

Article

Platform Revenue Strategy Selection Considering Consumer Group Data Privacy Regulation

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Abstract: In the era of big data, consumer group privacy has become an important source of revenue for the digital platform. Considering the situation that the platform collects consumer group data privacy to generate business revenue, we explore how the service matching level and commission rate affect the platform revenue, social welfare, and seller benefits. Based on the theory of group privacy, the three-party equilibrium evolution is solved by constructing a sequential game model including platform, seller, and consumer alliance. It is found that when the service matching level of the platform is greater than the threshold value, there are two main situations: on the one hand, if using the data privacy of a consumer group is subject to market regulation, the platform will set a high commission rate and service matching level in order to maximize profit. However, social welfare and seller's business benefit both reach a minimum in this case, and the three-party game cannot attain equilibrium. On the other hand, when the market governor relaxes the platform's regulation on the use of consumer group privacy data and data revenue efficiency is high enough, the platform can maximize the revenue by increasing the service matching level and reducing the commission rate. The optimal commission rate depends on the data revenue efficiency of the platform. Moreover, when the platform sets the highest commission rate and the service matching level is at a medium level, a stable partial equilibrium among the three-party will be achieved. These conclusions can give some insights into platform's business model choice decision.

Keywords: group privacy data; service matching level; platform revenue strategy; data regulation



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1. Introduction

In recent years, with the rapid progress of big data technology, some monopolistic digital platforms have used the privacy of consumers to carry out commercial activities, which significantly influence people's life. For example, the Didi Taxi platform controls people's travel, which makes the privacy of relevant location data privacy controlled by the platform in real time. Large online platforms such as eBay, Taobao, Jindong, etc. gather people's consumption amount and analyze their habits, thus recommending matching products through targeted advertising on digital platforms. These industry monopoly platforms use users' private information to match bilateral users and form specific advertising and commission model business [1,2]. Furthermore, platforms utilize consumer group data to provide merchants with business convenience such as matching pricing, thereby obtaining considerable income by extracting matching commission [3].

With the increase in platform data elements, the platform business model is changed. For example, some digital platforms do not simply rely on commission to earn profits but also taking data services as their main business model. There are an increasing number of platforms that regard more with data services as the main business model. The potential reason is that the user data flow has great importance attached, which also leads to the free strategy the platform sets for users in order to attract them. In this case, the platforms

will play two roles. Firstly, as intermediaries, platforms extract a transaction commission. Secondly, as data providers, the platforms obtain group consumers' private data as production materials for its platform services, such as targeted advertising business [4]. However, there is a contradiction between these two revenue models. The commission extraction model will increase platforms' profits, while it may raise the prices that the merchants set for consumers. Therefore, the purchase of consumers on the platforms will decrease, thereby affecting the amount of consumer data obtained and indirectly reducing the revenue of the platform's data service [5]. Recent work about platform revenue management, such as [1,6,7], mainly study the value of consumer data and the business model of the platform. As consumers' online activities are becoming increasingly frequent, more and more data are gathered by the platforms due to users' register and trade on the platforms. Including their personal data privacy, this consumer data information is considered as a hidden asset, which can be used to provide data element support for product match innovation online and offline. Considering the significant role that consumer data plays, it is worthwhile to explore the impact of it on platforms and consumers. Since consumers are growingly concerned about their privacy, there are increasingly strong voices to regulate how platforms use consumer data. For example, in early 2007, The European Consumers Union criticized Google for violating users' privacy rights [8]. The regulatory constraints of these consumer associations and other organizations cause invisible pressure on the business development of the platform, which makes the platform more cautious in the use of consumer data. Therefore, the sustainable benefits of platform-matching business depend not only on technical infrastructure but also on the market's regulation of the platform's use of consumer data to generate revenue. However, some prior works such as [7,9] claim that the regulations on platforms do not necessarily improve social welfare. Furthermore, some digital platforms only serve as market intermediaries and extract commissions to gain profits by matching transactions between merchants and consumers [10]. As intermediaries, platforms do not have direct pricing power over products, and the negative impact of platform service ecology on merchants' pricing and social welfare deserves further discussion [11,12].

Therefore, we focus on consumer group data privacy regulation and study the platform revenue strategy selection, which is based on the literature [1], regarding the level of platform matching level and commission rate. We also consider the differences in the description of privacy data used to improve matching and requesting consumer surplus with the literature [9]. Specifically, group data privacy is used to enhance platforms' benefits, and we analyze the impact of consumer privacy data on the platform's revenue strategy and social welfare.

The rest of the paper is organized in the following manner. In Section 2, we review the relevant literature. In Section 3, the background of the model is described and assumed, and the definitions of the related parameters are explained. In Section 4, we provide the results in equilibrium. In Section 5, we present the impact of different factors on social welfare, and our conclusions are given in Section 6.

2. Literature Review

2.1. Consumer Data Privacy and Social Welfare

In general, consumer data refers to the basic private information of consumers' physical condition, demand information, personal preference, behavior habits, and other characteristics. Affected by the factors of shopping scenarios, consumers will have completely different disclosure behaviors for their private information [13]. On the one hand, some consumers are keen on disclosing private information. For example, social consumers are accustomed to sharing shopping experiences with their relatives and friends. Some researches such as [8] show that consumers may disclose their privacy in order to obtain platforms' services. On the other hand, some consumers worry about privacy infringement caused by private data disclosure, which arouses their strong privacy concerns and reduces their disclosure on online platforms. These paradoxical disclosure decisions spawn privacy

paradox issues. In essence, the privacy paradox is derived from the complex scenarios of consumer data disclosure decisions and the multi-level, which means that there are Individual Privacy (IP) and Group Privacy (GP) levels [14].

Past work primarily focuses on individual privacy but seldom examines group data privacy. Among the literature focusing on individual privacy, most of them explore factors influencing information disclosure and sensitivity scales of individual privacy [15,16], privacy calculation theory (including privacy risk and benefit compensation) [4,17], and personal privacy protection methods and theory development [9,12]. From different disciplinary perspectives, these theoretical studies about individual privacy based on different disciplinary perspectives face complex application scenarios, and the large-scale commercial practice of individual privacy theory will spark many moral and legal challenges. Some of the literature on personal privacy protection indicates that individual privacy protection results in market inefficiency and does not improve social welfare [18]. Meanwhile, data privacy disclosure as the opposite of privacy protection makes social welfare better but at the cost of consumers' interests. For example, Shy (2016) considers the impact of different privacy protection degrees and switching costs on consumer surplus and social welfare. It is found that if consumer surplus and social welfare increase, firms need to recognize consumers' special switching costs. Meanwhile, Shy proves that compared with strong privacy regulation, weak privacy protection is more beneficial to firms [16]. Some scholars believe that a certain degree of consumer privacy disclosure will not hurt consumers but will improve personalized service, thereby enhancing consumer satisfaction [19–21]. Therefore, the duality of privacy is ubiquitous in our daily life. Firstly, it is difficult to describe a single unified theory of privacy economics, because privacy issues related to the economy arise in widely different contexts. Secondly, from theoretical and empirical perspectives, it is unclear that privacy protection will necessarily increase consumer surplus and social welfare. Thirdly, consumers often learn about imperfect or asymmetric information about when their data is collected, for what purpose, and what consequences, which make it hard for them to make informed decisions about their privacy [13]. Due to hidden features and behaviors, consumers have less information than app sellers, thus causing privacy uncertainty [22], which affects the perceived risks related to platform use and the price consumers are willing to pay [23]. Meanwhile, this study believes that privacy risk and privacy attitude are related to the willingness to be compensated/willingness to pay for privacy protection [17].

Advances in big data theory and technology have made personal data a tradable asset. The market for personal information is emerging, and new ways of assessing personal data are being proposed. Meanwhile, since individuals show huge privacy concerns, legal obligations to protect personal data are advocated. Combined with individual privacy protection, some scholars put forward the concept of exploring the commercial value of group privacy [15,23]. Group privacy is defined as a group that has the same information type in a particular context, such as a group in which people buy the same product. For those individuals with group privacy, they are less sensitive, enabling the use of group privacy to encounter relatively few moral and legal challenges. Therefore, commercial research on group privacy in the gray area has gradually attracted widespread attention. In an increasingly complex digital environment, a more general multi-level description is requested to explore complicated privacy decisions involving jointly owned (i.e., group) information. Given this, Belanger and James [14,24] propose the concept of Group Information Privacy and develop the multi-level Information Privacy theory, which is based on the Information Privacy norms and provides a preliminary conception of multi-level Information Privacy decision making. However, Kim et al. (2020) believes that with the development of online social networks and information technology, the disclosure of group privacy may lead to the violation of personal privacy (if it can be traced back to an individual). Therefore, while individual privacy rights are widely respected, attention should be paid to the maintenance of the privacy rights of social groups [25,26].

With the rapid popularization of online platforms, once people register on these social networks and shopping platforms, a lot of consumer data privacy can be easily obtained by commercial and data analysis tools, thus forming a specific group of private data. Big data technical analysis can analyze users' basic needs and preferences, and thereby pushing targeted advertisements to specific users through phone calls, SMS messages, and e-mail, which to a certain extent is a privacy violation [6,24,27,28]. More seriously, through big data technical analysis, consumer demand provides technical support for merchants to formulate price discrimination or product innovation [29]. In effect, these platforms' practices are achieved by collecting the group privacy of consumers with similar needs and tracing individual consumers. Therefore, studying the data decisions of group consumers can provide decision support for consumer data privacy protection, merchant pricing, and platform revenue strategy. In this paper, we consider the negative effects of consumer group privacy use and analyze the platform revenue and social welfare. It is different from the description in the literature [9] about how data are used to improve matching and extract consumer surplus. We mainly study the impact of consumer group privacy disutility on platform revenue strategy and social welfare when group data privacy is used for platform business innovation.

2.2. Platform Business Model and Data Strategy

At present, it is generally accepted in academic circles that digital platform business can be divided into two types: one is a Reseller platform such as Amazon, eBay, Jindong, etc., which resell the products of merchants on the platform to consumers or directly take a cut from the transactions between merchants and consumers. The other is the marketplace; as an independent market, it provides information matching services for merchants who enter the platform. It does not directly participate in product sales to customers but only provides data information service support for product sales, such as Alibaba, Global Resources, and other platforms [30–32]. In the existing literature, most papers focus on user attribution [16,23], network externalities [33], and revenue models of two-sided markets [1,2,34]. Chen (2016) believes that the matching rate of e-commerce platforms plays a crucial role in platform revenue. If the matching level is high, the commission model can generate more revenue; otherwise, the advertising model will generate more revenue [1]. With the advent of big data, consumer data privacy is widely used to improve the platforms' abilities to match bilateral users. In recent years, the literature on consumer data privacy and platform market competition-related research has sparked heated discussion. Hagiú (2014) believes that the platform's demand for users' private information depends on the market power of the platform. Platforms with more market power (monopoly) tend to face more informed users, while platforms with less market power (facing more intense competition) expect to reduce user information, which mainly depends on whether the platform can respond to user needs or not [30]. This demand response ability is also interpreted by many scholars as the matching efficiency of the platform. Hence, the increase in private information disclosure will improve platforms' matching efficiency to some extent, and it also relies on the degree of market competition and business model. Casadesus-Masanell (2015) believes that consumer data privacy is closely related to platform business model competition. Market competition leads to low information disclosed by consumers, but when consumers show a low willingness to pay, the increased intensity of market competition does not need to improve user privacy protection [35].

There is also a growing pool of literature on the optimal strategy about how the platforms gather consumer data privacy. Bloch et al. (2018) study the data acquisition behavior of monopolistic platforms and find that a platform's optimal strategy is to completely dominate the market or choose the highest level of data utilization and exclude users with high privacy costs from the platform. In addition, differentiated tax rates through different tax rates on the access gains and data gains of platforms are the most effective means of reducing platform data collection. Meanwhile, the introduction of platform opt-out

options may hurt users, because it will increase the level of data utilization [36]. Morath (2018) explores platform design in online marketplaces and proposed that consumers pay (non-monetary) costs due to privacy and security issues. Considering the potential purchases or the information value of consumers' registration, sellers benefit from the platform's requirement for users to register in advance. The platform's best choice includes pre-registration requirements and partial discounts offered to consumers, even if discounts distort product pricing decisions [37]. Kummer (2019) studies the transaction of data privacy in exchange for money in the smartphone application market. It is found that when developers provide applications to consumers at a lower price, they can obtain more access to personal privacy information [8]. Loertscher (2020) explores the change in market power caused by the reduction of platform matching levels and personal privacy. Platform profits and social surplus always increase as privacy decreases. However, consumer surplus is not monotonous concerning privacy. Without privacy, i.e., platforms collect more privacy, the matching rate will be perfect, which may result in platforms' complete information monopoly. Conversely, as the privacy gathered by platforms declines, the matching rate and social surplus tend to zero [9].

Therefore, previous studies focus on the value of user privacy information [13], motivation of disclosure [7,38], privacy disclosure, and competition in the two-sided market of the platform [35]. By contrast, we further reveal the impact of consumer data privacy disclosure level on the matching level of the platform, the consumer, and the merchants. Most papers admit that the use of consumer private information data by the platform will have negative effects on consumers [12]. Online consumers' privacy disclosure on the platform helps the personalized recommendation system and positively affects consumers' willingness to pay [38]. However, too much information disclosed by consumers will be used to conduct business development, such as enhancing the targeted ability of advertising recommendation systems, which obviously hurts consumers to some extent. De Corniere (2016) believes that the use of consumer information enhances the match between advertisers and consumers, but even if merchants do not discriminate on price, it also increases the price of products [6,15]. This result implies that platforms' dominance of information will ultimately negatively affect consumers' utility and purchasing decisions [6]. However, some research indicates that consumers may benefit from platforms' use of their data. For example, Ichihashi (2020) considers disclosure regulation and examines the effect of sellers' commitment about whether to use consumers' privacy to practice price discrimination. The author believes that sellers gain more benefits (than non-promises) when making a commitment, while consumers do the opposite [7].

Compared with the conclusions of different papers, it is widely accepted that platforms' use of consumer data hurts consumers precisely because the platform can use consumer data to practice commercial purposes such as product matching pricing in order to enhance profits. However, the balance between information disclosure data, merchant pricing, and a platform business model is requested. Specifically, the trade-off between privacy disclosure and consumer utility needs to be considered. A feasible way is to consider the negative effects such as price discrimination on consumers triggered by platforms' use of group privacy data and introduce these effects into relevant theoretical models.

In this paper, we consider the platform's two basic business capabilities to obtain profits: one is to directly connect with consumers to resell goods (the level of commission); the other is to act as an information service intermediary, providing the service of matching bilateral market transactions (matching level). Then, the product pricing of merchants is established, after which consumers' information data disclosure and purchasing decisions can be determined. Finally, we consider the regulation on platforms' using consumer group data privacy to generate revenue. Specifically, we analyze when with or without market regulation how platforms balance their strategies on a brokerage level and commission rate in order to maximize profits and improve social welfare at the same time. Ultimately, social welfare, platform, and merchants' income will reach a stable local equilibrium, which

will have an important impact on the healthy and sustainable development of the digital ecology of the platform.

Previous studies indicated that the service matching level would affect the transaction efficiency of the platform [10,34] but fail to answer the question that to what extent the matching value of platform services can trigger the platform to match bilateral transactions. In addition, the literature on the impact of platforms' capabilities about using consumer group data on social welfare is rare. Our paper significantly extends the existing literature in three aspects. Firstly, we assume that the commission rate and matching level will influence merchants' pricing decisions, and we introduce the concept of platform-matching level threshold. Only when the platform matching rate reaches or exceeds this threshold will merchants and consumers participate in the platform-matching transaction, after which the platform can obtain consumer data privacy. Secondly, we consider the business model of the platform under the regulation of consumer data use. We examine whether the platform can use consumer data privacy to create profits and explore the impact of the platform's two strategies (commission rate and service matching level) on social welfare. Thirdly, consumer data privacy affects the platform's business model and revenue strategy, which can further improve the matching and transaction commission pattern between platforms and merchants. Therefore, we provide new insights on business model innovation, which is driven by consumer group data.

3. Problem Description and Model

By constructing a dynamic sequential game model, this paper analyzes and discusses how the impacts of platforms' strategies about commission rate and matching level on consumers, merchants, and platforms change at different levels of consumer data use.

3.1. Problem Description

Consider that there is an e-commerce digital platform, a merchant, and two types of consumers online and offline. Firstly, the platform pre-decides to charge merchants a commission of online transactions (the percentage level r), which can also be explained as the platforms' market dominance rate, while merchants do not take a cut of offline transactions. Since the platform can achieve the transaction between buyer and seller more effectively, we denote the platforms' matching level as α . If the matching level of the platform is high, consumers are more willing to buy on the platform.

Merchants sell products online, i.e., on a platform, and offline, and the product price of the online platform and offline channels is consistent. For simplicity, the fixed cost and variable cost of merchants are set as zero.

Consumers can purchase products from merchants online and offline. If they purchase online, consumers need to submit their data to the platform to obtain products that are in line with their matching expectations, while consumers do not need to submit any data on offline purchase. Therefore, consumers can be divided into two types. For those consumers who purchase online, they will disclose information, which accounts for θ , while other consumers (which accounts for $1 - \theta$) purchase offline, and they will not disclose any data. For ease of exposition, the number of online consumers is explained as the total disclosed information that obtained by platforms, and it is controlled by consumers unions. Consumers' attitudes toward online use play a mediating role in the relationship between data privacy sensitivity regulating target accuracy and willingness to switch from online to offline channels [39]. In addition, as the consumer information collected by the platform forms an information dominance trend for individual consumers, the possession of consumer data information by the platform will have negative effects on consumers.

Therefore, given the total amount of information θ provided by the consumer union, the purchasing utility of consumers is expressed as follows:

$$u = u_{0i} - \beta(\theta) = \underbrace{\alpha x - p}_{\text{basic utility}} - \underbrace{\beta(\theta)}_{\text{group privacy disutility}}. \quad (1)$$

In Formula (1), $u_{0i} = V(\alpha) - p$, where $V(\alpha)$ is a function concerning consumers' willingness to pay. When α increases, the matching motivation of the platform is stronger, which enhances consumers' willingness to pay. We assume $V(\alpha) = \alpha x$, ($\alpha \leq \alpha \leq \bar{\alpha}$), in which x represents the platforms' capabilities for using consumer groups data. In addition, we assume that the information disclosure level of individual consumers in the same products is homogeneous. Therefore, the negative effect in utility is related to the amount of data that the platform obtains, and it is characterized as θx , i.e., $\beta(\theta) \equiv \theta x$.

Online consumers buying the same product on the platform need to disclose the same private data information, and they will receive more quickly push about merchants' products, thus forming a positive demand matching effect αx [33], but at the same time, online consumers also need to bear the potential privacy disclosure cost $\beta(\theta) \equiv \theta x$, i.e., individual consumers will incur a cost such as inconvenience costs when platforms gather the overall amount of consumer data privacy [12].

In addition, the consumers' private information in offline channels will not be recorded and traced. Therefore, only the consistency of the product price and demand is considered, and consumers' willingness to pay v remains the same as online, so we obtain the consumer utility function $u = v - p = \alpha x - \theta x - p$. We assume that the price of the product is related to the matching level and commission rate on the platform, and the price of the product is denoted as p . We consider that the total market demand share is standardized as one, and the product demand function in two channels is obtained as follows:

$$D(p(\alpha, r)) = \begin{cases} \theta(1 - p(\alpha, r)) & \text{online} \\ (1 - \theta)(1 - p(\alpha, r)) & \text{offline} \end{cases}, (0 \leq p(\alpha, r) \leq 1). \tag{2}$$

The model parameter definitions in the article are shown in Table 1.

Table 1. Parameter definitions.

Parameter	Definition
θ	(1) Percentage of consumers who choose to shop online ($0 \leq \theta \leq 1$); (2) The online disclosure level of each consumer is the same, so the level of the platform to obtain the overall market demand information is also θ .
α	Platform service match parameters ($0 \leq \alpha \leq 1$), the matching level can also be explained as the service (efficiency) level of the platform.
x	The level of consumers' data privacy information used by the platform ($x \geq 1$).
β	Consumer group information is a negative utility.
r	The level at which the platform charges merchants a commission of the transaction ($0 \leq r \leq 1$).
$p(\alpha, r)$	The unit product price set for both online and offline ($0 \leq p \leq 1$).
C_{off}	Fixed costs of offline channels for merchants.
v	Consumers' willingness to pay.
k	The revenue efficiency of platform's use of consumer data privacy ($0 \leq k \leq 1$).
$D(p)$	Consumer demand function.
u	The utility function of the consumer.
$\pi_s(p)$	Merchants' revenue.
$\pi_p(\alpha, r)$	Platform's revenue.
$SW(\alpha, r)$	Social welfare function.

3.2. Basic Assumption

Assumption 1. Consumers are rational in two channels, and they have the same basic willingness to pay for the same product. We also assume that consumers only purchase a unit product in a channel and the return behavior is not considered. Once consumers' online shopping behavior occurs, their data privacy will automatically be disclosed to the platform.

Assumption 2. The platform collects the same amount of data for each online consumer when they purchase the same product. In this way, the total amount of data information obtained by the platform can be regarded as the proportion of consumers participating in online shopping. The higher the proportion of online consumers, the greater the amount of group privacy data gathered by the platform. The proportion of online consumers is equivalent to the amount of privacy data obtained by the platform.

Assumption 3. We take this case as our benchmark that the platform only relies on a cut of product sales from merchants, and it has no direct commercial benefit from the consumer information acquired. In addition, it is unclear that market regulation is efficient; therefore, there is also an uncertainty of the benefits of innovation by the platform using the consumer data collected by the platform.

Assumption 4. Assume that the cost of the product offline is a fixed cost, while the online channel cost is set as zero, and the merchant monopolizes the product market. Meanwhile, merchants expect to expand online sales channels with the help of platform influence. Therefore, merchants can expand the market influence of products with small profits and quick sales through online channels.

3.3. Game Sequence

The sequence of the three-party game is set as follows:

Firstly, the platform determines the service matching level and commission rate, i.e., α and r . Secondly, the merchants determine the product price according to the service matching level and commission rate proposed by the platform. Finally, after consumers observe the price p of merchants, they decide whether to shop online or offline according to their consumption and privacy disclosure habits. There is also the consumer union to control the overall group data privacy information level θ that consumers disclose.

In addition, there is a two-stage game regarding market regulation on the use of consumer private data. In stage t_1 , the platform does not obtain the permission of the consumer union, or the service matching level α does not reach the threshold α^* , and the platform does not extract transaction commissions from the transaction between merchants and consumers. In this case, the platform simply collects consumer transaction data to carry out their service business. In stage t_2 , when the platform service matching level reaches the threshold α^* and is approved by the consumer union, the platform can not only extract transaction commission but also use consumer data as a factor of production to practice business model innovation and gain profits. The sequential game is shown in Figure 1.

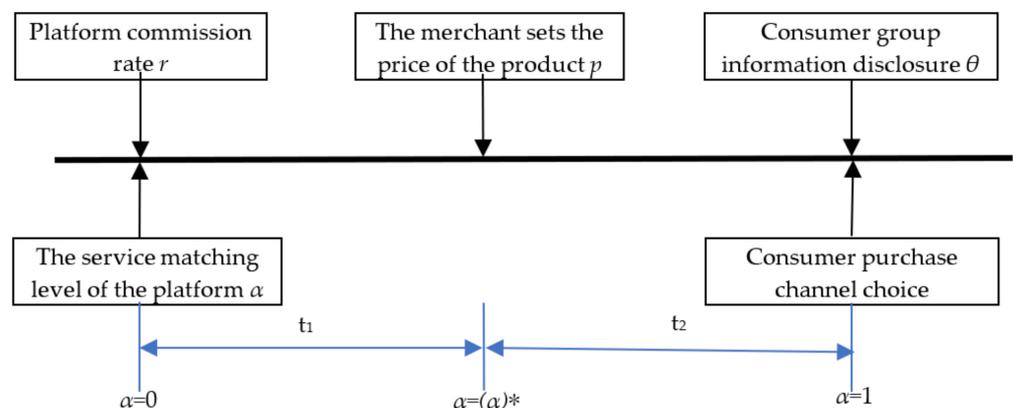


Figure 1. Sequential game model.

4. Equilibrium Analysis

4.1. Online Consumer Private Information Disclosure

We solve the three-party game equilibrium via backward induction. According to the online participation constraints of consumers $u \geq 0$, the expression of the information disclosure level of online consumer data can be obtained as follows:

$$\theta = \min \left\{ \frac{x\alpha - p}{x}, 1 \right\}. \tag{3}$$

Evidently, consumers expect that the higher the service matching level α of the platform, the more they are willing to buy and disclose private information on an online platform.

4.2. Merchant’s Product Pricing and Profit

According to Equation (3), the profit of merchants is the product of the online and offline demand and price. Therefore, the profit function of merchants is:

$$\pi_s = \theta p(1 - p)(1 - r) + (1 - \theta)p(1 - p) = \left[1 - \frac{(x\alpha - p)}{x}r \right] p(1 - p) - C_{off}. \tag{4}$$

According to the first-order condition $\frac{\partial \pi_s}{\partial p} = 0$, we can obtain $3rp^2 - 2(r + \alpha rx - x)p - (x - r\alpha x) = 0$. The following proposition shows the optimal price that the merchant set.

Proposition 1. *The equilibrium pricing expression of the merchant can be obtained as follows:*

$$p_s^* = \frac{r + \alpha rx - x + \sqrt{(r + \alpha rx - x)^2 + 3rx(1 - \alpha r)}}{3r} = \frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{(x^2\alpha^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r}. \tag{5}$$

Merchants’ pricing consists of three parts: the product base price, the service matching price, and the commission price, which jointly determine the market price of the product.

Since online transactions occur after consumers register and disclose private information on the platform, therefore, the constraint concerning online consumers participation is $\theta = \frac{x\alpha - p}{x} \geq 0$. Then, we obtain $x\alpha(x\alpha - 1)r \geq x(1 - 2x\alpha)$. We substitute p_s^* into the constraint of consumers participating in an online platform purchase, after which the constraints on the participation of merchants and consumers are obtained as follows.

$$s.t. \begin{cases} x\alpha(x\alpha - 1)r \geq x(1 - 2x\alpha) \\ r \in [0, 1] \\ \alpha \in [0, 1] \\ x \in [1, \infty) \end{cases} \Rightarrow \begin{cases} x\alpha \leq 1 \\ r \leq 1 \\ 0 \leq r \leq \frac{2x\alpha - 1}{\alpha(1 - x\alpha)} \end{cases} \tag{6}$$

To make the participation constraint condition strictly hold, it must be $\frac{2x\alpha - 1}{\alpha(1 - x\alpha)} \geq 1$, and we can obtain $\alpha \in [\frac{\sqrt{4x^2 + 1} + 1 - 2x}{2x}, 1]$. Therefore, Proposition 2 is obtained.

Proposition 2. $\alpha = \frac{\sqrt{4x^2 + 1} + 1 - 2x}{2x}$ is defined as the service matching threshold. If $\alpha \in [0, \frac{\sqrt{4x^2 + 1} + 1 - 2x}{2x})$, it indicates that the service matching motivation of the platform is low and cannot meet the constraints of consumer participation. Consumers will not consider shopping online on the platform. In addition, when the $\alpha \in [\frac{\sqrt{4x^2 + 1} + 1 - 2x}{2x}, 1], r \in (0, 1)$ condition occurs, consumers and merchants begin to participate in the platform for service matching transactions.

It is easy to know $\frac{\partial p_s^*}{\partial r} > 0, \frac{\partial p_s^*}{\partial \alpha} > 0, \frac{\partial p_s^*}{\partial \alpha} - \frac{\partial p_s^*}{\partial r} > 0$, which indicates that both the platform’s commission level and service matching level have a positive impact on the pricing of merchants, and the platform’s service matching motivation α has a greater impact on the equilibrium price p_s^* than the commission level r does.

By substituting the price (5) into Equation (4), the merchant revenue can be expressed as follows:

$$\pi_s|_{p=p_s^*} = \begin{cases} \left\{ \begin{aligned} &\left(\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right) \\ & * \left(\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right) \end{aligned} \right\} - C_{off} & \alpha \in \left[0, \frac{\sqrt{4x^2+1+1-2x}}{2x} \right) \\ \left\{ \begin{aligned} &\left[1 - \left(\frac{2x\alpha}{3} - \frac{1}{3} - \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right) \frac{r}{x} \right] \\ & * \left(\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right) \\ & * \left(\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right) \end{aligned} \right\} & \alpha \in \left[\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1 \right] \end{cases} \quad (7)$$

The variation trend of merchant revenue $\pi_s|_{p=p_s^*}$ is shown in Figure 2 below.

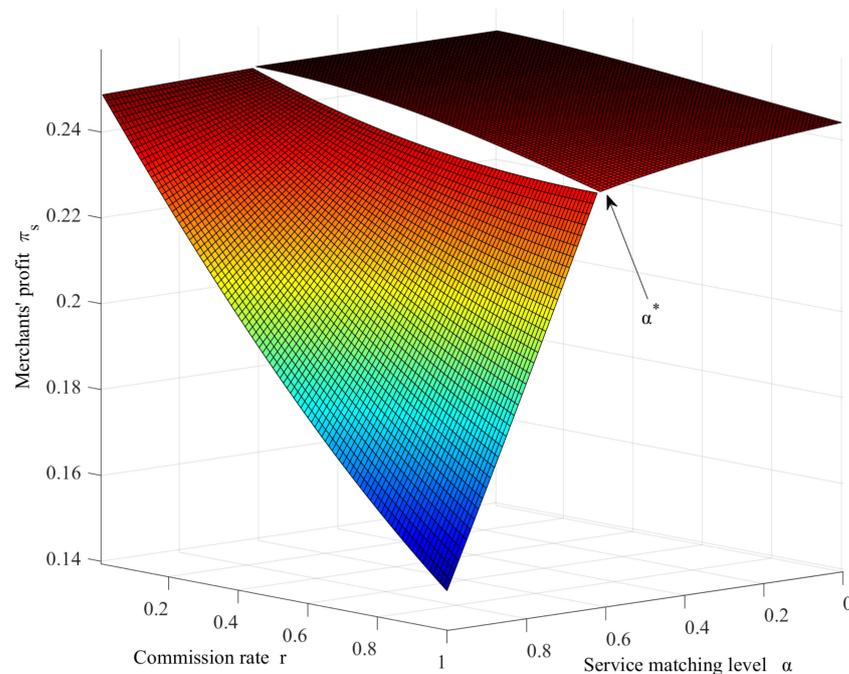


Figure 2. Merchants’ earnings change with service matching level and commission rate.

When $r \in [0, 1]$ and $\alpha \in [0, \frac{\sqrt{4x^2+1+1-2x}}{2x})$, it is easy to obtain $\frac{\partial \pi_s}{\partial \alpha} < \frac{\partial \pi_s}{\partial r} < 0$; that is, $\pi_s(\alpha, r)$ decreases in the interval. The maximum of the merchant income is $\pi_s(0, 0) = \frac{1}{4}$. When $r \in [0, 1]$ and $\alpha \in [\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1]$, according to L’Hospital’s rule, we obtain the equilibrium price:

$$\lim_{r \rightarrow 0} p_s^* = \frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{(x^2\alpha^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} = \frac{1}{3} + \frac{x\alpha}{3} + \frac{1 - 2x\alpha}{6} = \frac{1}{2}.$$

The maximum points of merchant income are all obtained at $r = 0$, and the extreme points are $\pi_s(\frac{\sqrt{4x^2+1+1-2x}}{2x}, 0) = \frac{1}{4}$ and $\pi_s(1, 0) = \frac{1}{4}$. At the threshold of the service matching level of the platform, i.e., when merchants and consumers join the platform, let $x = 1$; then, the revenue of merchants is $\pi_s(\frac{\sqrt{5}-1}{2}, 1) = 2361$.

Therefore, if a merchant joins the platform when the matching rate of the platform is low, the maximum ideal revenue solution is the set in which the platform’s commission

rate is zero, i.e., when $r = 0$ and $\alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1]$, $\pi_s|_{\max} = \pi_s(\alpha, 0) = \frac{1}{4}$. The results above imply that if the platform does not extract commission, even if the service matching level is low, the merchant will choose to join the platform considering the online channel's influence of the platform.

However, after the platform service matching motivation reaches the threshold $\frac{\sqrt{4x^2+1}+1-2x}{2x}$, merchants will decide whether to join the platform or not according to the platform commission rate, which obviously will reduce merchants' income. With the increase in the platform service matching level, consumers and merchants will complete more transactions on the platform online, so more information rent is extracted by the platform. However, when the matching level reaches the threshold, the influence of the platform commission rate on the merchants' income decreases.

There is a huge change in the merchants' profit when the platform's matching level reaches $\alpha^* = \frac{\sqrt{4x^2+1}+1-2x}{2x}$. As the platform's matching level keeps increasing, the merchants' profit declines, which to some extent gets lost from the commission rate. A feasible explanation is that the merchants' pricing goal changes after the matching service of the platform improving (α reach to threshold α^*). Therefore, even though there is a certain income loss, the merchant also tends to use the service channels of the platform to improve the product's marketing ability.

4.3. Platform Revenues

4.3.1. Consumer Data Privacy Use Is Regulated

The platform's revenue comes from online transaction commissions and the profits come from online consumer group data. Therefore, the platform revenue equations are shown as follows:

$$\pi_p(r) = \begin{cases} fk\theta x & \alpha \in [0, \frac{\sqrt{4x^2+1}+1-2x}{2x}) \\ r\theta p(1-p) + fk\theta x & \alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1] \end{cases} \quad (8)$$

From Equation (8), f represents the market regulation parameter of whether the platform can use consumer privacy information to generate income, i.e., $f \in \{0, 1\}$. For example, when $f = 0$ holds, there is market regulation. In other words, due to market regulation, platforms cannot make use of consumer data privacy to gain profits. Therefore, when the market controls the use of consumer data privacy, the revenue of the platform only comes from the market commission r of the online matching between merchants and consumers. k is the income-generating efficiency of the platform's use of consumers' private information data. When the platform cannot use consumer data to generate revenue, the platform revenue equation is in the following expression:

$$\pi_p(\alpha, r) = \begin{cases} 0 & \alpha \in [0, \frac{\sqrt{4x^2+1}+1-2x}{2x}), \\ r\theta p(1-p) = \frac{r}{x}(x\alpha - p)p(1-p) & \alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1] \end{cases} \quad (9)$$

Substitute Equation (5) into Equation (9), and we can obtain:

$$\pi_p(\alpha, r) = \begin{cases} 0 & \alpha \in [0, \frac{\sqrt{4x^2+1}+1-2x}{2x}), \\ \left\{ \begin{array}{l} \frac{r}{x} \left(\frac{2x\alpha}{3} - \frac{1}{3} - \frac{\sqrt{((x\alpha)^2+1-x\alpha)r^2+r(x-2x^2\alpha)+x^2-x}}{3r} \right) \\ * \left(\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2+1-x\alpha)r^2+r(x-2x^2\alpha)+x^2-x}}{3r} \right) \\ * \left(\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2+1-x\alpha)r^2+r(x-2x^2\alpha)+x^2-x}}{3r} \right) \end{array} \right\} & \alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1] \end{cases} \quad (10)$$

When the interval is $\alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1]$ and $r \in [0, 1]$, both $\frac{\partial \pi_p}{\partial \alpha} > 0$ and $\frac{\partial \pi_p}{\partial r} > 0$ exist. The optimal matching level and commission rate for maximizing the platform revenue are $(\alpha^*, r^*) = (1, 1)$, as shown in Figure 3 below. Therefore, the platform should

improve its service level—matching rate α as much as possible and make the platform occupy all product market shares through self-management or the overall acquisition of merchants (percentage $r = 1$) to achieve the optimal revenue.

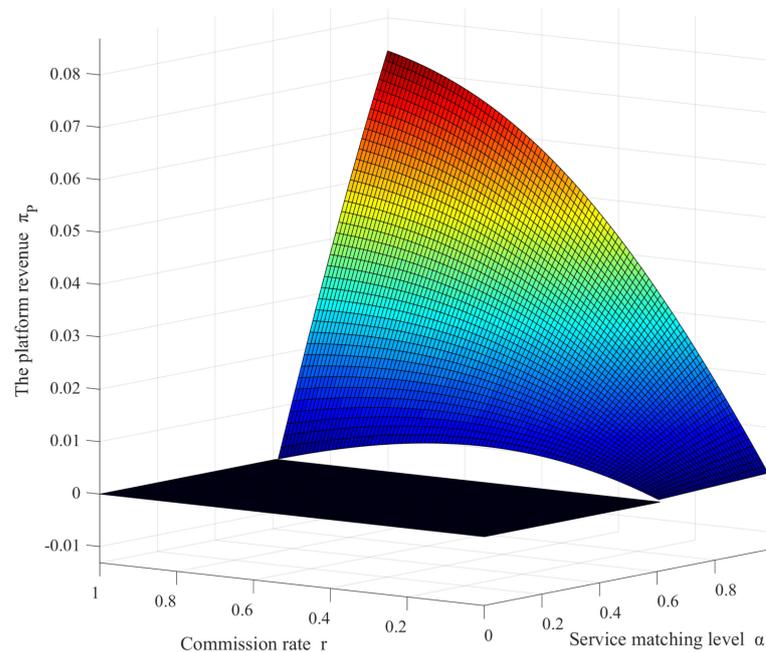


Figure 3. The platform revenue changes with the matching level and commission rate when the use of consumer data information is regulated.

As can be seen from Figure 3, after the service matching level reaches the threshold, the platform’s service matching level and commission rate will have a certain influence on its revenue. While when $\frac{\sqrt{4x^2+1}+1-2x}{2x} < \alpha_1 = \alpha_2$ and $r_1 < r_2$, there is $\frac{\partial \pi_p}{\partial \alpha} \Big|_{r=r_2} < \frac{\partial \pi_p}{\partial \alpha} \Big|_{r=r_1} < 0$, and when $r_1 = r_2$ and $\alpha_1 < \alpha_2$, $\frac{\partial \pi_p}{\partial r} \Big|_{\alpha=\alpha_2} < \frac{\partial \pi_p}{\partial r} \Big|_{\alpha=\alpha_1} < 0$. Therefore, the maximum revenue of the platform is:

$$\pi_p(r, \alpha) \Big|_{x=1} \Big|_{\max} = \pi_p(1, 1) = \frac{1}{x} \left(\frac{2x}{3} - \frac{1}{3} - \frac{1-x}{3} \right) \left(\frac{1}{3} + \frac{x}{3} + \frac{1-x}{3} \right) \left(\frac{2}{3} - \frac{x}{3} - \frac{1-x}{3} \right) = \frac{2}{9} - \frac{4}{27x} = \frac{2}{27}. \tag{11}$$

As shown in Figure 3, when the platform is subject to market regulation, the maximum point of the platform is (1, 1), which means that the platform needs to completely take over the market, i.e., set the commission level to one, and it also needs to improve the technical matching service (make the matching rate to one).

Under the above strategy of the platform, as the platform cannot use consumer privacy data to generate income, the revenue capability of the platform will no longer improve as consumer demand approaches saturation, as shown in Figure 4. Here, the data usage level is used to reflect the revenue of the platform, which is similar to the research results of [30].

It is evident that both merchants and platforms want more transactions to take place online to generate more revenue. It is accepted widely that the service matching level α is the key to improve the service level, which enables platforms and merchants to enhance more profits without increasing the commission rate r .

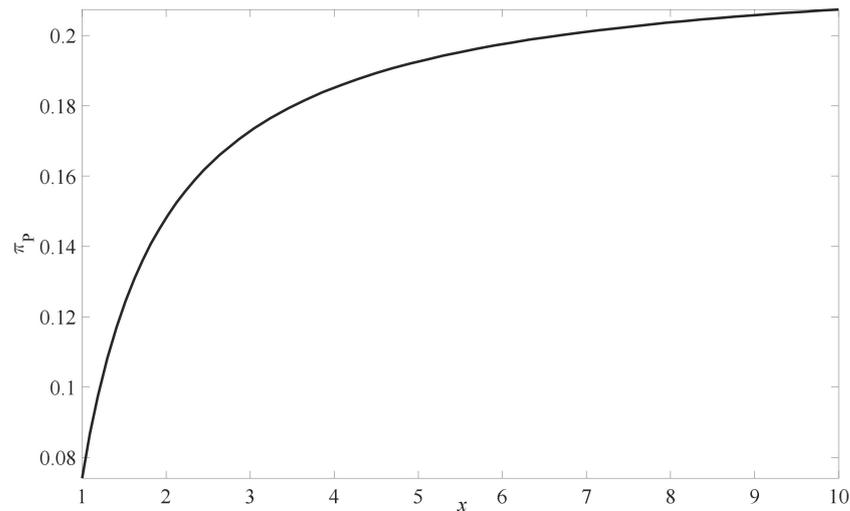


Figure 4. Platform revenue changes as consumer data usage level x under strategy $\pi_p(1,1)$.

If the platform wants to obtain more revenue, it needs to consider monetizing consumer group data privacy and generating revenue from the new value-added service model driven by consumer data. Therefore, we will discuss how the platform can replace the commission revenue strategy with consumer data-driven innovation next.

4.3.2. Consumer Group Data Privacy Use Is Unregulated

If the platform’s use of consumer data collected by the platform is not subject to market regulation, and the consumer group privacy disclosure value is $\theta \geq 0$, the platform will get an additional consumer group data privacy benefit of $k\theta$, which is as follows:

$$\pi_p(\alpha, r) = \begin{cases} 0 & \alpha \in [0, \frac{\sqrt{4x^2+1}+1-2x}{2x}), \\ r\theta p(1-p) + k\beta(\theta) = r(\frac{x\alpha-p}{x})p(1-p) + k\frac{x\alpha-p}{x} & \alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1] \end{cases} \quad (12)$$

Substitute Equation (5) into Equation (12), and the platform revenue expression is as follows:

$$\pi_p(\alpha, r) = \begin{cases} 0 & \alpha \in [0, \frac{\sqrt{4x^2+1}+1-2x}{2x}), \\ \left\{ \begin{aligned} & \frac{r}{x} \left(\frac{2x\alpha}{3} - \frac{1}{3} - \frac{\sqrt{((x\alpha)^2 - x\alpha + 1)r^2 + (x - 2\alpha x^2)r + x^2 - x}}{3r} \right) \\ & * \left(\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2 - x\alpha + 1)r^2 + (x - 2\alpha x^2)r + x^2 - x}}{3r} \right) \\ & * \left(\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2 - x\alpha + 1)r^2 + (x - 2\alpha x^2)r + x^2 - x}}{3r} \right) \\ & + \frac{k}{x} \left(\frac{2x\alpha}{3} - \frac{1}{3} - \frac{\sqrt{((x\alpha)^2 - x\alpha + 1)r^2 + (x - 2\alpha x^2)r + x^2 - x}}{3r} \right) \end{aligned} \right\} & \alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1] \end{cases} \quad (13)$$

When $\alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1]$, it is easy to obtain $\frac{\partial \pi_p(\alpha, r)}{\partial \alpha} > 0$, and for $r^* \in [0, 1]$, $\frac{\partial \pi_p(\alpha, r^*)}{\partial r^*} = 0$. Specifically, for $r \in [0, r^*]$, $\frac{\partial \pi_p(\alpha, r)}{\partial r} > 0$, while for $r \in [r^*, 1]$, $\frac{\partial \pi_p(\alpha, r)}{\partial r} < 0$. From here, we can see that the revenue of the platform will increase with the increase in the matching rate, and there is an optimal commission level, which also depends on the data generating efficiency k of the platform. According to L’Hospital’s rule, $\lim_{r \rightarrow 0} \frac{\sqrt{((x\alpha)^2+1-x\alpha)r^2+r(1-2x^2\alpha)+x^2-x}}{3r} = \frac{1-2\alpha}{6}$. $x = 1$

Therefore, the maximum of platform revenue within this range is:

$$\pi_p(\alpha, r) \Big|_{x=1}^{\max} = \pi_p(1, r^*) = r^* \left(\frac{1}{3} - \frac{\sqrt{r^{*2} - r^* + 1} - 1}{3r^*} \right)^2 \left(\frac{2}{3} + \frac{\sqrt{r^{*2} - r^* + 1} - 1}{3r^*} \right) + k \left(\frac{1}{3} - \frac{\sqrt{r^{*2} - r^* + 1} - 1}{3r^*} \right). \quad (14)$$

Proposition 3. When the platform uses consumer data privacy to generate income, the platform has an optimal commission rate, and the strategy to maximize the platform’s income is $(1, r^*)$.

The platform revenue changes with the commission rate, as shown in Figure 5 below.

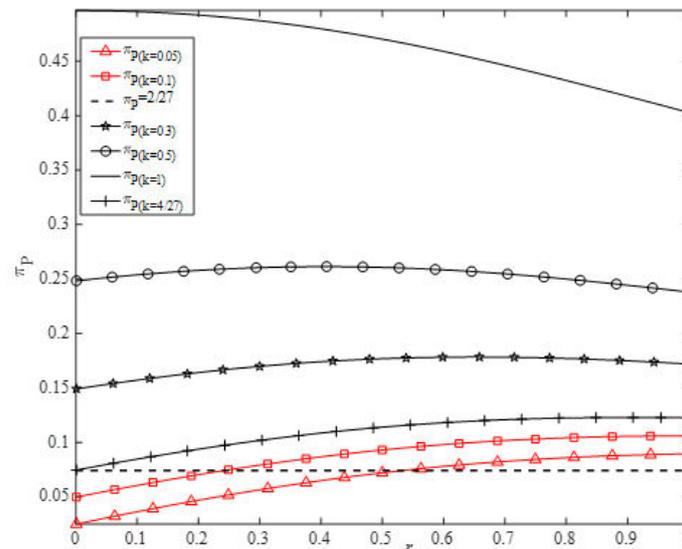


Figure 5. Platform’s revenue as commission rate changing when the consumer groups privacy is used.

Figure 5 shows that there is $r^* \in [0, 1]$, when $0 \leq k \leq \frac{4}{27}$, $\pi_p(\alpha, r) \Big|_{x=1}^{\max} = \pi_p(1, r^*) \leq \pi_p(1, 1)$, while when $\frac{4}{27} \leq k \leq 1$, we can obtain $\pi_p(\alpha, r) \Big|_{x=1}^{\max} = \pi_p(1, r^*) \geq \pi_p(1, 1)$, and when $k \rightarrow 1, r^* \rightarrow 0$.

Proposition 4. When the platform uses consumer data privacy to generate income, if the platform uses consumer data to generate income efficiency k reaches a certain level, the platform’s revenue will reduce when the platform’s commission rate increases, while when the platform’s matching rate increases, the platform’s revenue also increases.

Therefore, the relaxed regulation allows the platform’s profit to be greatly improved, and the maximum point is $(1, r^*)$. At this time, what the platform needs to do is to provide a better matching service (make the matching rate to one), and it should reduce the commission rate to r^* according to the change of the platform’s income-generating efficiency concerning the use of consumers’ data privacy. As shown in Figure 5, a comparison is made on whether the platform uses consumer data to generate income. It is found that when the income-generating efficiency of platform data is improved, the platform’s income is considerable. The expressions of Equations (10) and (13) are drawn as shown in Figure 6 below.

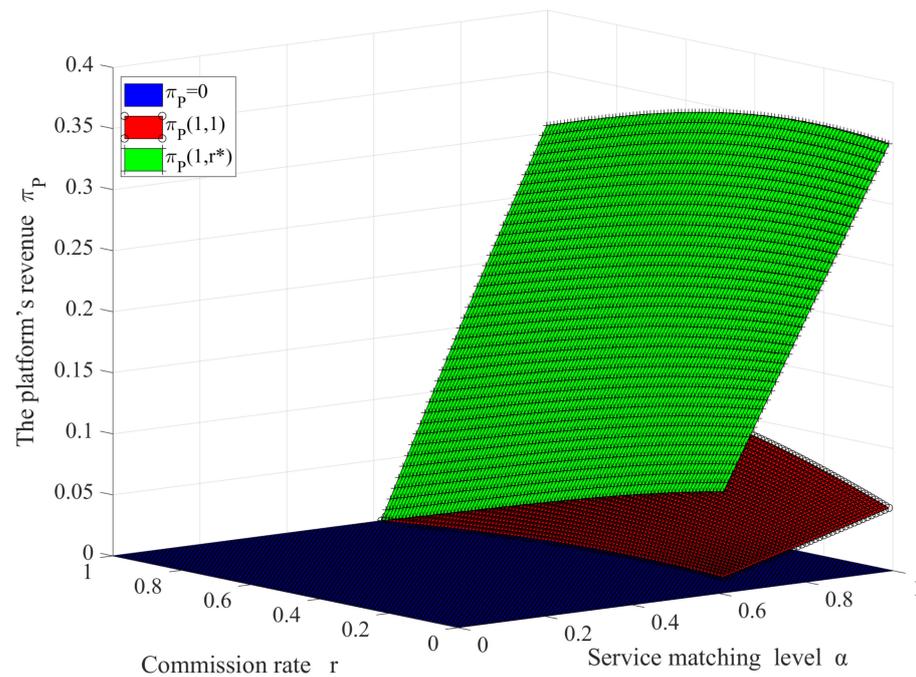


Figure 6. The platform’s revenue changes with the strategy $\pi_p(1, 1)$ and $\pi_p(1, 0)$.

5. Social Welfare Influence

The service matching effect of merchant price, the effect of commission, and the impact of consumer group data privacy on social welfare will be discussed here. Considering whether the platform will use consumer group data to carry out targeted advertising, product innovation, and other business methods to practice income realization, the social welfare function is expressed as follows:

$$SW = pD(p) + fk\theta = p(1 - p) + fk\theta = \left\{ \begin{array}{l} [\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2+1-x\alpha)r^2+r(x-2x^2\alpha)+x^2-x}}{3r}] \\ *[\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2+1-x\alpha)r^2+r(x-2x^2\alpha)+x^2-x}}{3r}] \end{array} \right\} + fk\theta. \tag{15}$$

5.1. The Influence of Platform Data Usage Level on Social Welfare

Under the market regulation, consumer private data cannot be used to improve social welfare. According to the formula of social welfare level, it is found that when $\alpha_1 = \alpha_2$ and $r_1 = r_2$, if the platform data use level $x_1 < x_2$, there must be $\frac{\partial SW}{\partial r} \Big|_{x=x_2} < \frac{\partial SW}{\partial r} \Big|_{x=x_1} < 0$ and $\frac{\partial SW}{\partial \alpha} \Big|_{x=x_2} < \frac{\partial SW}{\partial \alpha} \Big|_{x=x_1} < 0$. This indicates that the higher the level of platform data use x is, the more elastic the impact of the platform commission rate and service matching level on social welfare will be. To make it more intuitive, we take $x = 1$ and $x = 2$ respectively and put them into the social welfare formula to obtain the social welfare levels as follows:

$$SW|_{x=1} = p(1 - p) = \left\{ \begin{array}{l} [\frac{1}{3} + \frac{\alpha}{3} + \frac{\sqrt{(\alpha^2+1-\alpha)r^2+r(1-2\alpha)+1-1}}{3r}] \\ *[\frac{2}{3} - \frac{\alpha}{3} - \frac{\sqrt{(\alpha^2+1-\alpha)r^2+r(1-2\alpha)+1-1}}{3r}] \end{array} \right\} \tag{16}$$

$$SW|_{x=2} = p(1 - p) = \left\{ \begin{array}{l} [\frac{1}{3} + \frac{2\alpha}{3} + \frac{\sqrt{(4\alpha^2+1-2\alpha)r^2+r(2-8\alpha)+4-2}}{3r}] \\ *[\frac{2}{3} - \frac{2\alpha}{3} - \frac{\sqrt{(4\alpha^2+1-2\alpha)r^2+r(2-8\alpha)+4-2}}{3r}] \end{array} \right\}. \tag{17}$$

From Figure 7, it can be seen intuitively that the higher the level of platform data use, the greater the impact of social welfare level on the change of the platform’s commission rate and matching rate. This conclusion explains why platforms want to maximize the

collection of consumer data. A reasonable explanation is to use as much consumer data as possible to improve the matching rate and thus improve the level of social welfare. The higher the level of platform data use, the greater the impact of the social welfare platform matching rate and the rate of commission, and consumers will be more cautious about the platform to disclose private information.

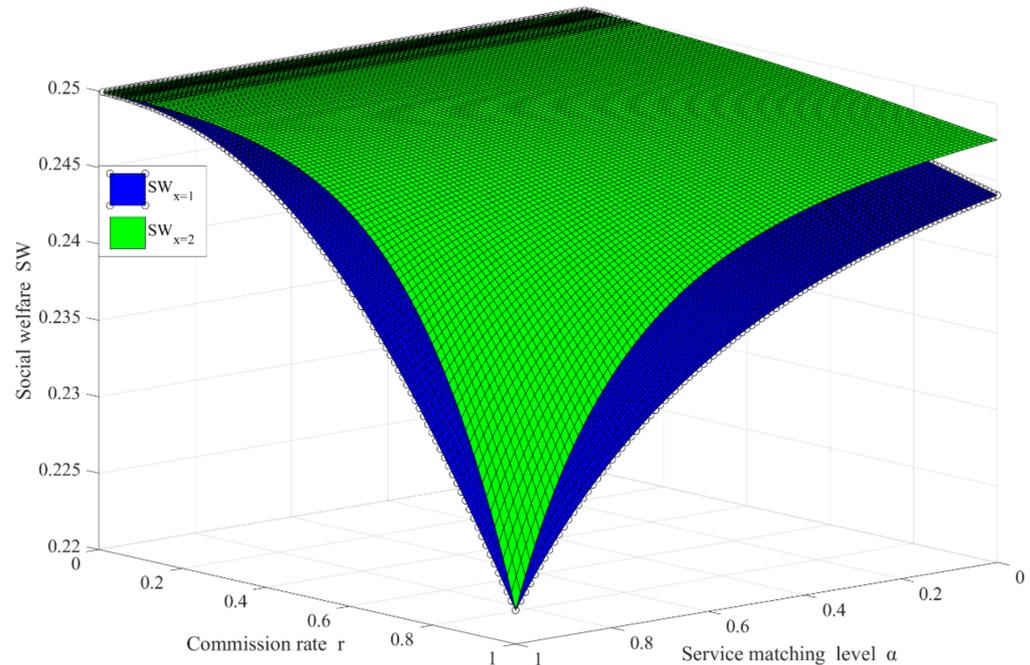


Figure 7. Level of platform data usage x on social welfare.

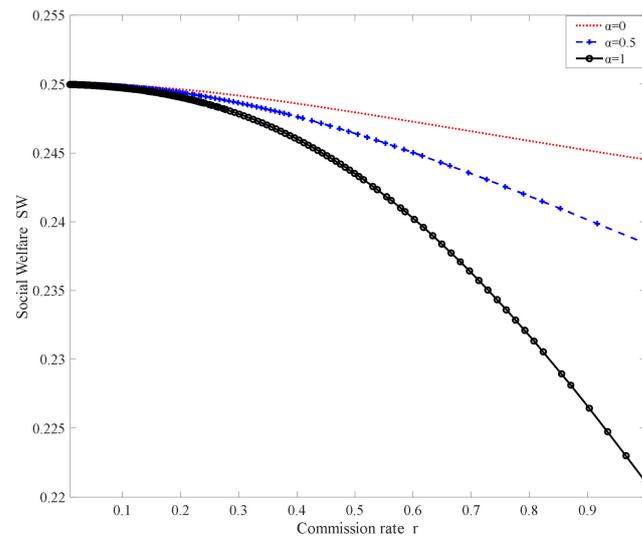
5.2. The Influence of Commission Rates on Social Welfare

Where the use of consumer data privacy is regulated, platforms cannot use consumer privacy to generate revenue. Due to $\frac{\partial SW}{\partial r} < 0$, $\alpha_1 = \alpha_2$, and $r_1 < r_2$, $\left. \frac{\partial SW}{\partial \alpha} \right|_{r=r_2} - \left. \frac{\partial SW}{\partial \alpha} \right|_{r=r_1} < 0$. The result indicates that the platform commission rate will reduce social welfare, and at the same service matching level, the higher the platform commission rates, the more serious the change of social welfare loss will be, especially in the case of high matching rates and high commission rates. This is because the platform commission rate increases the price of the product and shrinks the market demand, thereby sharply reducing the social welfare level, as shown in Figure 8a below.

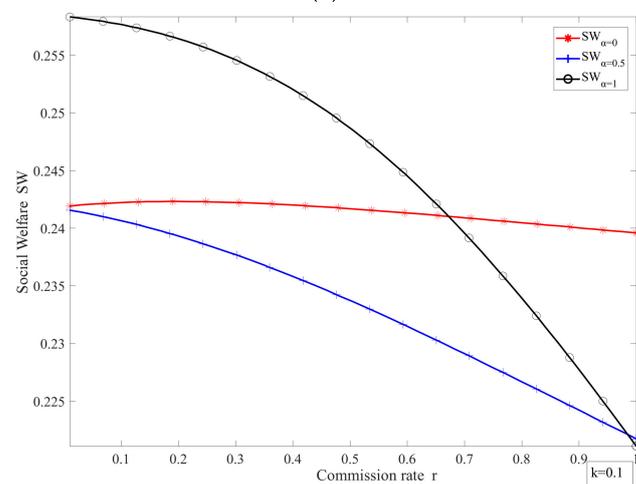
When the market relaxes the regulation, the social welfare will decline with the increase in service matching level and commission rates of the platform, as shown in Figure 8b.

5.3. The Influence of Service Matching Level on Social Welfare

When the use of consumer data privacy is regulated, the service matching level of the platform will also affect the level of social welfare, as shown in Figure 9a below. Different commission rates have different influences on social welfare. If the commission rate is low ($r \rightarrow 0$), the platform service matching level will have little influence on social welfare, i.e., $\lim_{r \rightarrow 0} \frac{\partial SW}{\partial \alpha} = 0$. If the level of commission is too high ($r \rightarrow 1$), the impact of service matching level on social welfare will increase with the increase in commission, i.e., $\frac{\partial^2 SW}{\partial \alpha^2} < 0$. When $r_1 = r_2$ and $\alpha_1 < \alpha_2$, there is $\left. \frac{\partial SW}{\partial r} \right|_{\alpha=\alpha_2} < \left. \frac{\partial SW}{\partial r} \right|_{\alpha=\alpha_1} < 0$.



(a)



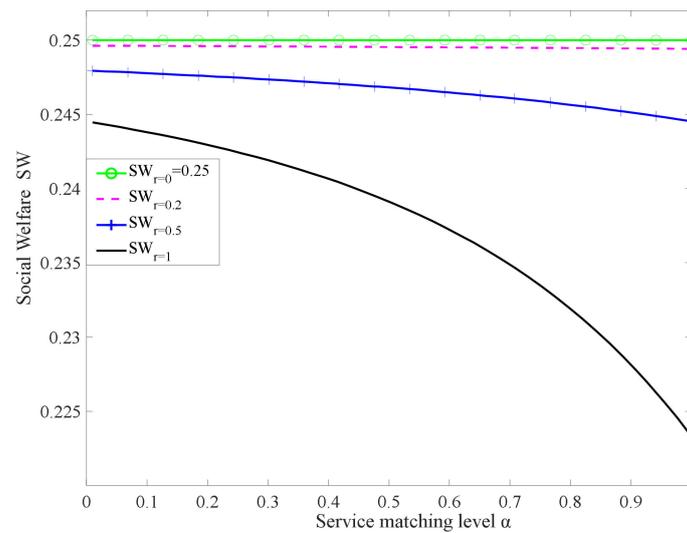
(b)

Figure 8. (a) The impact of commission rates r on social welfare (without privacy benefits). (b) The impact of commission rate r on social welfare (with consumer privacy benefits).

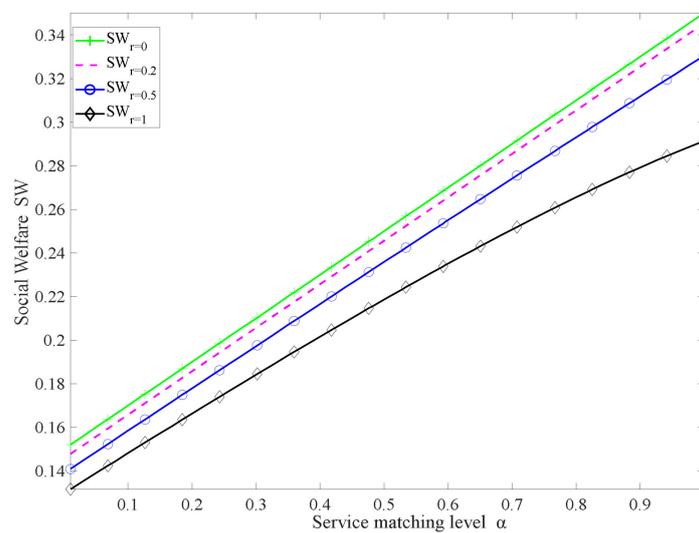
When the platform is unable to obtain privacy benefits, there is a synergistic relationship between the service matching level α of the platform and the commission rate r to improve or weaken social welfare; i.e., the matching level and the commission rate change the direction of social welfare in the same way. Meanwhile, when the platform can generate revenue from consumer privacy, the increase in the platform service matching level contributes to the improvement of social welfare, as shown in Figure 9b. In this case, $\frac{\partial SW}{\partial r} < 0$ and $\frac{\partial SW}{\partial \alpha} > 0$; i.e., the impact of the change concerning service matching level and commission rate on social welfare is opposite.

Corollary 1. *When the platform does not use consumer data privacy to generate income, the higher the level x of the platform’s use of consumer data, the more elastic the impact of the platform’s commission rate and service matching level on social welfare will be.*

It is easy to prove similar conclusions when platforms use consumer data privacy to generate revenue.



(a)



(b)

Figure 9. (a) The impact of matching rate on social welfare at different commission rates (without consumer privacy benefits). (b) The impact of matching level on social welfare at different commission rates (with consumer privacy benefits).

5.4. The Influence of Consumer Data Privacy on Social Welfare

Here, we consider two extreme cases. If consumer data privacy is strictly regulated by the market and platforms are not allowed to use consumer data privacy to carry out business model innovation gain revenue, then consumer group data privacy is not included in the social welfare function; i.e., $f = 0$. If the platform’s use of data privacy for consumer groups is not subject to market regulation, if the consumer union is willing to disclose, then the income generated by the platform’s use of data privacy is included in the social welfare function; i.e., $f = 1$. Therefore, the expression of the social welfare function is as follows:

$$SW = \begin{cases} p(1-p) & \alpha \in [0, 1] \\ \left\{ \begin{array}{ll} p(1-p) & \alpha \in [0, \frac{\sqrt{4x^2+1}+1-2x}{2x}] \\ p(1-p) + k\theta x & \alpha \in [\frac{\sqrt{4x^2+1}+1-2x}{2x}, 1] \end{array} \right\} & f = 1 \end{cases} \quad (18)$$

Take Equation (5) into Equation (18) above, then:

$$\text{SW} = \left\{ \begin{array}{l} \left\{ \begin{array}{l} \left[\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right] \\ * \left[\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right] \end{array} \right\} \begin{array}{l} \alpha \in [0, 1] \\ \alpha \in \left[0, \frac{\sqrt{4x^2 + 1} + 1 - 2x}{2x} \right) \end{array} \\ \\ \left\{ \begin{array}{l} \left[\frac{1}{3} + \frac{x\alpha}{3} + \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right] \\ * \left[\frac{2}{3} - \frac{x\alpha}{3} - \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right] \\ +k \left[\frac{2x\alpha}{3} - \frac{1}{3} - \frac{\sqrt{((x\alpha)^2 + 1 - x\alpha)r^2 + r(x - 2x^2\alpha) + x^2 - x}}{3r} \right] \end{array} \right\} \begin{array}{l} \alpha \in \left[\frac{\sqrt{4x^2 + 1} + 1 - 2x}{2x}, 1 \right] \end{array} \end{array} \right. \quad (19)$$

Corollary 2. When the platform does not use consumer data privacy to generate income, the platform will not give up the revenue, and the three parties cannot achieve equilibrium. When the platform uses consumer data privacy to generate revenue, the three-party equilibrium point is to maximize the service matching level and adjust the commission rate to r^* ; i.e., the platform's $(1, r^*)$ strategy is partial equilibrium. When $\alpha = 1$ and $k = 1$, $r^* = 0$. Relevant proof of Corollary 2 can be seen in Appendix A.

As can be seen from Figure 10, when the platform does not use consumer data to generate revenue, $\frac{\partial SW}{\partial r} < 0$ and $\frac{\partial SW}{\partial \alpha} < 0$. Therefore, the minimum of social welfare is $SW|_{(1,1)} = \frac{2}{9}$, and the maximum is $SW|_{(1,0)} = \frac{1}{4}$. In this case, the social welfare is less affected by the platform service matching level and commission rate.

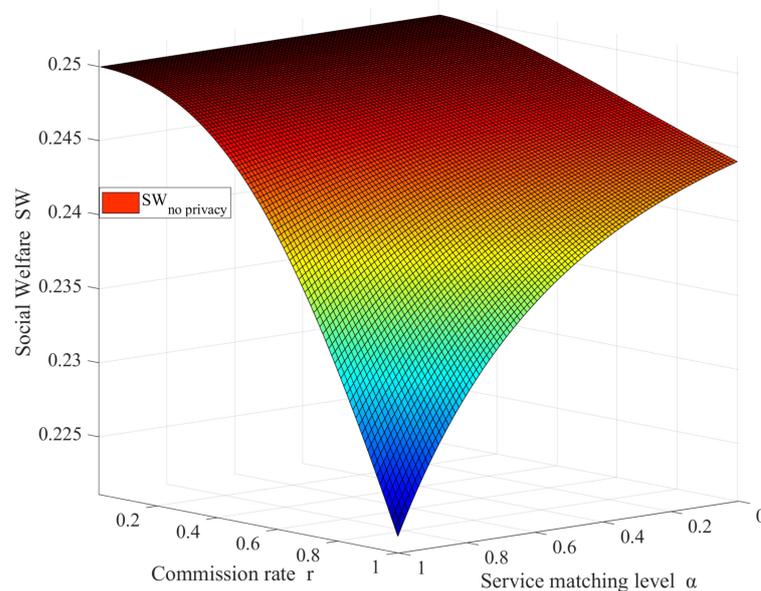


Figure 10. Changes in social welfare when the platform is without consumer data θ .

This is obvious from Figure 11.

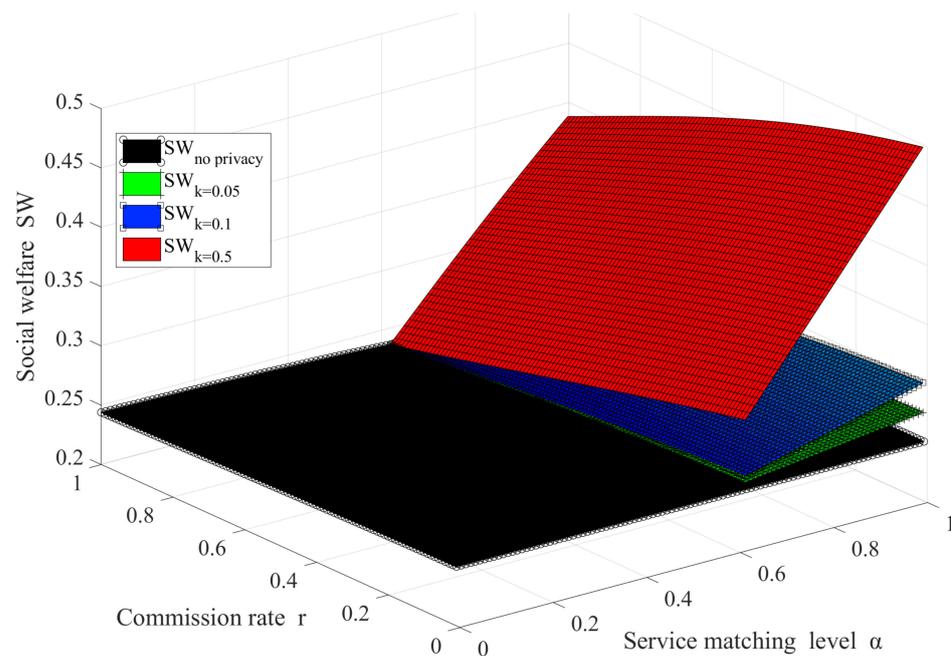


Figure 11. Influence of using consumer data to generate income on social welfare.

Firstly, if the platform does not monetize using consumer data privacy θ , the platform tends to maximize its revenue (maximizing the commission rate), i.e., (1, 1) strategy. At this point, the maximization point of the merchant income and social welfare (1,0) cannot be reached; i.e., the three parties fail to reach equilibrium. In reality, the platform needs to give up earnings in the short term (commission rate into $r = 0$) through the continuous upgrading of the service ability of the platform (service matching level of $\alpha \rightarrow 1$) to attract merchants and consumers to participate in the online channel of the platform. Then, gradually enhance the level of the commission rate (make commission rate into $r \rightarrow 1$), so that the result is a platform to take (1, 1) strategy to achieve maximum benefits. Then, minimize the merchant and social welfare; i.e., the platform will accelerate the extraction of consumer value by increasing the matching level and commission rate.

Additionally, if the platform can monetize using consumer data privacy θ , the optimal revenue strategy is (1, r^*). That is, the platform will adjust the market commission rate (rate $r = r^*$) and improve the service matching level (make the matching level $\alpha \rightarrow 1$). This strategy can maximize merchants and social welfare while improving platform revenue; i.e., (1, r^*) is the equilibrium point of the platform, merchants, and social welfare. If the platform continues to enhance the commission rate without improving the service matching level, it will not only reduce the platform’s income but also damage the social welfare, which needs to be paid attention to in future regulation.

5.5. Equilibrium Evolution Analysis

As shown in Figure 12, at stage t_1 , consumer data privacy is strictly regulated by the market, and the platform cannot make profits by relying on consumer data privacy but only by taking commission. In this case, the maximum point (α, r) of the platform income is (1, 1). The maximum point of the merchant income is $(\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1)$ and $(\frac{\sqrt{4x^2+1+1-2x}}{2x}, 0)$. The maximum point of the social welfare function is (1,0); therefore, the three parts cannot reach equilibrium.

At stage t_2 , when the use of consumer data privacy is deregulated, the platform relies on the innovation of consumer data elements to obtain benefits, and the equilibrium point (α, r) of the platform’s benefits is (1, r^*). The maximum points of merchant income are $(\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1)$, $(\frac{\sqrt{4x^2+1+1-2x}}{2x}, 0)$, and (1, r^*). The maximum of the social welfare can be obtained at point (1, r^*). Therefore, the platform will reduce the percentage to r^* , and

merchants will adjust the price according to the commission rate. Consequently, $(1, r^*)$ is the stable partial equilibrium point of the three-party game evolution, and the evolution rate depends on the platform’s ability to generate revenue by using consumer data privacy.

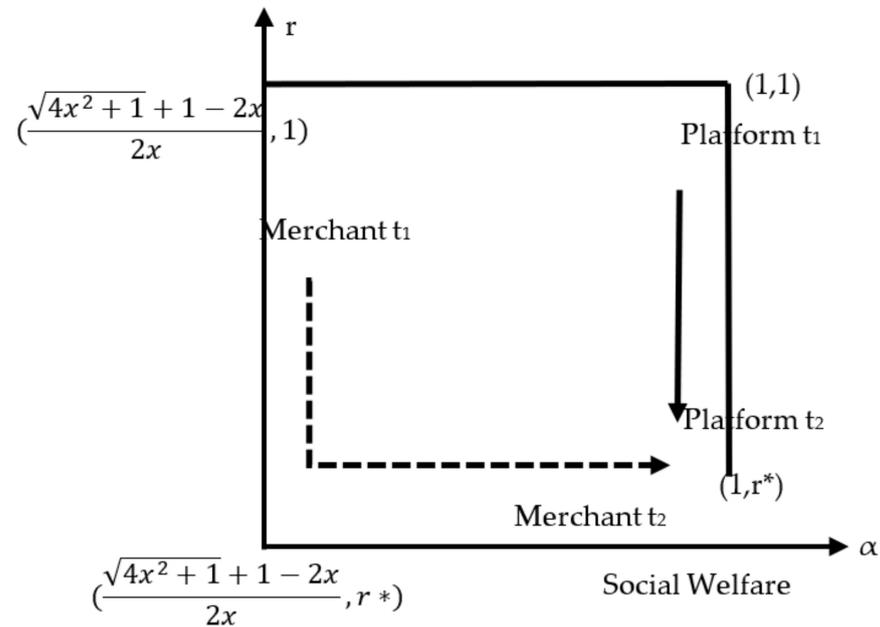


Figure 12. Game equilibrium evolution.

6. Conclusions

In this paper, the sequential game model of the platform, merchant, and consumer union is established, and the platform’s revenue strategy choice driven by consumer data is described. When the platform cannot or is not allowed to use consumer data to generate income, the optimal revenue strategy of the platform is to improve the market service matching level and the commission rate, so that both reach the ideal level, i.e., the strategy of $(1, 1)$, but this strategy does great damage to social welfare and cannot achieve three-party equilibrium. Meanwhile, if the platform obtains the data use permission of consumers and can use consumer group data to obtain service innovation benefits, the platform’s revenue strategy in equilibrium is $(1, r^*)$, which breaks the traditional market revenue-commission model and finally achieves stable partial equilibrium among merchants, platforms, and social welfare.

Through the model, we can also evaluate the impact of the platforms’ commission rate and matching level on social welfare. Our model considers when platform matching level reaches a certain threshold α^* , and it obtains several conclusions. Firstly, when the platform cannot use consumer data to gain revenue, the platform market commission rate and service matching level will have a negative influence on the social welfare, and this negative effect will enlarge as the platform’s consumer base increases. Secondly, when the platform can monetize with consumer data, the revenue will increase dramatically. At this point, the increase in platform matching level can significantly improve social welfare, while the increase in commission rate will still reduce the social welfare level.

If the digital platform could use digital technology properly to improve the matching level of bilateral users and can choose the product commission rate independently, a strategy of $(1, 1)$ is optimal. This is a kind of accelerating harvest scene of the market, which always hurts social welfare. Therefore, it is suggested that market regulation needs to improve the transparency of the platform’s practice concerning the commission rate. In other words, the social planners should participate in the market supervision and prevent the platform from manipulating the market commission rate to imbalance the product price and demand, thus avoiding hurting the social welfare.

The platform’s use of consumer data determines the trend of social welfare changes. Therefore, to establish a standard trading market incentives supervision mechanism, we suggest that the platform should be guided to properly use consumer data to conduct a data-driven business model innovation. The supervision of the service platform to carry out the product differentiation innovation rather than the use of price discrimination strategy should have great importance attached.

There are still some limitations in our model. Firstly, we only study the dimension of consumer group data quantity, and our study lacks further consideration of the dimension of consumer data quality. In addition, there is a lack of a more specific description of the platform’s ability to generate profit by using consumer data or the level of consumer group data privacy regulation. This extension may bring new discoveries to social welfare analysis and become our research direction in the future.

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Appendix A

Proof of Proposition 2. Solve the equation $\frac{2x\alpha-1}{\alpha(1-x\alpha)} \geq 1, \alpha \in [0, 1]$. That is, $x\alpha^2 + (2x - 1)\alpha - 1 \geq 0$. We can get $\alpha \geq \frac{\sqrt{4x^2+1}-2x}{2x}$, QED. \square

Proof of Proposition 3. It is easy to know that $\frac{\partial \pi_p}{\partial \alpha} > 0$; when $r \in [0, r^*)$, $\frac{\partial \pi_p}{\partial r} > 0$; $r \in [r^*, 1]$, $\frac{\partial \pi_p}{\partial r} < 0$. $\frac{\partial SW}{\partial r} < 0$, $\frac{\partial SW}{\partial \alpha} < 0$.

When $\alpha \in (0, 1), r \in (0, 1), x \in [1, \infty), (x^2\alpha^2 + 1 - x\alpha) \geq \frac{3}{4}, r^2 \geq 0$. When the equal sign condition is established, $\frac{\partial p_s^*}{\partial r} = 0$; therefore,

$$\begin{aligned} \frac{\partial p_s^*}{\partial r} &= \frac{2x\sqrt{(x^2\alpha^2+1-x\alpha)r^2+r(x-2\alpha x^2)+x^2}-2x^2+rx(2x\alpha-1)}{6r^2\sqrt{x^2\alpha^2+1-x\alpha)r^2+r(x-2\alpha x^2)+x^2}} \\ &= \frac{x(\sqrt{(x^2\alpha^2+1-x\alpha)r^2+rx(1-2x\alpha)+x^2}-x)}{3r^2\sqrt{x^2\alpha^2+1-x\alpha)r^2+r(x-2\alpha x^2)+x^2}} + \frac{rx(2x\alpha-1)}{6r^2\sqrt{x^2\alpha^2+1-x\alpha)r^2+r(x-2\alpha x^2)+x^2}} \\ \frac{\partial p_s^*}{\partial \alpha} &= \frac{x}{3} + \frac{\frac{1}{2}[(2x^2\alpha-x)r^2-2x^2r]}{3r\sqrt{(x^2\alpha^2+1-x\alpha)r^2+r(x-2\alpha x^2)+x^2}} > 0. \end{aligned}$$

It is easy to see $\frac{\partial p_s^*}{\partial r} > 0$, consumer participation constraint $x\alpha - p - \theta x \geq 0$, then $\frac{1}{2} \leq \frac{\sqrt{4x^2+1}-2x}{2x} \leq \alpha \leq 1, \theta = \min\left\{\frac{(x\alpha-p)}{x}, 1\right\}$. The platform does not use data privacy at this time, and $\pi_p(\alpha, r) = r\theta p(1-p) = rp(1-p)$.

Let $\frac{\partial \pi_p}{\partial r} = \frac{1}{x}[(x\alpha - p)p(1-p) + r(x\alpha - 2(x\alpha + 1)p + 3p^2)] \frac{\partial p}{\partial r} = 0$, we can get $r = r^* = \frac{(x\alpha - p_s^*)p_s^*(1-p_s^*)}{[2(x\alpha+1)p_s^*-3p_s^{*2}-x\alpha]\frac{\partial p_s^*}{\partial r}}$, QED. \square

Proof of Proposition 4. There are $\alpha \in [0, 1]$, $\frac{\partial \pi_p}{\partial \alpha} \geq 0$, $\frac{\partial SW}{\partial \alpha} \geq 0$, when $r \in [r^*, 1]$, $\frac{\partial \pi_p}{\partial r} \leq 0$, $\frac{\partial SW}{\partial r} \leq 0$.

Due to the $\pi_p(\alpha, r) = r\theta p(1 - p) + k\theta x = \frac{r}{x}(x\alpha - p)p(1 - p) + k(x\alpha - p)$,

$$SW = \begin{cases} p(1 - p) & \alpha \in [0, \frac{\sqrt{4x^2+1+1-2x}}{2x}] \\ p(1 - p) + k\theta x & \alpha \in [\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1] \end{cases}.$$

Without loss of generality, set the data usage level to $x = 1$. In the absence of privacy benefits, there is

$$\frac{\partial \pi_p}{\partial \alpha} = [(1 - \theta r)p(1 - p)]' = (\frac{\partial p}{\partial \alpha}r - r)(p - p^2) + (1 - \alpha r + pr)(1 - 2p)\frac{\partial p}{\partial r} > 0$$

$$\frac{\partial \pi_p}{\partial r} = (\alpha - p)p(1 - p) + r[\alpha - 2(\alpha + 1)p + 3p^2]\frac{\partial p}{\partial r} > 0$$

where there are privacy benefits to the platform,

$$\frac{\partial \pi_p}{\partial r} = \frac{1}{x}[(x\alpha - p)p(1 - p) + r(x\alpha - 2(x\alpha + 1)p + 3p^2)]\frac{\partial p}{\partial r} + kx - k\frac{\partial p}{\partial r}.$$

When $k > \frac{[(x\alpha - p)p(1 - p) + r(x\alpha - 2(x\alpha + 1)p + 3p^2)]\frac{\partial p}{\partial r}}{x\frac{\partial p}{\partial r}}$, it must be $\frac{\partial \pi_p}{\partial r} < 0$.

$$\frac{\partial SW}{\partial \alpha} = \begin{cases} (1 - 2p)\frac{\partial p}{\partial \alpha} & \alpha \in [0, \frac{\sqrt{4x^2+1+1-2x}}{2x}] \\ (1 - 2p)\frac{\partial p}{\partial \alpha} + kx - k\frac{\partial p}{\partial \alpha} & \alpha \in [\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1] \end{cases}, \text{ plug } p_s^* \text{ into the equation, we}$$

$$\text{can get } \frac{\partial SW}{\partial \alpha} > 0, \frac{\partial SW}{\partial r} = \begin{cases} (1 - 2p)\frac{\partial p}{\partial r} & \alpha \in [0, \frac{\sqrt{4x^2+1+1-2x}}{2x}] \\ (1 - 2p)\frac{\partial p}{\partial r} + kx - k\frac{\partial p}{\partial r} & \alpha \in [\frac{\sqrt{4x^2+1+1-2x}}{2x}, 1] \end{cases}. \text{ The same can}$$

be obtained, $\frac{\partial p_s^*}{\partial \alpha}$ and $\frac{\partial p_s^*}{\partial r}, \frac{\partial SW}{\partial r} < 0$, QED. \square

Proof of Corollary 1. When the platform does not use consumer data privacy to generate revenue, when $\alpha_1 = \alpha_2, r_1 = r_2$, if the platform has a level of consumer data use $x_1 < x_2$, it must have $\frac{\partial SW}{\partial r} \Big|_{x=x_2} < \frac{\partial SW}{\partial r} \Big|_{x=x_1} < 0, \frac{\partial SW}{\partial \alpha} \Big|_{x=x_2} < \frac{\partial SW}{\partial \alpha} \Big|_{x=x_1} < 0$, QED. \square

Proof of Corollary 2. From propositions 2 and 3, we can get $SW_{\max} = SW(1, 0)$. When $\alpha = 1$, the privacy revenue generation efficiency of the platform is $k = 1 > \frac{[(x\alpha - p)p(1 - p) + r(x\alpha - 2(x\alpha + 1)p + 3p^2)]\frac{\partial p}{\partial r}}{x\frac{\partial p}{\partial r}}$, and it must be $\frac{\partial \pi_p}{\partial r} < 0$, we can easily know that $SW_{\max} = SW(1, r^*)$, QED. \square

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