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Regulating the Big Data-Based Discriminatory Pricing in Platform Retailing: A Tripartite Evolutionary Game Theory Analysis

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Abstract: Nowadays, with the rapid development of the platform economy, Big Data-based Discriminatory Pricing (BDDP) has become a common phenomenon in which big data and algorithms are applied to excessively seize consumer surplus and thus damage the rights and interests of consumers. This work aims to explore the equilibrium strategies of the consumers, the government, and the service platform and discuss factors affecting the BDDP practice of the service platforms. This study constructs a tripartite evolutionary game model among consumers, service platforms, and the government. Two evolutionary equilibrium strategies are derived and validated using simulation. Numerical experiments are conducted using MATLAB to reveal players' evolutionary stability strategies under various settings. The study shows that (1) the strategies of the government and the platform always influence each other, (2) a reasonable adjustment of tax rate helps regulate the platform's behavior, and (3) the proportion of consumers who switch the platform after they realize themselves suffering BDDP is an important factor influencing platform's strategy. This study lastly summarizes the managerial insights for dealing with the platform's BDDP behavior and safeguarding consumers' rights from the perspectives of macro-regulation and privacy data protection. The conclusions of this study can help promote the high-quality development of the platform economy.

Keywords: big data-based discriminatory pricing; government regulation; dynamic evolutionary game; platform economy

MSC: 91A22

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1. Introduction

In recent years, with the rapid development of the service platform economy and the maturity and wide application of big data technology, more and more service platforms, i.e., e-commerce platforms, travel platforms, and online taxi platforms, have started to use big data-enabled technology and algorithms to understand consumer behaviors and utilize shopping data to achieve precise marketing and build clearer customer portraits [1,2].

However, the wide application of big data-enabled technology has brought some new social problems [3]. One of the prominent problems is that service platforms have been repeatedly exposed to tailored price discrimination, in which the same product is priced differently for different groups of customers. In particular, the price is set higher for regular customers who often purchase from the service platform. This pricing practice is particularly named by Big Data-based Discriminatory Pricing (BDDP) [4]. For example, in July 2021, China's first BDDP case was heard in court. A customer took a hotel booking software that used BDDP tactics to court after discovering that he had suffered BDDP. The court eventually ruled that the company should fully refund and be fined three times the amount as compensation.

BDDP, in nature, refers to the behaviors that operators collect, retrieve, analyze, and mine consumer preference data, and take advantage of the path dependence and information asymmetry of loyal customers to demand higher prices from them for the same goods or services than new consumers. The traditional first-level price discrimination is to classify consumers according to different purchasing preferences, and set different prices for different types of consumers, but service platforms use big data-enabled algorithms to have user portraits and more accurately understand the highest willing-to-pay price of each consumer for the product to seize the maximum consumer surplus. This kind of price discrimination may damage the legitimate interests of consumers and destroy the market rules and is not conducive to the long-term sustainable development of the platform economy. To address this issue, governments have introduced a series of laws and policies in recent years on BDDP, emphasizing the protection of consumer rights and interests.

While the relevant laws and regulations are provided to try to prohibit BDDP practice to a certain extent, the observations are still widely reported. To address the phenomenon, some scholars analyze the stable strategy and the factors affecting the behavior of two parties by constructing an evolutionary game model consisting of e-commerce enterprises and the government [5]. This paper applies evolutionary game theory to investigate how to regulate service platforms' BDDP behavior from the particular perspective of the government, with consideration of real-world modeling features. We believe this work is of practical significance to guide the healthy high-quality development of the platform economy. Specifically, this paper aims to answer the following questions:

(1) How to construct a tripartite evolutionary game model to explain the BDDP behavior of service platforms?

(2) What are the equilibrium strategies of the consumers, the government, and the service platform?

(3) How do factors, i.e., the success rate of government regulation, tax rate, and consumer platform switching behavior, affect BDDP practice of the service platforms?

We first construct a tripartite game model with consumers, the government, and the service platform with the purpose of how to regulate the big data-based discriminatory pricing in platform retailing. We then apply local stability analysis for the equilibrium strategies of each player. Combined with real-world situations, numerical simulation experiments are implemented to analyze the evolutionary path of the game players' strategies and stable equilibrium strategies. Factors that may impact the equilibrium strategies are discussed. Conclusions are drawn to provide suggestions and specific measures to regulate BDDP behavior.

Compared with related studies, i.e., [4,6], we emphasize the regulatory decisions of the government within the evolutionary pathway. Most previous studies regard the government's regulatory status as an external factor. Moreover, given the competitive market, we also incorporate the response strategies chosen by consumers when they become aware of the BDDP practice of the service platform. The customers may decide to switch the focus platform and customer churn is considered by the service platform when making the decision on BDDP.

The rest of this study is organized according to the following structure. Section 2 discusses related literature. Section 3 builds the tripartite evolutionary game theory mathematical models. Section 4 analyzes the stability of the evolutionary game model and Section 5 discusses factors that influence the strategies of the three players. We conclude this work in Section 6.

2. Literature Review

2.1. Emergence of BDDP and Related Concepts

With the rise of big data and mobile networks, businesses can cater to consumers' individual needs to a greater extent than ever before. However, big data also brings new challenges and can lead to consumer dissatisfaction [7]. In 2015, the White House released a government report detailing the concerns and policy suggestions regarding Big Data and Differential Pricing [8]. Since late 2018, big data-driven online consumer price discrimination has attracted significant social attention in China [9]. The prevalence of price discrimination or even personalized pricing is gradually emerging to the detriment of consumers [10,11]. The phenomenon of BDDP practices is recurring among service platforms in daily life, and its negative impact has sparked public concern and criticism [12,13]. Nowadays, the phenomenon of BDDP is mainly seen in the fields of airline booking services, online car services, take-away services, movie ticket booking services, and online channel merchandise retailing [14].

Although the concept of BDDP has not been fully defined, most scholars agree that it is a kind of price discrimination [15,16]. In a study of 1500 households in the U.S., 76% of consumers expressed chagrin that other consumers were paying a lower price for the same good or service, 87% felt that differential pricing was incorrect, and 91% were strongly dissatisfied with the behavior [17].

2.2. BDDP Using the Evolutionary Game Model

The evolutionary game theory combines static game theory analysis and dynamic evolutionary processes, emphasizing dynamic equilibrium [4,18]. It commonly takes the form of a two-party dynamic evolutionary game model [19–23] or a three-party dynamic evolutionary game model [24–26]. To address the phenomenon of BDDP, scholars have already used game theory and constructed a dynamic evolutionary game model to explore the inherent influence mechanism of service platforms and their price discriminatory behavior. Xing et al. [5] construct an evolutionary game model consisting of e-commerce enterprises and the government, analyzing the behavior evolution of each player and the conditions for stable solutions. They further conduct an evolutionary simulation analysis and discuss factors influencing the choice of strategy in numerical simulations. Yu and Li [27] systematically analyze the stable strategy and the factors affecting the behavior of both parties based on a two-party game model between merchants and consumers. Li et al. [28] analyze and compare the action strategy combinations of consumer groups with different behavioral characteristics by constructing a multi-stage repeated game model between buyers and sellers to provide a reference for the strategic choices of consumers and merchants. Wang et al. [29] applied a tripartite evolutionary game model, consisting of digital platforms, governments, and users, to address the consequences of data abuse.

Some scholars also consider factors such as consumers' price sensitivity in their models. For example, Peng et al. [30] construct a dynamic evolutionary game model for the e-commerce platform and users with different sensitivity to price and conclude that the proportion of price-sensitive frequent visitors and new high-stickiness users, as well as the fines from regulators, are the key factors affecting the stable state of the evolutionary game system.

In addition, some scholars also introduce additional players when studying the phenomenon of BDDP and adopt a tripartite dynamic evolutionary game model. Li et al. [31] analyze the behavior of the three parties in a live-streaming e-commerce platform system, which consists of a live platform, suppliers, and anchors, using a tripartite dynamic evolution game model. They then simulate the strategy evolution process using Netlogo, then analyze the behavior among the three parties, and propose basic strategies and specific measures to regulate the behavior of suppliers and anchors accordingly. Furthermore, only a few scholars adopt a four-party evolutionary game model in their research. For example, in exploring the regulatory strategy against e-commerce companies' BDDP practice, Xiao [32] constructs a four-party evolutionary game model consisting of the government, e-commerce platforms, e-commerce companies, and consumers, and analyzes the four-party stable behavioral strategies.

2.3. Summary of Related Research

The work of Liu et al. [4] is the one closest to our work. Liu et al. [4] construct a tripartite evolutionary game model among consumers, service platforms, and the government to explore ways to regulate service platforms' BDDP behavior and propose a governance mechanism to prevent service platforms from implementing BDDP. The main difference from our paper is that we explore consumer behaviors from the perspective of whether they choose the platform or not, while Liu et al. [4] focus on consumers' evaluation of the service platform. Chai and Wang [6] is another related article that emphasizes the effect of technology diffusion on the choice of BDDP or not. They combine diffusion theory and evolutionary game theory to explore the behavioral strategy choices of the government, consumers and suppliers when the two-sided platform implements BDDP. While Chai and Wang [6] also explores the strategies of multiple players when facing BDDP, besides possible external regulation from the government, we additionally consider the possibility that consumers may not continue to consume on the platform after realizing that they have experienced BDDP. The study places more emphasis on the different role characteristics of the three parties.

While there are a few articles that focus on BDDP behavior, we have the following observations based on the aforementioned literature review:

(1) With regard to BDDP, most of the existing studies focus on the behavioral strategies of consumers and platforms, either ignoring the influence of the government on market regulation or simply considering it as an external factor [33]. They mainly suggest government actions from the macro perspective of legislation and policy regulation, and seldom analyze specific factors in government's decisions, such as tax rates, regulatory success rates, fines, etc., into the quantitative model. This model is much closer to reality and provides a more straightforward view of the impact of government strategy on platform behavior and consumer behavior.

(2) Among the existing studies on BDDP, few papers use the tripartite dynamic evolutionary game approach, and most studies focus on two-party game model. Some of them consider players' strategy space in a relatively simplified way in the mathematical model with no comprehensive consideration of real-world interaction factors. Regulating the big data-based discriminatory pricing in platform retailing requires the joint actions of the government, the service platforms and consumers.

(3) This study simultaneously places the government, the service platforms, and consumers in a dynamic evolutionary game model, and may obtain more comprehensive conclusions compared with the two-party model. The tripartite dynamic evolutionary game model applied in this study considers some complex realistic factors, such as consumers' platform switching behavior, the success rate of government regulation, the government's penalties on BDDP practice, and the government's taxation rate. The interplay among the consumers, the service platform, and the government is fully discussed in this study. Thus, our model is more relevant to a real-world situation and can provide more practical suggestions for better regulating the behavior of service platforms.

3. Mathematical Models

Evolutionary game theory regards people as imperfectly rational game players that go through the process of trial, error and imitation, and finally evolve to reach the equilibrium state. Evolutionary game theory has been widely applied in various settings [34–36]. Given that government regulatory actions have an impact on platform and consumer strategy choices, this study selects three players, namely the government, service platform, and consumers, to construct the evolutionary game model, which is in line with real-world situations. The strategic choices of these players change over time. The research objective is to understand the dynamic process of the evolution of the players' behavior and to explain how they reach a steady state. Then, this paper solves the replication dynamic equations, which refer to the dynamic differential equation of the frequency of adopting a particular strategy in a group so that to bring higher benefits than the average of others, to find the equilibrium points and the stabilization strategies.

3.1. Assumptions

To facilitate the modeling of the tripartite game, this study makes the following assumptions:

(1) This study assumes that consumers, the service platform, and the government are boundedly rational so that interest maximization at each stage is sought.

(2) The decision-making of all relevant players is independent. In the same decision stage, the three decision-makers do not know each other's strategies and their choices of strategies are influenced by the results of the previous stage of the game. This is a common setup in an evolutionary game.

(3) This paper assumes that the service platform's BDDP price is close to but not exactly equal to the first-level price discrimination [37]. Thus, the consumer surplus of the purchase of the product or service is slightly above zero. The customer surplus is T and the difference between the highest willing-to-pay price for a product or service and the basic price of the platform is V.

(4) This paper discusses the situation of how the government imposes regulation on a platform. The government either adopts strict or lenient regulatory practices for the service platform. Implementing strict or lenient regulatory practices may lead to different implementation costs and success rates. Upon discovering BDDP practice, a penalty is imposed on the service platform.

(5) The sunk cost for customers to choose goods or services from the platform is fixed at the value of C_5.

We assume the fixed cost of implementing BDDP practice is C_3, and the fixed cost of not adopting BDDP practice is C_4, $C_3 > C_4$. The basic profit when the platform chooses the uniform pricing strategy is W_2. Under BDDP practice, the basic profit of the service platform is W_1. Due to the implementation and operational cost related to data collection and processing under BDDP practice, $W_2 > W_1$. Since BDDP is regarded as one that is closest to the first-level price discrimination, the platform can capture the additional profit of $(V - T)$, and thus the total profit is $(W_1 + V - T)$. Because of the additional profit, $(V - T)$, the total payoff when BDDP is adopted is relatively larger than one under the uniform pricing practice.

If the service platform implements BDDP strategy, the probability of consumers realizing that they have experienced BDDP is η. In such a situation, consumers' mental loss is M_1. The proportion of consumers, α, may decide to switch away from the service platform after discovering that they have experienced BDDP and incur a total cost, M_2, which comprises switch costs and mental loss.

The government adopts either strict or lenient regulations for this service platform. When the government adopts strict regulation, the implementation cost is C_1, the regulation success rate is β. When the government adopts lenient regulation, the implementation cost is C_2, the success rate of regulation is γ, $\gamma < \beta$. The amount of penalty imposed on the service platform upon being found for BDDP is F. In addition, the service platform needs to pay taxes at the rate of r.

At each stage, the probability that consumers choose the service platform is x, the probability that the government adopts a strict regulatory strategy is y, and the probability that the platform implements BDDP strategy is z ($0 < x, y, z < 1$). All model parameters are listed in Table 1.

Table 1. Model parameters.

Parameter	Descriptions
T	The customer surplus
V	The difference between the highest willing-to-pay price for a product or service and the basic price of the platform
C_1	The implementation cost when the government adopts strict regulation
C_2	The implementation cost when the government adopts lenient regulation
C_3	The fixed cost of implementing BDDP practice
C_4	The fixed cost of not adopting BDDP practice
C_5	The sunk cost for customers to choose goods or services from the platform
W_1	The basic profit of the service platform under BDDP practice
W_2	The basic profit when the platform chooses the uniform pricing strategy
M_1	The consumers' mental loss if the service platform implements BDDP strategy
M_2	The total cost when consumers decide to switch away from the service platform after discovering that they have experienced BDDP, which comprises switch costs and mental loss
η	The probability of consumers realizing that they have experienced BDDP if the service platform implements BDDP strategy
α	The proportion of consumers that may decide to switch away from the service platform after discovering that they have experienced BDDP
β	The success rate of regulation when the government adopts strict regulation
γ	The success rate of regulation when the government adopts lenient regulation
F	The amount of penalty imposed on the service platform upon being found for BDDP
r	The tax rate of the platform
x	The probability that consumers choose the service platform
y	The probability that the government adopts a strict regulatory strategy
z	The probability that the platform implements BDDP strategy

3.2. Model Construction

Based on the aforementioned assumptions, the payoff matrix of the consumer, government, and service platform is constructed as shown in Table 2.

Table 2. Payoff matrix.

		% of Consumers Choose the Platform (x)	% of Consumers Do Not Choose This Platform (1 − x)
Strict regulation (y)	BDDP (z)	$V - C_5 - \eta M_1$ $\beta F - C_1 + r(W_1 + V - T)(1-\alpha)$ $(1-r)(W_1 + V - T)(1-\alpha) - C_3 - \beta F$	$V - C_5 - M_2$ $\beta F - C_1$ $-\beta F - C_3$
	Uniform Pricing (1 − z)	$V - C_5$ $-C_1 + rW_2$ $(1-r)W_2 - C_4$	$V - C_5 - M_2$ $-C_1$ $-C_4$
Lenient regulation (1 − y)	BDDP (z)	$V - C_5 - \eta M_1$ $\gamma F - C_2 + r(W_1 + V - T)(1-\alpha)$ $(1-r)(W_1 + V - T)(1-\alpha) - C_3 - \gamma F$	$V - C_5 - M_2$ $\gamma F - C_2$ $-\gamma F - C_3$
	Uniform Pricing (1 − z)	$V - C_5$ $-C_2 + rW_2$ $(1-r)\, W_2 - C_4$	$V - C_5 - M_2$ $-C_2$ $-C_4$

The derivation of Table 2 is straightforward. We take the scenario when the service platform adopts a BDDP strategy and the government adopts strict regulation as an illustrative example. Under this scenario, the service platform gains additional consumer surplus at the potential expense of penalty incurred by the government. Since the proportion of consumers, α, may switch the service platform, the revenue of the service platform is $(1-r)(W_1 + V - T)(1-\alpha)$. In the case that the government regulatory measures are effective, the platform's BDDP behavior may be found and punished and the penalty fee

βF is incurred. Besides, considering the operating cost of adopting BDDP strategy, the net profit of the platform is $(1-r)(W_1+V-T)(1-\alpha)-C_3-\beta F$.

Let the expected utility of consumers who choose the service platform be U_{11} and the expected utility of the remaining consumers be U_{12}, respectively. Equations (1) and (2) denote U_{11} and U_{12}, respectively.

$$U_{11} = yz(V - C_5 - \eta M_1) + y(1-z)(V - C_5) + (1-y)z(V - C_5 - \eta M_1) + (1-y)(1-z)(V - C_5) \tag{1}$$

$$U_{12} = yz(V - C_5 - M_2) + y(1-z)(V - C_5 - M_2) + (1-y)z(V - C_5 - M_2) + (1-y)(1-z)(V - C_5 - M_2) \tag{2}$$

We let $\overline{U}_1$ denote the expected payoff among all consumers and, $\overline{U}_1$ is calculated as shown in Equation (3).

$$\overline{U}_1 = xU_{11} + (1-x)\,U_{12} \tag{3}$$

Let the expected utility of the government in the cases of strict and lenient regulations be U_{21} and U_{22} , respectively. Equations (4) and (5) denote be U_{21} and U_{22}, respectively.

$$U_{21} = xz[\beta F - C_1 + r(W_1 + V - T)(1-\alpha)] + x(1-z)(-C_1 + rW_2) + (1-x)z(\beta F - C_1) + (1-x)(1-z)(-C_1) \tag{4}$$

$$U_{22} = xz[\gamma F - C_2 + r(W_1 + V - T)(1-\alpha)] + x(1-z)(-C_2 + rW_2) + (1-x)z(\gamma F - C_2) + (1-x)(1-z)(-C_2) \tag{5}$$

The expected payoff of the government, $\overline{U}_2$, is then denoted by Equation (6).

$$\overline{U}_2 = yU_{21} + (1-y)U_{22} \tag{6}$$

Let the expected utility of the service platform when it adopts BDDP and does not adopt BDDP be U_{31} and U_{32} , respectively. We use $\overline{U}_3$ to be the expected profit. Equations (7)–(9) show U_{31}, U_{32} and $\overline{U}_3$.

$$\begin{aligned} U_{31} = \; & xy[(1-r)(W_1+V-T)(1-\alpha) - C_3 - \beta F] + (1-x)y(-\beta F - C_3) \\ & +x(1-y)[(1-r)(W_1+V-T)(1-\alpha) - C_3 - \gamma F] \\ & +(1-x)(1-y)(-\gamma F - C_3) \end{aligned} \tag{7}$$

$$\begin{aligned} U_{32} = \; & xy[(1-r)\,W_2 - C_4] + (1-x)y(-C_4) + x(1-y)[(1-r)\,W_2 - C_4] \\ & +(1-x)(1-y)(-C_4) \end{aligned} \tag{8}$$

$$\overline{U}_3 = zU_{31} + (1-z)U_{32} \tag{9}$$

Let the replication dynamic equations for the consumers, the government, and the service platform be $F(x)$, $F(y)$, and $F(z)$, respectively. Equations (10)–(12) show $F(x)$, $F(y)$, and $F(z)$.

$$F(x) = dx/dt = x\big(U_{11} - \overline{U}_1\big) = x(1-x)(U_{11} - U_{12}) = x(1-x)(M_2 - z\eta M_1) \tag{10}$$

$$\begin{aligned} F(y) &= dy/dt = y\big(U_{21} - \overline{U}_2\big) = y(1-y)(U_{21} - U_{22}) \\ &= y(1-y)[zF(\beta-\gamma) - C_1 + C_2] \end{aligned} \tag{11}$$

$$\begin{aligned} F(z) \; &= dz/dt = z\big(U_{31} - \overline{U}_3\big) = z(1-z)(U_{31} - U_{32}) = z(1-z) \\ & [x(1-r)(W_1+V-T)(1-\alpha) - x(1-r)\,W_2 - yF(\beta-\gamma) - C_3 + C_4 - \gamma F] \end{aligned} \tag{12}$$

4. Tripartite Evolutionary Game Stability Analysis

4.1. Analysis of Evolutionary Paths

According to Friedman's method, the Evolutionary Stability Strategy (ESS) of the equation is derived from the local stability analysis of the Jacobi matrix, $\boldsymbol{J}$. The Jacobi matrix constructed in this work is:

$$\boldsymbol{J} = \begin{bmatrix} (1-2x)(M_2 - z\eta M_1) & 0 & x(1-x)(-\eta M_1) \\ 0 & (1-2y)[zF(\beta-\gamma) - C_1 + C_2] & y(1-y)F(\beta-\gamma) \\ z(1-z)\begin{bmatrix}(1-r)(W_1+V-T)(1-\alpha) \\ -(1-r)W_2\end{bmatrix} & z(1-z)[-F(\beta-\gamma)] & (1-2z)\begin{bmatrix}x(1-r)(W_1+V-T)(1-\alpha) - x(1-r)W_2 \\ -yF(\beta-\gamma) - C_3 + C_4 - \gamma F\end{bmatrix} \end{bmatrix}$$

According to the theory of differential equations, let $F(x) = 0,\ F(y) = 0,\ F(z) = 0$. By solving the replication dynamic equations, we obtain eight local equilibrium points, namely E1 (0, 0, 0), E2 (0, 0, 1), E3 (0, 1, 0), E4 (0, 1, 1), E5 (1, 0, 0), E6 (1, 0, 1), E7 (1, 1, 0) and E8 (1, 1, 1). When the equilibrium point is E1 (0, 0, 0), $J_1 = \begin{bmatrix} M_2 & 0 & 0 \\ 0 & -C_1+C_2 & 0 \\ 0 & 0 & -C_3+C_4-\gamma F \end{bmatrix}$. In a similar approach, the other seven equilibria are substituted into the Jacobi matrix, and the eigenvalues of the Jacobi matrix corresponding to each equilibrium point can be obtained, as shown in Table 3.

Table 3. Eigenvalues of the Jacobi matrix of the gaming system.

Equilibrium Point	λ_1	λ_2	λ_3
E1	M_2	$-C_1+C_2$	$-C_3+C_4-\gamma F$
E2	$M_2-\eta M_1$	$F(\beta-\gamma)-C_1+C_2$	$-(-C_3+C_4-\gamma F)$
E3	M_2	$-(-C_1+C_2)$	$-F(\beta-\gamma)-C_3+C_4-\gamma F$
E4	$M_2-\eta M_1$	$-[F(\beta-\gamma)-C_1+C_2]$	$-[-F(\beta-\gamma)-C_3+C_4-\gamma F]$
E5	$-M_2$	$-C_1+C_2$	$(1-r)(W_1+V-T)(1-\alpha)-(1-r)W_2-C_3+C_4-\gamma F$
E6	$-(M_2-\eta M_1)$	$F(\beta-\gamma)-C_1+C_2$	$-[(1-r)(W_1+V-T)(1-\alpha)-(1-r)W_2-C_3+C_4-\gamma F]$
E7	$-M_2$	$-(-C_1+C_2)$	$(1-r)(W_1+V-T)(1-\alpha)-(1-r)W_2-F(\beta-\gamma)-C_3+C_4-\gamma F$
E8	$-(M_2-\eta M_1)$	$-[F(\beta-\gamma)-C_1+C_2]$	$-[(1-r)(W_1+V-T)(1-\alpha)-(1-r)W_2-F(\beta-\gamma)-C_3+C_4-\gamma F]$

We then discuss whether the eigenvalues of equilibrium points are positive or negative. An equilibrium point belongs to the ESS point only when all the eigenvalues of the Jacobi matrix, $(\lambda_1,\ \lambda_2,\ \lambda_3)$, are negative [38]. Table 3 shows the results of the stability analysis of the eight partial equilibria derived above. According to the assumptions made in the following two scenarios, we calculate and list for each equilibrium point whether its eigenvalues are positive or negative.

We next determine which of the following cases the equilibrium point belongs to (1) ESS point (2) saddle point or (3) non-stable point. After analysis, we find that there are two possible stable points, namely E6 and E7, and they are ESS points only when they satisfy the assumptions of Scenario 1 and Scenario 2 respectively. All other points cannot satisfy the condition of eigenvalue less than zero at the same time, so they are all unstable points or saddle points.

Scenario 1. *$M_2 - \eta M_1 > 0$, $F(\beta-\gamma) - C_1 + C_2 < 0$, and $(1-r)(W_1+V-T)(1-\alpha) - (1-r)W_2 - C_3 + C_4 - \gamma F > 0$. This occurs when the government chooses lenient regulation, the benefit of consumers choosing the service platform is more than that when they do not choose this service platform, and the benefit of adopting BDDP for the service platform is relatively larger. As shown in Table 4, the eigenvalue of the equilibrium point, E6 (1, 0, 1), is negative. Thus, E6 (1, 0, 1) represents the evolutionary stability strategy. Figure 1 shows the phase diagram of the evolutionary game from the other equilibrium points towards E6 (1, 0, 1).*

Table 4. Stability Analysis of Local Equilibrium Point in Scenario 1.

Equilibrium Point	λ_1	λ_2	λ_3	Stability
E1 (0, 0, 0)	$+$	$-$	$-$	Saddle
E2 (0, 0, 1)	$+$	$-$	$+$	Saddle
E3 (0, 1, 0)	$+$	$+$	$-$	Saddle
E4 (0, 1, 1)	$+$	$+$	$+$	Non-Stable
E5 (1, 0, 0)	$-$	$-$	$+$	Saddle
E6 (1, 0, 1)	$-$	$-$	$-$	ESS
E7 (1, 1, 0)	$-$	$+$	$\pm$	Saddle
E8 (1, 1, 1)	$-$	$+$	$\pm$	Saddle

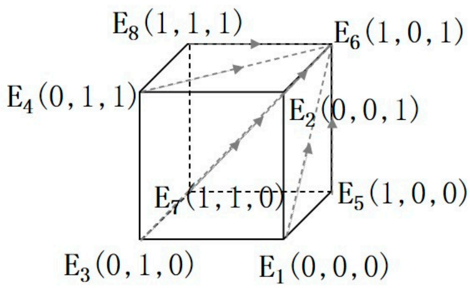

Figure 1. The conversion from other equilibrium points to the ideal equilibrium point in Scenario 1.

Scenario 2. $M_2 - \eta M_1 > 0, C_1 < C_2$, $(1-r)(W_1+V-T)(1-\alpha) - (1-r)W_2 - \beta F < C_3 - C_4$. *It occurs when the government adopts strict regulations and consumers choose this service platform, the gain of the platform when choosing BDDP strategy is relatively smaller. As shown in Table 5, the equilibrium point is E7 (1, 1, 0). The eigenvalue of E7 (1, 1, 0) is negative, so E7 (1, 1, 0) is the ESS point. In this case, the customer chooses this service platform, the government adopts strict regulation, service platform does not adopt BDDP practice. Figure 2 shows the phase diagram towards the ESS point.*

Table 5. Stability Analysis of Local Equilibrium Point in Scenario 2.

Equilibrium Point	λ_1	λ_2	λ_3	Stability
E1 (0, 0, 0)	$+$	$+$	$-$	Saddle
E2 (0, 0, 1)	$\pm$	$+$	$+$	Saddle
E3 (0, 1, 0)	$+$	$-$	$-$	Saddle
E4 (0, 1, 1)	$\pm$	$-$	$+$	Saddle
E5 (1, 0, 0)	$-$	$+$	$\pm$	Saddle
E6 (1, 0, 1)	$\pm$	$+$	$\pm$	Non-Stable
E7 (1, 1, 0)	$-$	$-$	$-$	ESS
E8 (1, 1, 1)	$\pm$	$-$	$+$	Saddle

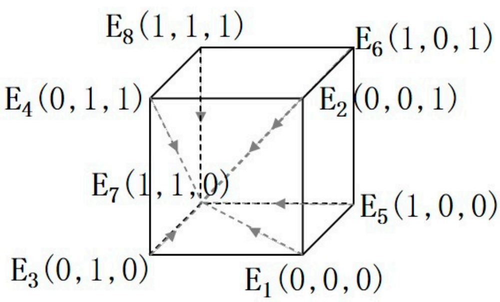

Figure 2. The conversion from other equilibrium points to the ideal equilibrium point in Scenario 2.

4.2. Simulation Analysis of Scenarios 1 and 2

We utilize MATLAB to simulate the different strategies of the three players and visualize the evolutionary equilibrium stability in Scenarios 1 and 2. The parameter values used in Scenario 1 are shown in Table 6. These input values are set based on a preliminary survey on a China takeaway service platform.

Table 6. Parameter Values of Payoff Matrix.

Parameter	Value	Parameter	Value
M_1	1	β	0.6
M_2	1.5	γ	0.2
r	0.25	F	6
V	6	C_1	8
T	1.3	C_2	3
α	0.2	C_3	5
W_1	16	C_4	2.5
W_2	10	η	0.6

In this case, the government adopts strict regulation. Set the initial values $x = 0.2$, $y = 0.8$, $z = 0.5$, and $x = 0.5$, $y = 0.8$, $z = 0.2$ respectively. Figures 3 and 4 show the simulation results and visualize that the ESS is all finalized at point E6 (1, 0, 1), conforming to the analytical result.

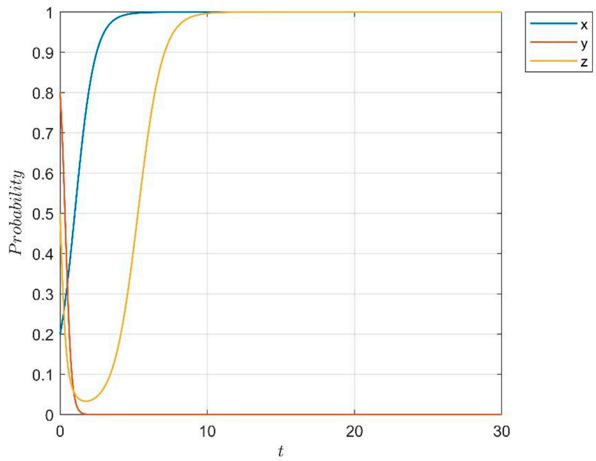

Figure 3. Simulation results of the evolutionary game with initial values $x = 0.2$, $y = 0.8$, $z = 0.5$.

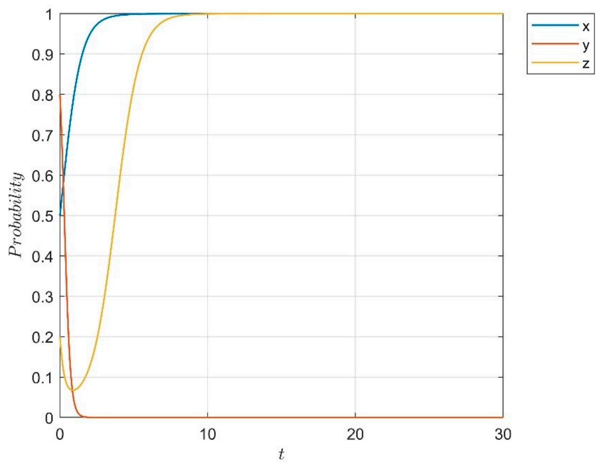

Figure 4. Simulation results of the evolutionary game with initial values $x = 0.5$, $y = 0.8$, $z = 0.2$.

We next simulate the evolutionary path under Scenario 2. Let the parameters of the payment matrix be as shown in Table 7.

Table 7. Parameter values of the payoff matrix.

Parameter	Value	Parameter	Value
M_1	1	β	0.6
M_2	1.5	γ	0.2
r	0.25	F	12
V	6	C_1	5
T	1.3	C_2	7
α	0.2	C_3	5
W_1	16	C_4	2.5
W_2	10	η	0.6

Set the initial values $x = 0.2$, $y = 0.5$, $z = 0.8$, $x = 0.1$, $y = 0.3, z = 0.6$. Figures 5 and 6 show the simulation results and verify that the final ESS is E7 (1, 1, 0).

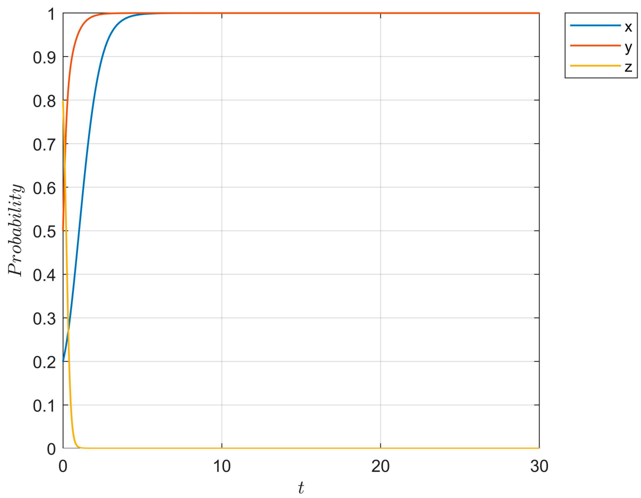

Figure 5. Simulation results of the evolutionary game with initial $x = 0.2$, $y = 0.5$, $z = 0.8$.

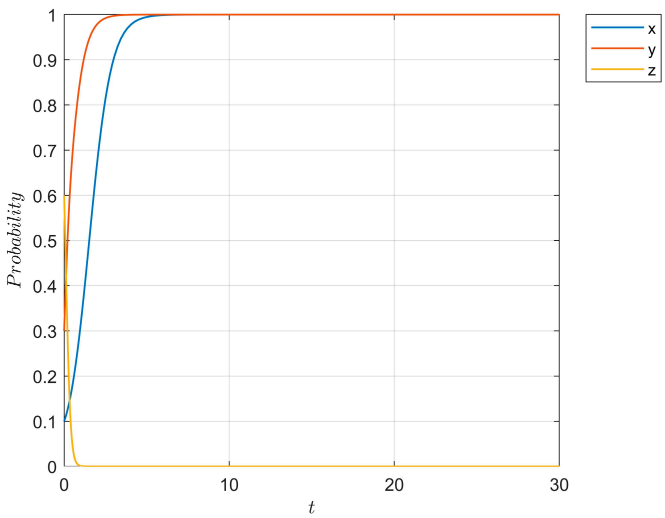

Figure 6. Simulation results of the evolutionary game with initial $x = 0.1$, $y = 0.3$, $z = 0.6$.

5. Analysis of Factors Affecting Stability

In what follows, we analyze some important factors influencing the stability of the tripartite evolutionary game. Due to the page limit, we focus on three important parameters, namely (1) strict regulatory success rate, γ, (2) government tax rate, r, and (3) the proportion of consumers who switch platforms after realizing they had suffered from BDDP, α.

We set the other parameters as fixed values, i.e., $\gamma = 0.02$, $M_1 = 15$, $M_2 = 5$, $V = 10$, $T = 3$, $W_1 = 27$,$W_2 = 21$, $F = 20$, $C_1 = 15$, $C_2 = 10$, $C_3 = 9$, $C_4 = 7$. We set the initial values of x , y , z as 0.5. We run simulation experiments, using MATLAB for different parameter values and produce a trend graph of the behavior of the three players over time. Some managerial insights are consequentially provided.

5.1. Impact of Strict Regulatory Success Rate on the Behaviors of Three Players

To investigate the impact of the change in the values of parameters β, we set β as 0.1, 0.3, 0.5, 0.7, and 0.9, respectively. Figure 7 shows the evolutionary trajectory of consumer strategy over time. When the success rate of strict government regulation is low, consumers are in a wait-and-see state and cannot reach a stable state. With a moderate increase in the success rate of strict regulation, the consumer strategy evolves towards choosing the service platform and finally reaches a stable state.

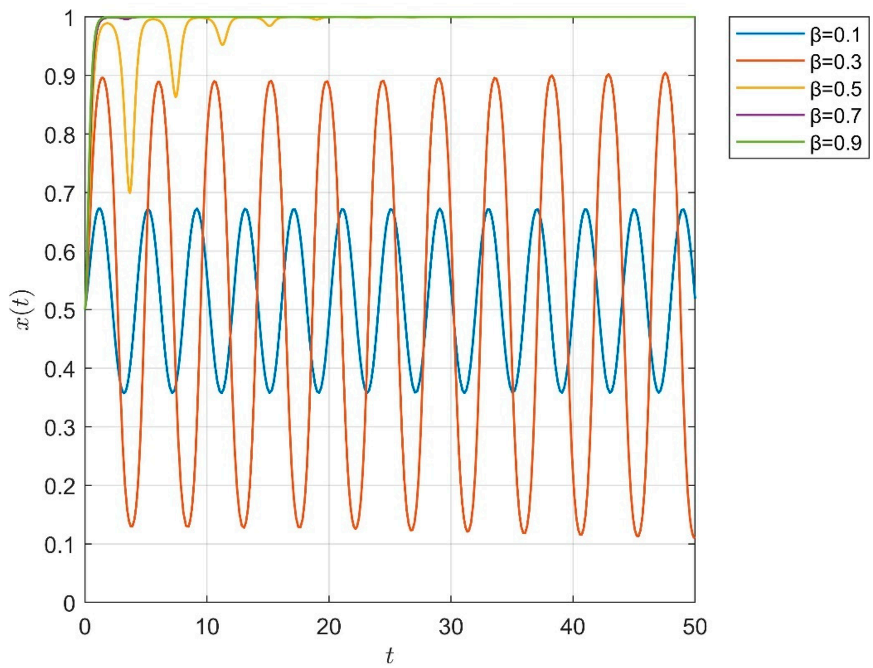

Figure 7. The decision of consumers influenced by β.

The evolutionary trajectory of the government's strategy over time is shown in Figure 8. When the success rate of strict government regulation is small, the government evolves toward a lenient regulation policy. When the success rate of strict regulation increases, the evolution of government strategy cannot reach a steady state. Compared with the fluctuation of the platform's strategy, as shown in Figure 9, the government determines to apply strict regulation when the service platform chooses BDDP strategy. On the contrary, the government chooses lenient regulation when the platform does not adopt BDDP.

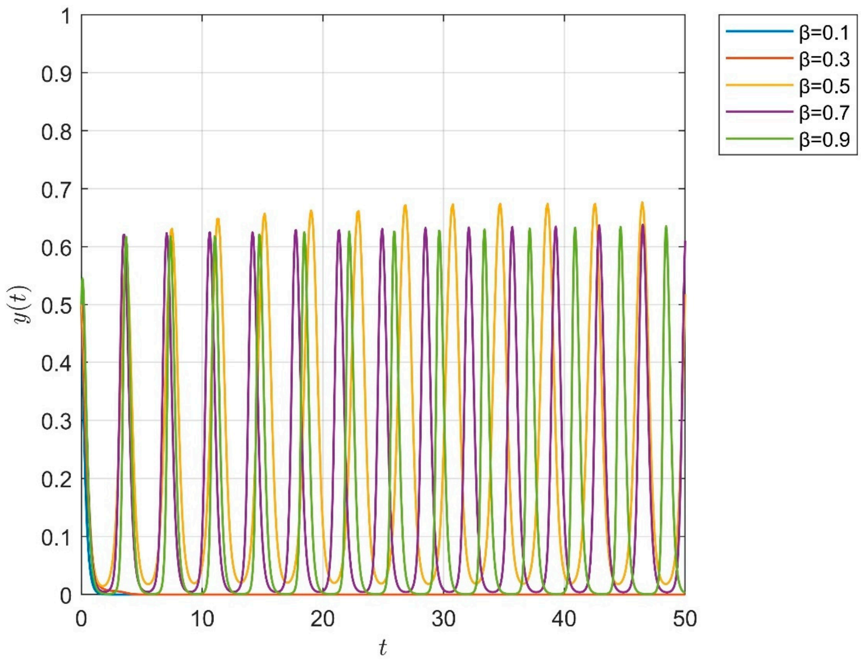

Figure 8. The decision of the government influenced by β.

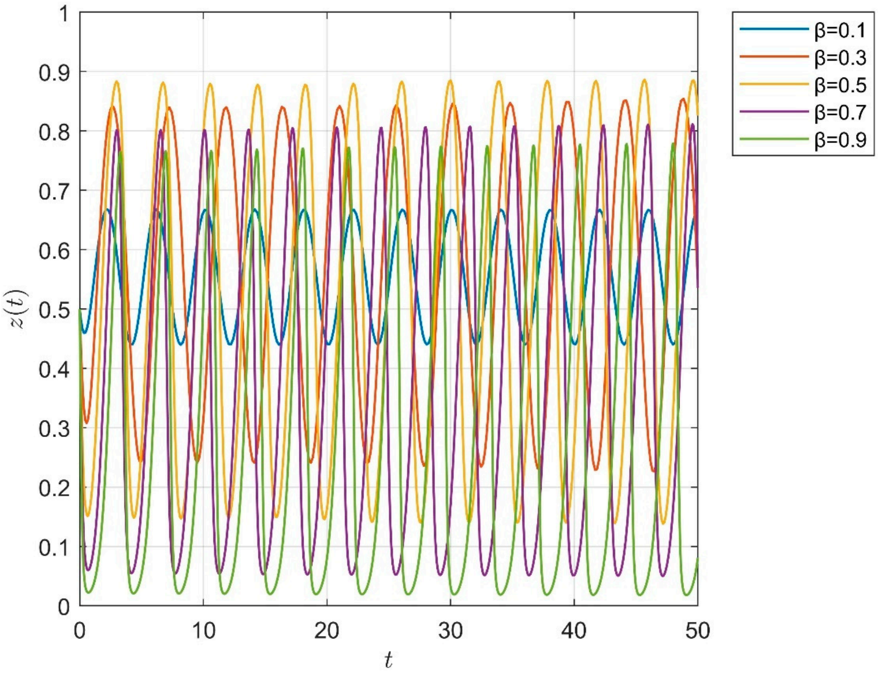

Figure 9. The decision of the service platform influenced by β.

The evolutionary trajectory of platform strategy over time is shown in Figure 9. Regardless of the success rate of strict government regulation, the service platform cannot reach a stable state. With the increase in the success rate of strict regulation, the fluctuation of the platform strategy curve becomes larger, and cannot reach a stable state. Compared with the fluctuation of the government's strategy, as shown in Figure 8, the service platform does not select the BDDP strategy when the government tends to strictly regulate. The platform selects the BDDP strategy when the government tends to choose lenient regulation.

In a nutshell, as the success rate of strict regulation increases, consumers gradually evolve toward choosing the service platform and eventually reach a stable state. On the contrary, a lower success rate of strict regulation leads to a stable state of the government, resulting in a lenient regulation policy. A service platform cannot reach a stable state regardless of the success rate of strict regulation. At a relatively large value of the success rate of strict regulation, these strategies of the government and the service platform influence each other.

5.2. Impact of the Government Tax Rate on the Behaviors of Three Players

r is the tax rate levied by the government on the platform, and when it takes different values (from 0.1 to 0.9 at the interval of 0.2), the simulation results of the evolutionary game are shown in Figure 10. Since it is unlikely that the tax rate is too large in reality, the discussion here is to provide an intuitive basis.

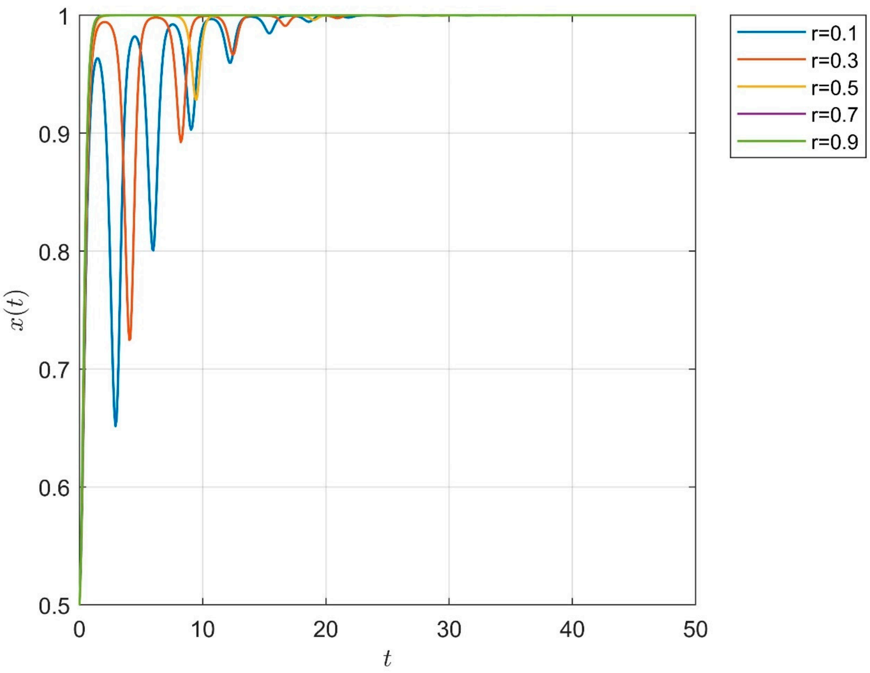

Figure 10. The decision of consumers influenced by r.

The evolutionary trajectory of consumer strategy over time is shown in Figure 10. When the tax rate levied by the government on the platform is small, consumers' strategy appears to fluctuate initially and then converge to a stable state, i.e., choosing the service platform. With the increase in the tax rate levied by the government on the service, consumers reach a stable state more quickly.

The evolutionary trajectory of the government's strategy over time is shown in Figure 11. When the tax rate levied by the government on platform earnings is small, the government cannot reach a stable state and changes with the platform's strategy, i.e., the government tends to strictly regulate when the platform implements BDDP, and the government tends to have lenient regulation when the platform implements uniform pricing practice. When the tax rate levied by the government on platform earnings increases, the government's strategy evolves in the direction of lenient regulation and finally reaches a steady state.

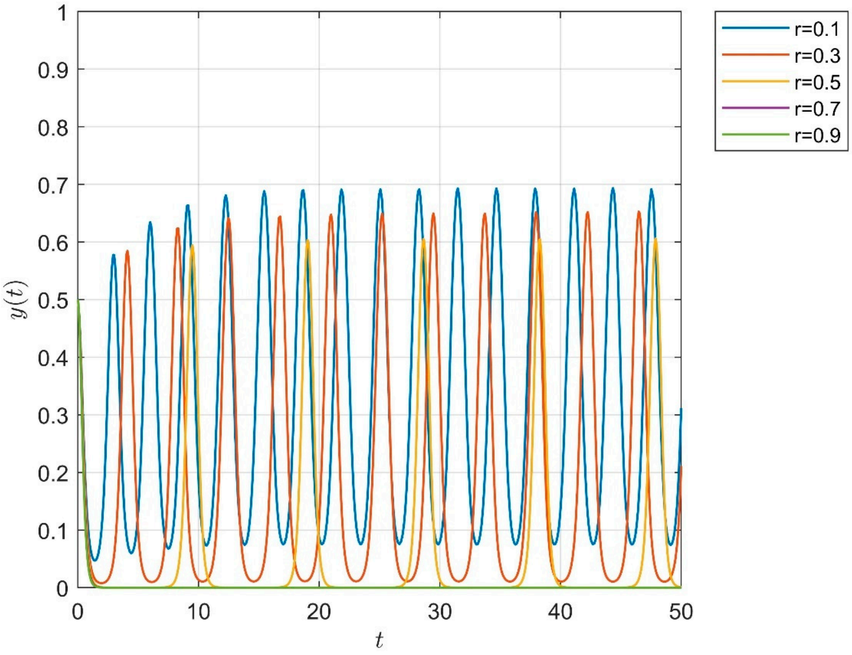

Figure 11. The decision of the government influenced by r.

The evolutionary trajectory of platform strategy over time is shown in Figure 12. When the tax rate levied by the government on platform earnings is small, the platform strategy is unstable, fluctuating between BDDP and uniform pricing. As the tax rate levied by the government on the platform increases, the platform gradually evolves its strategy in the direction of uniform pricing and finally reaches a stable state.

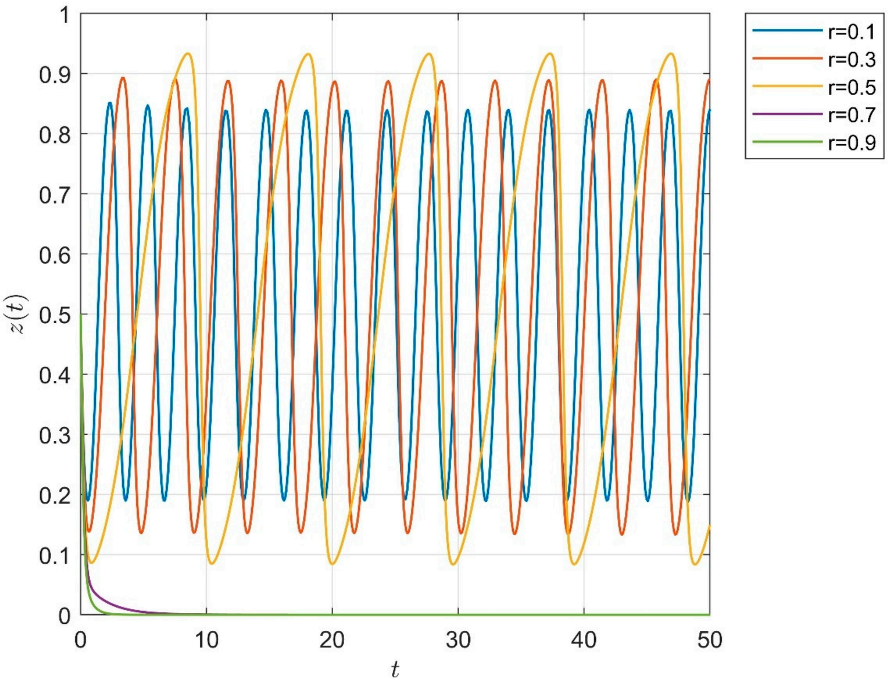

Figure 12. The decision of the service platform influenced by r.

In conclusion, when the tax rate levied by the government on the platform is small, the service platform's strategy fluctuates between BDDP and uniform pricing and the government also fluctuates between strict and lenient regulation in the same pattern. As the tax rate levied by the government on the platform's earnings increases, the platform evolves in the direction of uniform pricing with the consideration of the excessive taxation burden, and the government's strategy evolves in the direction of lenient regulation. Regardless of the tax rate, the consumers choose the platform and remain stable.

5.3. Impact of the Proportion of Consumers Who Switch Platforms after Realizing They Had Suffered from BDDP

The proportion of consumers who switch the platform after discovering being price discriminated against is α. We simulate the trajectory of the three-party evolutionary game among consumers, government, and platform when α takes values of 0.1, 0.3, 0.5, 0.7, and 0.9.

The evolutionary trajectory of consumer strategy over time is shown in Figure 13. When the proportion of consumers who switch platforms after discovering they had suffered from BDDP is small, consumers choose the platform and reach a stable state. With the increase in the proportion of consumers who switch platforms after discovering they had suffered from BDDP, consumers will initially struggle to choose the platform or not and eventually evolve to a stable state as time changes, sticking with the service platform.

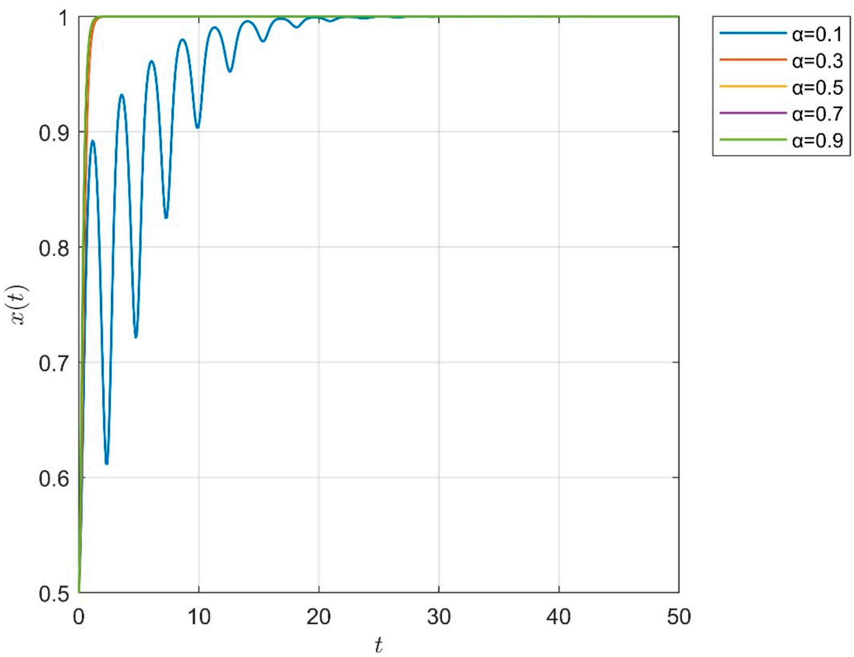

Figure 13. The decision of consumers influenced by α.

The evolutionary trajectory of the government's strategy over time is shown in Figure 14. When the proportion of consumers who switch platforms after discovering themselves suffering from price discrimination is small, the government's strategy cannot reach a steady state and changes with the strategy of the platform. When the proportion of consumers who switch platforms after discovering themselves suffering from BDDP increases, the government strategy evolves toward lenient regulation and eventually reaches a steady state.

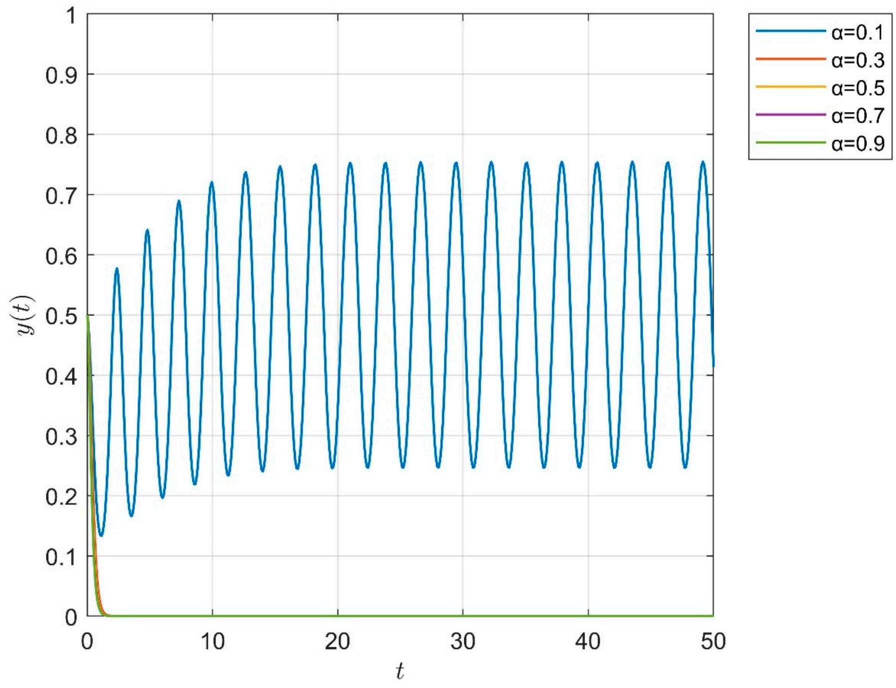

Figure 14. The decision of the government influenced by α.

The evolutionary trajectory of platform strategy over time is shown in Figure 15. When the proportion of consumers who switch platforms after discovering themselves suffering from BDDP is small, the platform oscillates between BDDP strategy and uniform pricing strategy in consideration of the government's regulatory policy, and cannot reach a stable state. When the proportion of consumers who switch platforms after discovering themselves suffering from BDDP increases, the platform's strategy gradually evolves to the direction of uniform pricing in consideration of the long-term loss caused by consumer churn and finally reaches a stable state.

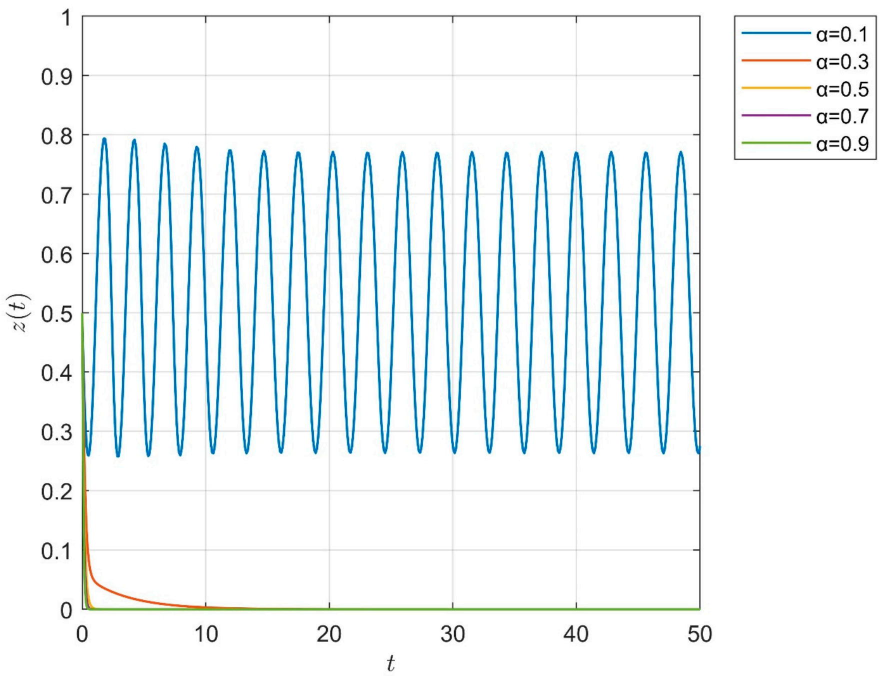

Figure 15. The decision of the service platform influenced by α.

Overall speaking, when the proportion of consumers who switch platforms after discovering they had suffered from BDDP is relatively small, consumers stick to the service platform, and the choices of the government and the service platform are unstable. With the increase in the proportion of consumers who switch platforms after discovering they had suffered from BDDP, the service platform prefers a uniform pricing strategy considering the long-term loss caused by consumer churn, and the government chooses the lenient regulation strategy.

6. Conclusions

We construct a tripartite evolutionary game model of consumers, the government, and the service platform to address the problem of big data-based price discrimination in retailing. We analyze the evolutionary paths of the behavioral strategies of the three players and draw the following conclusions:

(1) Under the assumptions of the model in this work, there are two evolutionary equilibrium points, namely E6 (1, 0, 1) and E7 (1, 1, 0). E6 (1, 0, 1) corresponds to a state where consumers choose this platform, the government adopts lenient regulation, and the service platform adopts BDDP. The platform can gain more profit when applying BDDP. Accordingly, the government can levy more taxes and fees to maximize the government's benefits. When the platform is in a monopoly or duopoly position, the cost for consumers to switch platforms is high, so they have to continue to purchase products or services from the platform and reach a stable state. E7 (1, 1, 0) corresponds to the state that consumers choose this platform, the government applies strict regulations, and the service platform implements a uniform pricing strategy. The government chooses to strictly regulate to maintain a healthy market rule. With the higher success rate of its strict regulation, the platform that implements BDDP may receive greater penalties, which may exceed the consumer surplus captured by BDDP practice. Eventually, the platform implements uniform pricing to avoid being punished. Moreover, in many countries, consumers' data is protected by law and thus BDDP practice and other abuse of customer privacy is prohibited. Under such a situation, consumers' rights and interests are protected and more consumers are attracted to choose this service platform. As the number of consumers choosing the platform grows, both platform's revenue and the government's tax income increase. Eventually, all three players reach a stable state. In summary, both equilibrium strategies are consistent with reality and represent the most profitable situation for all three parties.

(2) When the success rate of strict regulation is large, the strategies of the government and the platform influence each other, and the fluctuation curves of the two players tend to be the same. When the platform chooses BDDP strategy, the government carries out strict regulations to regulate the platform's behavior in time. With the change of time, the platform converges to choose a uniform pricing strategy. When the government tends to loosen the regulation, the platform notices the change keenly and tends to choose BDDP strategy to gain more benefits.

(3) Taxation has a great impact on the strategy of the service platform, and a reasonable adjustment of the tax rate helps regulate the behavior of platforms. When the government levies a larger tax rate on platform earnings, the platform chooses uniform pricing and evolves to a stable state considering that too much tax leads to a reduction in total earnings. Therefore, the government should play a macro-regulatory role by adjusting tax rates according to the behavior of service platforms in the market, and when platforms implement BDDP behavior, the government should appropriately adjust the tax rate levied on platform revenue. However, the tax rate set by the government cannot be too high due to the demand of considering the negative impact on the overall economic performance and the production and operation of enterprises caused by a high tax rate. To maintain the market rule and create a good consumption environment, the tax rate should be set at an appropriate level.

(4) When the proportion of consumers who switch platforms after finding to be pricing discriminated is small, a large number of consumers stick with the platform. The strategy of the government and the platform is unstable. When the proportion of consumers who switch platforms after they find to be pricing discriminated increases, the platform prefers a uniform pricing strategy considering the long-term loss caused by consumer churn.

In summary, this paper aims to address the problem of BDDP practice within the frame of a tripartite evolutionary game theory. Several managerial insights are provided. Firstly, the service platform's BDDP initiative is highly influenced by the government's policy. A direct economic policy, such as strict regulation, tax and penalty, may immediately change the platform's behavior, but such a state is at risk of high social governance costs and behavior rebound. We suggest the government should keep a close watch on the platform's BDDP behavior and implement economic policies at the appropriate time with the appropriate intensity of social governance. One real-world business case is that China government charged a huge amount of fine for the major takeaway platform for disrupting the market order in 2021. The service platform gradually rectified its behavior and disclosed partially its algorithms to be more customer- and employee-oriented friendly. Secondly, consumers also have an equally important role in regulating BDDP behavior. Consumers should raise their awareness of their rights to maintain their legitimate interests by timely discovering that they have been pricing discriminated. consumer's personal data should not be used by platforms for unfair competition such as BDDP, and should be protected by legislation. In this vein, the government has the responsibility to take action to protect the rights of consumers.

We believe this study is highly relevant in practice as it addresses the critical need for efficient and fair pricing policies in the platform economy. The conclusion and managerial insights may be applied in guiding for high-quality development of the platform economy. There are several limitations of this paper and thus future research is required. Firstly, theoretical analysis is derived based on mathematical assumptions. While we conducted surveys for input values in the numerical experiments, future studies could further focus on the empirical examinations of the theoretical results. Secondly, many service platforms may offer offline establishments for consumers, which complicates the tripartite evolutionary game. It is worthwhile exploring the evolutionary paths in the omni-channel retailing setting. Thirdly, this paper considers consumers' platform-switching behavior to implicitly reflect the existence of competition in the market. While it is appropriate to avoid confusing situations with multiple platform players, future research could explicitly model the competitive relationship in a duopoly or a market with more than two service platforms, and their interactive behavior. Lastly, sustainability considerations, such as excessive consumption and circular economy, may be worthwhile in future research. By incorporating sustainability, future research could help provide a more comprehensive understanding of the impact of big data-driven technologies in the platform economy.

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