sustainability

MDPI

Essay

Research on E-Commerce Platforms' Return Policies Considering Consumers Abusing Return Policies

Huixin Liu * and Feng Du

School of Management, Zhengzhou University, Zhengzhou 450001, China; 18839100307@163.com
* Correspondence: liuhuixin@zzu.edu.cn

Abstract: Currently, major e-commerce platforms are competing to improve their return services, while merchants are suffering from consumers abusing return policies. We developed a dual oligopoly model consisting of two e-commerce platforms, one offering a lenient return policy and the other enforcing a stringent one, to investigate the effectiveness of lenient return policies in the presence of opportunistic consumers. We examine the impact of the proportion of opportunistic consumers, cross-network effects, gains from dishonest returns, and penalties on the scale of users and profits for both platforms. The findings indicate that: (1) As the proportion of opportunistic consumers increases, multi-homing merchants tend to be single-homing on a platform with a stringent return policy. This reduces the number of consumers on a platform with a lenient return policy and lowers the platform's profit. Moreover, increased gains from dishonest returns worsen the situation. (2) Network effects on merchants from the consumer side significantly affect the effectiveness of lenient return policies. (3) Enforcement of penalties for dishonest returns could prevent an exodus of consumers and merchants from platforms that offer lenient return policies. However, it does not raise profits. In other words, its impact on the success of lenient return policies is limited.

Keywords: consumer return policy; fraudulent returns; network effect; e-commerce platform

check for updates

Citation: Liu, H.; Du, F. Research on E-Commerce Platforms' Return Policies Considering Consumers Abusing Return Policies. *Sustainability* **2023**, *15*, 13938. https://doi.org/10.3390/su151813938

Academic Editors: Massoud Moslehpour, Dian Ekowati and Ranfeng (Stella) Qiu

Received: 17 July 2023
Revised: 10 September 2023
Accepted: 14 September 2023
Published: 20 September 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The emergence of e-commerce platforms, such as online marketplaces and shopping websites, has broken down geographical barriers and made it more convenient for sellers and consumers to engage in transactions. As a type of two-sided market, e-commerce platforms can leverage network effects to expand their user base and gain a competitive advantage. In other words, the more users there are on one side of the platform, the more utility it provides to users on the other side, leading to a higher willingness of users to join the platform [1]. Some e-commerce platforms employ various incentives, such as offering lenient return policies, to indirectly increase the scale of their seller base by attracting consumers. Since online consumers cannot physically try or inspect the item they aim to buy, they may find it mismatched or unsatisfactory after receiving their package [2]. To reduce shopping risks for consumers and gain a competitive edge, platforms offer lenient return services to encourage repeat purchases, thereby attracting more users to join the platform. In China, some platforms extend the legally mandated 7-Day Return Policy period and offer services like Instant Refunds. For example, JD.com offers Flash Refunds, where an automatic refund is initiated as soon as a consumer's return request is accepted and they upload their return tracking number. Tmall introduces Quick Refunds, where funds are refunded as soon as the returned item is shipped. Vipshop initiates refunds as soon as the courier picks up the returned item.

The platform's lenient return policy is based on the assumption that consumers will not abuse these privileges and reasonably return unsatisfactory goods according to their needs [3]. In fact, some consumers misuse return policies, engaging in practices such as opportunistic returns and fraudulent returns. According to a Wall Street Journal article, a survey involving 63 retailers in the United States found that 11% of returns were considered potentially fraudulent [4]. For instance, a buyer intentionally rents clothing during holidays, leading to a surge in costume returns within the return window for the seller. In the case of fraudulent returns, a buyer might take advantage of the time gap between the platform's instant refund and the inspection of the returned item to engage in practices such as returning counterfeit items while mailing empty packages. These consumers often plan to return items even before making a purchase, resulting in an artificially inflated return rate for merchants [5]. It, in turn, increases the cost of reverse logistics management and inventory holding for merchants, potentially causing them to miss out on resale opportunities [6]. Based on the above phenomena, we raise the following questions:

First, does the lenient return policy implemented by a platform work effectively in a competitive market when considering consumer abuse of return policies and cross-network effects?

Second, if it does not work, should that platform implement punitive measures to enhance the success of the lenient return policy?

While some researchers have explored the impact of consumer abuse of return policies on monopolistic retailers, there is a gap in the literature regarding the impact of such behavior on operators in a competitive environment. To investigate the impact of consumer abuse of return policies, we draw inspiration from the work of Shang et al. [7] to use the proportion of opportunistic consumers as an indicator of market health and examine its impact on the competitiveness of the platform. Our study differs from their work in two ways. First, they investigated the impact of the extent of wardrobing on retailers' pricing and refunds in a monopolistic environment. We study this problem in the context of two competing platforms. Second, we consider the case where the return policy is not introduced by the merchant but by the platform. In reality, more and more companies are joining e-commerce platforms. When a platform introduces a new return policy, firms on that platform often have little choice but to follow it. The presence of cross-network effects places a heightened emphasis on the user base of a platform, potentially requiring platforms that employ lenient return policies to tolerate a certain level of bad consumer behavior in order to maintain a competitive advantage in the user base. Obviously, the platform owner and the merchant do not always have the same objective, especially when the platform does not share the return cost with the merchant. If the merchant has the opportunity to operate on other platforms, the merchant's departure may invalidate the return policy due to cross-network externalities. However, much of the literature has primarily examined the factors that influence retailers to adopt lenient return policies without considering the impact of factors such as network effects within a two-sided market on a platform's return service strategy.

In the second question, we address the actions the platform will take in response to opportunistic consumers. When dealing with opportunistic consumer behavior, researchers have focused on policy details. Khouja and Hammami [8] compared a return policy in which refunds for returned products are provided in cash to one where refunds are issued in the form of store credit or gift cards (SC/GC). Altug et al. [9] analyzed two policies: targeted refund and menu refund. We propose that the platform take regulatory measures and impose penalties on opportunistic consumers. This would reduce consumer fraud return revenue and incur certain regulatory costs for the platform, which could either support the return policies or erode the platform's profits.

To address the aforementioned issues, we developed a Hotelling model consisting of two e-commerce platforms that offer different return policies: lenient vs. stringent. In this model, consumers are single-homing and merchants are partially multi-homing. Our study reveals that the proportion of opportunistic consumers in the market significantly influences the affiliation of merchants. It compels multi-homing merchants to switch to single-homing on platforms without opportunistic consumers. This, in turn, reduces the consumer base of platforms that offer lenient return policies and results in lower profits compared to their competitors. Moreover, the success of the lenient return policy also depends on the network effect. Negative network effects induced by opportunistic consumers can make lenient return policies susceptible to failure. Restricting consumer access to services can help mitigate their impact on platform profits. Finally, punitive measures implemented by platforms with lenient return policies have limited effectiveness. They are only viable if the proportion of opportunistic consumers is relatively low and the punitive measures are of moderate intensity.

Our structure is arranged as follows: In Section 2, we review the relevant literature. In Section 3, we present the model and provide its solutions. In Section 4, we assess the impact of key factors on the scale of the two-sided user base and the profits of the two platforms. Finally, in Section 5, we present conclusions and management insights.

2. Literature Review

2.1. Research on Cross-Network Externality

One of the key features of two-sided platforms is the cross-network effect, where the user number on one side of the platform significantly impacts the utility of users on the other side [10,11]. Based on this, many scholars have explored its impact on platform pricing models [12–14], market structure [15–17], and operational service strategies [18–20]. Our work is related to research on platform pricing and operational service strategies. Armstrong [21] first utilized the Hotelling model to discover that the platform's optimal pricing is determined by cross-network externalities, user attribution behavior, and charging models. Dou [18] studied investment and pricing strategies for one-sided value-added services within two-sided platforms. His findings reveal that platforms tend to charge higher prices to users who have already invested, while pricing for those who have not is affected by cross-network externalities. Dou's work is primarily based on a single monopolistic platform, but other scholars have examined platform pricing and operational service strategies in a competitive environment. In the work of Aloui and Jebsi [22], the presence of cross-network externalities in a duopoly platform market reduces the intensity of platform competition and influences pricing strategies. Ji and Wang [23] considered the impact of platform differentiation and pricing order on platform competition, showing that enhanced cross-network externalities can increase the scale of multi-homing users when users are partially multi-homing. Gui et al. [24] set up a competitive service investment model to explore platform investment in user-value-added services. Similar to our work, Zhao and Wang [25] analyzed how two-sided platforms should set optimal pricing and buyer value-added service strategies in a competitive environment where seller users are partially multi-homing. They found that platform pricing for users is influenced by cross-network externalities, buyer value-added service utility coefficients, and marginal investment costs. In our work, for the purpose of comparing return service strategies, we assume that only one of the platforms provides lenient return services as a value-added service to consumers. In the setting of cross-network externality, we consider the presence of opportunistic consumers who bring negative utility to the platform merchants. We extend their study by examining how this negative utility affects platform pricing and the provision of return services.

2.2. Research on Return Policies

Research on return policies has focused on the choices made by retailers, including options such as full refunds, partial refunds, or no-refund policies [26–29]. Most studies suggest that lenient return policies, such as full refunds and no-questions-asked returns, can reduce consumers' perceived risk, boost their willingness to purchase, and consequently increase sales [30,31]. Wood [32] argued that lenient return policies send quality signals, reduce consumers' pre-purchase deliberation time, and facilitate buying. Li and Li [33] established an online retail model consisting of a monopoly retailer and heterogeneous-preference consumers. They concluded that no-questions-asked returns are the optimal strategy for online retailers with medium-quality products. Stock and Mulki [34] analyzed three methods of processing product returns. Their study focused on whether allowing returns and offering full or partial refunds would benefit online retailers. Some scholars have extended these concepts to competitive environments. Chen and Grewal [35] used a Stackelberg model to analyze how new entrants would choose between full refunds, partial refunds, or no refunds under the presence of an incumbent's full refund policy. Huang et al. [36], under the assumption of limited consumer rationality, studied the impact of product quality on competitive retailers' refund guarantee strategies. In addition to studying the impact on retailer profits, scholars have also considered its impact on retailer channel choices. Chen and Chen [37] showed that when products are distributed through both retail and online channels, refund guarantees affect retailers' channel choices. Ofek et al. [38] studied the pricing strategies of two competing retailers and the impact of adding an online channel with consideration of returns. Chen and Bell [39] investigated how companies can use different return strategies, namely full refunds and no refunds, to segment the market into dual channels and increase profits. The above studies focus on retailers and their optimal return strategies in the face of consumer returns. However, as consumers and merchants increasingly engage in platform transactions, the dominance of the platforms in service provision becomes more prominent, and most merchants have to follow suit. Therefore, to attract consumers, platforms may introduce more lenient and expedited return policies and services. There is limited literature on platform return policies. The optimal choice of a return policy may vary between platforms and retailers due to their different objectives. Thus, it is necessary to investigate how consumer return behavior affects the choice of platform return policies.

2.3. Research on Consumer Abuse of Return Policies

Opportunistic consumer abuse of return policies includes opportunistic returns and fraudulent returns [5,40]. Opportunistic returns are instances where consumers intentionally rent products for short-term use. Common examples include wardrobing and retail borrowing. Wardrobing is frequently associated with clothing products, where consumers may purchase clothing for a specific occasion and then return the item after the event, requesting a refund because it falls within the retailer's return window [7,41]. Retail borrowing is described as consumers purchasing items with the intention to return them once they have fulfilled their needs [42,43]. Fraudulent returns involve consumers returning second-hand or damaged products [3,44] and price arbitrage [45], where non-original items are returned while still demanding a full refund. These return practices are all unjustified and take advantage of lenient return policies by using returns as a means of obtaining products. In the study of consumer abuse return policies, Harris [44], through empirical analysis of service personnel and fraudulent returners, identified eight factors that increase consumers' tendencies towards fraudulent returns. Chang and Guo [3] examined the impact of ethical efforts by online retailers and consumer personalities on fraudulent returns. Phau [40] investigated the attitudes and intentions of Chinese consumers regarding wardrobing and found that they are primarily related to key social factors such as experience and knowledge of return policies. Beyond these empirical studies, several scholars have explored the impact of consumer opportunistic practices on retailer operations. Altug et al. [9], using a newsvendor model, compared the optimal decisions and profits of retailer-led category return policies and consumer-driven menu-based return policies in scenarios with and without opportunistic consumers. They concluded that menu-based return policies are more robust. Ülkü and Gürler [5] constructed a news vendor model considering opportunistic consumers and determined the optimal order quantities for retailers when demand and valuation uncertainties exist. Li et al. [46] studied retailers' pre-sale strategies for fashion products in the presence of opportunistic consumers and found that offering partial refunds reduced moral hazard for consumers. Khouja and Hammami [8] compared two different refund strategies and found that offering store credits or gift cards rather than cash refunds can effectively deter consumers from wardrobing and benefit retailers. Shang et al. [7] examined the impact of the extent of wardrobing and its benefits on pricing and profits for a monopoly retailer and screened wardrobers from ordinary consumers using price/refund menus. Unlike the work of Shang et al., we use the proportion of opportunistic consumers to represent the health of the market environment and investigate its impact on merchant affiliation and platform return policies in a competitive environment. We have enriched the study of wardrobing.

In summary, as more merchants and consumers join the platform, offering consumers lenient return policies has become a common strategy employed by major e-commerce platforms to attract users. However, existing research has paid limited attention to the impact of opportunistic consumer abuse of return practices on platform return policies. To bridge this gap, we integrate two-sided market theory and the Hotelling model to investigate their impact on the return policy of the platform and provide recommendations for the platform to select appropriate services.

3. Basic Model

3.1. Players

Drawing on existing research on competing platforms [21,47,48], we employ the Hotelling model to describe the competitive environment between two e-commerce platforms, Platform 1 and Platform 2. Consider a market with these two competing two-sided e-commerce platforms, Platform 1 and Platform 2, positioned at opposite ends of the linear market segment [0,1]. Platform 1 is located at the end of 0, while Platform 2 is located at the end of 1. They compete to attract users by facilitating the transaction between merchants (denoted as a) and consumers (denoted as b), while charging registration fees p_{bi} for merchants and p_{ai} for consumers, $i \in \{1, 2\}$, respectively. The model is visually represented in Figure 1.

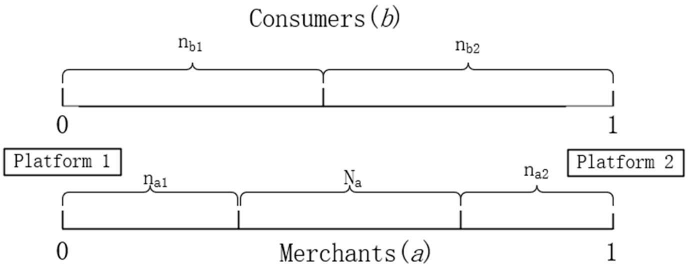

Figure 1. Dual oligopoly platform competition model.

It is assumed that the two platforms provide the same basic services to their consumers but with different return services. Platform 1 implements a lenient return policy and offers high-quality return services, such as instant refunds, aimed at reducing the logistics waiting time for consumers and encouraging repeat purchases to generate more trading opportunities for merchants. However, challenges arise in ensuring the authenticity and integrity of returned items due to inaccurate information and a lack of effective risk monitoring during the return process. This leads to consumer behaviors such as opportunistic returns, fraudulent returns, and incomplete returns. On the other hand, Platform 2 has a strict return policy and offers a low-quality return service, in which the merchant decides whether to issue a refund after rigorously inspecting the returned item. Consequently, refunds are unlikely to be successful for consumers who opportunistically exploit lenient return policies.

For simplicity, we assume that the total size of merchants or consumers in the market is both 1, and each follows a uniform distribution on the line segment [0,1] [48]. Due to the constraint that consumers (b) can only return items to the platform where they initially made their purchase, we assume that each consumer exclusively joins only one platform. In other words, each consumer is single-homing on one platform. We denote the number of consumers on the platform i as n_{bi}, and thus we have $n_{b1} + n_{b2} = 1$, and $0 \leq n_{b1}, n_{b2} \leq 1$. In the context of lenient return policies, consumers are more likely to engage in abusive return practices, including opportunistic or fraudulent returns. Therefore, we make the assumption that a proportion of consumers, denoted as λ, in the market will engage in abusive return behavior [7]. These consumers are classified as opportunistic consumers, while the rest are considered ordinary consumers and are honest consumers. As we can see, λ serves as a practical and crucial indicator of the return policy environment in the market. A larger λ may result in substantial losses for the affected merchants. However, for those merchants operating on the platform, it can be challenging to deviate from the platform's prescribed policies. Implementing stringent measures, such as raising restocking fees, could not only jeopardize the marketing advantage associated with lenient return policies but also potentially upset their other customers [9].

In our model, we assume that merchants have the option of being single-homing or multi-homing. Let N_a represent the number of multi-homing merchants. We denote the number of single-homing merchants on the platform i as n_{ai}. Thus, we have $n_{a1} + n_{a2} + N_a = 1$, and $0 \leq n_{a1}, n_{a2}, N_a \leq 1$. As shown in Figure 1, there are n_{b1} consumers and $n_{a1} + N_a$ merchants joining Platform 1 and n_{b2} consumers and $n_{a2} + N_a$ merchants joining Platform 2.

3.2. User Utility and Platform Profit

The two platforms compete for both consumers and merchants. The interaction between consumers and merchants on a platform is assumed to follow the model detailed by Belleflamme and Peitz [49]. In this model, consumers purchase one unit of a perfectly differentiated product offered by each active merchant on a platform. Each transaction benefits α for the consumer, and it can be interpreted as a cross-network externality [18]. Then, αn_{ai} represents the cross-network utility that merchants bring to a consumer. However, only transactions involving ordinary consumers yield benefits β for the merchant. β is also interpreted as the cross-network externality and βn_{bi} represents the cross-network utility that consumers bring to a merchant on a platform, $0 \leq \alpha, \beta \leq 1$. Trading with opportunistic consumers results in both direct and indirect losses for a merchant, denoted as ω and η, respectively. Furthermore, ω is an additional benefit for opportunistic consumers. For example, an undetected fraudulent return may result in a valuable item being obtained by the consumer, leading to not only the loss of that item for the merchant but also additional operational expenses, including delivery and packaging costs. Additionally, there is another explanation for why η, an opportunistic consumer, can introduce additional verification procedures or incur costs related to risk avoidance that are unnecessary when all consumers are honest.

Consumers and merchants also benefit individually from the fundamental services provided by the platforms. We assume that these benefits are consistent across the two platforms and denote them as v_b for the consumer and v_a for the merchant. These values are high enough for both platforms to serve the entire market, $0 \leq v_a, v_b \leq 1$. Without loss of generality, the level of return service on Platform 2 is set to 0, while the level of return service on Platform 1 is denoted as m. As customers may have varying perceptions of fairness regarding the service on the platform [50], we denote the service perception coefficient of a consumer as θ, and then the utility derived from this service for the consumer is expressed as θm, $0 \leq \theta, m \leq 1$.

Consumers and merchants each choose to join Platform 1 or Platform 2 based on their individual utilities. To facilitate later analysis, we will separately consider ordinary consumers and opportunistic consumers. We denote the utilities of the ordinary consumer joining Platform 1 and Platform 2 as U_{b1}^1 and U_{b2}^1, respectively, with corresponding numbers denoted as $(1-\lambda)n_{b1}^1$ and $(1-\lambda)n_{b2}^1$, where $0 \leq n_{b1}^1, n_{b2}^1 \leq 1$ and $n_{b1}^1 + n_{b2}^1 = 1$. It is important to note that $1-\lambda$ represents all the ordinary consumers in the market. Then, the sum of the ordinary consumers on both platforms equals the total number of ordinary consumers in the market. The utilities of opportunistic consumers joining Platform 1 and Platform 2 are denoted as U_{b1}^2 and U_{b2}^2, with corresponding numbers represented by λn_{b1}^2 and λn_{b2}^2, where $0 \leq n_{b1}^2, n_{b2}^2 \leq 1$ and $n_{b1}^2 + n_{b2}^2 = 1$. Similar to ordinary consumers, the sum of opportunistic consumers on both platforms equals the total number of opportunistic consumers in the market. Based on the Hotelling model, let x_1 represent the distance of an ordinary consumer in the market from Platform 1. It constitutes the transportation cost for ordinary consumers to Platform 1. Since we are not focusing on transportation costs for both merchants and consumers, its coefficient is assumed to be 1 [51]. The following is the same: Then, let x_2 denote the distance of an opportunistic consumer from Platform 1. The distance of a single-homing merchant on Platform 1 is denoted as y_1, and the distance of a single-homing merchant on Platform 2 from Platform 1 is denoted as y_2.

Thus, for ordinary consumers, we have:

$$U_{b1}^1 = v_b + \theta m + \alpha(n_{a1} + N_a) - p_{b1} - x_1, \tag{1}$$

$$U_{b2}^1 = v_b + \alpha(n_{a2} + N_a) - p_{b2} - (1 - x_1), \tag{2}$$

For opportunistic consumers, we have:

$$U_{b1}^2 = v_b + \theta m + (\alpha + \omega)(n_{a1} + N_a) - f - p_{b1} - x_2, \tag{3}$$

$$U_{b2}^2 = v_b + \alpha(n_{a2} + N_a) - p_{b2} - (1 - x_2), \tag{4}$$

Assume, for simplicity, that all merchants have zero marginal costs. Then, the utility of a single-homing merchant on Platform 1, located at y_1, is given by:

$$U_{a1} = v_a + \beta(1 - \lambda)n_{b1}^1 - (\eta + \omega)\lambda n_{b1}^2 - p_{a1} - y_1, \tag{5}$$

The utility of a single-homing merchant on Platform 2, located at y_2, is given by:

$$U_{a2} = v_a + \beta n_{b2} - p_{a2} - (1 - y_2), \tag{6}$$

That of a multi-homing merchant is:

$$U_{a2} = v_a + \beta n_{b2} - p_{a2} - (1 - y_2), \tag{7}$$

We also assume that both platforms have zero marginal costs. Platform 1's profit includes registration fees received from consumers and merchants, revenue from penalties imposed on opportunistic consumers, the cost of checking and verifying those penalties, and the cost of return service. We set the cost of return service as $\frac{1}{2}k_1 m^2$, where k_1 is the cost coefficient of lenient return policy on Platform 1 [24]. The penalty imposed on opportunistic consumers by Platform 1 is denoted as f, the penalty cost coefficient is denoted as k_2, and the incurred penalty cost is $\frac{1}{2}k_2 f^2$. As for Platform 2, its profit includes registration fees received from consumers and merchants. Thus, the profits of Platforms 1 and 2 are π_1 and π_2, respectively.

$$\pi_1 = p_{a1}(n_{a1} + N_a) + p_{b1}n_{b1} + \lambda n_{b1}^2 f - \frac{k_2}{2}f^2 - \frac{k_1}{2}m^2, \tag{8}$$

$$\pi_2 = p_{a2}(n_{a2} + N_a) + p_{b2}n_{b2} \tag{9}$$

3.3. Analysis of Platform Competition

First, we will derive the equilibrium under the return policies implemented by the two platforms. Subsequently, we will investigate the impact of cross-network effects (α and β), the proportion of opportunistic consumers (λ), direct losses incurred due to opportunistic or fraudulent returns (ω), and penalties imposed by Platform 1 (f) through numerical simulations.

Equilibrium Analysis

Since the utility indifference points of ordinary consumers or opportunistic consumers between the two platforms are determined by conditions $U_{b1}^1 = U_{b2}^1$ and $U_{b1}^2 = U_{b2}^2$, we can calculate these utility indifference points as follows:

$$x_1^* = \frac{1}{2}[\theta m + \alpha(n_{a1} - n_{a2}) + p_{b2} - p_{b1} + 1], \tag{10}$$

$$x_2^* = \frac{1}{2}[p_{b2} - p_{b1} - f + \theta m + \alpha(n_{a1} - n_{a2}) + \omega(1 - n_{a2}) + 1] \tag{11}$$

Normalizing the market user base to 1 makes it easier to determine the number of users in each segment. By $n_{b1}^1 = x_1^*$ and $n_{b1}^2 = x_2^*$, we have:

$$n_{b1}^1 = \frac{1}{2}[\theta m + \alpha(n_{a1} - n_{a2}) + p_{b2} - p_{b1} + 1], \tag{12}$$

$$n_{b1}^2 = \frac{1}{2}[p_{b2} - p_{b1} - f + \theta m + \alpha(n_{a1} - n_{a2}) + \omega(1 - n_{a2}) + 1] \tag{13}$$

Given that the proportion of opportunistic consumers is denoted as λ in the market, we can determine the number n_{b1} of consumers in Platform 1 and the number n_{b2} of consumers in Platform 2 as follows:

$$n_{b1} = (1-\lambda)n_{b1}^1 + \lambda n_{b1}^2, \tag{14}$$

$$n_{b2} = (1-\lambda)(1 - n_{b1}^1) + \lambda(1 - n_{b1}^2) \tag{15}$$

Similarly, for merchants we have:

$$n_{a1} = 1 + p_{a2} - \beta n_{b2} - v_a, \tag{16}$$

$$n_{a2} = 1 + p_{a1} - v_a - \beta(1-\lambda)n_{b1}^1 + (\eta + \omega)\lambda n_{b1}^2, \tag{17}$$

$$N_a = 2v_a + \beta(1-\lambda)n_{b1}^1 - (\eta+\omega)\lambda n_{b1}^2 + \beta n_{b2} - p_{a1} - p_{a2} - 1 \tag{18}$$

Then, the profit functions for Platforms 1 and 2 are as follows:

$$\begin{aligned}\pi_1 = {} & p_{a1}\left\{1 - [\tfrac{2\lambda(\eta+\omega+\beta)-2\beta}{2+\omega(\eta+\omega)\lambda}]n_{b1}^1 - \tfrac{2p_{a1}+\lambda(\eta+\omega)(\omega v_a - f)}{2+\omega(\eta+\omega)\lambda} - 1 + v_a]\right\} + p_{b1}\left\{\tfrac{\lambda(\omega v_a - f)-\lambda\omega p_{a1}}{2+\omega(\eta+\omega)\lambda}\right. \\ & \left. + \tfrac{[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]}{2+\omega(\eta+\omega)\lambda}n_{b1}^1\right\} + \lambda f\left\{1 + \tfrac{2\omega[\beta(1-\lambda)-\lambda(\eta+\omega)]}{2[2+\omega(\eta+\omega)\lambda]}\right\}n_{b1}^1 + \lambda f\tfrac{\omega[-2p_{a1}+2v_a+\lambda f(\eta+\omega)]}{2[2+\omega(\eta+\omega)\lambda]}, \\ & -\tfrac{\lambda}{2}f^2 - \tfrac{k_2}{2}f^2 - \tfrac{k_1}{2}m^2\end{aligned} \tag{19}$$

$$\begin{aligned}\pi_2 = {} & p_{a2}\left\{1 - \tfrac{\beta[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]}{2+\omega(\eta+\omega)\lambda}n_{b1}^1 + \tfrac{\lambda\beta\omega p_{a1}-\lambda\beta(\omega v_a - f)}{2+\omega(\eta+\omega)\lambda} - p_{a2} + \beta + v_a - 1\right\} + \\ & p_{b2}\left\{1 - \tfrac{[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]n_{b1}^1}{2+\omega(\eta+\omega)\lambda} + \tfrac{\lambda\omega p_{a1}-\lambda(\omega v_a - f)}{2+\omega(\eta+\omega)\lambda}\right\}\end{aligned} \tag{20}$$

In terms of the profit function (19) for Platform 1 and the profit function (20) for Platform 2, we can determine the conditions under which the optimal profit values exist for Platform 1 and Platform 2.

When $(2-\alpha\beta)\left\{2 - \frac{\alpha}{2+\omega(\eta+\omega)\lambda}[4\beta - \lambda(\eta+\omega+\beta)(2 - \omega\beta + \lambda\omega\beta)]\right\} > 0$ and $2[2 + \lambda(1-\lambda)\omega(\eta+\omega+\beta)](2-\alpha\beta) - [\lambda(\eta+\beta) - (\alpha+\beta)]^2 > 0$, there are optimal prices for Platform 1 to maximize its profit.

Then, for Platform 2, we can determine the conditions for the profit function to have a maximum. When

$[\lambda(1-\lambda)\alpha\beta\omega(\eta+\omega+\beta)-2\alpha\beta+\lambda\alpha(\eta+\omega+\beta)(2-\omega\beta+\lambda\omega\beta)+4+2\lambda\omega(\eta+\omega)][4+2\lambda\omega(\eta+\omega)-4\alpha\beta+\lambda\alpha(\eta+\omega+\beta)(2-\omega\beta+\lambda\omega\beta)]>0$

and

$4\{\alpha[\lambda(1-\lambda)\beta\omega(\eta+\omega+\beta)-2\beta+\lambda(\eta+\omega+\beta)(2-\omega\beta+\lambda\omega\beta)]+2[2+\lambda\omega(\eta+\omega)]\}-(\alpha+\beta)^2[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]>0,$

there are optimal prices for Platform 2 to maximize its profit.

Under the conditions mentioned above, we can determine the profits of both platforms and the optimal pricing for users.

Theorem 1. *The optimal profits of Platforms 1 and 2 are as follows:*

$$\pi_1^* = p_{a1}^*(1-Qx_1^*-R)+p_{b1}^*(Gx_1^*+H)+\lambda f(1+\frac{\omega A}{2C})x_1^*+\lambda f\frac{\omega B}{2C}-\frac{\lambda}{2}f^2-\frac{k_2}{2}f^2-\frac{k_1}{2}m^2$$

$$\pi_2^* = p_{a2}^*(1-Kx_1^*-L)+p_{b2}^*(1-Gx_1^*-H)$$

The optimal prices on Platforms 1 and 2 are given by:

$$p_{b1}^*=\frac{M_3}{M_0},\ p_{a1}^*=\frac{M_1}{M_0},\ p_{b2}^*=\frac{M_4}{M_0},\ p_{a2}^*=\frac{M_2}{M_0}$$

The user scale for consumers and merchants is: $n_{b1}^*=Gx_1^*+H$, $n_{b2}^*=1-Gx_1^*-H$,

$$n_{a1}^*=Kx_1^*+L,\ n_{a2}^*=Qx_1^*+R\ N_a^*=1-(K+Q)x_1^*-(L+R)$$

where $x_1^*=-\frac{\alpha(\lambda\beta\omega+2)M_1}{(2-\alpha E)CM_0}+\frac{\alpha M_2}{(2-\alpha E)M_0}-\frac{M_3}{(2-\alpha E)M_0}+\frac{M_4}{(2-\alpha E)M_0}+\frac{\alpha F_1+2D_1}{2-\alpha E}$.

Proof and expressions of M_0, M_3, M_1, M_4 *and* M_2 *can be found in Appendix A.*

Given the complexity of the expressions obtained from the above model for equilibrium pricing, user scale, and profit for both platforms, it becomes challenging to perform a theoretical analysis of consumer opportunistic practices on the platform's return policy. Therefore, we perform a numerical analysis of the obtained results using MATLAB 2019b software to gain further insights. This analysis specifically considers the scenario where the number of multi-homing merchants is satisfied $N_a \geq 0$, and explores the impact of parameter variation on the outcome of the competition between platforms.

4. Analysis

In accordance with the conditions outlined in Section 3, there is a maximum profit value for both platforms. Therefore, referring to Li [52] and Zhang [53], as well as to satisfy the assumptions of the model, we take $\alpha = 0.5$, $\beta = 0.5$, and assume $\eta = 0.3$, $m = 0.4$, $\theta = 0.4$, $\omega = 0.3$, $f = 0.3$, $v_a = 0.9$, $k_1 = k_2 = 0.5$. The proportion of opportunistic consumers in the market ranges from 0 to 1.

4.1. The Impact of the Proportion of Opportunistic Consumers λ on the Equilibrium of Platform Competition

Proposition 1. *There is a threshold value of* $\overline{\lambda}$. *When* $\lambda < \overline{\lambda}$, *providing a lenient return policy would enable the platform to outperform its competitors; otherwise, such a return policy would result in failure.*

Given that λ serves as an indicator of environmental health, our initial focus is to examine its impact on platform competition. As depicted in Figure 2a, when the proportion of opportunistic consumers is relatively small (specifically, less than 0.4), the number of consumers on Platform 1 exceeds that on its competitor, Platform 2. However, this trend in consumer scale reverses as the proportion increases, although the difference between the two platforms remains minimal. In Figure 2b, when the proportion reaches approximately 0.1, the number of merchants on Platform 1 starts to fall behind Platform 2. In addition, as the proportion continues to rise, single-homing merchants on Platform 1 experience a slight decrease in scale, while multi-homing merchants witness a notable decrease. In turn, the number of single-homing merchants on Platform 2 has grown consistently. This suggests that the increasing presence of opportunistic consumers is compelling multi-homing merchants to opt for single-homing on rival platforms.

From Figure 2c,d, it is shown that as λ increases, Platform 1 reduces its pricing for merchants while increasing its pricing for consumers. However, as shown in Figure 2e,f, these actions prove ineffective in reversing its declining profitability trend, primarily due to the decreasing number of merchants. When comparing Figure 2b,f, we observe that the shift of multi-homing merchants has brought benefits to Platform 2, despite Platform 2 maintaining consistent pricing for them. However, the growing number of single-homing merchants enables Platform 2 to charge consumers higher prices, as its expanding scale could benefit consumers through cross-network effects.

In summary, we can conclude that it is essential for a platform seeking to enhance its services for consumers to control the proportion of opportunistic consumers and keep it within a reasonable range. Failing to do so could result in a competitive setback due to the network effect between consumers and merchants.

4.2. The Impact of Cross-Network Effect

In this section, we will explore the impact of parameters α, β, η, and ω. Here, α and β denote positive cross-network externality obtained by ordinary consumers and merchants, respectively. While η indicates negative cross-network externalities obtained by merchants resulting from opportunistic consumers. In contrast, ω represents an interactive cause-and-effect relationship between consumers and merchants, where the cost incurred by a merchant is a sunk cost that provides no benefit to any member of the platform.

Proposition 2. *If the network externality parameter (α) for consumers from merchant scale is below a certain threshold $\overline{\alpha}$, platforms will benefit from providing a lenient return policy. However, the larger the value of η, the smaller the value of $\overline{\alpha}$. Although a large ω may attract opportunistic consumers, it could also drive away merchants. Thus, a platform offering such a service may find itself in a disadvantageous position when λ exceeds a certain threshold.*

From Figure 3a,b, it can be observed that competition is primarily influenced by the benefit a consumer derives from interaction with merchants. In Figure 3a, when α is below a certain threshold with a fixed value of β, Platform 1's profit is greater than that of Platform 2. However, when α exceeds that threshold, Platform 1's profit is less than that of Platform 2. A higher η reduces the scope of victory for lenient return policy providers, as an increasing value of η reduces the above threshold under the same α and β in Figure 3b compared with Figure 3a. In Figure 3c, we can see that for any α, the larger β is, the smaller the platform's revenue becomes. When comparing Figures 2b and 3d, we can deduce that a combination of large λ and η would compel multi-homing merchants to become single-homing on a platform without opportunistic consumers. Even though consumers benefit significantly from the scale of merchants, specifically when α is large, they may still leave Platform 1. Consequently, when both λ and η are relatively high, Platform 1 faces difficulties in generating profits.

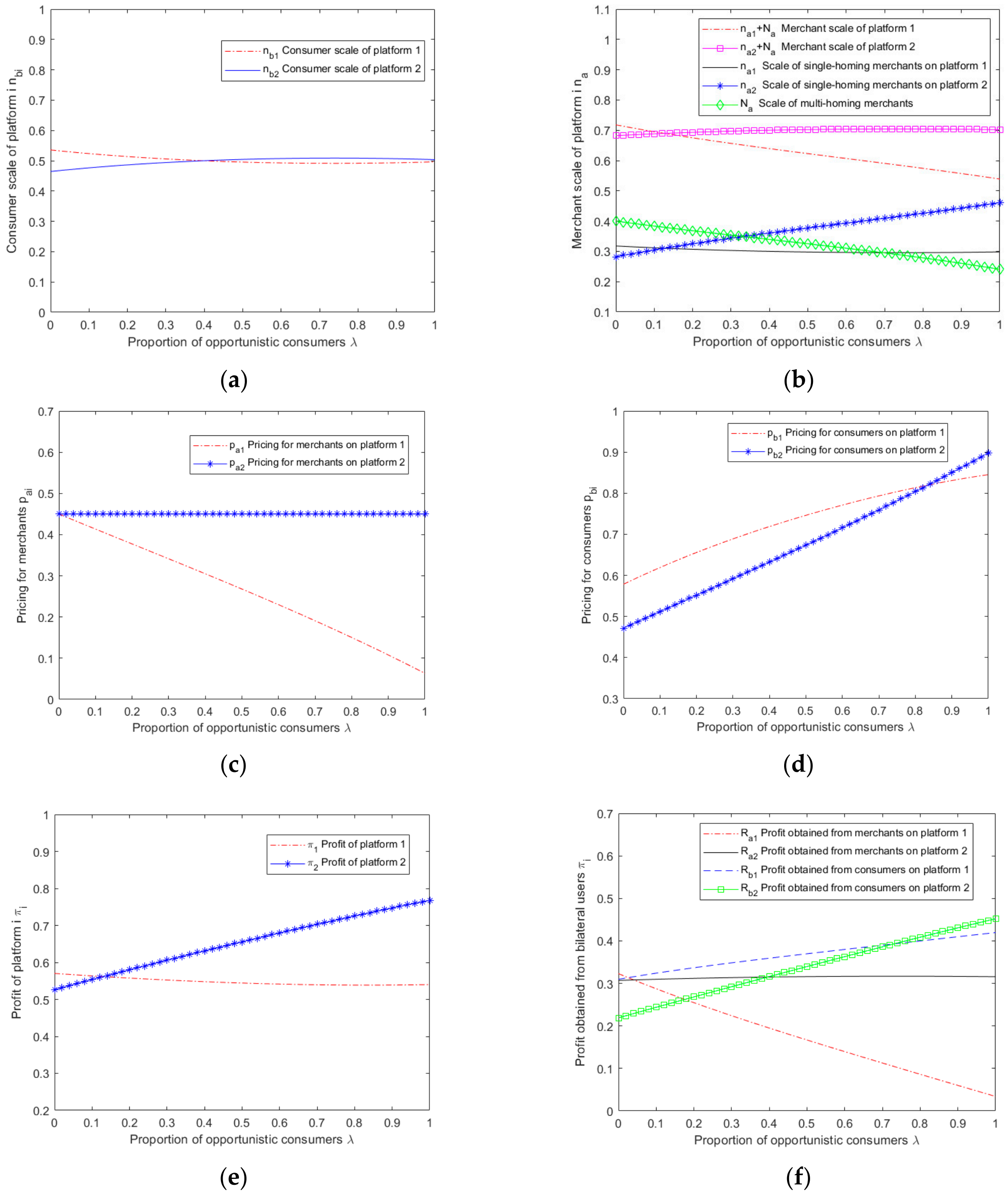

Figure 2. Impact of proportion λ on user scale, pricing, and profit: (**a**,**b**) are changes in the scale of consumers and merchants; (**c**,**d**) are changes in pricing for merchants and consumers; (**e**) is the profit trend of the two platforms; (**f**) is the profit source.

While maintaining constant values for other parameters, we investigate how the proportion λ and the benefit ω affect the user scale of Platform 1. We examine various values of ω, including 0.1, 0.3, 0.6, 0.9, and 1.2, to illustrate the growing advantage an opportunistic consumer gains from trading with a merchant. It is crucial to emphasize that ω also represents a loss for a merchant trading with an opportunistic consumer. The results are depicted in Figure 4.

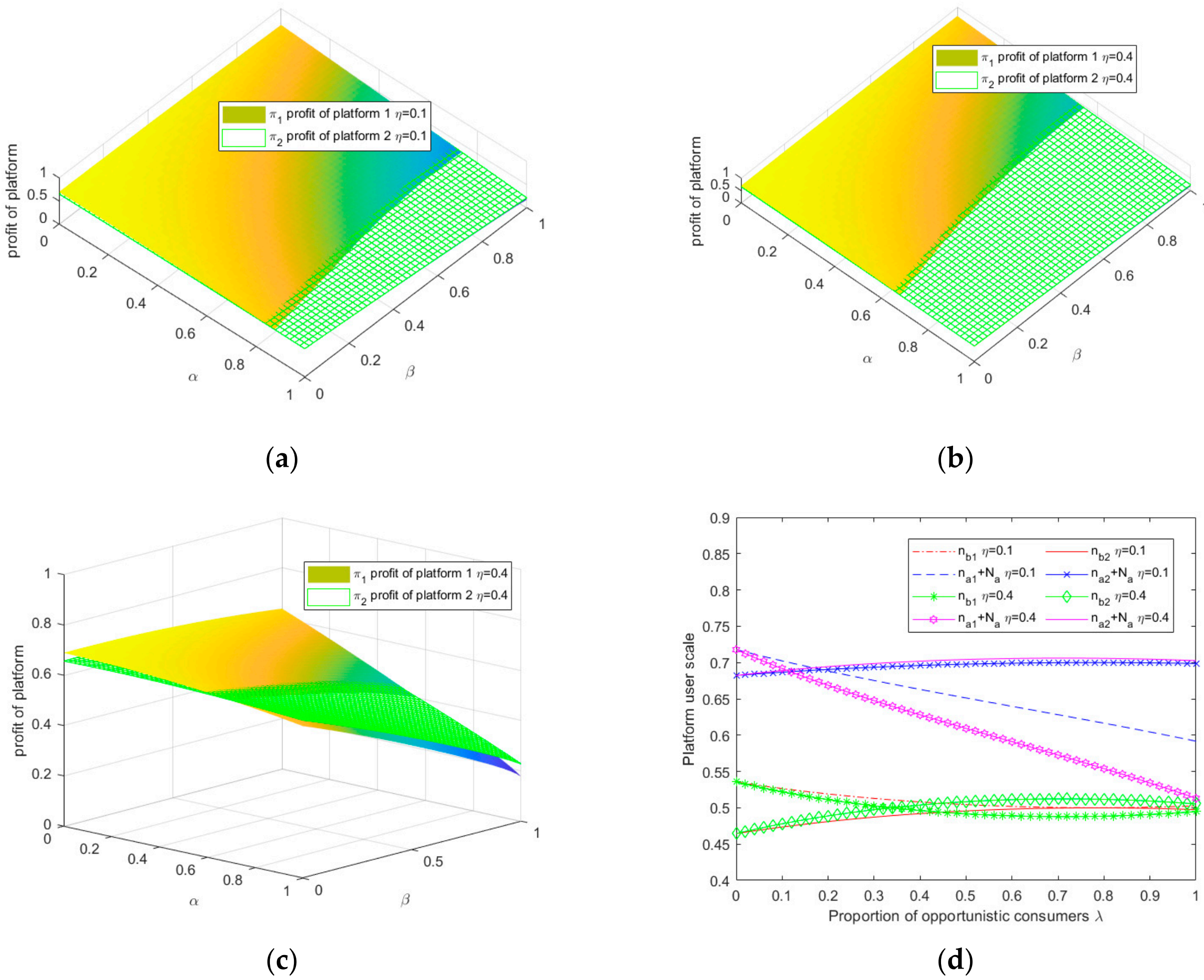

Figure 3. Impact of cross-network effect: (**a**–**c**) show the profit comparison between Platform 1 and 2 under the variation of α and β when η is 0.1, 0.4, and 0.4, respectively; (**d**) shows the user scale changes with λ when η is 0.1 and 0.4.

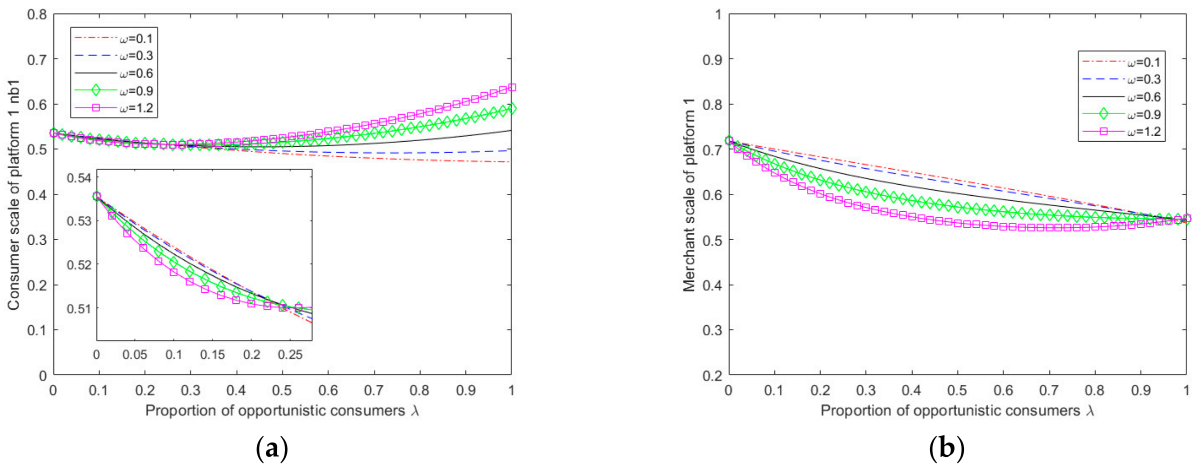

Figure 4. Impact of benefit ω: (**a**,**b**) are changes in the scale of consumers and merchants, respectively.

In Figure 4a, when λ is relatively low, specifically less than 0.25, indicating a lower presence of opportunistic consumers in the market, the impact of ω on the consumer scale of Platform 1 is rather modest. However, once λ exceeds the threshold of 0.25, Platform 1, which offers a lenient return policy, experiences a noticeable increase in the number of consumers as ω increases. In Figure 4b, as ω increases, the merchant scale of Platform 1 undergoes a rapid decline. However, when λ is larger than 0.5, its rate of decline slows down as ω increases. Figure 4 illustrates that higher ω has the potential to attract a larger number of consumers while simultaneously compelling more merchants to exit the platform. In reality, many e-commerce platforms implement measures to mitigate the impact of consumer abuse of return policies based on the influence of ω. They control the potential scope of losses for merchants by setting limits on instant refunds offered to consumers. For example, JD.com offers "lightning refund" services, where consumers are categorized based on their creditworthiness and different refund limits are set according to their credit levels. This approach ensures high-quality services for consumers while safeguarding the rights of merchants. In addition, some platforms have established different return and refund policies based on the value of the goods, with lenient return policies limited to lower-value items. Consumers who purchase these items can benefit from the platform's high-quality return and refund service. Platforms reduce the benefits that opportunistic consumers gain from trading.

4.3. The Effect of Penalty f

While maintaining constant values for other parameters and setting ω to 0.3, we analyze the effect of the penalty f imposed by Platform 1. We investigate various values of f, including 0, 0.2, 0.4, 0.6, and 0.8, to show how these penalty levels affect the outcome of the competition. The results are illustrated in Figure 5.

Figure 5a,b illustrate that, for any given λ, the implementation of strict penalties can result in an increase in both consumer and merchant participation on Platform 1. As the severity of the penalty increases, the rate of decline in scale diminishes. However, it is important to note that platform penalties can only partially mitigate the decrease in user participation and do not fully reverse the overall trend of diminishing merchant presence. This underscores the significance of strict penalties in assisting Platform 1 to mitigate user attrition when dealing with opportunistic consumers. It highlights the importance of Platform 1, which offers a lenient return policy, to monitor and penalize consumers who engage in abusive returns to prevent significant user losses. JD.com, for example, has implemented monitoring measures for consumer returns, lowering the level of dishonest consumers and permanently denying them access to lightning refunds and other premium after-sales services. Figure 5c,d shows that as the penalty for opportunistic consumers increases, the implementation of stringent penalty measures by Platform 1 incurs excessive costs, leading to a competitive disadvantage. As revealed in Figure 5e,f, the increasing penalty f reduces the scope of victory for lenient return policy providers, putting Platform 1 at a disadvantage. Consequently, we may conclude that:

Punishing dishonest returns is not an effective means of mitigating the adverse ecological impacts caused by opportunistic consumers. Therefore, rather than relying on penalties to improve the shopping ecosystem of the platform, it is more effective to implement a strict return policy.

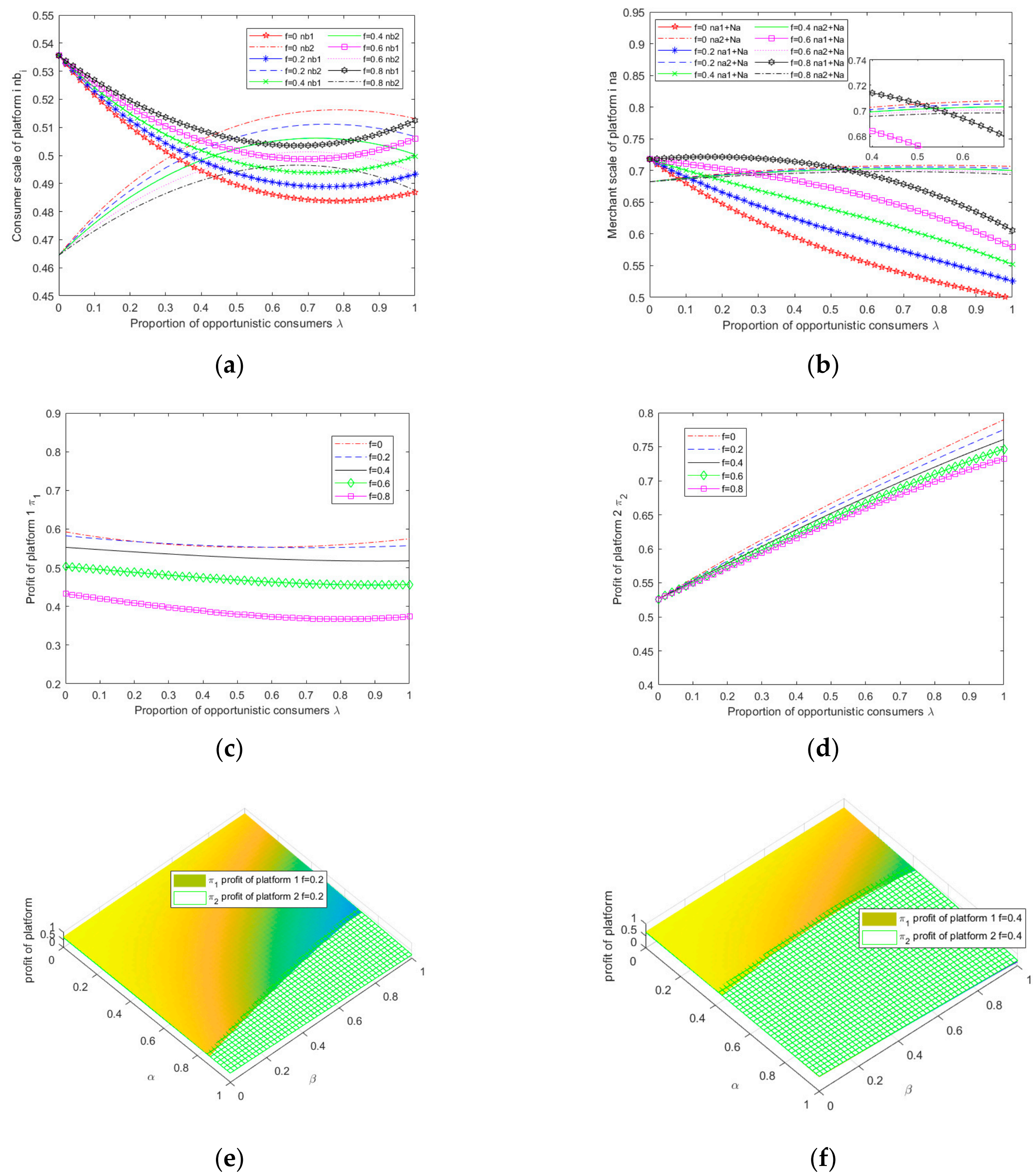

Figure 5. Impact of penalty f: (**a**,**b**) are changes in the scale of consumers and merchants; (**c**,**d**) are profit trends of Platform 1 and 2; (**e**,**f**) show a comparison of the profit of Platform 1 and 2 under variations of α and β when f is 0.2 and 0.4, respectively.

5. Conclusions and Management's Insights

5.1. Platform Strategy

User scale plays a key role in the growth of e-commerce platforms. Offering lenient return policies has emerged as a crucial strategy to attract users. However, some customers abuse these lenient return policies, resulting in opportunistic or fraudulent returns that cause additional losses to merchants and may worsen the overall market environment. This study establishes a duopoly platform competition model to investigate the effectiveness of lenient return policies in gaining a competitive advantage in the presence of opportunistic consumers. By formulating and solving the profit functions of a platform that offers lenient return policies and a platform that does not provide similar services, we examine the impact of various factors, including the proportion of opportunistic consumers, the cross-network effect, benefits from abusive returns, and the platform's penalty, on the user scale and profits of both platforms. The following conclusions and management insights were drawn:

(1) As the proportion of opportunistic consumers in the market increases, the scale of single-homing merchants remains stable. However, multi-homing merchants tend to exit platforms that offer lenient return policies and become single-homing on rival platforms. This results in a reduction in the scale of the platform's consumer base and lower profits compared to its competitors. This outcome implies that if a platform intends to implement a lenient return policy, it is of paramount importance to take measures to prevent dishonest returns and protect the interests of merchants who tend to be multi-homing.
(2) The success of a lenient return policy also depends on the network benefit parameters, especially on the consumer side. If consumers are highly sensitive to their interactions with merchants, implying that the merchant side is the bottleneck in a two-sided platform, such a lenient return policy is prone to failure in a market characterized by high opportunism. In addition, negative network effects due to opportunistic consumers can exacerbate the situation for merchants. Therefore, platforms that offer lenient return policies should set limits on how much consumers can avail themselves of these services. This will help mitigate the adverse impact of dishonest returns on platform profits.
(3) Will it be effective if platforms wish to implement regulations that support lenient return policies in the presence of opportunistic consumers? Yes, it can be effective if the proportion of such consumers is relatively small and the penalties are at a moderate level. Otherwise, merchants may choose to stay, but consumers may opt out, and the competitor wins.

5.2. Research Limitations and Recommendations

(1) Since this study assumes that consumers independently decide whether to abuse the platform's return policy and does not consider the impact of platform punishment, future research should incorporate the influence of platform punishment on the proportion of consumers abusing return policies into the model and examine its implications for platform service selection.
(2) Moreover, the current model solution does not account for dynamic game theory. Future research could explore the derivation of the model from the perspective of dynamic game theory.

Author Contributions: Conceptualization, H.L.; funding acquisition, H.L.; project administration, H.L.; supervision, H.L.; validation, H.L.; formal analysis, F.D.; investigation, F.D.; methodology, F.D.; resources, F.D.; writing—original draft, F.D.; writing—review and editing, F.D.; data curation, F.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

From the profit function (19), we can derive the Hessian matrix for Platform 1 with respect to p_{a1} and p_{b1} as follows:

$$\begin{bmatrix} \frac{4\alpha\beta-8}{(2-\alpha E)C} & \frac{2[\lambda(\eta+\beta)-(\alpha+\beta)]}{(2-\alpha E)C} \\ \frac{2[\lambda(\eta+\beta)-(\alpha+\beta)]}{(2-\alpha E)C} & \frac{-4-2\lambda\omega(1-\lambda)(\eta+\omega+\beta)}{(2-\alpha E)C} \end{bmatrix}$$

where

$$C = 2+\omega(\eta+\omega)\lambda,\ E = \frac{1}{C}[4\beta-\lambda(\eta+\omega+\beta)(2-\omega\beta+\lambda\omega\beta)]$$

When the matrix is negative-definite, the profit function of Platform 1 reaches its maximum value, and the optimal prices p_{a1} and p_{b1} exist. Hence, when $(2-\alpha\beta)(2-\alpha E) > 0$ and $2CG(2-\alpha\beta) - [\lambda(\eta+\beta)-(\alpha+\beta)]^2 > 0$, optimal prices p_{a1} and p_{b1} exist, where:

$$G = \frac{1}{C}[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]$$

From the profit function (20), we can derive the Hessian matrix for Platform 2 with respect to p_{a2} and p_{b2} as follows:

$$\begin{bmatrix} \frac{-2[\alpha(K-E)+2]}{2-\alpha E} & -\frac{K+\alpha G}{2-\alpha E} \\ -\frac{K+\alpha G}{2-\alpha E} & \frac{-2G}{2-\alpha E} \end{bmatrix}$$

where

$$K = \frac{\beta}{C}[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]$$

Then, when $[\alpha(K-E)+2](2-\alpha E) > 0$ and $4G[\alpha(K-E)+2] - (K+\alpha G)^2 > 0$, optimal prices p_{a2} and p_{b2} exist.

Proof of Theorem 1. From the expressions for x_1^* and x_2^*, it follows that $x_2^* = x_1^* + T$, where $T = \frac{1}{2}[\omega(1-n_{a2}) - f]$. Then, the difference in the number of single-homing merchants satisfies $n_{a1} - n_{a2} = \frac{2}{\alpha}x_1^* - \frac{2}{\alpha}D$ and $n_{a1} - n_{a2} = Ex_1^* + F$, where

$$D = -\frac{1}{2}[p_{b1} - p_{b2} - \theta m - 1] \text{ and } F = -\frac{\lambda\beta\omega+2}{C}p_{a1} + p_{a2} + \frac{\lambda[\beta-(\eta+\omega)]}{C}(\omega v_a - f) - \beta.$$

Hence, we have $x_1^* = \frac{\alpha F+2D}{2-\alpha E}$ and $x_2^* = [1+\frac{\omega A}{2C}]x_1^* + \frac{\omega B - Cf}{2C}$.

That is $x_1^* = -\frac{\alpha(\lambda\beta\omega+2)}{(2-\alpha E)C}p_{a1} + \frac{\alpha}{2-\alpha E}p_{a2} - \frac{1}{2-\alpha E}p_{b1} + \frac{1}{2-\alpha E}p_{b2} + \frac{\alpha F_1 + 2D_1}{2-\alpha E}$, where $F_1 = \frac{\lambda[\beta-(\eta+\omega)]}{C}(\omega v_a - f) - \beta$ and $D_1 = \frac{1}{2}(\theta m + 1)$.

Each user scale satisfies: $n_{b1} = Gx_1^* + H$; $n_{b2} = 1 - Gx_1^* - H$; $n_{a1} = Kx_1^* + L$; $n_{a2} = Qx_1^* + R$; $N_a = 1 - (K+Q)x_1^* - (L+R)$, where $R = \frac{2}{C}p_{a1} + \frac{\lambda(\eta+\omega)}{C}(\omega v_a - f) + 1 - v_a$, $G = \frac{1}{C}[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]$, $H = -\frac{\lambda\omega}{C}p_{a1} + \frac{\lambda(\omega v_a - f)}{C}$, $Q = \frac{2}{C}[\lambda(\eta+\omega+\beta)-\beta]$, $K = \frac{\beta}{C}[2+\lambda(1-\lambda)\omega(\eta+\omega+\beta)]$, and $L = -\frac{\lambda\beta\omega}{C}p_{a1} + p_{a2} + \frac{\lambda\beta(\omega v_a - f)}{C} + 1 - \beta - v_a$.

Under the profit function maximization, the optimal pricing for each user is: $p_{a1}^* = \frac{M_1}{M_0}$, $p_{a2}^* = \frac{M_2}{M_0}$, $p_{b1}^* = \frac{M_3}{M_0}$, $p_{b2}^* = \frac{M_4}{M_0}$, where

$$M_0 = -4a^3C^2G^2[\beta CG - QC + S] + a^2[8C^3G^3 - 4C^2G^2S^2 - 12C^3G^3\beta^2 + 2C^3G^2QS - 24C^3EG^2\beta + 20C^3G^2K\beta + 8C^3EGQ - 8C^2EGS - 8C^3GKQ + 8C^2GKS + 4C^3G^2Q\lambda w - 4C^2G^2S\lambda w] + a[48C^3G^2\beta + 24C^3G^3\beta - 8C^3G^3\beta^3 - 16C^3GQ + 16C^2GS + 48C^3EG^2 - 40C^3G^2K - 16C^2EGS^2 + 16C^2GKS^2 + 4C^3G^2K\beta^2 + 4C^3G^2Q\beta^2 - 4C^2G^2S\beta^2 - 8C^2G^2S^2\beta + 4C^3EGQS - 6C^3GKQS + 2C^3G^2QS\beta + 8C^3EGQ\lambda w - 8C^2EGS\lambda w - 8C^3GKQ\lambda w + 8C^2GKS\lambda w] + 16C^3G^3\beta^2 + 4Q\lambda wC^3G^2\beta^2 - 8KC^3G^2\beta - 96C^3G^2 + 2KQC^3GS\beta - 8QC^3GS - 16Q\lambda wC^3G - 4C^2G^2S^2\beta^2 - 4\lambda wC^2G^2S\beta^2 + 32C^2GS^2 + 16\lambda wC^2GS$$

$$M_1 = A_1[(-C^3G^3)a^2 + (5C^3G^2K - 6C^3EG^2 - 3C^3G^3\beta)a - 2C^3G^3\beta^2 + KC^3G^2\beta + 12C^3G^2] + A_2[(QC^3G^2 - 2SC^2G^2)a^2 + (C^3G^2Q\beta - 4C^2G^2S\beta + 2C^3EGQ - 8C^2EGS - 3C^3GKQ + 8C^2GKS)a + KQC^3G\beta - 4QC^3G - 2SC^2G^2\beta^2 + 16SC^2G] + A_3[(-2QC^3G^2 + 2SC^2G^2)a + (2QC^3G^2 - 2SC^2G^2)\beta] + A_4[(2QC^3G^2 - 2SC^2G^2)a^2 + (2C^3G^2Q\beta - 2C^2G^2S\beta + 4C^3EGQ - 4C^2EGS - 4C^3GKQ + 4C^2GKS)a - 8GQC^3 + 8GSC^2]$$

$$M_2 = A_1[(-4C^2G^2)a^2 + (2C^2G^2\beta + 2C^2GK - 2C^2G^2S - 4C^2G^2\lambda w)a + (2C^2G^2\lambda w - 2C^2G^2S)\beta + 4C^2GKS + 2C^2GK\lambda w] + A_2[(4\beta C^2G^2 - 4SCG)a^2 + (4C^2G^2\beta^2 - 8C^2G^2 + 2C^2KQ + 4CGS\beta - 8C^2GK\beta - 2C^2GQ\beta - 4CGS\lambda w)a + (-8C^2G^2 - 2Q\lambda wC^2G + 4S\lambda wCG)\beta + 16C^2GK + 2C^2KQ\lambda w] + A_3[(-12\beta C^2G^2 + 4QC^2G - 4SCG)a + 24C^2G^2 + 2QC^2GS + 4Q\lambda wC^2G - 8CGS^2 - 4\lambda wCGS] + A_4[8C^2G^2\beta a^2 + (8C^2G^2\beta^2 - 16C^2G^2 + 4CGS^2 + 4CGS\beta - 4C^2GK\beta - 4C^2GQ\beta)a + (-16C^2G^2 - 4Q\lambda wC^2G + 4CGS^2 + 4\lambda wCGS)\beta + 8C^2GK - 2C^2KQS]$$

$$M_3 = A_1[(-2C^2G^2)a^3 + (4C^2GK - 4C^2EG - 2C^2G^2S - 2C^2G^2\lambda w)a^2 + (8C^2G - 2C^2G^2\beta^2 - 4C^2G^2S\beta - 8C^2EGS + 8C^2GKS - 4C^2EG\lambda w + 4C^2GK\lambda w)a + (-2C^2G^2S - 2C^2G^2\lambda w)\beta^2 + 16C^2GS + 8C^2G\lambda w] + A_2[(4\beta C^2G^2 - 2QC^2G)a^3 + (8C^2G^2\beta^2 - 8C^2G^2 - 4C^2EQ + 4C^2KQ + 16C^2EG\beta - 16C^2GK\beta - 2C^2GQ\lambda w)a^2 + (8C^2Q - 16C^2G^2\beta + 4C^2G^2\beta^3 - 32C^2EG + 32C^2GK - 32C^2G\beta - 2C^2GQ\beta^2 - 4C^2EQ\lambda w + 4C^2KQ\lambda w)a + (-8C^2G^2 - 2Q\lambda wC^2G)\beta^2 + 64C^2G + 8C^2Q\lambda w] + A_3[(-4C^2G^2\beta)a^2 + (4C^2G^2\beta^2 + 8C^2G^2 - 2QSC^2G)a - 8\beta C^2G^2 + 2QS\beta C^2G] + A_4[4C^2G^2\beta a^3 + (4C^2G^2\beta^2 - 8C^2G^2 + 2C^2GQS + 8C^2EG\beta - 8C^2GK\beta)a^2 + (16C^2GK - 16C^2EG - 8C^2G^2\beta - 16C^2G\beta + 4C^2EQS - 4C^2KQS + 2C^2GQS\beta)a + 32C^2G - 8C^2QS]$$

$$M_4 = A_1[(6C^2GK - 8C^2EG - 2C^2G^2\beta)a^2 + (16C^2G - 4C^2G^2\beta^2 - 4C^2EGS + 2C^2GKS - 8C^2EG\lambda w + 6C^2GK\lambda w - 2C^2G^2\beta\lambda w)a + (-4C^2G^2\lambda w)\beta^2 + (-2C^2GKS)\beta + 8C^2GS + 16C^2G\lambda w] + A_2[(8CKS - 8CES - 2C^2KQ - 4CGS\beta + 8C^2EG\beta - 4C^2GK\beta + 2C^2GQ\beta)a^2 + (16CS - 16C^2EG + 8C^2GK - 16C^2G\beta + 4C^2GK\beta^2 - 4CGS\beta^2 - 8CES\lambda w + 8CKS\lambda w - 2C^2KQ\lambda w - 4CGS\beta\lambda w + 2C^2GQ\beta\lambda w)a - 8GKC^2\beta + 32GC^2 - 4GS\lambda wC\beta^2 + 16S\lambda wC] + A_3[(4\beta C^2G^2 - 4QC^2G + 4SCG)a^2 + (8C^2G^2\beta^2 - 8C^2G^2 - 2QC^2GS - 4Q\lambda wC^2G + 4CGS^2 + 4\lambda wCGS)a - 16bC^2G^2 + 4bCGS^2] + A_4[(16C^2EG\beta - 4CGS\beta - 12C^2GK\beta + 4C^2GQ\beta)a^2 + (24C^2GK - 32C^2EG + 8CES^2 - 8CKS^2 - 32C^2G\beta + 2C^2KQS - 4CGS\beta\lambda w + 4C^2GQ\beta\lambda w)a + 64GC^2 - 16CS^2]$$

Thus, the profits of Platform 1 and Platform 2 are:

$$\pi_1^* = p_{a1}^*(1 - Qx_1^* - R) + p_{b1}^*(Gx_1^* + H) + \lambda f(1 + \frac{\omega A}{2C})x_1^* + \lambda f\frac{\omega B}{2C} - \frac{\lambda}{2}f^2 - \frac{k_2}{2}f^2 - \frac{k_1}{2}m^2$$

$$\pi_2^* = p_{a2}^*(1 - Kx_1^* - L) + p_{b2}^*(1 - Gx_1^* - H)$$

□

References

1. Rysman, M. Competition between Networks: A Study of the Market for Yellow Pages. *Rev. Econ. Stud.* **2004**, *71*, 483–512. [CrossRef]
2. Radhi, M. Service Decisions in a Two-Echelon Retailing System with Customer Returns. *J. Theor. Appl. Electron. Commer. Res.* **2022**, *17*, 1219–1242. [CrossRef]
3. Chang, H.H.; Guo, Y.Y. Online Fraudulent Returns in Taiwan: The Impacts of E-retailers' Transaction Ethics and Consumer Personality. *J. Retail. Consum. Serv.* **2021**, *61*, 102529. [CrossRef]
4. Safda, K. How Your Returns are Used against You at Best Buy, Other Retailers. *Wall Str. J.* **2018**. Available online: https://www.bespacific.com/how-your-returns-are-used-against-you-at-best-buy-other-retailers (accessed on 15 August 2023).
5. Ülkü, M.A.; Gürler, Ü. The Impact of Abusing Return Policies: A Newsvendor Model with Opportunistic Consumers. *Int. J. Prod. Econ.* **2018**, *203*, 124–133. [CrossRef]
6. Yan, R.L.; Pei, Z. Return Policies and O2O Coordination in the E-tailing Age. *J. Retail. Consum. Serv.* **2019**, *50*, 314–321. [CrossRef]
7. Shang, G.Z.; Ghosh, B.P.; Galbreth, M.R. Optimal Retail Return Policies with Wardrobing. *Prod. Oper. Manag.* **2017**, *26*, 1315–1332. [CrossRef]
8. Khouja, M.; Hammami, R. Optimizing Price, Order Quantity, and Return Policy in the Presence of Consumer Opportunistic Behavior for Online Retailers. *Eur. J. Oper. Res.* **2023**, *309*, 683–703. [CrossRef]
9. Altug, M.S.; Aydinliyim, T.; Jain, A. Managing Opportunistic Consumer Returns in Retail Operations. *Manag. Sci.* **2021**, *67*, 5660–5678. [CrossRef]
10. Hagiu, A. Pricing and commitment by two-sided platforms. *RAND J. Econ.* **2006**, *37*, 720–737. [CrossRef]
11. Song, P.J.; Xue, L.; Rai, A. The Ecosystem of Software Platform: A Study of Asymmetric Cross-side Network Effects and Platform Governance. *MIS Q.* **2018**, *42*, 121–142. [CrossRef]
12. Caillaud, B.; Jullien, B. Chicken & Egg: Competition among Intermediation Service Providers. *RAND J. Econ.* **2003**, *34*, 309–328. [CrossRef]
13. Hagiu, A.; Hałaburda, H. Information and Two-sided Platform Profits. *Int. J. Ind. Organ.* **2014**, *34*, 25–35. [CrossRef]
14. Cachon, G.P.; Daniels, K.M.; Lobel, R. The Role of Surge Pricing on a Service Platform with Self-Scheduling Capacity. *Manuf. Serv. Oper. Manag.* **2017**, *19*, 368–384. [CrossRef]
15. Rochet, J.C.; Tirole, J. Two-sided Markets: A Progress Report. *RAND J. Econ.* **2006**, *37*, 645–667. [CrossRef]
16. Athey, S.; Calvano, E.; Gans, J.S. The Impact of Consumer Multi-homing on Advertising Markets and Media Competition. *Manag. Sci.* **2018**, *64*, 1574–1590. [CrossRef]
17. Bakos, Y.; Halaburda, H. Platform Competition with Multihoming on Both Sides: Subsidize or Not? *Manag. Sci.* **2020**, *66*, 5599–5607. [CrossRef]
18. Dou, G.W.; He, P. Value-added Service Investing and Pricing Strategies for a Two-sided Platform under Investing Resource Constraint. *J. Syst. Sci. Syst. Eng.* **2017**, *26*, 609–627. [CrossRef]
19. Liu, W.H.; Yan, X.Y.; Wei, W.Y. Pricing Decisions for Service Platform with Provider's Threshold Participating Quantity, Value-added Service and Matching Ability. *Transp. Res. Part E Logist. Transp. Rev.* **2019**, *122*, 410–432. [CrossRef]
20. Basu, A.; Bhaskaran, S.; Mukherjee, R. An Analysis of Search and Authentication Strategies for Online Matching Platforms. *Manag. Sci.* **2019**, *65*, 2412–2431. [CrossRef]
21. Armstrong, M. Competition in Two-sided Markets. *RAND J. Econ.* **2006**, *37*, 668–691. [CrossRef]
22. Aloui, C.; Jebsi, K. Optimal Pricing of a Two-sided Monopoly Platform with a One-sided Congestion Effect. *Int. Rev. Econ.* **2010**, *57*, 423–439. [CrossRef]
23. Ji, H.L.; Wang, X.F. Competition Model of Two-sided Markets with Platform Differentiation and Users Partially Multihoming. *Syst. Eng. Theory Pract.* **2014**, *34*, 1398–1406.
24. Gui, Y.M.; Wu, Z.; Gong, B.G. Value-added Service Quality Investment Competition of Bilateral Platform in Competitive Environment. *J. Syst. Sci. Math. Sci.* **2022**, *42*, 3273–3287.
25. Zhao, F.Y.; Wang, Y. Value-added Service and Pricing Strategies of Duopoly Two-sided Platforms with Sellers Partially Multihoming. *Front. Sci. Technol. Eng. Manag.* **2020**, *39*, 76–82.
26. Mukhopadhyay, S.K.; Setoputro, R. Reverse Logistics in E-business: Optimal Price and Return Policy. *Int. J. Phys. Distrib. Logist. Manag.* **2004**, *34*, 70–89. [CrossRef]
27. Su, X. Consumer Returns Policies and Supply Chain Performance. *Manuf. Serv. Oper. Manag.* **2009**, *11*, 595–612. [CrossRef]
28. Akçay, Y.; Boyacı, T.; Zhang, D. Selling with Money-Back Guarantees: The Impact on Prices, Quantities, and Retail Profitability. *Prod. Oper. Manag.* **2012**, *22*, 777–791. [CrossRef]
29. Li, Y.J.; Xu, L.; Li, D. Examining Relationships Between the Return Policy, Product Quality, and Pricing Strategy in Online Direct Selling. *Int. J. Prod. Econ.* **2013**, *144*, 451–460. [CrossRef]
30. Pei, Z.; Paswan, A.; Yan, R. E-tailer's Return Policy, Consumer's Perception of Return Policy Fairness and Purchase Intention. *J. Retail. Consum. Serv.* **2014**, *21*, 249–257. [CrossRef]
31. Batarfi, R.; Jaber, M.Y.; Aljazzar, S.M. A Profit Maximization for a Reverse Logistics Dual-channel Supply Chain with a Return Policy. *Comput. Ind. Eng.* **2017**, *106*, 58–82. [CrossRef]
32. Wood, S.L. Remote Purchase Environments: The Influence of Return Policy Leniency on Two-Stage Decision Processes. *J. Mark. Res.* **2001**, *38*, 157–169. [CrossRef]

33. Li, J.B.; Li, Y. Optimal Online Pricing and Compensation Strategy in MBG Returns Policy. *Syst. Eng. Theory Pract.* **2016**, *36*, 2811–2819.
34. Stock, J.R.; Mulki, J.P. Product Returns Processing: An Examination of Practices of Manufacturers, Wholesalers/Distributors, and Retailers. *J. Bus. Logist.* **2009**, *30*, 33–62. [CrossRef]
35. Chen, J.; Grewal, R. Competing in a Supply Chain via Full-refund and No-refund Customer Returns Policies. *Int. J. Prod. Econ.* **2013**, *146*, 246–258. [CrossRef]
36. Huang, Z.S.; Nie, J.J.; Zhao, Y.X. Money-back guarantee in the presence of bounded rational consumers. *Chin. J. Manag. Sci.* **2016**, *24*, 116–123.
37. Chen, B.T.; Chen, J. Compete in Price or Service? —A Study of Personalized Pricing and Money Back Guarantees. *J. Retail.* **2017**, *93*, 154–171. [CrossRef]
38. Ofek, E.; Katona, Z.; Sarvary, M. "Bricks and Clicks": The Impact of Product Returns on the Strategies of Multichannel Retailers. *Market. Sci.* **2011**, *30*, 42–60. [CrossRef]
39. Chen, J.; Bell, P.C. Implementing Market Segmentation Using Full-refund and No-refund Customer Returns Policies in a Dual-channel Supply Chain Structure. *Int. J. Prod. Econ.* **2012**, *136*, 56–66. [CrossRef]
40. Phau, I.; Akintimehin, O.O.; Shen, B. "Buy, wear, return, repeat": Investigating Chinese Consumers' Attitude and Intentions to Engage in Wardrobing. *Strateg. Chang.* **2022**, *31*, 345–356. [CrossRef]
41. Mun, J.M.; Ju, H.W.; Johnson, K.K.P. Young Consumers and Retail Borrowing: Application of the Theory of Planned Behavior. *J. Glob. Fash. Mark.* **2014**, *5*, 60–73. [CrossRef]
42. Young, M.; Piron, F. Retail Borrowing: Insights and Implications on Returning Used Merchandise. *Int. J. Retail. Distrib. Manag.* **2000**, *28*, 27–36. [CrossRef]
43. Hjort, K.; Lantz, B. (R)e-tail Borrowing of Party Dresses: An Experimental Study. *Int. J. Retail. Distrib. Manag.* **2012**, *40*, 997–1012. [CrossRef]
44. Harris, L.C. Fraudulent Return Proclivity: An Empirical Analysis. *J. Retail.* **2008**, *84*, 461–476. [CrossRef]
45. Zhang, D.; Frei, R.; Senyo, P.K. Understanding Fraudulent Returns and Mitigation Strategies in Multichannel Retailing. *J. Retail. Consum. Serv.* **2023**, *70*, 103145. [CrossRef]
46. Li, Y.J.; Xu, L.; Choi, T.M. Optimal Advance-Selling Strategy for Fashionable Products with Opportunistic Consumers Returns. *IEEE Trans. Syst. Man Cybern. Syst.* **2014**, *44*, 938–952. [CrossRef]
47. Rasch, A.; Wenzel, T. Piracy in a Two-sided Software Market. *J. Econ. Behav. Organ.* **2013**, *88*, 78–89. [CrossRef]
48. Dou, Y.F.; Wu, D.J. Platform Competition under Network Effects: Piggybacking and Optimal Subsidization. *Inform. Syst. Res.* **2021**, *32*, 820–835. [CrossRef]
49. Belleflamme, P.; Peitz, M. Platform Competition: Who Benefits from Multihoming? *Int. J. Ind. Organ.* **2019**, *64*, 1–26. [CrossRef]
50. Chen, J.; Yu, B.; Chen, B.T. Lenient vs. Stringent Returns Policies in the Presence of Fraudulent Returns: The Role of Customers' Fairness Perceptions. *Omega* **2023**, *117*, 102843. [CrossRef]
51. Sui, R.H.; Zhang, X.M.; Dan, B. Bilateral Value-added Service Investment in Platform Competition with Cross-side Network Effects under Multihoming. *Eur. J. Oper. Res.* **2023**, *304*, 952–963. [CrossRef]
52. Li, J.; Zhang, Y.L. Pricing Strategy of the Platform Considering Network Effects and Business Expansion. *Syst. Eng. Theory Pract.* **2020**, *40*, 593–604.
53. Zhang, C.; Tian, Y.X.; Xiao, M. Value-added Service Investing and Pricing Strategies of Multilateral Distribution Platform with Consideration of Cross-network Externalities. *Syst. Eng. Theory Pract.* **2019**, *39*, 3084–3309.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.