service price is*

$$p^* = \frac{\theta_n a_n + \theta_h a_h - \theta_n \beta_n - \theta_h \beta_h + \mu + bc}{2b}. \tag{4}$$

From Eqs. (1) and (4), we obtain the optimal demand during off-peak and peak hours under the fixed pricing policy, respectively, that is,

$$d_n^{F*} = \frac{(2-\theta_n)a_n - \theta_h a_h - (2-\theta_n)\beta_n + \theta_h \beta_h - bc + \mu}{2}, \tag{5}$$

$$d_h^{F*} = \frac{(2-\theta_h)a_h - \theta_n a_n - (2-\theta_h)\beta_h + \theta_n \beta_n - bc + \mu}{2}. \tag{6}$$

Substituting Eq. (4) into Eq. (2), we can obtain the platform's optimal profit under the fixed pricing policy, that is,

$$\Pi^{F*} = \frac{(\theta_n a_n + \theta_h a_h - \theta_n \beta_n - \theta_h \beta_h - bc + \mu)^2}{4b}. \tag{7}$$

Similar to Krass et al. [35], the consumer surplus in this study refers to the surplus obtained by consumers from accepting B2C car-sharing services. Referring to Krass et al. [35], Singh and Vives [36], and Chen et al. [37], we can express the consumer surplus under the fixed pricing policy as $CS^F = \frac{\theta_n (d_n^F)^2 + \theta_h (d_h^F)^2}{2b}$. From Eqs. (5) and (6), the optimal consumer surplus can be further expressed as

$$CS^{F*} = \frac{\theta_n(a_n - \beta_n - bc + \mu)^2 + \theta_h(a_h - \beta_h - bc + \mu)^2 + 3\theta_n\theta_h(a_n - a_h - \beta_n + \beta_h)^2}{8b} \tag{8}$$

Referring to Krass et al. [35] and Choi [38], we can express the social welfare under the fixed pricing policy as $SW^F = \Pi^F + CS^F$. From Eqs. (7) and (8), the optimal social welfare can be further expressed as

$$SW^{F*} = \frac{(\theta_n a_n + \theta_h a_h - \theta_n \beta_n - \theta_h \beta_h - bc + \mu)^2}{4b} + \frac{\theta_n(a_n - \beta_n - bc + \mu)^2 + \theta_h(a_h - \beta_h - bc + \mu)^2 + 3\theta_n\theta_h(a_n - a_h - \beta_n + \beta_h)^2}{8b}. \tag{9}$$

As b, θ_n, θ_h, β_n, and β_h are the key parameters affecting the market demand and the platform's profit, we conduct a sensitivity analysis on these parameters. From Eqs. (4)–(7), we obtain the following corollary.

Corollary 1. *Under the fixed pricing policy, the effects of the main parameters on the optimal outcomes are given in* Table 2.

Corollary 1 indicates that the optimal service price, market demand, and platform's profit decrease with the demand sensitivity to the service price under a fixed pricing policy. This is because the more sensitive consumers are to the service price, the lower the market demand. Lower market demand leads the sharing platform to set a lower service price to attract consumers, reducing the platform's profit. The platform's optimal profit increases with the proportion of off-peak hours to one day and the proportion of peak hours to one day. Additionally, we find that the impact of the inconvenience cost on the mar-

Table 2
The effects of the main parameters on the optimal outcomes under the fixed pricing policy.

	p^*	d_n^{F*}	d_h^{F*}	Π^{F*}
$b\uparrow$	↓	↓	↓	↓
$\theta_n\uparrow$	N/A	N/A	N/A	↑
$\theta_h\uparrow$	N/A	N/A	N/A	↑
$\beta_n\uparrow$	↓	↓	↑	↓
$\beta_h\uparrow$	↓	↑	↓	↓

Notes: ↑: increase; ↓: decrease; N/A: none.

ket demand is nonmonotonic. For example, the market demand during off-peak hours decreases with the inconvenience cost during off-peak hours, but increases with the inconvenience cost during peak hours. The reason for this result is that the difference between the inconvenience cost during peak hours and that during off-peak hours can increase when the inconvenience cost during off-peak hours decreases, which means that more consumers may choose to use shared-cars during off-peak hours.

3.2. Dynamic pricing policy

Referring to Cachon et al. [10], Wang et al. [29], and Huang et al. [30], we can express the demand in the car-sharing market under the dynamic pricing policy as

$$d_j^{\,S} = a_j - bp_j - \beta_j + \gamma, \tag{10}$$

We take the peak hour ($j = h$) as an example to specify the demand function. The market demand during peak hours is $d_h^{\,S} = a_h - bp_h - \beta_h + \gamma$. We assume that a_h is sufficiently large to ensure positive platform profit [32]. As the service price during peak hours is usually higher than that during off-peak hours, we assume $p_n < p_h$.

When the platform adopts the dynamic pricing policy, the profit function of the platform can be expressed as

$$\Pi^{\,S} = (p_n - c)\theta_n d_n^{\,S} + (p_h - c)\theta_h d_h^{\,S}. \tag{11}$$

In Eq. (11), the first and second terms denote the profit obtained by the platform during off-peak and peak hours, respectively. Similar to the case where the platform adopts a fixed pricing policy, we provide the expected profit function of the platform under a dynamic pricing policy, that is, $E(\Pi^S) = (p_n - c)(a_n - bp_n - \beta_n + \mu)\theta_n + (p_h - c)(a_h - bp_h - \beta_h + \mu)\theta_h$. Further, we construct the platform's profit maximization model under the dynamic pricing policy as

$$\max_{p_n, p_h} \; E(\Pi^S) = (p_n - c)(a_n - bp_n - \beta_n + \mu)\theta_n + (p_h - c)(a_h - bp_h - \beta_h + \mu)\theta_h \tag{12a}$$

$$\text{s.t. } p_n \leqslant p_h. \tag{12b}$$

We obtain the following proposition using the Karush-Kuhn-Tucker (KKT) method to solve Eq. (12).

Proposition 2. *When the platform adopts the dynamic pricing policy, the optimal service prices during off-peak and peak hours can be expressed respectively as*

$$p_n^* = \frac{a_n - \beta_n + bc + \mu}{2b}, \tag{13}$$

$$p_h^* = \frac{a_h - \beta_h + bc + \mu}{2b}. \tag{14}$$

From Eqs. (10), (13), and (14), we obtain the optimal demand during off-peak and peak hours under the dynamic pricing policy, respectively, that is,

$$d_n^{\,S*} = \frac{a_n - bc - \beta_n + \mu}{2}, \tag{15}$$

$$d_h^{\,S*} = \frac{a_h - bc - \beta_h + \mu}{2}. \tag{16}$$

Substituting Eqs. (13) and (14) into Eq. (11), we obtain the platform's optimal profit under the dynamic pricing policy, that is,

$$\Pi^{S*} = \frac{\theta_n(a_n - bc - \beta_n + \mu)^2 + \theta_h(a_h - bc - \beta_h + \mu)^2}{4b}. \tag{17}$$

Similar to the case where the platform implements a fixed pricing policy, the consumer surplus under the dynamic pricing policy can be expressed as $CS^{S} = \frac{\theta_n (d_n{}^S)^2 + \theta_h (d_h{}^S)^2}{2b}$. From Eqs. (15) and (16), the optimal consumer surplus can be further expressed as.

$$CS^{S*} = \frac{\theta_n (a_n - bc - \beta_n + \mu)^2 + \theta_h (a_h - bc - \beta_h + \mu)^2}{8b}. \tag{18}$$

Under the dynamic pricing policy, social welfare can be expressed as $SW^S = \Pi^S + CS^S$ [35,38]. From Eqs. (17) and (18), the optimal social welfare can be further expressed as

$$SW^{S*} = \frac{3\theta_n (a_n - bc - \beta_n + \mu)^2 + 3\theta_h (a_h - bc - \beta_h + \mu)^2}{8b}. \tag{19}$$

As b, θ_n, θ_h, β_n, and β_h are the key parameters affecting the market demand and the platform's profit, we conduct sensitivity analysis on these parameters. By Eqs. (13)-(17), we can obtain the following corollary.

Corollary 2. *Under the dynamic pricing policy, the effects of the main parameters on the optimal outcomes are given in* Table 3.

Corollary 2 indicates that the optimal service prices, market demand, and platform's profit decrease with the demand sensitivity to the service prices under the dynamic pricing policy; the platform's optimal profit increases with the proportion of off-peak hours to one day and the proportion of peak hours to one day; the optimal service price during off-peak hours decreases with the inconvenience cost; the optimal service price during peak hours decreases with the inconvenience cost. This is because market demand decreases when consumers' inconvenience costs increase. This negative effect is mitigated by the platform lowering its service price to maintain market demand. Additionally, an increase in the inconvenience cost can reduce demand and harm the platform's profit regardless of peak or off-peak hours. This finding provides significant implications for B2C car-sharing platforms. Platforms need to take some measures to reduce consumers' inconvenience costs, such as increasing the number of shared-cars.

4. Analysis and discussion

This section compares the optimal service prices, market demands, platform's profits, consumer surpluses, and social welfares under the two pricing policies to determine a the decision-making basis for choosing the pricing policy and setting the service prices for the platform.

We obtain the following proposition by comparing the service prices under the two pricing policies.

Proposition 3. $p_n^* < p^* < p_h^*$.

Proposition 3 indicates that the optimal service price during peak hours under the dynamic pricing policy is higher than that under the fixed pricing policy, whereas the optimal service price under the fixed pricing policy is higher than that during off-peak hours under the dynamic pricing policy. This result provides an important managerial insight for the platform: when the dynamic pricing policy is adopted, the service price must be set higher than the optimal service price under the fixed pricing policy during peak hours. Parallelly, the platform also needs to set a lower service price than the optimal service price under the fixed pricing policy during off-peak hours. Furthermore, we find that the platform will set a lower service price than the optimal service price under the fixed pricing policy during off-peak hours when adopting the dynamic pricing policy, which is beneficial to consumers.

We obtain the following proposition by comparing the market demands under the two pricing policies.

Proposition 4. (a) $d_n^{S*} > d_n^{F*}$, $d_h^{S*} < d_h^{F*}$; (b) *if* $\theta_h \leqslant \theta_n$, $d_n{}^{S*} + d_h{}^{S*} \leqslant d_n^{F*} + d_h^{F*}$, *otherwise*, $d_n{}^{S*} + d_h{}^{S*} > d_n^{F*} + d_h^{F*}$.

Proposition 4 (a) shows that the demand under the dynamic pricing policy is higher than that under the fixed pricing policy during off-peak hours. Meanwhile, the demand under the dynamic pricing policy is lower than that under the fixed pricing policy during peak hours. This is because, under the dynamic pricing policy, some consumers who are not eager to use

Table 3
The effects of the main parameters on the optimal outcomes under the dynamic pricing policy.

	p_n^*	p_h^*	d_n^{S*}	d_h^{S*}	Π^{S*}
$b\uparrow$	↓	↓	↓	↓	↓
$\theta_n\uparrow$	N/A	N/A	N/A	N/A	↑
$\theta_h\uparrow$	N/A	N/A	N/A	N/A	↑
$\beta_n\uparrow$	↓	N/A	↓	N/A	↓
$\beta_h\uparrow$	N/A	↓	N/A	↓	↓

Notes: ↑: increase; ↓: decrease; N/A: none.

shared-cars during peak hours may choose to use them during off-peak hours because of the higher service price during peak hours. This result indicates that implementing the dynamic pricing policy can help to reduce the demand during peak hours, which can alleviate traffic pressure during peak hours to a certain extent.

Proposition 4 (b) indicates that if the proportion of peak hours to one day is smaller than the proportion of off-peak hours to one day, then the total demand under the dynamic pricing policy is lower than that under the fixed pricing policy, and vice versa. This result can be explained as follows. Implementing the dynamic pricing policy can reduce the demand during peak hours and increase the demand during off-peak hours when the peak hours are shorter than the off-peak hours. As the decrease in the demand during peak hours is greater than the increase in the demand during off-peak hours, the total market demand will decrease. The managerial implication for the sharing platform is that in the early stage of development, the sharing platform needs to adopt a fixed pricing policy, which can help the platform quickly occupy the market; in the mature stage of development, the sharing platform can adopt a dynamic pricing policy to obtain more profit.

We obtain the following proposition by comparing the platform's profits under the two pricing policies.

Proposition 5. $\Pi^{S*} > \Pi^{F*}$.

Proposition 5 indicates that the platform's profit under the dynamic pricing policy is higher than that under the fixed pricing policy. There are two main reasons for this finding. One is that the platform charges each consumer a higher service price during peak hours, which plays a positive role in improving the platform's profit. The other is that implementing the dynamic pricing policy increases the demand during off-peak hours (see Proposition 4), which can help to increase the platform's profits. This finding can provide an important implication for the platform on the choice of pricing policy, that is, the platform pursuing profit maximization should adopt the dynamic pricing policy because implementing the dynamic pricing policy can improve the platform's profitability.

We obtain the following proposition by comparing the consumer surpluses under the two pricing policies.

Proposition 6. $CS^{S*} < CS^{F*}$.

Proposition 6 shows that the consumer surplus under the dynamic pricing policy is lower than that under the fixed pricing policy. This result can be interpreted as follows. Under the dynamic pricing policy, the platform charges each consumer a higher service price during peak hours, which may cause consumer dissatisfaction and harm the interests of many consumers. This result is similar to that of implementing the dynamic pricing policy in the C2C car-sharing market. This is because whether in the B2C or C2C car-sharing markets, the essence of the dynamic pricing policy is to charge consumers a higher service price during peak hours. However, as consumers are generally price-sensitive, increasing the service price will decrease demand, reducing consumer surplus. The managerial implication of this result for the platform is that if the platform wants to retain its consumers, a dynamic pricing policy should be adopted cautiously.

We obtain the following proposition by comparing the social welfares under the two pricing policies.

Proposition 7. $SW^{S*} < SW^{F*}$.

Proposition 7 shows that the social welfare under the dynamic pricing policy is lower than that under the fixed pricing policy. This finding can be explained as follows. Implementing the dynamic pricing policy is profitable for the platform (see Proposition 5), but can decrease the consumer surplus (see Proposition 6). As the decrease in the consumer surplus is higher than the increase in the platform's profit, implementing the dynamic pricing policy decreases the social welfare. This result can provide a managerial insight for the platform. Implementing a dynamic pricing policy is not a good choice for a platform considering social welfare.

5. Extension

Implementing a dynamic pricing policy can increase the platform's profit but decrease the consumer surplus. Due to a loss of consumer interest, the platform may lose consumers or face lawsuits from consumers. Hence, the platform may focus on consumer surplus while pursuing profit maximization. This section considers the case where the platform's goal is to maximize social welfare (i.e., the platform's profit and consumer surplus).

The market demands during peak and off-peak hours can be expressed as $\bar{d}_h^S = a_h - b\bar{p}_h - \beta_h + \gamma$ and $\bar{d}_n^S = a_n - b\bar{p}_n - \beta_n + \gamma$, respectively. Under the goal of maximizing social welfare, the objective function of the platform can be expressed as

$$\bar{SW}^S = (\bar{p}_n - c)\theta_n\bar{d}_n^S + (\bar{p}_h - c)\theta_h\bar{d}_h^S + \frac{\theta_n(\bar{d}_n^S)^2 + \theta_h(\bar{d}_h^S)^2}{2b}. \tag{20}$$

In Eq. (20), the first and second terms denote the profit obtained by the platform during off-peak and peak hours, respectively, and the third term denotes consumer surplus. Furthermore, the expected objective function of the platform is given by $E(\bar{SW}^{S}) = (\bar{p}_n - c)(a_n - b\bar{p}_n - \beta_n + \mu)\theta_n + (\bar{p}_h - c)(a_h - b\bar{p}_h - \beta_h + \mu)\theta_h + \frac{\theta_n(a_n - b\bar{p}_n - \beta_n + \mu)^2 + \theta_h(a_h - b\bar{p}_h - \beta_h + \mu)^2}{2b}$. Thus, we can construct the social welfare maximization model of the platform as follows.

$$\max_{\bar{p}_n, \bar{p}_h} E(\bar{SW}^{S}) = (\bar{p}_n - c)(a_n - b\bar{p}_n - \beta_n + \mu)\theta_n + (\bar{p}_h - c)(a_h - b\bar{p}_h - \beta_h + \mu)\theta_h + \frac{\theta_n(a_n - b\bar{p}_n - \beta_n + \mu)^2 + \theta_h(a_h - b\bar{p}_h - \beta_h + \mu)^2}{2b} \tag{21a}$$

$$\text{s.t. } \bar{p}_n \leqslant \bar{p}_h. \tag{21b}$$

We obtain the following proposition using the KKT method to solve Eq. (21).

Proposition 8. *Under the goal of maximizing social welfare, when the platform adopts the dynamic pricing policy, the optimal service price is* $\bar{p}_n^* = c$ *during off-peak hours and* $\bar{p}_h^* = c$ *during peak hours.*

From $\bar{p}_n^*$ and $\bar{p}_h^*$, we obtain the optimal market demands during off-peak and peak hours, respectively, that is, $\bar{d}_n^{S*} = a_n - \beta_n - bc + \mu$ and $\bar{d}_h^{S*} = a_h - \beta_h - bc + \mu$. Furthermore, we can also obtain the platform's optimal profit, the optimal consumer surplus, and the optimal social welfare, respectively, that is, $\bar{\Pi}^{S*} = 0$, $\bar{CS}^{S*} = \frac{\theta_n(a_n - bc - \beta_n + \mu)^2 + \theta_h(a_h - bc - \beta_h + \mu)^2}{2b}$, $\bar{SW}^{S*} = \frac{\theta_n(a_n - bc - \beta_n + \mu)^2 + \theta_h(a_h - bc - \beta_h + \mu)^2}{2b}$.

Comparing the optimal service prices, platform's profits, consumer surpluses, and social welfares under the two objectives of profit maximization and social welfare maximization, we obtain the following proposition.

Proposition 9. (a) $\bar{p}_n^* < p_n^*$, $\bar{p}_h^* < p_h^*$; (b) $\bar{\Pi}^{S*} < \Pi^{S*}$; (c) $\bar{CS}^{S*} > CS^{S*}$; (d) $\bar{SW}^{S*} > SW^{S*}$.

Proposition 9 (a) indicates that the service prices during peak and off-peak hours under the goal of the social welfare maximization are lower than those under the goal of the profit maximization, respectively. The managerial implication of this result is that compared with the goal of profit maximization, the platform needs to set lower service price(s) when it aims to maximize social welfare.

Proposition 9 (b) shows that the optimal platform's profit under the goal of the social welfare maximization is lower than that under the goal of the profit maximization. This is because the platform will set lower service price(s) when it considers both its profit and consumer surplus, weakening the platform's profitability.

Proposition 9 (c) indicates that compared with the goal of the profit maximization, the consumer surplus can increase when the goal is social welfare maximization. This is because consumers can benefit from the platform's lower service price(s).

Proposition 9 (d) shows that the optimal social welfare for social welfare maximization is higher than that for profit maximization. This is because when the platform focuses on social welfare maximization, the increase in the consumer surplus is greater than the decrease in the platform's profit, which can increase social welfare.

6. Case study

This section presents a case study to illustrate the application of the model described.

To solve the problem of location design and relocation of shared-cars, Chang et al. [6] conducted a study using Zipcar's demand and operational data in Boston. By analyzing the data used by Chang et al. [6], we obtain the values of some parameters. In Boston, 7:00–9:00 a.m. and 4:00–6:00 p.m. are peak hours. Thus, peak hours are 4 h, and off-peak hours are 20 h in one day. Thus, the proportion of peak hours to one day and the proportion of off-peak hours to one day are 0.167 and 0.833, respectively. Additionally, referring to the Zipcar's order data in the Boston area from October 1 to November 30, 2014 collected by Chang et al. [6], including the number of orders per hour of one day, it can be estimated that the average demands during peak and off-peak hours in one day are 1394 and 2722.5, respectively, and μ is 57.75. Thus, we obtain that the average hourly demands during peak and off-peak hours as, 349 and 136, respectively. To optimize the design of the one-way car-sharing service, Jorge et al. [28] constructed an integer programming model to select a set of new one-way services and applied the model to the operating network of Zipcar in Boston. According to Jorge et al. [28], the fuel and maintenance fees per 20 min are 0.442 USD and 0.034 USD, respectively. If we consider that the average time for consumers who use shared-cars is one hour, then the operating cost per car is 1.428 USD. By analyzing the information provided by Jorge et al. [28], we find that the demand sensitivity to service price is 18.9.

According to the Zipcar data and Eqs. (7) and (17), we can obtain the expected profit that Zipcar can earn within one day under the fixed pricing policy, that is, 453.26 USD, and the expected profit that Zipcar can earn within one day under the dynamic pricing policy, that is, 600.48 USD. This result indicates that Zipcar should adopt the dynamic pricing policy in Boston as it is lucrative. Moreover, by Eqs. (5), (6), (13), and (14), we can express the optimal service prices during off-peak and peak hours, respectively, that is,

$$p_n^* = \frac{3d_n^{F*} + d_h^{F*}}{4b} + c, \tag{22}$$

$$p_h^* = \frac{3d_h^{F*} + d_n^{F*}}{4b} + c, \tag{23}$$

According to the Zipcar data and Eqs. (22)–(23), we can provide a managerial implication on service pricing for Zipcar. For off-peak and peak hours, the service prices that Zipcar needs to set are 11.44 USD per hour and 17.07 USD per hour, respectively.

7. Conclusions

This study examines the B2C car-sharing platform's optimal decision on the pricing policy during peak and off-peak hours. For the two pricing policies that the platform can choose: fixed pricing policy and dynamic pricing policy, we construct the demand functions of the B2C car-sharing market and the profit maximization models of the platform, respectively, and obtain the optimal outcomes. Based on this, we analyze the effects of pricing policy selection on the service price, market demand, platform's profit, consumer surplus, and social welfare, and discuss the platform's optimal decision on pricing policy under different conditions. Furthermore, we provide an extended study in which the platform aims to maximize social welfare. Finally, we present a case study to illustrate the application of the model presented in this study.

The important findings obtained in this study are summarized as follows. First, implementing the dynamic pricing policy can decrease the demand during peak hours and increase the demand during off-peak hours, which can alleviate traffic pressure during peak hours to a certain extent. In addition, we find that the proportion of peak hours to one day is a key factor influencing a platform's pricing policy choice. When the proportion of peak hours to one day is relatively small, adopting a dynamic pricing policy reduces the total market demand. Second, the platform's profit under the dynamic pricing policy is higher than that under the fixed pricing policy, but the consumer surplus and social welfare under the dynamic pricing policy are lower than those under the fixed pricing policy, respectively. Third, the service prices during peak and off-peak hours for social welfare maximization are lower than those for profit maximization.

These findings can provide useful managerial implications for decisions of a B2C car-sharing platform. First, in the early stage of development, the platform needs to implement a fixed pricing policy, whereas in the mature stage of development, the platform should adopt a dynamic pricing policy. Second, the platform should choose a dynamic pricing policy to obtain maximum profit. In this case, the platform needs to evaluate the size of the potential market, the inconvenience costs to consumers, and the degree of the consumers' sensitivity to the service price fully when setting the service prices during peak and off-peak hours. Third, compared with pursuing profit maximization, the platform needs to set lower service prices when pursuing social welfare maximization.

Future research can be extended. In reality, multiple B2C car-sharing platforms face competition. Studying the optimal pricing policies for multiple platforms in a competitive environment may be interesting.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Proof of Proposition 1. *We can get* $\frac{d^2E(\Pi^F)}{dp^2} = -2b\theta_n - 2b\theta_h < 0$, *thus* $E(\Pi^F)$ *is a concave function with respect to p. Let* $\frac{dE(\Pi^F)}{dp} = 0$, *we can obtain* $p^* = \frac{\theta_n a_n + \theta_h a_h - \theta_n \beta_n - \theta_h \beta_h + \mu + bc}{2b}$.

Proof of Corollary 1. *We can get* $\frac{dp^*}{db} = -\frac{\theta_n(a_n - \beta_n) + \theta_h(a_h - \beta_h) + \mu}{2b^2}$. *Since* a_n *and* a_h *are sufficiently large,* $\frac{dp^*}{db} < 0$. *Furthermore, we can get* $\frac{dd_n^{F*}}{db} = \frac{dd_h^{F*}}{db} = -\frac{c}{2} < 0$, $\frac{\partial \Pi^{F*}}{\partial b} = \frac{-2bc(\theta_n N + \theta_h H) - (\theta_n N + \theta_h H)^2}{4b^2} < 0$, *where* $N = a_n - bc - \beta_n + \mu$, $H = a_h - bc - \beta_h + \mu$. *Similarly, we can analyze the effects of* θ_n, θ_h, β_n, *and* β_h *on* p^*, d_n^{F*}, d_h^{F*}, *and* Π^{F*}.

Proof of Proposition 2. *We can get* $\frac{\partial E(\Pi^S)}{\partial p_n} = \theta_n(a_n - 2bp_n - \beta_n + bc + \mu)$ *and* $\frac{\partial E(\Pi^S)}{\partial p_h} = \theta_h(a_h - 2bp_h - \beta_h + bc + \mu)$*, as well as the Hessian matrix* $H = \begin{bmatrix} -2b\theta_n & 0 \\ 0 & -2b\theta_h \end{bmatrix}$*. Further, we construct the Lagrange function, that is,* $L(p_n, p_h, k) = (p_n - c)(a_n - bp_n - \beta_n + \mu)\theta_n + (p_h - c)(a_h - bp_h - \beta_h + \mu)\theta_h + k(p_n - p_h)$*. The corresponding KKT conditions can be expressed as*

$$\begin{cases} \frac{\partial L}{\partial p_n} = \theta_n(a_n - bp_n - \beta_n + \mu) - b\theta_n(p_n - c) + k = 0 \\ \frac{\partial L}{\partial p_h} = \theta_h(a_h - bp_h - \beta_h + \mu) - b\theta_h(p_h - c) - k = 0 \\ k(p_n - p_h) = 0 \\ k \geqslant 0 \end{cases}$$

According to $p_n \leqslant p_h$, we can get $k = 0$. Therefore, the optimal prices can be expressed as $p_n^* = \frac{a_n - \beta_n + bc + \mu}{2b}$ and $p_h^* = \frac{a_h - \beta_h + bc + \mu}{2b}$.

Proof of Corollary 2. *We can obtain* $\frac{dp_n^*}{db} = -\frac{a_n - \beta_n + \mu}{2b^2} < 0$ *and* $\frac{dp_h^*}{db} = -\frac{a_h - \beta_h + \mu}{2b^2} < 0$*, as well as* $\frac{dd_n^{S*}}{db} = \frac{dd_h^{S*}}{db} = -\frac{c}{2} < 0$ *and* $\frac{\partial \Pi^{S*}}{\partial b} = \frac{-2bc(\theta_n N + \theta_h H) - (\theta_n N^2 + \theta_h H^2)}{4b^2} < 0$*. Analogously, we can analyze the effects of* θ_n*,* θ_h*,* β_n*, and* β_h *on* p_n^**,* p_h^**,* d_n^{S*}*,* d_h^{S*}*, and* Π^{S*}*.*

Proof of Proposition 3. *We can get* $p_h^* - p^* = \frac{\theta_n(a_h - a_n - \beta_h + \beta_n)}{2b}$ *and* $p_n^* - p^* = \frac{\theta_h(a_n - a_h - \beta_n + \beta_h)}{2b}$*. Since* a_h *is sufficiently large and* $a_h > a_n$*,* $p_h^* > p^*$ *and* $p_n^* < p^*$*, thus there is* $p_n^* < p^* < p_h^*$*.*

Proof of Proposition 4. *(a) We can get* $d_n^{S*} - d_n^{F*} = \frac{\theta_h(a_h - a_n - \beta_h + \beta_n)}{4} > 0$*, that is,* $d_n^{S*} > d_n^{F*}$*. We can also get* $d_h^{S*} - d_h^{F*} = -\frac{\theta_n(a_h - a_n - \beta_h + \beta_n)}{4} < 0$*, that is,* $d_h^{S*} < d_h^{F*}$*. (b)*$d_n^{F*} + d_h^{F*} = \theta_h(a_n - bc - \beta_n + \mu) + \theta_n(a_h - bc - \beta_h + \mu)$*,* $d_n^{S*} + d_h^{S*} = \frac{a_n + a_h - \beta_n - \beta_h - 2bc + 2\mu}{2}$*, thus* $d_n^{S*} + d_h^{S*} - (d_n^{F*} + d_h^{F*}) = \frac{(\theta_h - \theta_n)(a_h - a_n - \beta_h + \beta_n)}{2}$*. Since* a_h *is sufficiently large and* $a_h > a_n$*, when* $\theta_h \leqslant \theta_n$*, there is* $d_n^{S*} + d_h^{S*} \leqslant d_n^{F*} + d_h^{F*}$*; when* $\theta_h > \theta_n$*, there is* $d_n^{S*} + d_h^{S*} > d_n^{F*} + d_h^{F*}$*.*

Proof of Proposition 5. *Let* $N = a_n - bc - \beta_n + \mu$ *and* $H = a_h - bc - \beta_h + \mu$*, we can obtain* $\Pi^{S*} - \Pi^{F*} = \frac{\theta_n N^2 + \theta_h H^2 - (\theta_n N + \theta_h H)^2}{4b}$*. After simplification, we can get* $\Pi^{S*} - \Pi^{F*} = \frac{\theta_n \theta_h}{4b}(N - H)^2$*, thus* $\Pi^{S*} > \Pi^{F*}$*.*

Proof of Proposition 6. *Let* $N = a_n - bc - \beta_n + \mu$ *and* $H = a_h - bc - \beta_h + \mu$*, we can get* $CS^{F*} - CS^{S*} = \frac{\theta_n}{8b}[(2 - \theta_n)N - \theta_h H]^2 + \frac{\theta_h}{8b}[(2 - \theta_h)H - \theta_n N]^2 - \frac{\theta_n}{8b}N^2 - \frac{\theta_h}{8b}H^2$*. After simplification,* $CS^{F*} - CS^{S*} = \frac{3\theta_n\theta_h}{8b}(N - H)^2 > 0$*, thus* $CS^{S*} < CS^{F*}$*.*

Proof of Proposition 7. *Let* $N = a_n - bc - \beta_n + \mu$ *and* $H = a_h - bc - \beta_h + \mu$*, we can obtain* $SW^{S*} - SW^{F*} = \Pi^{S*} - \Pi^{F*} + CS^{S*} - CS^{F*} = \frac{\theta_n\theta_h}{4b}(N - H)^2 - \frac{3\theta_n\theta_h}{8b}(N - H)^2$*. After simplification,* $SW^{S*} - SW^{F*} = -\frac{\theta_n\theta_h}{8b}(N - H)^2$*, thus* $SW^{S*} < SW^{F*}$*.*

Proof of Proposition 8. *We can get* $\frac{\partial E(\bar{SW}^S)}{\partial \bar{p}_n} = -b\theta_n(\bar{p}_n - c)$ *and* $\frac{\partial E(\bar{SW}^S)}{\partial \bar{p}_h} = -b\theta_h(\bar{p}_h - c)$*, as well as the Hessian matrix* $H = \begin{bmatrix} -b\theta_n & 0 \\ 0 & -b\theta_h \end{bmatrix}$*. Further, we construct the Lagrange function, that is,* $G(\bar{p}_n, \bar{p}_h, t) = (\bar{p}_n - c)(a_n - b\bar{p}_n - \beta_n + \mu)\theta_n + (\bar{p}_h - c)(a_h - b\bar{p}_h - \beta_h + \mu)\theta_h + \frac{\theta_n(a_n - b\bar{p}_n - \beta_n + \mu)^2 + \theta_h(a_h - b\bar{p}_h - \beta_h + \mu)^2}{2b} + t(\bar{p}_n - \bar{p}_h)$*. The corresponding KKT conditions can be expressed as*

$$\begin{cases} \frac{\partial G}{\partial \bar{p}_n} = -b\theta_n(\bar{p}_n - c) + t = 0 \\ \frac{\partial G}{\partial \bar{p}_h} = -b\theta_h(\bar{p}_h - c) - t = 0 \\ t(\bar{p}_n - \bar{p}_h) = 0 \\ t \geqslant 0 \end{cases}$$

According to $\bar{p}_n \leqslant \bar{p}_h$, we can get $t = 0$. Thus, the optimal service prices can be expressed as $\bar{p}_n^* = c$ and $\bar{p}_h^* = c$.

Proof of Proposition 9. (*a*) *We can get* $p_n^* - \bar{p}_n^* = \frac{a_n - \beta_n - bc + \mu}{2b} > 0$ *and* $p_h^* - \bar{p}_h^* = \frac{a_h - \beta_h - bc + \mu}{2b} > 0$. *Thus, there are* $\bar{p}_n^* < p_n^*$ *and* $\bar{p}_h^* < p_h^*$. (*b*) *We can get* $\Pi^{S*} - \bar{\Pi}^{S*} = \frac{\theta_n(a_n - bc - \beta_n + \mu)^2 + \theta_h(a_h - bc - \beta_h + \mu)^2}{4b} > 0$, *thus*, $\bar{\Pi}^{S*} < \Pi^{S*}$. (*c*) *We can get* $CS^{S*} - \bar{CS}^{S*} = -\frac{3(\theta_n(a_n - bc - \beta_n + \mu)^2 + \theta_h(a_h - bc - \beta_h + \mu)^2)}{8b} < 0$, *thus* $\bar{CS}^{S*} > CS^{S*}$. (*d*) *We can get* $SW^{S*} - \bar{SW}^{S*} = -\frac{\theta_n(a_n - bc - \beta_n + \mu)^2 + \theta_h(a_h - bc - \beta_h + \mu)^2}{8b} < 0$, *thus*, $\bar{SW}^{S*} > SW^{S*}$.

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