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Optimal trade-in strategy of business-to-consumer platform with dual-format retailing model☆

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ABSTRACT

B2C platforms are increasingly implementing trade-in programs to boost sales. Most of these platforms have adopted dual-format retailing model including both self-run stores and third-party stores. Under trade-in program framework, B2C platforms will determine the optimal trade-in rebate, and whether to offer the rebate to consumers with gift card (GC) or cash coupon (CC). GC can only be used in self-run stores, while CC can be used in both stores. To entice more consumers to trade-in products, platforms may launch trade-in efforts in the market. To address such decision-making challenges, we consider a B2C platform who owns a self-run store and hosts a third-party store, and examine the optimal trade-in strategy for the platform by developing four theoretical models. We first present two models without considering trade-in efforts, i.e., one model regarding GC payment, and one model regarding CC payment, and then extend them by taking trade-in efforts into consideration. Some interesting findings and insights are achieved. In particular, we find that both GC and CC do not always benefit the platform. Interestingly, offering high quality and low selling price for products in both the self-run store and the third-party store are also not always beneficial to the platform. So is the competition between both stores. Launching trade-in efforts may lead to a lower trade-in rebate but a higher profit for the platform. A counterintuitive finding is obtained that a higher gift card redemption rate is not beneficial to the platform, and vice versa.

1. Introduction

Consumers are increasingly purchasing on online retailing platforms, e.g., Amazon.com and JD.com. To retain consumers and expand market share, many platforms adopt trade-in programs to entice the existing consumers to make repeat purchases, and further attract potential new comers to buy products. Typical trade-in program as a service in a business-to-consumer (B2C) platform operates as follows. Consumers firstly turn in used products to the platform. When receiving used products, the platform will check the products and offer consumers special discounts, which can be used in their future purchases. This discount is referred to as trade-in rebate [1]. Finally, consumers can use trade-in rebates to buy any desirable products on the platform. Trade-in programs are widely observed on B2C platforms such as Amazon.com, Bestbuy.com, JD.com, Suning.com and Gome.com.cn.

Traditional trade-in programs are extensively used in durable product markets, e.g., automobile, household appliances, electronics and technology industries [1–3]. In traditional trade-in programs, trade-in rebates are commonly redeemed toward repeat purchases of successive-generation products of used products. Consequently, trade-in can serve as an effective new product sales mechanism [2]. For instance, sales percent of new car through trade-in is approximately 57% in automobile industry [4]. However, in B2C transactions, trade-in is regarded as an important strategic leverage of B2C platforms to entice the existing consumers to make further purchases for any desired products to increase profitability. Furthermore, trade-in program can accept any specified used products regardless of whether bought from the platforms. In this regard, this program can effectively attract new consumers to make deals on platforms. Motivated by these evidences, the primary goal of this paper is to examine the optimal trade-in strategy of B2C platforms.

In recent years, many B2C platforms are increasingly adopting "dual-format" retailing model to sell products. In such a retailing model, in addition to self-run stores, third-party stores are also hosted. An increasing prevalence of third-party stores are widely observed in e-commerce platforms [5], e.g., Amazon.com,

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Walmart Marketplace, JD.com, Suning.com and Gome.com.cn, and these stores have largely facilitated e-commerce growth [6]. A recent report shows that third-party transactions in Amazon.com account for roughly 40% of its total sales [7]. JD.com also reports that there are approximately 99,000 third-party sellers on its marketplace as of December 31, 2015 [8].

On dual-format retailing B2C platforms, trade-in rebates are usually offered to consumers with gift card (GC) or cash coupon (CC). Some platforms like Amazon.com and JD.com, offer trade-in rebates with GC, while others (e.g., Suning.com and Gome.com.cn) use CC. For example, Gome.com.cn use “red coupon” to pay the rebates. Both GC and CC contain a value of trade-in rebate that can be redeemed toward future product purchases. Notably, GC is usually used to buy products from self-run stores, while CC is applicable to both self-run and third-party stores. Intuitively, CC may offer consumers more choices for shopping than GC. However, it may lead to the competition between self-run stores and third-party stores. Hence, these B2C platforms may face an important challenge: which payment (GC or CC) is better for offering trade-in rebates to consumers?

Trade-in rebate generally specifies the conditions under which B2C platforms can accept trade-in products for some rebates. In general, trade-in products can serve as a significant source of revenue for B2C platforms. When receiving traded-in products, platforms transfer these products to manufacturers. Manufacturers may generate some revenue (or equivalently cost saving) either by totally remanufacturing these products and selling them as new through platforms, or by reusing some components, or even by recycling the material [1]. These revenue can be seen as actual residual values of used products. Accordingly, if the rebate is too large, i.e., especially larger than actual residual value, platforms may incur some losses from trade-in programs. In contrast, if the rebate is too small, consumers would not participate in trade-in programs. Hence, how to determine a suitable trade-in rebate is an important decision-making issue for B2C platforms.

As platforms can obtain profits from both disposing used products and selling new products, platforms may exert sales efforts with respect to trade-in program to entice more replacement consumers to conduct trade-in transactions. Many platforms such as Amazon.com, JD.com, Gome.com.cn and Suning.com offer free shipping or door-to-door recovery services to replacement consumers who are willing to participate in trade-in activities. In particular, Suning.com provides each consumer who trade-in a used phone a chance to obtain a “red envelope” that contains certain monetary value as a gift in the summer of 2017 [9]. Notably, these sales efforts are typically launched by platforms, and for ease of notations, we use “trade-in effort” to represent this sales effort in this study. Note that, trade-in effort may directly affect consumer behaviors, and thus the optimal decisions on trade-in rebate and strategies. Hence, how to determine their trade-in effort levels is also an important issue for B2C platforms.

The aforementioned evidences and findings raise the following questions: (1) How do platforms determine whether to pay trade-in rebates with GC or CC? (2) How to determine the optimal trade-in rebates? (3) How do platforms determine their optimal trade-in effort levels?

Despite the importance of trade-in strategy including payment mode and rebate value to B2C platforms, the prior studies have not well documented the above described issues. The primary goal of this paper is to fill this gap. To this end, we consider a B2C platform with a self-run store and a third-party store, and focus on replacement (or trade-in) consumers who own used durable products. We then develop four theoretical models, i.e., two models without considering trade-in efforts under GC and CC payment modes, respectively, and two models considering trade-in efforts under GC and CC payment modes, respectively. To investigate the optimal trade-in strategy, i.e., trade-in payment and rebate, we first examine the optimal trade-in strategy by comparing the platform’s optimal decisions and profits obtained from models under GC and CC payment modes without trade-in efforts. To identify the impact of trade-in efforts on the platform’s optimal trade-in strategy, we then compare the platform’s optimal decisions and profits obtained from the two models under GC and CC with trade-in efforts. Since gift cards may not be fully redeemed in practice, further extension by considering the impacts of the redemption rate of gift card on the platform’s optimal decisions and profits is presented. Some important findings and management insights are obtained.

The remainder of this paper is organized as follows. Section 2 reviews the most relevant literature. In Section 3, we present our theoretical models. The results are also provided in this section. In Section 4, the optimal trade-in strategies and trade-in effort levels are analytically examined, and the optimal profits of the platform are also investigated. Section 5 provides concluding remarks. All the proofs are offered in Appendix A.

2. Literature review

Our work lies at the intersection of trade-in rebate, platform-based online retailing and sales efforts. We review the most relevant studies in this section.

2.1. Trade-in rebate

An increasing number of studies have explored economic motivations for firms to offer trade-in rebates. Klemperer [10] shows that consumers incur switching costs for changing firms, if the original firm from which consumers bought products offers trade-in services. Van Ackere and Reyniers [11] indicate that the primary goal of trade-in rebate is to increase purchase frequency. Zhu et al. [4] reveal that trade-in consumers exhibit higher willingness-to-pay for new products than consumers who just buy new products alone, and find that trade-ins can effectively increase sales percent of new car in automobile industry. Rao et al. [12] theoretically and empirically examine the motivation of implementing trade-ins, and find that trade-ins can effectively increase firm profits. Furthermore, Li and Xu [13] show that, for a product with technology innovations, trade-in can protect firms against the risk caused by uncertain innovation process.

Another stream of research focuses on examining the optimal trade-in rebates and product prices for firms, e.g., Van Ackere and Reyniers [11] and Fudenberg and Tirole [14]. These studies explore the optimal product prices and trade-in rebates under a two-period framework. In the first period, pricing decisions are made by segmenting consumers into potential replacement consumers and first-time buyers for new generation products. In the second period, firms determine the optimal trade-in rebates for upgrades toward repeat purchases, or discounts of selling old models. Following this framework, Yin and Tang [15] study the optimal customer purchasing decision under trade-in programs with up-front fees, and find that a firm is always better off offering trade-ins. By considering forward looking consumers, Yin et al. [16] show that these consumers are willingness to pay higher prices than their product valuations. Chen [17] further shows that strategic consumer choice among three options (i.e., no trade-ins, trade-ins to replacement consumers with high quality used goods, and trade-ins to all replacement consumers) depends critically on the features and prices of new goods. Zhu et al. [18] apply a two-period model to examine the competition between two firms, and derive the equilibrium decisions of the two firms. Unlike these studies that model consumer expectations in dynamic settings, Ray et al. [1] assume that the technology related to a durable product is relatively stable and examine firm decisions at the time of offering trade-in. They find that whether trade-in rebate increases or decreases with durability relies on whether a firm is dealing with a low-durability or an inherently highly durable product.

Notably, replacement consumers through turning in used products can obtain trade-in rebates, which can be seen as price discrimination for further purchases. Agrawal et al. [3] examine the impact of trade-in rebate on price discrimination, and find that a firm can conduct perfect price discrimination through a trade-in rebate. To achieve a better price discrimination, Chen and Hsu [19] explore when and how a firm offers a trade-in rebate, and find that the rebate magnitude increases with deterioration rate and decreases with customer willingness for trade-ins. Kwon et al. [20] empirically investigate the informational role of trade-ins for pricing durable goods by using the transaction data from Power Information Network (PIN). Their results show that the dealer charges a higher price to consumers who have traded-in vehicles than those who have not. Chen [17] also examines the effect of price discrimination on the choice of trade-in policies.

Obviously, the aforementioned studies have well documented the issues of trade-in motivations, rebate decision and price discrimination for traditional manufacturers. Trade-in rebates are offered by firms to consumers who have owned products bought from them. Unlike these studies, we focus on exploring the optimal trade-in strategy for B2C platforms. Trade-in rebates of a platform can offer to consumers who have specific old products regardless of whether bought from the platforms. Note that, offered rebates can be used by consumers to buy their desired products no matter whether within or out of the scope of categories regarding used products.

2.2. Platform-based online retailing model and sales efforts

Recently, platform-based online retailing model has drawn extensive concerns in the literature. Jiang et al. [21] investigate how a platform owner such as Amazon learns about the demand for the “mid-tail” products sold by third-party sellers, and then cherry-picks the successful products to stock and sell it by itself. Ryan et al. [22] examine the conditions under which the retailer sells products on its own website or as a third-party seller sells products on another marketplace. Mantin et al. [6] explore the strategic role of third-party marketplaces in online retailing, and find that third-party marketplaces benefit retailers and hurt manufacturers. Hagiu and Wright [23] attempt to determine whether an intermediary functions as a marketplace, a reseller or a hybrid. They find that which choice is preferred depends on whether the intermediary and suppliers have more important information relevant to the optimal tailoring of marketing activities for each specific product. Similarly, Abhishek et al. [24] attempt to identify under what conditions agency selling or reselling is better for online retailers. They find that online retailers prefer agency selling when electronic channel has a negative effect on the demand of traditional channel, while prefer reselling when electronic channel has a significant positive effect on the demand of traditional channel.

Note that, the aforementioned studies mainly focus on examining retailing models of online platforms or retailers. Following these studies, we attempt to examine the optimal trade-in strategy for B2C platforms, which has not been addressed in the literature. One relevant study is Li et al. [2]. They empirically investigate the impact of accurate prediction of return flow on trade-in effect and efficiency by using a real dataset of a high-tech company, and find that this prediction is important for firms to offer suitable trade-in rebates. Notably, their work is conducted for business-to-business transactions, and the optimal decision on trade-in rebate is not examined.

Our study is evidently related to sales efforts in platform-based transactions. Sales efforts have been demonstrated to be important in enhancing competitiveness for firms [25–27]. Interestingly, Xing and Liu [28] show that an online retailer may take free riding of a brick-and-mortar retailer’s sales efforts, and present some contracts with price match including selective compensation rebate, target rebate and wholesale price discount to coordinate the brick-and-mortar retailer’s sales efforts. In online settings, platforms and third-party sellers may also launch sales efforts. Jiang et al. [21] indicate that third-party sellers may hide their demands by strategically lowing service levels, while the platform can invest in consumer reviews to learn about third-party seller demands. They find that identifying the real demands of third-party sellers is not necessarily beneficial to the platform. Cao and He [29] examine the interaction of sales efforts between a B2C platform and a third-party seller, and show that the platform may take a free riding from the third-party seller’s sales efforts. These studies have addressed the interactions between sellers, or between platforms and third-party sellers. None has examined the impact of sales efforts on trade-in rebate decision in B2C settings.

This paper attempts to identify the optimal trade-in strategy for B2C platforms with dual-format retailing model. To the best of our knowledge, this is the first study to address this issue in the context of online retailing. It is also the first paper to specifically examine the impact of sales efforts on trade-in rebate decision. Some new managerial insights are obtained.

3. Theoretical models

Consider a B2C platform who owns a self-run store and hosts a third-party store. Each store sells a new product online to the same group of consumers. These two products are imperfect substitute, and for simplicity, are denoted as product p and product t for those sold by self-run store and third-party store, respectively. We focus on consumers who have the same category of used (old) durable products with the same residual values. We further assume that each consumer has one old product. Consumers are enticed to participate in the trade-in program. Consumers who participate in the program are referred to as trade-in or replacement consumers, each of whom will buy at most one unit of new product online.

Trade-in sequence on the platform is summarized as two stages. In the first stage, replacement consumers turn in used products to the platform. When receiving used products, the platform offers certain trade-in rebates by using GC or CC to consumers after assessing used product residual values. Replacement consumers then decide whether to accept the rebates. In the second stage, GC or CC can be redeemed toward new product purchases. Notably, GC is only applicable in the self-run store, while CC can be used in both stores. Accordingly, the platform makes two important decisions, i.e., trade-in rebate payment mode (i.e., GC or CC) and associated rebate value. To examine the optimal trade-in strategy, we assume that both the platform and third-party seller are rational and self-interested. Since the self-run store is owned by the platform, we will refer to it as the platform in the following part. The notations used in this paper are summarized in Table 1.

In our models, p_r and e are decision variables, while other parameters are exogenous. When receiving old products, the platform firstly assesses their actual residual values (v) and offers trade-in rebates (p_r) to consumers. Obviously, both the platform and consumers may incur some costs through trade-in flow. These costs are generally rather small, and can be omitted. From another perspective, incurred cost of the platform may have been considered when determining actual residual values of used products. Notably, actual residual values of used products can serve as a revenue source for the platform.

Table 1
Summary of notations.

Notation	Interpretation
p_r	Trade-in rebate (e.g., $)
M_j	Potential market size regarding GC payment ($j=g$) or CC payment ($j=c$)
ϕ	Consumer valuation of used product (e.g., $)
θ	Durability parameter of used product ($\theta<1$)
x_i	Product quality of the platform ($i=p$) or third-party seller ($i=t$)
τ	Competition parameter
v	Per unit used product actual residual value (e.g., $)
p_i	Product price of the platform ($i=p$) or third-party seller ($i=t$) (e.g., $)
c_i	Unit product cost of the platform ($i=p$) or third-party seller ($i=t$) (e.g., $)
f	Referral fee percentage
e	Trade-in effort level
β	Trade-in effort sensitivity coefficient
m	Marginal cost of trade-in effort level
D_j	Demand associated with trade-in program ($j=g$ or c)
$\prod_i$	Profit of the platform or the third-party seller ($i=p$ or t)

Notably, in traditional trade-in program, trade-in rebate is commonly regarded as a price discrimination for product exchange [3,17]. In such a case, trade-in activity can be seen as a product exchange process, in which retailers may first provide the price discounts according to consumers' used products, and then consumers will decide whether to accept the discounts for further purchases. Accordingly, consumers may consider total utilities of both trading-in used products and buying the same type of new products as their used products. Unlike the traditional trade-in program, as mentioned earlier, trade-in transactions on B2C platforms can be separated into two stages. In the first stage, consumers will decide whether to accept the offered trade-in rebates according to their valuation of used products. If consumers obtain a negative utility from trade-in service in the first stage, they will not conduct the deal of trade-in used products. If consumers accept the trade-in rebates, they will then decide whether to buy their desired new products online according to the utilities from purchasing new products by considering product quality and prices in the second stage. If consumers can obtain positive utilities derived from new product purchases, they will buy the products; otherwise, they will not buy the products. Note that, these new products may not be the same categories as consumers' used products. According to these typical considerations, we find that consumer decisions on trade-in used products and new product purchases are independent and separated. As a consequence, consumers will consider their utilities in each stage to decide whether to accept the rebates and purchase new products.

In practice, consumers may be heterogeneous with respect to residual values of used products. Similar to Van Ackere and Reyniers [11], Rao et al. [12] and Miao et al. [30], used product valuation is represented by $\theta\phi$. Note that, ϕ is consumer initial valuation of their used products, and is uniformly distributed over [0, 1]. Thus, consumer utility function regarding trade-in in the first stage is defined as

$$u_1 = p_r - \theta\phi. \tag{1}$$

This utility function indicates that consumer utility increases in trade-in rebate while decreases in consumer valuation of used product residual value. When $u\geq 0$, consumers may conduct trade-ins; otherwise, consumers may not. It is easy to derive trade-in demand function, i.e.,

$$D_j = M_j p_r/\theta \ \ (j=g \text{ or } c) \tag{2}$$

In the second stage, consumers may decide whether to buy new products online. As trade-in rebates can be redeemed to buy any desired new products on the platforms regardless of whether these new products are the same types as their used products. In general, consumers can always find their desired products on the platforms. If not, they can wait to buy their favorite products in the near future. In this regard, we assume that each trade-in consumer will buy a new product online, and thus product demand is equal to the trade-in demand. Since GC is only applicable in the self-run store, product demand under GC is $D_g = M_g p_r/\theta$. CC can be used in both stores, product demand in this case is $D_c = D_{cp} + D_{ct} = M_c p_r/\theta$, where D_{cp} and D_{ct} represent product demands of the self-run store and third-party store, respectively. As CC may attract more consumers who prefer the third-party store to participate in trade-in program, without loss of generality, we assume that $M_c \geq M_g$.

Notably, consumers may carefully consider new product valuation including product quality or service levels, product prices and also their preferences for self-run stores and third-party stores. For ease of expositions, we use product quality to represent product valuation for each store, i.e., x_i ($i=p$ and t) denotes quality level of the products sold by self-run store and third-party store, respectively. Similar to Kourandi et al. [31], we further assume that consumers are allowed to be heterogeneous with respect to their natural preferences for self-run stores and third-party stores. This preference can be regarded as a typical psychological distance from the self-run store and third-party store, which generally relies on their preference degrees regarding both stores. Following Hotelling [32] and Wu [33], we consider that consumer preference degree to the self-run store is denoted by α, and is distributed uniformly on a Hotelling line [0, 1]. Thus, we assume that self-run store is located to the left at 0, while third-party store is located to the right at 1. Then, the preferences to the self-run store and third-party store are α and $1-\alpha$, respectively. Following Hotelling [32], for consumers with a preference degree α to the self-run store on the Hotelling line, their utility functions for the two stores' products are defined as

$$\begin{aligned} u_{2p} &= x_p - p_p - \tau\alpha, \\ u_{2t} &= x_t - p_t - \tau(1-\alpha). \end{aligned} \tag{3}$$

Note that, u_{2p} and u_{2t} denote the utilities derived from buying new products from the self-run store and third-party store, respectively; $\tau\alpha$ and $\tau(1-\alpha)$ refer to the disutility with a visit of the self-run store and third-party store, respectively, where τ refers to the degree of competition between both stores [31]. Consumers may choose a store's product where they can get a higher utility. Thus, following Hotelling [32], the marginal consumer indifference between these two stores can be easily obtained. To this end, we set $u_{2p}(\bar{\alpha}) = u_{2t}(\bar{\alpha})$, where $\bar{\alpha}$ is the indifference point between purchasing product p and product t. It is easy to get the indifference point, i.e., $\bar{\alpha} = 1/2 + (x_p - x_t - p_p + p_t)/(2\tau)$. If trade-in consumers with a preference degree α less than the threshold $\bar{\alpha}$ will purchase new products from the self-run store; otherwise, they buy new products from the third-party store.

Hence, product demands of both stores are expressed as

$$\begin{aligned} D_{cp} &= \bar{\alpha} M_c p_r/\theta, \\ D_{ct} &= (1-\bar{\alpha}) M_c p_r/\theta. \end{aligned} \tag{4}$$

To identify the optimal trade-in strategy for B2C platforms, we present our theoretical models under both payment modes (i.e., GC and CC) without considering trade-in efforts in what follows, and then extend them with incorporating trade-in efforts.

3.1. Base models

In this sub-section, we present two models under GC and CC payment modes without considering trade-in efforts, i.e., model

Table 2
The optimal solutions and the optimal platform's profits.

Model	The platform's optimal decisions and profits
GCB	$p_r^{GCB*} = (p_p - c_p + v)/2$, $\prod_p^{GCB*} = M_g(p_p - c_p + v)^2/(4\theta)$.
CCB	$p_r^{CCB*} = [\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v]/2$, $\prod_p^{CCB*} = M_c[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v]^2/(4\theta)$.
GCE	$p_r^{GCE*} = (p_p - c_p + v)(m\theta - M_g\beta^2)/(2m\theta - M_g\beta^2)$, $e^{GCE*} = (p_p - c_p + v)M_g\beta/(2m\theta - M_g\beta^2)$, $\prod_p^{GCE*} = mM_g(p_p - c_p + v)^2/(4m\theta - 2M_g\beta^2)$.
CCE	$p_r^{CCE*} = [\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v](m\theta - M_c\beta^2)/(2m\theta - M_c\beta^2)$, $e^{CCE*} = [\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v]M_c\beta/(2m\theta - M_c\beta^2)$, $\prod_p^{CCE*} = mM_c[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v]^2/(4m\theta - 2M_c\beta^2)$.
GCBR	$p_r^{GCBR*} = (p_p - c_p + v)/(2\gamma)$, $\prod_p^{GCBR*} = M_g(p_p - c_p + v)^2/(4\theta\gamma)$.
GCER	$p_r^{GCER*} = (p_p - c_p + v)(m\theta - M_g\gamma\beta^2)/[\gamma(2m\theta - M_g\gamma\beta^2)]$, $e^{GCER*} = M_g\beta(p_p - c_p + v)/(2m\theta - M_g\gamma\beta^2)$, $\prod_p^{GCER*} = mM_g(p_p - c_p + v)^2/[2\gamma(2m\theta - M_g\gamma\beta^2)]$.

GCB (base model under GC payment mode) and model CCB (base model under CC payment).

3.1.1. Model GCB: base model under GC payment

As GC is only redeemed toward buying products from the self-run store, all potential trade-in consumers may make deals in the self-run store. The platform's total profit is sourced from two streams: one is obtained from trade-in used products (i.e., actual residual values minus trade-in rebates), and the other is sales profit gained from new product sales in the self-run store. The platform's profit is expressed as

$$\prod_p^{GCB}(p_r) = D_g(v - p_r) + D_g(p_p - c_p). \tag{5}$$

Note that, $D_g(v - p_r)$ is the platform's profit derived from trade-in transactions, and $D_g(p_p - c_p)$ is the profit gained from new product sales in the self-run store. The platform aims to determine the optimal trade-in rebate to maximize its profit. It is easy to obtain the optimal rebate and profit of the platform. The results are reported in Table 2.

3.1.2. Model CCB: base model under CC payment

Under this model, potential trade-in consumers may buy products from the self-run store or the third-party store. Similar to model GCB, the platform's total profit is gained from both trade-in service and sales profit. Notably, sales profit depends on two parts: profit obtained from new product sales in the self-run store and transaction fee charged from the third-party store's sales. Thus, the third-party store's profit is formulated as

$$\prod_t^{CCB} = D_{ct}[(1-f)p_t - c_t]. \tag{6}$$

Obviously, the third-party store's profit completely depends on product sales. In Eq. (6), f is a referral fee percentage (i.e., a fraction of the selling price) charged by the platform for per unit product sales from the third-party store. To prevent the third-party seller from exiting from the platform, it is practical to assume that $f < 1$.

The platform's profit is formulated as

$$\prod_p^{CCB}(p_r) = D_c(v - p_r) + D_{cp}(p_p - c_p) + fD_{ct}p_t. \tag{7}$$

Note that, $D_c(v - p_r)$ is the profit generated from traded-in products; $D_{cp}(p_p - c_p)$ and $fD_{ct}p_t$ are the self-run store sales profit and transaction fee charged from the third-party store, respectively. We can easily obtain the optimal trade-in rebate and the platform's optimal profit. The results are reported in Table 2.

3.2. Extended models

In this sub-section, we extend the two base models by incorporating trade-in efforts. To capture more market share, the platform may launch sales efforts with respect to trade-in program to entice more replacement consumers to conduct such transactions. As suggest by Dumrongsiri et al. [34] and Zhang et al. [35], sales efforts can improve consumer utility. Hence, consumer utility function regarding trade in used products in the first stage can be extended as

$$u_1^E = p_r + \beta e - \theta\phi. \tag{8}$$

According to this utility function, it is easy to derive trade-in demand functions, i.e.,

$$D_j^E = M_j(p_r + \beta e)/\theta \ \ (j = g \text{ or } c) \tag{9}$$

Similar to the base case without trade-in efforts, product demand function under GC in such extended case is $D_g^E = M_g(p_r + \beta e)/\theta$, and product demand functions under CC for the self-run store and third-party store are $D_{cp}^E = \bar{\alpha}M_c(p_r + \beta e)/\theta$ and $D_{ct}^E = (1-\bar{\alpha})M_c(p_r + \beta e)/\theta$, respectively. We also assume that $M_c \geq M_g$ in the extended case.

Any effort will generally incur certain cost. Following Jiang et al. [21] and Cao and He [29], we assume that trade-in effort cost takes a quadratic form and depends on trade-in effort level. Similar assumptions can be found in the literature, e.g., Lau et al. [36] and Kaya [37]. Therefore, trade-in effort cost of the platform is expressed as $me^2/2$. Similar to Lau et al. [36], to avoid degenerated infinite effort situations, we assume that $m > M_c\beta^2/\theta$.

We then present the two extended models by considering the platform trade-in efforts. Under GC payment mode, by considering trade-in efforts, the corresponding model (model GCE: Extended model under GC payment model) regarding the platform's profit is expressed as

$$\prod_p^{GCE}(p_r, e) = D_g^E(v - p_r) + D_g^E(p_p - c_p) - me^2/2. \tag{10}$$

In such a case, the platform aims to maximize its profit by determining the optimal trade-in rebate and trade-in efforts. The results are also shown in Table 2.

With regard to CC payment mode, the extended model, i.e., model CCE (Extended model under CC payment) can be formulated as the following two equations. The first one is the profit model regarding the third-party store, i.e.,

$$\prod_t^{CCE} = D_{ct}^E[(1-f)p_t - c_t], \tag{11}$$

and the second one regarding the platform's profit is expressed as

$$\prod_p^{CCE}(p_r, e) = D_c^E(v - p_r) + D_{cp}^E(p_p - c_p) + D_{ct}^E fp_t - me^2/2. \tag{12}$$

It is easy to obtain the optimal decisions and the platform's profit in this case, and the results are reported in Table 2.

4. Analysis

We in this section consider two scenarios: basic scenario and extended scenario. In the basic scenario, we examine the optimal trade-in strategy by comparing the platform's optimal profits and trade-in rebates under models GCB and CCB. In the extended scenario, we attempt to explore the impact of trade-in efforts on the platform's decisions and profits under models GCE and CCE. We further extend the models under GC payment mode to consider the redemption rate regarding gift cards and examine the impact of the rate on the platform's optimal decisions and profits.

4.1. Basic scenario

The platform may offer trade-in rebates with GC or CC. Which payment is better for the platform? The following theorem answers this question.

Theorem 1. *When $fp_t < p_p - c_p$ and $M_c/M_g < \overline{\lambda}_B$, GC outperforms CC, where $\overline{\lambda}_B = A^2/B^2$, $A = p_p - c_p + v$ and $B = \bar{\alpha}(p_p - c_p) + (1 - \bar{\alpha})fp_t + v$; otherwise, CC outperforms GC.*

Theorem 1 shows that GC is a better choice than CC for the platform, when fp_t is less than unit product sales profit of the self-run store, and the ratio M_c/M_g is less than a particular threshold $\overline{\lambda}_B$. Otherwise, the platform is better off choosing CC to offer trade-in rebates. We illustrate Theorem 1 as follows. The condition $fp_t < p_p - c_p$ means that the platform will gain more unit product sales profit through selling products in the self-run store than charged fee from the third-party store. In this case, if $M_c/M_g < \overline{\lambda}_B$, which indicates that M_c is not sufficiently large relative to M_g, CC cannot attract sufficiently large number of consumers to conduct trade-ins. In such a circumstance, when CC is chosen, CC cannot lead to sufficient increase in the product demand of the third-party store, and therefore the profit increment sourced from charged fee. CC cannot effectively increase the platform's profit to cover possible incurred relative profit loss (i.e., $p_p - c_p - fp_t$) for the platform. Hence, the platform may have less incentive to offer trade-in rebates with CC, and GC is a better choice. However, when M_c is sufficiently large, i.e., $M_c/M_g \geq \overline{\lambda}_B$, CC has high potential to expand the trade-in demand. In this circumstance, CC can effectively increase product demand, and thus the platform's profitability. Such an increase may counteract the relative revenue loss. Accordingly, even when $fp_t < p_p - c_p$, if M_c is sufficiently large, it is better for the platform to pay trade-in rebates with CC than GC. However, when $fp_t \geq p_p - c_p$, the platform can obtain more profit from product sales in the third-party store than the self-run store. As such, the platform may have more incentive to offer trade-in rebate payment with CC than GC, regardless of whether $M_c/M_g \geq \overline{\lambda}_B$ holds.

Notably, in common sense, when the platform obtains more profit from product sales in the third-party store than the self-run store, he will close the self-run store. However, this case may not always be true in practice. According to seller central of Amazon.com, referral fee percentages for different products sold by third-party stores are 6%, 8%, 12%, 15%, 16%, 20% and 45%, respectively, where 15% is the referral fee percentage for most product categories [38]. It can be further derived from 2016 Annual Report of Amazon.com that, its operating margin in 2016 is equal to 2.985% [39]. As such, it can be inferred that, Amazon.com may obtain more unit product sales profit from the third-party stores than the self-run store on average. In practice, B2C platforms may also consider the scale issue when deciding whether to close self-run stores or not. On the one hand, although the unit product sales profit of the self-run store is lower than that of the third-party store, if its sales scale is sufficiently large, the platform may still obtain relatively large profit from the self-run store. On the other hand, two different stores on the platform can attract more consumers to enter into the platform than only one third-party store. This may lead to more product sales, and thus more profitability for the platform.

To better illustrate Theorem 1, we apply a numerical example by setting $x_p = 0.9$, $x_t = 0.85$, $p_p = 0.3$, $p_t = 0.29$, $c_p = 0.27$, $\theta = 0.5$, $v = 0.1$, τ=0.5, $M_g = 500$, and increasing f and M_c from zero to 0.2 and 500 to 1000, respectively. The platform's profits under models GCB and CCB regarding f and M_c are depicted in Fig. 1.

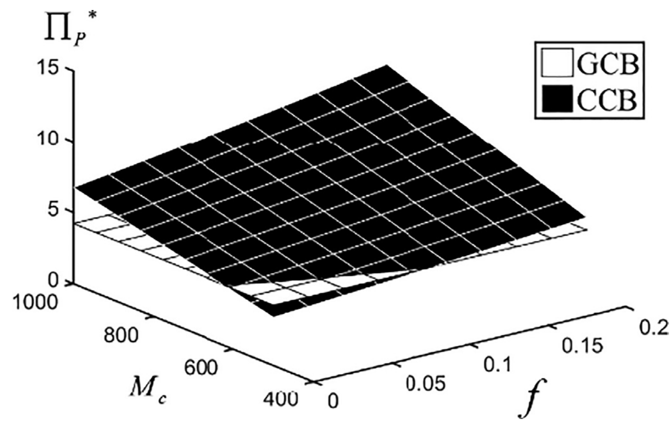

Fig. 1. The platform's profits regarding $f$and M_c.

Fig. 1 shows that, when $f < 0.1034$(i.e., $fp_t < 0.03 = p_p - c_p$), $M_c < 625.813$ and $M_c/M_g < \overline{\lambda}_B$, the platform gains more profit under model GCB (white grid area) than that under model CCB (black grid area); otherwise, he obtains more profit under model CCB than model GCB. Note that, $\overline{\lambda}_B$ varies with f. In particular, when $f = 0$, $M_c = 625.813$ and $\bar{\lambda}_B = 1.252$.

Theorem 1 characterizes the choice of trade-in rebate mode and associated conditions. What payment can offer a larger rebate? The following proposition answers this question.

Proposition 1. *When $fp_t < p_p - c_p$, $p_r^{GCB^*} > p_r^{CCB^*}$; otherwise, $p_r^{GCB^*} \leq p_r^{CCB^*}$.*

Proposition 1 shows that, when $fp_t < p_p - c_p$, the optimal trade-in rebate under model GCB is larger than that under model CCB; otherwise, the former is not larger than the latter. When $fp_t < p_p - c_p$, per unit product sales from the self-run store can lead to more profit for the platform than from the third-party store. In such a context, when using GC, the platform is better off offering a relatively large rebate. This can increase product demand, and thus can lead to more profit for the platform, which may compensate for possible loss incurred by offering a high rebate. When implementing CC, some trade-in consumers may buy products from the third-party store. This results in a lower total profit than that under model GCB. Thus, the platform may has less incentive to provide a higher trade-in rebate. This insight can partly explain why JD.com can provide a higher rebate (i.e., 3650 CNY) for iPhone 6s plus than that of GOME.com.cn (i.e., 3150 CNY) (see JD.com and GOME.com.cn). In contrast, when the condition $fp_t \geq p_p - c_p$ holds, the platform may have more motivation to provide a higher trade-in rebate under model CCB than under model GCB.

According to the findings in Theorem 1 and Proposition 1, we find that when $fp_t < p_p - c_p$, if $M_c/M_g < \overline{\lambda}_B$, GC is better for both the platform and consumers; otherwise, CC is better for the platform but worse for consumers than GC. However, when $fp_t \geq p_p - c_p$, CC is typically better for both the platform and consumers.

In practice, the platform may determine the optimal trade-in rebate by trade-offing its revenue and actual residual values of used products. An interesting finding below states this formally.

Proposition 2. *Under model GCB, when $p_p - c_p \geq v$, $p_r^{GCB^*} \geq v$; otherwise, $p_r^{GCB^*} < v$. Similarly, under model CCB, when $\bar{\alpha}(p_p - c_p) + (1 - \bar{\alpha})fp_t \geq v$, $p_r^{CCB^*} \geq v$; otherwise, $p_r^{CCB^*} < v$.*

Note that, $p_p - c_p$ is the net profit generated from per unit new product sales from the self-run store under model GCB, and $\bar{\alpha}(p_p - c_p) + (1 - \bar{\alpha})fp_t$ can be seen as the average profit obtained from per unit new product sales under model CCB. Proposition 2 indicates that, when per unit new product sales profit is relatively large, i.e., not less than v, the optimal trade-in rebate is larger than or equal to actual residual value of the used product (v); otherwise, it is less than v. The rationale for this is intuitive and summarized as follows. When per unit product sales profit is relatively large, the platform is better off offering a large trade-in rebate. Providing such rebate can attract more consumers to conduct trade-ins, and this can increase demand and thus can generate more profit to cover the loss caused by paying a large rebate. In contrast, when per unit product sales profit is relatively small, the platform has less incentive to provide a large rebate. This proposition indicates that, when the platform's unit sales profit (or average unit sales profit) is larger than the used product's actual residual value, the platform is willing to endure temporary loss by providing a relatively high trade-in rebate.

We next examine the impacts of the main market parameters, i.e., v, x_p, x_t, p_p and p_t on the optimal trade-in rebates and achieve the following proposition.

Proposition 3. *The monotonicity of the optimal trade-in rebate is characterized as*

(a) Both $p_r^{GCB^*}$ and $p_r^{CCB^*}$ increase with v;
(b) When $fp_t < p_p - c_p$, $p_r^{CCB^*}$ increases (decreases) with $x_p(x_t)$; otherwise, $p_r^{CCB^*}$ decreases (increases) with $x_p(x_t)$;
(c) When $fp_t < p_p - c_p - 2\tau\bar{\alpha}$, $p_r^{CCB^*}$ decreases with p_p; otherwise, $p_r^{CCB^*}$ increases with p_p.
(d) When $fp_t \geq p_p - c_p + 2\tau(1-\bar{\alpha})f$, $p_r^{CCB^*}$ decreases with p_t; otherwise, $p_r^{CCB^*}$ increases with p_t.

Proposition 3 shows the optimal trade-in rebate monotonicity. Since actual value of residual value v can be seen as the revenue generated from traded-in products, when v increases, the platform can gain more profit from trade-ins. Thus, the platform may have more incentive to provide a higher rebate. Furthermore, such a higher rebate may lead to a higher demand, and this leads to more sales profit for the platform. Similar results are also found in traditional trade-in related studies, e.g., Ray et al. [1], Yin et al. [16] and Desai et al. [40]. Proposition 3(a) is intuitive and can be supported by the practice. Residual values of kitchen appliances such as dishwasher and oven are typically small, and these products are less included in trade-in programs for purchasing their new generation products [16]. However, we can widely observe that trade-in programs are offered by almost all major retailers for smartphones such as iPhones due to their relatively high residual values [41]. These two evidences partly suggest that, used products with relatively low residual values are usually offered relatively low trade-in rebates, and vice versa.

Note that, in Proposition 3(b), x_p and x_t are the quality levels or consumer initial valuations of the products sold by the self-run store and the third-party store, respectively, which can improve consumers utilities. When $fp_t \leq p_p - c_p$, the platform can gain more per unit product sales profit from the self-run store than the third-party store. As x_p increases, product demand of the self-run store increases, the platform has more incentive to increase the trade-in rebate to further expand product demand, and thus to pursue more profit. However, as x_t increases, product demand of the third-party store goes up, and that of the self-run store decreases. In this circumstance, the platform will reduce the trade-in rebate so as to obtain more profit through trading in used products. In contrast, when $fp_t > p_p - c_p$, the platform can gain more per unit product sales profit from the third-party store than the self-run store. In such a case, as x_p (x_t) increases, product demand of the third-party store decreases (increases), thus the platform will reduce (increase) the trade-in rebate.

Proposition 3(c) shows that, when $fp_t < p_p - c_p - 2\tau\bar{\alpha}$, which means that the platform obtain much less profit from the third-party store than the self-run store, the optimal trade-in rebate decreases with product price p_p regarding the self-run store. However, when the condition does not hold, the optimal trade-in rebate increases with product price p_p. As p_p increases, product demand of the self-run store decreases while that of the third-party store increases, which may reduce the platform's total profit. In this case, the platform will reduce the rebate value to obtain more profit from trading-in used products. Otherwise, the platform's total profit increases when p_p goes up. The platform may increase the trade-in rebate to entice more replacement consumers to conduct trade-in transactions.

Proposition 3(d) shows that, when $fp_t \geq p_p - c_p + 2\tau(1-\bar{\alpha})f$, which indicates that the platform obtains much more profit from the third-party store than the self-run store, the optimal trade-in rebate decreases with product price p_t. However, when the condition is not satisfied, the optimal trade-in rebate increases with p_t. This finding is similar to that in Proposition 3(c), and thus the illustration is omitted.

By examining the impacts of v, x_p, x_t, p_p and p_t on the platform's profit, we have the following conclusion:

Proposition 4. *The monotonicity of the platform's profit is characterized as*

(a) $\prod_p^{GCB^*}$ and $\prod_p^{CCB^*}$ increase with v;
(b) when $fp_t < p_p - c_p$, $\prod_p^{CCB^*}$ increases (decreases) with x_p (x_t); otherwise, $\prod_p^{CCB^*}$ decreases (increases) with x_p (x_t);
(c) When $fp_t < p_p - c_p - 2\tau\bar{\alpha}$, $\prod_p^{CCB^*}$ decreases with p_p; otherwise, $\prod_p^{CCB^*}$ increases with p_p.
(d) when $fp_t \geq p_p - c_p + 2\tau(1-\bar{\alpha})f$, $\prod_p^{CCB^*}$ decreases with p_t; otherwise, $\prod_p^{CCB^*}$ increases with p_t.

Proposition 4(a) shows that, as v increases, the platform's profits under both models GC and CCB also increase. This is intuitive and can be supported by Proposition 3(a). According to Warman [42], trade-ins for "few months old" smart phones increased 44% of traded-in smart phones in 2013, which indicates that trade-in service significantly boosts new product sales. This evidence can directly support this result.

Proposition 4(b) shows that, the platform does not always benefit from offering high-quality products in its self-run store and the third-party store. The rationale of this proposition is similar to Proposition 3(b), and thus omitted here. Similarly, the illustrations of Proposition 4(c) and (d) are also omitted here.

It is noteworthy that, τ in this study can be used to represent the degree of competition between the self-run store and the third-party store, which may directly influence the optimal trade-in rebate decisions and the platform's profits. To characterize these impacts, we have the following proposition:

Proposition 5. *The impacts of τ on the platform's optimal trade-in rebate and profit are as follows:*

(a) When $x_p - p_p \geq x_t - p_t$, if $fp_t < p_p - c_p$, both $p_r^{CCB^*}$ and $\prod_p^{CCB^*}$ decrease with τ; otherwise, both $p_r^{CCB^*}$ and $\prod_p^{CCB^*}$ increase with τ;
(b) When $x_p - p_p < x_t - p_t$, if $fp_t < p_p - c_p$, both $p_r^{CCB^*}$ and $\prod_p^{CCB^*}$ increase with τ; otherwise, both $p_r^{CCB^*}$ decrease with τ.

Proposition 5 shows the effect of the competition between the self-run store and the third-party store on the platform's optimal trade-in rebate and profits as well as associated conditions. The condition $x_p - p_p \geq x_t - p_t$ means that the product valuation regarding product quality and price of the self-run store is larger than that of the third-party store. When this condition holds, if $fp_t < p_p - c_p$, the self-run store will have some market advantages over the third-party store. In this case, as τ goes up, the competition between both stores reinforces and product demand of the self-run store decreases and thus profit goes down. Accordingly, the platform may reduce the trade-in rebate to obtain some profit from trading-in used products in order to counteract the loss generated from the decrease in product demand. By contrast, the platform's profit and the optimal trade-in rebate will increase with τ. When the condition $x_p - p_p < x_t - p_t$ is satisfied, the case is contrary to that when $x_p - p_p \geq x_t - p_t$ holds, and we omitted here.

4.2. Extended scenario

In this scenario, the platform exerts trade-in efforts to entice more replacement consumers to trade-in products. Similar to Theorem 1, we have the following finding:

Remark 1. When $fp_t < p_p - c_p$ and $M_c/M_g < \overline{\lambda}_E$, GC outperforms CC; otherwise, CC outperforms GC, where $\overline{\lambda}_E = [2m\theta A^2 - \beta^2 M_c(A^2 - B^2)]/(2m\theta B^2)$.

Note that, Remark 1 is almost the same as Theorem 1 except the threshold $\overline{\lambda}_E = [2m\theta A^2 - \beta^2 M_c(A^2 - B^2)]/(2m\theta B^2)$. This remark further enforces the adaptability of Theorem 1.

In general, sales efforts can help to capture more market share, and thus may obtain more profit. Is this true in the trade-in transactions on B2C platforms? What impact of the trade-in efforts imposes on the optimal trade-in rebate? The following findings formally answer these questions.

Proposition 6. *When launching trade-in efforts, $p_r^{GCB^*} > p_r^{GCE^*}$ and $p_r^{CCB^*} > p_r^{CCE^*}$, while $\prod_p^{GCB^*} < \prod_p^{GCE^*}$ and $\prod_p^{CCB^*} < \prod_p^{CCE^*}$.*

Proposition 6 shows that the optimal trade-in rebate without launching trade-in efforts is larger than that launching trade-in efforts, whereas the optimal profit of the platform without exerting trade-in efforts is less than that exerting trade-in efforts. If the platform exerts trade-in efforts, replacement consumers can obtain more utilities from trade-in service, and more consumers will participate in trade-in transactions. Inevitably, launching any trade-in efforts will incur some particular costs. In such a context, the platform may reduce the trade-in rebate in order to counteract the costs associated with trade-in efforts. Nevertheless, trade-in efforts can help to increase trade-in product demands under both GC and CC payment modes, respectively. This, on the one hand, may offset the decrease in trade-in product demand caused by trade-in rebate reduction under each payment mode. On the other hand, when trade-in rebate goes down, the platform can obtain more profit from trade-in used products.

By examining the impact of trade-in efforts on the optimal decisions in the extended scenario, an interesting finding is achieved:

Proposition 7. *When exerting trade-in efforts, $e^{GCE^*}(e^{CCE^*})$ increases with M_g (M_c), while $p_r^{GCE^*}(p_r^{CCE^*})$ decreases with M_g (M_c).*

Proposition 7 shows that, regardless of whether under GC payment model or CC payment mode, the optimal level of trade-in efforts increases with the potential market size, whereas the optimal trade-in rebate decreases with it. As the potential market size increases, the platform has more motivation to launch more trade-in efforts to entice more replacement consumers to conduct trade-in transactions. When trade-in effort level increases, the corresponding cost goes up. Thus, the platform may reduce the trade-in rebate to cut down some loss. This in turn can generate more profit from the used products trade-in transactions. This proposition means that the potential market size in the extended scenario has some negative effect on the optimal trade-in rebate value, which is not found in the basic scenario.

We next compare the optimal trade-in effort levels under GC and CC payment modes, and have the following conclusion:

Proposition 8. *When $fp_t < p_p - c_p$ and $M_c/M_g < \lambda_{E1}$, $e^{GCE^*} > e^{CCE^*}$; otherwise, $e^{GCE^*} \leq e^{CCE^*}$, where $\lambda_{E1} = A/B - M_c\beta^2(A - B)/(2m\theta B)$.*

Similar to those in Theorem 1, the two conditions $fp_t < p_p - c_p$ and $M_c/M_g < \lambda_{E1}$ have the same implications except that the threshold λ_{E1} is different from $\bar{\lambda}_B$. Proposition 8 shows that, when both the conditions hold, the platform under CC payment mode has less incentive to launch more trade-in efforts than that under GC payment mode. However, when one of these two conditions is not satisfied, the platform may exert more efforts under CC payment mode than that under CC payment. The reasons for this proposition are summarized as follows. When both conditions $fp_t < p_p - c_p$ and $M_c/M_g < \lambda_{E1}$ hold, the platform can obtain a higher sales profit from the self-run store than the third-party store, and the potential market size regarding GC is not much less than that of CC. In this case, the platform under GC payment mode will have more incentive to launch a higher trade-in effort than under CC payment mode to improve its profitability, and thus $e^{GCE^*} > e^{CCE^*}$. However, when $fp_t < p_p - c_p$ does not hold, the platform will obtain more sales profit from the third-party store than the self-run store. In such a circumstance, even if the potential market size regarding GC payment is not much less than that of CC payment (i.e., $M_c/M_g < \lambda_{E1}$), the platform may have less motivation to exert more trade-in effort under GC payment mode than under CC payment mode. Similar result comes when the condition $M_c/M_g < \lambda_{E1}$ is not satisfied.

As the optimal trade-in rebate decisions are influenced by the effort levels, we then investigate which mode (GC or CC) can offer a higher trade-in rebate. This is characterized by the following conclusion.

Proposition 9. *When $fp_t < p_p - c_p$ or $M_c/M_g > \lambda_{E2}$, $p_r^{CCE^*} < p_r^{GCE^*}$; otherwise $p_r^{CCE^*} \geq p_r^{GCE^*}$, where $\lambda_{E2} = [(2m^2\theta^2 + M_gM_cb^4)(B - A) + m\theta b^2 M_g(2A - B)]/[m\theta b^2 M_g(2B - A)]$.*

Proposition 9 shows, when $fp_t < p_p - c_p$ or $M_c/M_g > \lambda_p$, the optimal trade-in rebate under model GCE is larger than that under model CCE; otherwise, the optimal trade-in rebate under model CCE is larger than that under model GCE. Unlike Proposition 1, in the extended scenario, any one of the two conditions holds, $p_r^{CCE^*} < p_r^{GCE^*}$, and only when both the conditions are not satisfied, $p_r^{CCE^*} \geq p_r^{GCE^*}$. When the condition $fp_t < p_p - c_p$ holds, the platform can obtain more unit product sales profit from its self-run store than the third-party store. The platform may capture more market share by offering a higher trade-in rebate under GC payment mode; while under CC payment mode, the platform may reduce trade-in rebate in order to obtain more profit from trading in used products. When $M_c/M_g > \lambda_{E2}$, potential market size under CC payment mode is sufficiently larger than that under GC payment mode. According to Proposition 6, a large M_c will lead to a small $p_r^{CCE^*}$, and a small M_g can result in a large $p_r^{GCE^*}$. However, when both conditions do not hold, which means that the potential market size is not sufficiently large and the platform will get less unit profit from the self-run store than that of the third-party store under CC payment mode compared to under GC payment mode. In such a context, the platform may have more incentive to offer a higher trade-in rebate to increase trade-in demand, and thus generate more profit.

To better illustrate Proposition 9, we present a numerical example as follows. To this end, we set $x_p = 0.9$, $x_t = 0.85$, $p_p = 0.3$, $p_t = 0.29$, $c_p = 0.25$, $\theta = 0.5$, $\nu = 0.1$, τ=0.1, $\beta = 0.1$, $m = 50$ and $M_g = 500$, and increase f and M_c from zero to 0.4 and 500 to 1000, respectively. The optimal trade-in rebate under models GCE and CCE regarding f and M_c are depicted in Fig. 2.

Fig. 2 shows that, when $f \leq 0.1724$ (i.e., $fp_t \leq 0.05 = p_p - c_p$), $M_c \leq 883.8$ and $M_c/M_g \leq \lambda_{E2}$, the optimal trade-in under model CCE

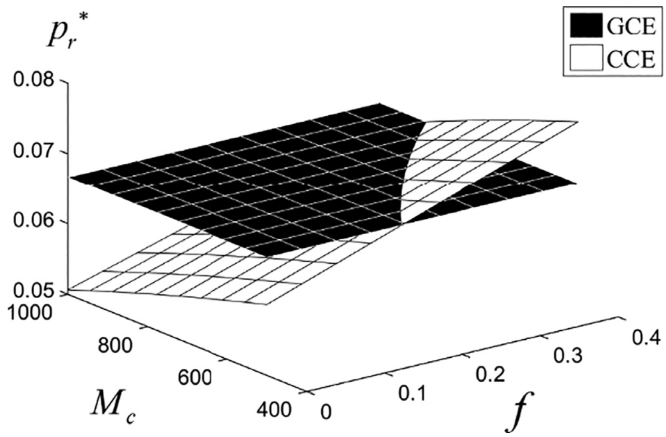

Fig. 2. The optimal trade-in rebate under models GCE and CCE regarding *f* and M_c.

is larger than that under model GCE (white grid area); otherwise, the optimal trade-in under model GCE is larger (black grid area).

4.3. Further extension

In this sub-section, we will examine the impact of redemption rate with respect to gift card (GC) on the optimal decisions and profits of the platform. Due to some practical reasons, e.g., loss of cards and expiration of cards, redemption rate regarding gift card may be less than 100% [43]. In this regard, some consumers may redeem only part of the card's full value, while others may not use the gift card at all. Notably, in online retailing settings, the expiration of gift cards may not occur. For instance, Amazon.com's gift cards are always effective, and JD.com allows consumers to redeem their gift cards' values during future 36 months. These evidences suggest that consumers may have enough time and more chances to redeem their gift cards in future purchases. Nevertheless, consumers may still lose their cards for unexpected reasons. Unlike gift card, cash coupon is always offered by online retailers with electronic forms and never expires. Consequently, the redemption rate of cash coupon can be regarded as 100%, while that of gift card may be less than 100%.

Generally speaking, consumers may not consider that they will not use or lose gift cards when making decisions on trade-in transactions. Furthermore, in practice, even if some consumers lose their gift cards, they may also come to platform to buy products. Hence, the redemption rate may have no effects on trade-in product and product demand, but will have impact on the platform's profit. Following Khouja et al. [43] and Zhang et al. [44], we assume that the redemption rate of gift card γ ($\gamma \in (0, 1]$). Thus, γD_g consumers will redeem their gift cards, while the remaining consumers $(1-\gamma)D_g$ will not use their cards. Based on Eq. (5), when γ is considered, the profit function takes the form (model GCBR):

$$\prod_p^{GCBR}(p_r) = D_g(v - p_r) + D_g(p_p - c_p) + (1-\gamma)D_g p_r. \tag{13}$$

Note that, the first two terms are the same as those in Eq. (5). The third term indicates that the offered trade-in rebates are not redeemed, and thus can be regarded as an additional source of profit for the platform.

Similarly, when the trade-in efforts are taken into account, based on Eq. (10), the platform's profit function is formulated as (model GCER)

$$\prod_p^{GCER}(p_r, e) = D_g^E(v - p_r) + D_g^E(p_p - c_p) + (1-\gamma)D_g^E p_r - me^2/2. \tag{14}$$

According to the platform's profit functions defined in Eqs (13) and (14), we can easily obtain the optimal decisions and profits, and the results are also presented in Table 2.

By examining the impact of γ on the optimal trade-in rebates, trade-in efforts and profits, we find that our major findings and insights remain unchanged when the redemption rate is considered. Nevertheless, we find that there exist certain effects of γ on the optimal trade-in rebates (i.e., p_r^{GCBR*} and p_r^{GCER*} in the absence of and presence of trade-in efforts, respectively), trade-in effort level (e^{GCER*}) and profits. Hence, we have the following proposition:

Proposition 10. *The effects of the redemption rate on the optimal decisions and profits are characterized as*

(a) p_r^{GCBR*} *and* p_r^{GCER*} *decrease with* γ*;*
(b) e^{GCER*} *increases with* γ*;*
(c) $\prod_P^{GCBR*}$ *and* $\prod_P^{GCER*}$ *decease with* γ*.*

Proposition 10(a) shows that the optimal trade-in rebates decrease with the redemption rate regardless of whether or not considering trade-in efforts. As γ increases, more consumers will redeem their gift cards, and the platform's profit derived from unredeemed GC values (i.e., $(1-\gamma)D_g p_r$) decreases. In such a case, the platform may accordingly reduce the optimal rebate to counteract this loss.

Proposition 10(b) shows the optimal trade-in effort level increases with the redemption rate. When γ increases, according to Proposition 10(a), the optimal trade-in rebate decreases. This will lead to decrease in trade-in demand. To cover this loss, the platform may launch more trade-in efforts to entice more consumers to conduct trade-in transactions.

Proposition 10(c) shows that, the platform's optimal profit is decreasing in the redemption rate regardless of whether considering trade-in efforts or not. When the retailer does not launch trade-in efforts, the optimal trade-in rebate decreases with γ (Proposition 10(a)). The platform may incur profit loss caused by the reductions from both unredeemed gift cards and trade-in demand. Therefore, the platform is not beneficial when γ increases. When launching trade-in efforts, although the platform will exert more trade-in efforts to increase trade-in demand, trade-in effort costs will accordingly increase. This will further reduce the platform's profit. This proposition suggests a counterintuitive finding that the redemption rate has certain negative effect on the platform's profit, which is similar to that found in Zhang et al. [44], but contrary to that found in Khouja et al. [43].

5. Conclusions

B2C platforms are increasingly adopting trade-in programs to entice consumers to make more purchases. Some platforms such as Amazon.com and JD.com conduct their transactions relying heavily on dual-format retailing model, which includes self-run stores and third-party stores. These platforms may offer their trade-in rebates with GC or CC. GC and CC are used toward product purchases from self-run stores and both stores, respectively. In such a circumstance, it is important for platforms to determine whether to offer trade-in rebates with GC or CC, and then the optimal trade-in rebates. To entice more consumers to conduct trade-in transactions, platforms may exert trade-in related sales efforts on the platform. Thus, it is also important to identify the impact of trade-in efforts on the optimal decisions regarding trade-in strategy. Since the redemption rate regarding gift card may be less than 100%, we further consider this issue in the analysis.

To address the aforementioned issues, we consider a B2C platform owning a self-run store and hosting a third-party store, and these two stores sell two imperfect substitute new products online. We focus on consumers who have the same category of used durable products with the same residual values. Used products may not be in the same category as new products, and may not be bought from the platform early. We develop theoretical models to examine the optimal trade-in strategy and associated decisions for the platform.

Some important findings and management insights are summarized as follows.

- When the platform gains more per unit product sales profit from the self-run store than the third-party store and consumers are not sufficiently willing to use CC, GC is better for the platform. Otherwise, CC benefits the platform. In general, the better choice of payment also benefits consumers. One exception is that, when the platform gains more per unit product sales profit from the self-run store than the third-party store, the choice of CC may hurt consumers accompanied by a relatively low rebate.
- Interestingly, the platform may set a relatively large trade-in rebate (i.e., larger than actual residual value) for used products when unit new product sales profit is larger than the actual residual value of used products, and vice versa.
- The platform does not always benefit from offering products with high quality and low selling price in both the self-run store and the third-party store, and also the market competition between both stores.
- Launching trade-in efforts leads to a lower trade-in rebate but a higher profit for the platform. When exerting trade-in efforts on the platform, potential market size has a positive effect on the effort level but negative effect on the trade-in rebate value. The platform does not always launch more efforts and offer a higher rebate under GC payment mode than under CC payment mode. In particular, when per unit product sales profit from the self-run store is sufficiently large and potential market size under CC payment mode is not sufficiently large, the platform may exert more efforts under GC payment model than under CC payment mode. Interestingly, when only one of these two conditions holds, the platform will offer a higher trade-in rebate under GC payment mode than under CC payment mode.
- When the redemption rate of gift card is taken into consideration, we find that the optimal trade-in rebate decreases with the rate, while the optimal trade-in effort level increases. Counterintuitively, a higher redemption rate of gift card may hurt the platform, and vice versa.

There are some possible extensions of this study. First, we have not considered consumer trade-in costs including both shipping cost or mailing fee and psychological cost such as time investment. These costs may influence consumer behaviors for trading-in used products. Our models may generate different results when these costs are considered. Second, competition between two or more platforms may occur when they offer trade-in programs simultaneously. Thus, it is interesting to examine the optimal decisions in a competitive market. These issues can be seen as important extensions in future studies.

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Appendix A

Proof of Theorem 1. By comparing the platform's profits under models GCB and CCB, we have $\prod_p^{CCB^*}/\prod_p^{GCB^*} = (M_c/M_g)[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + \nu]/(p_p - c_p + \nu)^2$.

For ease of notations, set $A = p_p - c_p + \nu$, $B = \bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + \nu$ and $\overline{\lambda}_B = A^2/B^2$. Since $M_c/M_g \geq 1$, it is easy to verify that, when the conditions $fp_t < p_p - c_p$ and $M_c/M_g < \overline{\lambda}_B$ hold, $\prod_p^{CCB^*}/\prod_p^{GCB^*} < 1$. Otherwise, $\prod_p^{CCB^*}/\prod_p^{GCB^*} \geq 1$.

Proof of Proposition 1. By comparing the optimal trade-in rebates under models GCB and CCB, we have $p_r^{CCB^*} - p_r^{GCB^*} = (1-\overline{\alpha})[fp_t - (p_p - c_p)]/2$. It is easy to verify that, when $fp_t < p_p - c_p$ holds, $p_r^{GCB^*} > p_r^{CCB^*}$; otherwise, $p_r^{GCB^*} \leq p_r^{CCB^*}$.

Proof of Proposition 2. According to $p_r^{GCB^*} = (p_p - c_p + \nu)/2$, we have $p_r^{GCB^*} - \nu = (p_p - c_p - \nu)/2$. Thus, it is easy to obtain that, when $p_p - c_p \geq \nu$, $p_r^{GCB^*} \geq \nu$; otherwise, $p_r^{GCB^*} < \nu$. The proof for this proposition under model CCB is similar to that under model GCB, and omitted here.

Proof of Proposition 3. According to the optimal trade-in rebate under model GCB as shown in Table 2, we have $\partial p_r^{GCB^*}/\partial \nu = 1/2 > 0$. Thus, we can conclude that $p_r^{GCB^*}$ is increasing in ν. The proof for that $p_r^{CCB^*}$ is increasing in ν under model CCB is similar to that under model GCB, and omitted here.

As for the monotonicity of the optimal trade-in rebate regarding x_p and x_t under model CCB, we have $\partial p_r^{CCB^*}/\partial x_p = (p_p - c_p - fp_t)/(4\tau)$ and $\partial p_r^{CCB^*}/\partial x_t = -(p_p - c_p - fp_t)/(4\tau)$. It is easy to verify that, when $fp_t < p_p - c_p$, $\partial p_r^{CCB^*}/\partial x_p \geq 0$ and $\partial p_r^{CCB^*}/\partial x_t \leq 0$; otherwise, $\partial p_r^{CCB^*}/\partial x_p < 0$ and $\partial p_r^{CCB^*}/\partial x_t > 0$.

As for the optimal trade-in rebate monotonicity regarding p_p and p_t under model CCB, we have $\partial p_r^{CCB^*}/\partial p_p = [fp_t - (p_p - c_p) + 2\tau\bar{\alpha}]/(4\tau)$ and $\partial p_r^{CCB^*}/\partial p_t = [(p_p - c_p) + 2\tau(1-\bar{\alpha})f - fp_t]/(4\tau)$. It is easy to verify that, when $fp_t < p_p - c_p - 2\tau\bar{\alpha}$, $\partial p_r^{CCB^*}/\partial p_p < 0$; otherwise, $\partial p_r^{CCB^*}/\partial p_p \geq 0$. However, when $fp_t \geq p_p - c_p + 2\tau(1-\bar{\alpha})f$, $\partial p_r^{CCB^*}/\partial p_t \leq 0$; otherwise, $\partial p_r^{CCB^*}/\partial p_t > 0$.

Proof of Proposition 4. To prove the monotonicity of platform's profits regarding ν under models GCB and CCB, we have $\partial \prod_p^{GCB^*}/\partial \nu = M_g(p_p - c_p + \nu)/(2\theta) \geq 0$ and $\partial \prod_p^{CCB^*}/\partial \nu = M_c[(p_p - c_p - fp_t)(x_p - p_p - x_t + p_t) + \tau(p_p - c_p + fp_t + 2\nu)]/(4\theta\tau) \geq 0$. Thus, both $\prod_p^{GC^*}$ and $\prod_p^{CCB^*}$ are increasing in ν.

As for the platform's optimal profit monotonicity regarding x_p and x_t under model CCB, we have $\partial \prod_p^{CCB^*}/\partial x_p = M_c(p_p - c_p - fp_t)[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + \nu]/(2\theta)$ and $\partial \prod_p^{CCB^*}/\partial x_t = -M_c(p_p - c_p - fp_t)[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + \nu]/(2\theta)$. It is easy to verify that, when $fp_t < p_p - c_p$, $\partial \prod_p^{CCB^*}/\partial x_p > 0$ and $\partial \prod_p^{CCB^*}/\partial x_t < 0$; otherwise, $\partial \prod_p^{CCB^*}/\partial x_p \leq 0$ and $\partial \prod_p^{CCB^*}/\partial x_t \geq 0$.

To prove the platform's optimal profit monotonicity regarding p_p and p_t under model CCB, we have $\partial \prod_p^{CCB^*}/\partial p_p = M_c[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + \nu][fp_t - (p_p - c_p) + 2\tau\bar{\alpha}]/(4\tau\theta)$ and $\partial \prod_p^{CCB^*}/\partial p_t = M_c[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + \nu][(p_p - c_p) + 2\tau(1-\bar{\alpha})f - fp_t]/(4\tau\theta)$. It is easy to verify that, when $fp_t < p_p - c_p - 2\tau\bar{\alpha}$, $\partial \prod_p^{CCB^*}/\partial p_p < 0$; otherwise, $\partial \prod_p^{CCB^*}/\partial p_p \geq 0$. And when $fp_t \geq p_p - c_p + 2\tau(1-\bar{\alpha})f$, $\partial \prod_p^{CCB^*}/\partial p_t \leq 0$; otherwise, $\partial \prod_p^{CCB^*}/\partial p_t > 0$.

Proof of Proposition 5. To prove the impacts of τ on the platform's optimal trade-in rebate and profit, we have $\partial p_r^{CCB^*}/\partial \tau =$

$-(p_p - c_p - fp_t)(x_p - x_t - p_p + p_t)/(4\tau^2)$ and $\partial \prod_p^{CCB^*}/\partial\tau = -M_c[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v](p_p - c_p - fp_t)(x_p - x_t - p_p + p_t)/(4\theta\tau^2)$. Thus, we have, when$x_p - p_p \geq x_t - p_t$, if $fp_t < p_p - c_p$, $\partial p_r^{CCB^*}/\partial\tau \leq 0$ and $\partial \prod_p^{CCB^*}/\partial\tau \leq 0$; otherwise, $\partial p_r^{CCB^*}/\partial\tau \geq 0$ and $\partial \prod_p^{CCB^*}/\partial\tau \geq 0$. And when $x_p - p_p < x_t - p_t$, if $fp_t < p_p - c_p$, $\partial p_r^{CCB^*}/\partial\tau > 0$ and $\partial \prod_p^{CCB^*}/\partial\tau > 0$; otherwise, $\partial p_r^{CCB^*}/\partial\tau \leq 0$ and $\partial \prod_p^{CCB^*}/\partial\tau \leq 0$.

Proof of Remark 1. The proof of this remark is similar to that of Theorem 1, and thus omitted here.

Proof of Proposition 6. Based on the platform's optimal decisions and profits as reported in Table 2, we have $p_r^{GCE^*} - p_r^{GCB^*} = -M_g\beta^2(p_p - c_p + v)/(4m\theta - 2M_g\beta^2) < 0$,

$$p_r^{CCE^*} - p_r^{CCB^*} = -M_c\beta^2[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v]/(4m\theta - 2M_c\beta^2) < 0,$$

$$\prod_p^{GCE^*} - \prod_p^{GCB^*} = M_g(p_p - c_p + v)^2[1/(4\theta - 2M_g\beta^2/m) - 1/(4\theta)] > 0,$$

$$\prod_p^{CCE^*} - \prod_p^{CCB^*} = M_c[\bar{\alpha}(p_p - c_p) + (1-\bar{\alpha})fp_t + v]^2 \times [1/(4\theta - 2M_g\beta^2/m) - 1/(4\theta)] > 0.$$

Thus, this proposition can be directly obtained.

Proof of Proposition 7. To prove the impacts of parameters M_g on the trade-in rebate and trade-in efforts under model GCE, we have $\partial p_r^{GCE^*}/\partial M_g = -(p_p - c_p + v)\beta^2 m\theta/(2m\theta - M_g\beta^2)^2 < 0$ and $\partial e^{GCE^*}/\partial M_g = 2p_r^{GCE^*}/(2m\theta - M_g\beta^2) > 0$.

The proof for this proposition under model CCE is similar to that under model GCE, and thus omitted here.

Proof of Proposition 8. Based on the optimal trade-in effort as shown in Table 2, we have $e^{GCE^*} - e^{CCE^*} = M_g[2m\theta\beta(A - BM_c/M_g) + M_c\beta^3(B-A)]/[(2m\theta - M_c\beta^2)(2m\theta - M_g\beta^2)]$. Thus, when $fp_t < p_p - c_p$ and $M_c/M_g < \lambda_{E1}$, $e^{GCE^*} - e^{CCE^*} > 0$; otherwise, $e^{GCE^*} - e^{CCE^*} \leq 0$, where $\lambda_{E1} = A/B - M_c\beta^2(A-B)/(2m\theta B)$.

Proof of Proposition 9. Based on the optimal trade-in rebate as reported in Table 2, we have $p_r^{CCE^*} - p_r^{GCE^*} = M_g[(B-A)(2m^2\theta^2/M_g - m\theta\beta^2) + m\theta\beta^2 A - m\theta\beta^2(2B-A)M_c/M_g]$. Thus, when $fp_t \geq p_p - c_p$ and $M_c/M_g \leq \lambda_{E2}$, $p_r^{CCE^*} - p_r^{GCE^*} \geq 0$; otherwise, $p_r^{CCE^*} - p_r^{GCE^*} \leq 0$, where $\lambda_{E2} = [(B-A)(2m^2\theta^2/M_g - m\theta\beta^2) + m\theta\beta^2 A]/[m\theta\beta^2(2B-A)]$.

Proof of Proposition 10. To examine the impacts of the redemption rate on the optimal trade-in rebate, trade-in effort and the platform's profit, we have

$$\partial p_r^{GCBR^*}/\partial\gamma = -(p_p - c_p + v)/(2\gamma^2) < 0,$$

$$\partial p_r^{GCER^*}/\partial\gamma = -(p_p - c_p + v)[{M_g}^2\beta^4\gamma^2 + 2\theta m(\theta m - M_g\beta^2\gamma)]/[\gamma^2(2\theta m - M_g\beta^2\gamma)^2] < 0,$$

$$\partial e^{GCER^*}/\partial\gamma = {M_g}^2\beta^3(p_p - c_p + v)/(2\theta m - M_g\beta^2\gamma)^2 > 0,$$

$$\partial \prod_P^{GCBR^*}/\partial\gamma = -M_g(p_p - c_p + v)^2/(4\gamma^2\theta) < 0 \text{ and}$$

$$\partial \prod_P^{GCER^*}/\partial\gamma = -M_g m(p_p - c_p + v)^2(\theta m - M_g\beta^2\gamma)/[\gamma^2(2\theta m - M_g\beta^2\gamma)^2] < 0.$$

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