Online ride-hailing regulation: A simulation study based on evolutionary game theory

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Abstract:

Game theory contributes to the quantitative study of online ride-hailing regulations; however, prior game models of the online ride-hailing market fail to comprehensively consider government regulation strategies as well as multiple stakeholders in various regulation contexts. This study constructs two system dynamic models of evolutionary games among online ride-hailing platforms, drivers, and passengers. One is the basic model not subject to government regulations, while the other considers government regulations systematically regarding penalty policy, incentive policy, policy adaptability, and public participation. By solving and simulating the model, we study evolutionary stable strategies to control fluctuations in the game process. The results show that an unregulated online ride-hailing system is volatile, and government regulations help stabilize the system. The effect of government regulations can be optimized by adopting a dynamic penalty with a greater initial

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force, considering platforms as agents in incentive policy, improving policy adaptability, and rewarding public participation.

Keywords: Online ride-hailing regulation; Evolutionary game; System dynamics; Simulation experiment

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Introduction

As a representative application of the sharing economy in the field of transportation, online ride-hailing has revived idle vehicles, seats, driving abilities, and other transportation resources, providing people with intelligent and personalized ride-hailing services (Chalermpong et al. 2022; Zuo et al. 2019). However, the extensive growth of online ride-hailing has resulted in regulation problems that are difficult to keep up with the rapid development of practice in a timely manner, resulting in a gray zone with vague regulations and vacuum rules (Cetin & Deakin 2019). Furthermore, an effective regulatory strategy for the ride-hailing industry is yet to be fully developed. The illegal operation of online ride-hailing has resulted in frequent reports of property and safety damage to passengers in China (Jiang & Zhang 2019). This has become an important issue that urgently needs to be solved (Kauffman and Naldi 2020; Pawlicz 2019).

Regulation of ride-hailing also has drawn academic attention. Researchers have affirmed the importance of regulations from the perspectives of consumer safety and information privacy (Zhang 2019). Meanwhile, some scholars suggest that appropriately regulating the emerging sharing economy requires further study (Kauffman and Naldi 2020; Yu et al. 2020). Owing to the bounded rationality of participants in the ride-hailing market, evolutionary game theory has demonstrated explanatory power for understanding the dynamic regulatory process of the ride-hailing system (Lei et al. 2020).

Despite these advancements, the lack of an overall consideration of the ride-hailing system is a prominent gap in regulation studies in this field. Prior literature on online ride-hailing regulation only considers two-way or three-way gaming (Lu et al. 2019; Yu et al. 2020). Even in a tripartite game, the role of government regulation only takes into account incentives or penalties. However, regulation of the online ride-hailing market is affected by major stakeholders, including online ride-hailing platforms, drivers, passengers, and the government. According to evolutionary game theory, these stakeholders participate in the online ride-hailing market with different roles and interests, causing different influences on the regulation of online ride-hailing (Wang et al. 2020). For example, policy adaptability of platforms and drivers, and passengers' participation in regulation are essential issues in this context. However, such effects have not been comprehensively examined in presented game models. To formulate optimal policies that balance the interests of all stakeholders, a gaming model that systematically considers the government regulation strategies and the interaction among the main stakeholders (i.e., online ride-hailing platforms, drivers, and passengers) in different regulation contexts is urgently needed.

To fix this void, we adopt evolutionary game theory and system dynamics to study the gaming mechanism of the major stakeholders in the online ride-hailing market (i.e., online ride-hailing platforms, drivers, and passengers). We construct two system dynamic models of the online ride-hailing market. One model does not consider government regulations, while the other is equipped with government regulations in terms of penalty policy, incentive policy, policy adaptability, and public participation. Furthermore, to suppress the fluctuation of game players' strategies, we explore optimized regulatory measures via simulation experiments regarding the four aspects.

This study contributes to the ride-hailing literature by developing an evolutionary game model that focuses on the entire online ride-hailing market, and not merely on some of its participants. This advances our understanding of the gaming relationship among the major stakeholders in the online ride-hailing market. Moreover, it offers a systematic view of the government's regulations and the alignment of the other three stakeholders by showing ways to reduce the volatility of the game process and optimize the regulatory effect of the online ride-hailing market.

Related works

As a typical form of transportation in the sharing economy, online ride-hailing can meet people's diverse travel needs, effectively use vehicle and road resources, and help relieve urban traffic pressure (Tafreshian et al. 2020). However, it also poses several problems, such as security risks and regulatory difficulties (Kauffman and Naldi 2020). A literature review reveals that previous studies on online ride-hailing have focused on a variety of topics, including impact on traditional ride-hailing, consumer behavior, operation strategy of the ride-hailing platform, and policy and regulation of ride-hailing among others (Tirachini 2020).

In terms of online ride-hailing regulations, most of the research discussed relevant issues from the perspectives of theoretical discussion and case analysis (Yu et al. 2020). For example, referring to the history of the regulation of ride-hailing, one study indicated that traditional taxicab markets and ridesharing services should be regulated differently (Cetin and Deakin 2019). Similarly, scholars have stated that to adapt to the Internet sharing economy, online ride-hailing requires a different regulatory response than traditional ones (Hong and Lee 2018; Jiang and Zhang 2019). The effect of ride-hailing regulations has been extensively discussed, and their pros and cons have been argued (Pawlicz 2019). However, most scholars have endorsed the essential role of regulations considering protection of consumer safety and other benefits, as well as promoting a healthy ride-hailing industry (Akyelken et al. 2018).

Most of the existing research on ride-hailing regulations remain in the qualitative discussion and reasoning stages. Some scholars have recently applied game models to quantitatively study ride-hailing regulations. Evolutionary game theory overcomes the assumption of perfect rationality in the traditional game theory and focuses on the dynamic process of game-playing, which contributes to uncovering regulation strategies in the ride-hailing context (Lei et al. 2020; Friedman 1998). In the evolutionary game, players with bounded rationality dynamically make responses to the initial strategy and other participants' action strategies until reaching an equilibrium solution. Considering the uncertainty in the dynamic process rather than the specific interaction mechanism, the main idea of the evolutionary game is to find the frequencies of strategies adopted by participants in dynamic balance.

With these traits, evolutionary game theory has demonstrated explanatory power in understanding the dynamic processes of ride-hailing systems. For example, Sun et al. (2019) constructed a two-dimensional evolutionary game model between the government and ride-hailing platforms, and provided evidence for whether ride-hailing platforms require strict regulation under the current Internet setting. Furthermore, some scholars have established evolutionary game models that consider three players to study the regulation strategies of the online ride-hailing market. Lei et al. (2020) clarified the regulation strategies of multiple subjects (i.e., transportation network companies, drivers, and passengers) involved in the ride-hailing industry and indicated that the evolutionarily stable strategy of a single subject is affected by the strategies of the other two subjects. Pu et al. (2020) analyzed the main factors determining the optimal supervision strategies of online ride-hailing based on a tripartite evolutionary game model between the platform, passengers, and drivers. Wang et al. (2020) described the interaction mechanism of the government supervision department, online vehicle platform security monitoring department, and car-sharing owner from an evolutionary game theory perspective in the process of China's Internet ride-hailing operation. Additionally, evolutionary game theory also helps to explore other dynamic mechanisms in online ride-hailing systems, such as the ride-hailing service mode choice (Bai et al. 2019), collaborative consumption between passengers and drivers (Huang et al. 2020) among others.

However, the proposed game models are either limited to two stakeholders or consider three stakeholders yet government regulation only from a punitive or incentive perspective. Models that consider government regulations comprehensively are still missing. Owing to this gap, prior research has failed to offer systematic online ride-hailing regulation strategies. Therefore, to provide guidance for online ride-hailing regulation in line with reality, this study examines the systematic game mechanism of major stakeholders (i.e., online ride-hailing platforms, drivers, and passengers) in the online ride-hailing market based on evolutionary game theory. Regulatory strategies of the online ride-hailing market are proposed in terms of penalty policy, incentive policy, policy adaptability, and public participation.

Evolutionary game model and assumptions

In this study, online ride-hailing regulations involve four heterogeneous entities: online ride-hailing platforms, drivers, passengers, and the government. The relationships among the four players involved in online ride-hailing regulation are presented in Fig. 1.

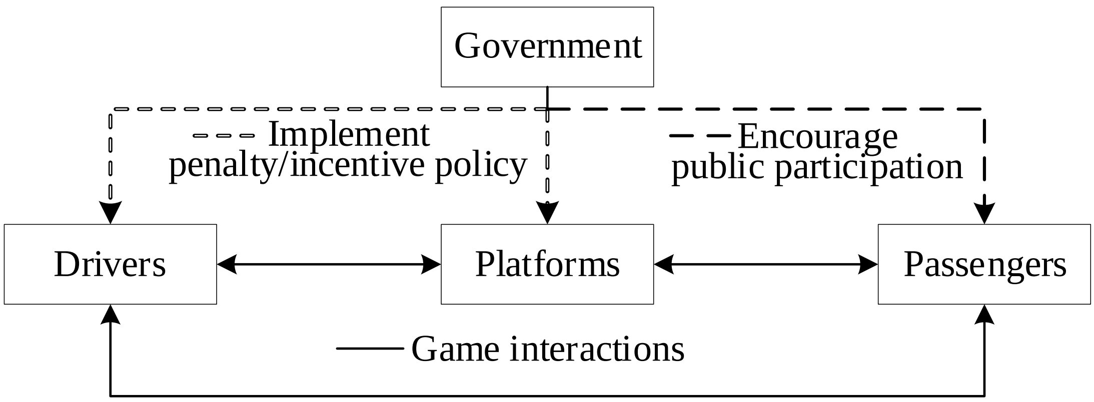

Figure 1. Quadripartite interactions diagram

Considering the government’s interaction with the other three players, we elaborated on the government's regulatory strategies from the following four aspects: penalty policy, incentive policy, policy adaptability, and public participation. First, a penalty policy is a common method to ensure that market entities are law-abiding and correct violators (Becker 1968). As per existing studies, fines have not only become a regular punitive measure, but the force of the penalty under the dynamic mechanism has also played a role (Polinsky and Shavell 1991). Second, an incentive policy refers to the regulatory means by which the government uses rewards to motivate market entities to behave lawfully (Li et al. 2019). The government usually adopts principal-agent cooperation to ensure effective incentives for market entities (Pavlou et al. 2007). Hence, considering online ride-hailing platforms as agents of government regulations, this study introduces the proportion of government rewards between online ride-hailing platforms and drivers into the model. Third, policy adaptability is related to the effect of government regulation on the online ride-hailing market. For the inconstant economy, an adaptive regulation that keeps abreast of the business practice can carry out better results (Akyelken et al. 2018). Here, we employ the error rate of the government's regulation to reflect the probability of regulatory failure due to poor policy adaptation. Finally, public participation is welcomed and pursued by service-oriented governments (Lee et al. 2017). Participating in the regulation of the online ride-hailing market not only safeguards passengers' rights and interests but also benefits the government. Therefore, our model considers the influence of public participation on government regulations.

Online ride-hailing platforms have two strategies for dealing with government regulations: positive and negative cooperation. A positive cooperation strategy refers to an online ride-hailing platform that complies with the regulations, actively supervises drivers, and responds to passengers. In this case, online ride-hailing platforms benefit from cooperation with the government and bear the supervision cost (Li et al. 2019). In contrast, online ride-hailing platforms can be driven by other interests to adopt negative cooperation strategies, such as cutthroat competition, neglected supervision, and encroachment of passengers' privacy (Zuo et al. 2019). While pursuing the interests brought about by negative cooperation strategies, online ride-hailing platforms also face government fines, reputation loss, and a crisis of trust.

Furthermore, the drivers can choose either a legal or an illegal operation strategy. The former implies that the drivers follow government regulations and the operating rules of the online ride-hailing platforms. The latter refers to drivers' violation of regulations or operating rules such as overloading and risky driving. Once their illegal operations are discovered, the drivers must accept penalties and losses from the online ride-hailing platforms or government (Ganapati and Reddick 2018).

Passengers are also essential players whose role has been mostly unheeded in existing game models of online ride-hailing regulations (Lei et al. 2020). Regarding public participation in online ride-hailing regulations, passengers face the choice between monitoring and non-monitoring strategies. Passengers with the monitoring strategy accuse drivers and online ride-hailing platforms of illegal behavior. For example, passengers can file a complaint about unreasonable charges with the Consumer Protection Agency, so the regulatory authority of the government can impose penalties for illegal behaviors in the market. The opposite strategy means that no such indirect monitoring is performed. Under the monitoring strategy, they may shoulder the cost of monitoring such as time and energy, suffer from psychological depression, and receive rewards from online ride-hailing platforms (Pu et al. 2020).

Based on the above systematic analysis of the interactions among the four players in the online ride-hailing regulation, we identify the pure strategy set of online ride-hailing platforms, drivers, and passengers. The pure strategy set for online ride-hailing platforms is {positive cooperation, negative cooperation}, that for drivers is {legal operation, illegal operation}, and that for passengers is {monitoring, non-monitoring}. The government plays a regulatory role in four areas: penalty policy, incentive policy, policy adaptability, and public participation. To understand the dynamic gaming system better, we propose the following reasonable assumptions:

Assumption 1: The probability of online ride-hailing platforms choosing the positive cooperation strategy is x $(1 \geq x \geq 0)$, and that of choosing the negative cooperation strategy is $1-x$. The drivers operate legally at a rate y $(1 \geq y \geq 0)$, and $1-y$ represents the probability of drivers' irregular behaviors. Additionally, we set the probability of passengers participating in monitoring as z $(1 \geq z \geq 0)$, and that of the non-monitoring strategy as $1-z$.

Assumption 2: The normal benefit obtained by online ride-hailing platforms from a positive cooperation strategy is R_1 $(R_1 > 0)$. When adopting a positive cooperation strategy, online ride-hailing platforms need to invest resources to operate the platforms, supervise drivers, and respond to passengers. We set the relevant cost to be C_1 $(C_1 > 0)$. Additionally, we assume that only when online ride-hailing platforms can obtain an extra benefit ΔR_1 $(\Delta R_1 > 0)$, will they adopt a negative cooperation strategy. Similarly, we set R_2 $(R_2 > 0)$ as the normal benefit of the drivers that operate legally, and ΔR_2 $(\Delta R_2 > 0)$

serves as the extra benefit of the drivers that operate illegally. Moreover, passengers devote their time and energy when they participate in the monitoring. The cost of passenger monitoring is denoted as C_2 $(C_2 > 0)$. No cost is incurred if the passengers are not interested during monitoring.

Assumption 3: When drivers operate illegally, regardless of whether passengers participate in monitoring, the online ride-hailing platforms that adopt a negative cooperation strategy will suffer a reputation loss S_1 $(S_1 > 0)$. Moreover, if passengers participate in monitoring, it will cause trust loss S_2 $(S_2 > 0)$ to the online ride-hailing platforms that adopt a negative cooperation strategy, bringing psychological loss S_3 $(S_3 > 0)$ to passengers due to platforms' negligence. Instead, regardless of the drivers' strategy, online ride-hailing platforms adopt a positive cooperation strategy that always actively responds to the voices of passengers, which contributes to passenger satisfaction. R_3 $(R_3 > 0)$ represents the psychological benefit that platforms bring to the passengers.

Assumption 4: If online ride-hailing platforms adopt a positive cooperation strategy, the drivers will be penalized by the platforms owing to an illegal operation. The immediate receivers of the drivers' services are passengers, not online ride-hailing platforms. Hence, we assume that online ride-hailing platforms have an error rate s $(1 \geq s \geq 0)$ to fail to be aware of drivers' violations. If the passengers that adopt the monitoring strategy report the drivers' irregular behavior to the online ride-hailing platforms, then $s = 1$, and the platform will impose a penalty M $(M > 0)$ on drivers and give a reward R_4 $(R_4 > 0)$ to passengers.

Assumption 5: Regarding the government's regulations, the online ride-hailing platforms that adopt negative cooperation or drivers operating illegally will face a fine imposed by the government. Here, P_1 $(P_1 > 0)$ represents the government's penalty to platforms, and w $(w \geq 1)$ is the force of government's penalty to platforms. P_2 $(P_2 > 0)$ represents the government's penalty to drivers, and v $(v \geq 1)$ is the force of the government's penalty to drivers. In contrast, if the online ride-hailing platforms or drivers adopt the opposite strategy, they will share a reward R_5 $(R_5 > 0)$ offered by the government in proportion to the principal-agent mechanism of incentive policy. We set the proportion of the government's reward for platforms as r $(1 \geq r \geq 0)$, so the proportion of that for drivers is $1 - r$. Additionally, to maximize regulatory effectiveness, the government will give a reward R_6 $(R_6 > 0)$ to passengers to encourage public participation. Furthermore, passengers participating in monitoring also play a positive role in government regulations. We set the degree of impact of passengers' monitoring as u $(u \geq 1)$. Moreover, an overly serious punishment can provoke collective resistance and thus be unenforceable. Hence, we introduce policy adaptability in our models, we use an error rate t $(1 \geq t \geq 0)$ to reflect the probability of regulatory failure.

Table 1. Variables in the game model

Variable	Meaning of variable	Remark
R_1	Normal benefit of platforms from positive cooperation	$(0,\infty)$
ΔR_1	Extra benefit of platforms from negative cooperation	$(0,\infty)$
R_2	Normal benefit of drivers from legal operation	$(0,\infty)$
ΔR_2	Extra benefit of drivers from illegal operation	$(0,\infty)$

R_3	Psychological benefit of passengers while successful monitoring	$(0,\infty)$
R_4	Platforms' reward to passengers	$(0,\infty)$
R_5	Government's reward to platforms and drivers	$(0,\infty)$
R_6	Government's reward to passengers	$(0,\infty)$
C_1	Cost of platforms' positive cooperation	$(0,\infty)$
C_2	Cost of passenger monitoring	$(0,\infty)$
S_1	Reputation loss of platforms caused by drivers' illegal operation	$(0,\infty)$
S_2	Trust loss of platforms caused by being negative with passengers	$(0,\infty)$
S_3	Psychological loss of passengers caused by platforms' negative cooperation	$(0,\infty)$
M	Platforms' penalty to drivers	$(0,\infty)$
P_1	Government's penalty to platforms	$(0,\infty)$
P_2	Government's penalty to drivers	$(0,\infty)$
x	Probability of positive cooperation of online ride-hailing platforms	$[0,1]$
y	Probability of legal operation of drivers	$[0,1]$
z	Probability of passenger monitoring	$[0,1]$
r	Proportion of government's reward for platforms	$[0,1]$
s	Error rate of platforms' positive cooperation (Probability that the platforms fail to be aware of drivers' violation)	$[0,1]$
t	Error rate of government regulations due to poor policy adaptability	$[0,1]$
w	Force of government's penalty to platforms	$[1,\infty)$
v	Force of government's penalty to drivers	$[1,\infty)$
u	Impact degree of passengers' monitoring	$[1,\infty)$

Based on the above assumptions and analysis, we considered two different scenarios: one without government regulations and the other with government regulations. The payoff matrix among multiple stakeholders is then developed, as shown in Table 2.

Table 2. Payoff matrix among multiple stakeholders

The market without government regulations

Platforms	Drivers	Passengers	
		Monitoring	Non-monitoring
	Legal operation	R_1-C_1	R_1-C_1

Positive cooperation		R_2 R_3-C_2	R_2 0
	Illegal operation	R_1-C_1+M R_2+ΔR_2-M R_3+R_4-C_2	R_1-C_1+$(1$-$s)M$-S_1 R_2+ΔR_2-$(1$-$s)M$ 0
Negative cooperation	Legal operation	R_1+ΔR_1 R_2 -C_2	R_1+ΔR_1 R_2 0
	Illegal operation	R_1+ΔR_1-S_1-S_2 R_2+ΔR_2 -C_2-S_3	R_1+ΔR_1-S_1 R_2+ΔR_2 0

The market with government regulations

Platforms	Drivers	Passengers	
		Monitoring	Non-monitoring
Positive cooperation	Legal operation	R_1+rR_5-C_1 R_2+$(1$-$r)R_5$ R_3-C_2	R_1+rR_5-C_1 R_2+$(1$-$r)R_5$ 0
	Illegal operation	R_1+R_5-C_1+M R_2+ΔR_2-M-$uv(1$-$t)P_2$ R_3+R_4+R_6-C_2	R_1+R_5-C_1+$(1$-$s)M$-S_1 R_2+ΔR_2-$(1$-$s)M$-$v(1$-$t)P_2$ 0
Negative cooperation	Legal operation	R_1+ΔR_1-$uw(1$-$t)P_1$ R_2 R_6-C_2	R_1+ΔR_1-$w(1$-$t)P_1$ R_2 0
	Illegal operation	R_1+ΔR_1-S_1-S_2-$uw(1$-$t)P_1$ R_2+ΔR_2-$uv(1$-$t)P_2$ R_6-C_2-S_3	R_1+ΔR_1-S_1-$w(1$-$t)P_1$ R_2+ΔR_2-$v(1$-$t)P_2$ 0

Note: The payoffs in each case are presented in an order of platforms, drivers, and passengers.

Solving the model

According to the evolutionary game theory, the participants decide their strategies according to their expected payoffs. The replicator dynamics equation indicates the evolution mechanisms of participants. When the replicator dynamics equation is equal to zero, the game is in a temporary evolutionary stable equilibrium state. Based on the above assumptions and payoff matrix, we compute the replicator dynamics equation of the platforms, drivers, and passengers.

We first consider the situation that government do not carry out any regulations. Let π_x be the expected payoffs of the platforms that adopt a positive cooperation strategy and π_{1-x} refer to the expected payoffs of the platforms that adopt a negative cooperation strategy. π_x and π_{1-x} are expressed as follows:

$$\begin{aligned}\pi_x &= yz(R_1 - C_1) + y(1-z)(R_1 - C_1) + (1-y)z(R_1 - C_1 + M) \\ &\quad + (1-y)(1-z)[R_1 - C_1 + (1-s)M - S_1] \\ &= R_1 - C_1 + (1-y)(M - Ms - S_1) + z(y-1)(R_1 - C_1 - Ms - S_1)\end{aligned} \tag{1-1}$$

$$\begin{aligned}\pi_{1-x} &= yz(R_1 + \Delta R_1) + y(1-z)(R_1 + \Delta R_1) + (1-y)z(R_1 + \Delta R_1 - S_1 - S_2) \\ &\quad + (1-y)(1-z)(R_1 + \Delta R_1 - S_1) = R_1 + \Delta R_1 - (1-y)(S_1 + zS_2)\end{aligned} \tag{1-2}$$

The average expected payoff of platforms is: $\bar{\pi}_x = x\pi_x + (1-x)\pi_{1-x}$

The replicator dynamics equation of platforms is:

$$\begin{aligned}F(x) &= \frac{dx}{dt} = x(\pi_x - \bar{\pi}_x) \\ &= x(1-x)\{-C_1 - \Delta R_1 + (1-y)[M + Ms(z-1) + (S_1 + S_2)z]\}\end{aligned} \tag{1-3}$$

Similarly, the expected payoffs of the drivers with different strategies (legal or illegal operations) when government regulation is absent are π_y and π_{1-y}:

$$\pi_y = R_2 \tag{1-4}$$

$$\pi_{1-y} = xz(R_2 + \Delta R_2 - M) + x(1-z)(R_2 + \Delta R_2 - (1-s)M) + (1-x)z(R_2 + \Delta R_2) + (1-x)(1-z)(R_2 + \Delta R_2) = R_2 + \Delta R_2 + Mx(s - sz - 1)$$

(1-5)

The replicator dynamics equation of drivers is:

$$F(y) = \frac{dy}{dt} = y(\pi_y - \bar{\pi}_y) = y(1-y)[Mx(1 + sz - s) - \Delta R_2]$$

(1-6)

The expected payoffs of the passengers with different strategies (monitoring or non-monitoring) when government regulation is absent are π_z and π_{1-z}:

$$\pi_z = xy(R_3 - C_2) + x(1-y)(R_3 + R_4 - C_2) + (1-x)y(-C_2) + (1-x)(1-y)(-C_2 - S_3) = x(1-y)(R_4 + S_3) + xR_3 - C_2 - (1-y)S_3$$

(1-7)

$$\pi_{1-z} = 0$$

(1-8)

The replicator dynamics equation of the passengers is:

$$F(z) = \frac{dz}{dt} = z(\pi_z - \bar{\pi}_z) = z(1-z)[x(R_4 + S_3) - xy(R_4 + S_3) + xR_3 - C_2 - (1-y)S_3]$$

(1-9)

We then consider the game model that government plays a regulatory role in the market, wherein the expected payoffs of the platforms with different strategies (positive or negative cooperation) are π'_x and π'_{1-x}:

$$\begin{aligned}\pi_x' &= yz(R_1 + rR_5 - C_1) + y(1-z)(R_1 + rR_5 - C_1) + (1-y)z(R_1 + R_5 - C_1 + M) \\ &\quad + (1-y)(1-z)[R_1 + R_5 - C_1 + (1-s)M - S_1] \\ &= R_1 - C_1 + (1-y)(R_5 + M) + ryR_5 - (1-y)(1-z)(sM + S_1)\end{aligned} \tag{2-1}$$

$$\begin{aligned}\pi_{1-x}' &= yz[R_1 + \Delta R_1 - uw(1-t)P_1] + y(1-z)[R_1 + \Delta R_1 - w(1-t)P_1] \\ &\quad + (1-y)z[R_1 + \Delta R_1 - S_1 - S_2 - uw(1-t)P_1] \\ &\quad + (1-y)(1-z)[R_1 + \Delta R_1 - S_1 - w(1-t)P_1] \\ &= R_1 - (1-y)(S_1 + zS_2) + (1-t)(wz - w - uwz)P_1 + \Delta R_1\end{aligned} \tag{2-2}$$

The replicator dynamics equation of platforms is:

$$\begin{aligned}F'(x) &= x(\pi_x' - \overline{\pi}'_x) \\ &= x(1-x)[-C_1 + ryR_5 + (1-y)(R_5 + M) - (1-y)(1-z)sM \\ &\quad + z(1-y)(S_1 + S_2) + (1-t)(w + uwz - wz)P_1 - \Delta R_1]\end{aligned} \tag{2-3}$$

The expected payoffs of drivers with different strategies (legal or illegal operations) under the regulation of the government are π_y' and π_{1-y}':

$$\begin{aligned}\pi_y' &= xz[R_2 + (1-r)R_5] + x(1-z)[R_2 + (1-r)R_5] + (1-x)zR_2 + (1-x)(1-z)R_2 \\ &= R_2 + x(1-r)R_5\end{aligned} \tag{2-4}$$

$$\begin{aligned}\pi_{1-y}' &= xz[R_2 + \Delta R_2 - M - uv(1-t)P_2] + x(1-z)[R_2 + \Delta R_2 - (1-s)M - v(1-t)P_2] \\ &\quad + (1-x)z[R_2 + \Delta R_2 - uv(1-t)P_2] + (1-x)(1-z)[R_2 + \Delta R_2 - v(1-t)P_2] \\ &= R_2 + \Delta R_2 + x(s - 1 - sz)M + (1-t)(zv - v - zvu)P_2\end{aligned} \tag{2-5}$$

The replicator dynamics equation of drivers is:

$$F'(y) = y(\pi'_y - \bar{\pi}'_y)$$
$$= y(1-y)[x(M + R_5 - rR_5 - sM + zsM) - (1-t)(zv - v - zvu)P_2 - \Delta R_2]$$

(2-6)

The expected payoffs of passengers with different strategies (monitoring or non-monitoring) under the regulation of the government are π'_z and π'_{1-z}:

$$\pi'_z = xy(R_3 - C_2) + x(1-y)(R_3 + R_4 + R_6 - C_2) + (1-x)y(R_6 - C_2)$$
$$+ (1-x)(1-y)(R_6 - C_2 - S_3) = R_2 + x(1-r)R_5$$
$$= -C_2 + R_6 - S_3 + x(R_3 + R_4 + S_3) + yS_3 - xy(R_4 + R_6 + S_3)$$

(2-7)

$$\pi'_{1-z} = 0$$

(2-8)

The replicator dynamics equation of passengers is:

$$F'(z) = z(\pi'_z - \bar{\pi}'_z)$$
$$= z(1-z)[-C_2 + x(R_3 + R_4) - (1-x)(1-y)S_3 - xyR_4 + (1-xy)R_6]$$

(2-9)

Stability analysis of the evolutionary game

According to the evolutionary principle, the players change their strategies over time until they acquire a stable state, which is called an evolutionary stable strategy (ESS). The replication dynamics is a dynamic differential equation describing the speed and direction of strategic adjustment. Referring to the stability theorem of differential equation and the nature of ESS, to obtain the equilibrium solution of the tripartite evolutionary game, replicator dynamics equation set is required as shown in (1-10) or (2-10) for a circumstance without or with government regulations respectively.

$$\begin{cases} F(x) = x(1-x)\{-C_1 - \Delta R_1 + (1-y)[M + Ms(z-1) + (S_1+S_2)z]\} = 0 \\ F(y) = y(1-y)[Mx(1+sz-s) - \Delta R_2] = 0 \\ F(z) = z(1-z)[x(R_4+S_3) - xy(R_4+S_3) + xR_3 - C_2 - (1-y)S_3] = 0 \end{cases} \tag{1-10}$$

$$\begin{cases} F'(x) = x(1-x)\begin{bmatrix} -C_1 + ryR_5 + (1-y)(R_5+M) - (1-y)(1-z)sM \\ +z(1-y)(S_1+S_2) + (1-t)(w+uwz-wz)P_1 - \Delta R_1 \end{bmatrix} = 0 \\ F'(y) = y(1-y)[x(M + R_5 - rR_5 - sM + zsM) - (1-t)(zv - v - zvu)P_2 - \Delta R_2] = 0 \\ F'(z) = z(1-z)[-C_2 + x(R_3+R_4) - (1-x)(1-y)S_3 - xyR_4 + (1-xy)R_6] = 0 \end{cases} \tag{2-10}$$

By solving equation (1-10), we get eight equilibrium points.$E_1(0,0,0)$, $E_2(0,0,1)$, $E_3(0,1,0)$, $E_4(0,1,1)$, $E_5(1,0,0)$, $E_6(1,0,1)$, $E_7(1,1,0)$, $E_8(1,1,1)$. In addition, when $x_0, y_0, z_0 \in [0,1]$ and equation (1-11) is satisfied, $E_9(x_0, y_0, z_0)$ is also the equilibrium point in the equilibrium solution domain.

$$\begin{cases} -C_1 - \Delta R_1 + (1-y)[M + Ms(z-1) + (S_1+S_2)z] = 0 \\ Mx(1+sz-s) - \Delta R_2 = 0 \\ x(R_4+S_3) - xy(R_4+S_3) + xR_3 - C_2 - (1-y)S_3 = 0 \end{cases} \tag{1-11}$$

In equation (2-10), there are also eight special equilibrium points $E_1 \sim E_8$. Besides, we can obtain the equilibrium point $E_9'(x_0', y_0', z_0')$ by solving equation (2-11).

$$\begin{cases} -C_1 + ryR_5 + (1-y)(R_5+M) - (1-y)(1-z)sM \\ +z(1-y)(S_1+S_2) + (1-t)(w+uwz-wz)P_1 - \Delta R_1 = 0 \\ x(M + R_5 - rR_5 - sM + zsM) - (1-t)(zv - v - zvu)P_2 - \Delta R_2 = 0 \\ -C_2 + x(R_3+R_4) - (1-x)(1-y)S_3 - xyR_4 + (1-xy)R_6 = 0 \end{cases} \tag{2-11}$$

In the replicator dynamic system of evolutionary game, the stable point obtained by the replicator dynamics equations must be strictly at a Nash equilibrium of pure strategy (Friedman,1998). Since the solution of E_9 and E_9' is a mixed strategy Nash equilibrium, we only consider the asymptotic stability of the other eight equilibrium points ($E_1 \sim E_8$). To solve the partial derivative of the replicator dynamics equations with respect to each game group, the Jacobean matrix J and J' are defined as follow:

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix}$$

$$= \begin{bmatrix} (1-2x)\{-C_1 - \Delta R_1 + (1-y)[M + Ms(z-1) + (S_1+S_2)z]\} & x(x-1)[M + Ms(z-1) + (S_1+S_2)z] & x(1-x)[(1-y)(S_1+S_2+Ms)] \\ y(1-y)(Ms - M - Msz) & (1-2y)[Mx(1+sz-s) - \Delta R_2] & (1-y)Msxy \\ z(1-z)[(R_4+S_3)(1-y)+R_3] & z(1-z)(S_3 - x(S_3+R_4)) & (1-2z)[x(R_4+S_3) - xy(R_4+S_3) + xR_3 - C_2 - (1-y)S_3] \end{bmatrix} \tag{1-12}$$

$$J' = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix}$$

$$= \begin{bmatrix} (1-2x)\{-C_1 - \Delta R_1 + (1-y)[M + Ms(z-1) + (S_1+S_2)z]\} & x(x-1)[M + Ms(z-1) + (S_1+S_2)z] & x(1-x)[(1-y)(S_1+S_2+Ms)] \\ y(1-y)(Ms - M - Msz) & (1-2y)[Mx(1+sz-s) - \Delta R_2] & (1-y)Msxy \\ z(1-z)[(R_4+S_3)(1-y)+R_3] & z(1-z)(S_3 - x(S_3+R_4)) & (1-2z)[x(R_4+S_3) - xy(R_4+S_3) + xR_3 - C_2 - (1-y)S_3] \end{bmatrix} \tag{2-12}$$

According to Lyapunov's system stability theory, the stability of a strategy can be judged by the eigenvalue of Jacobean matrix (Lyapunov,1992). Only when all eigenvalues of a matrix are negative can the strategy represented by an equilibrium point become an ESS. We substitute the equilibrium points ($E_1 \sim E_8$) into J and J' separately to obtain corresponding eigenvalues. Table 3 presents the stability analysis based on the eigenvalues.

Table 3. Stability analysis of equilibrium points

Equilibrium point	Eigenvalues	Stability conditions
For the matrix J (the market without government regulations)		
$E_1(0,0,0)$	$\lambda_1 = -C_2 - S_3$ $\lambda_2 = -\Delta R_2$ $\lambda_3 = M - C_1 - \Delta R_1 - Ms$	The equilibrium point $E_1(0,0,0)$ is the ESS, if $M - C_1 - \Delta R_1 - Ms < 0$. Otherwise, it is an unstable point or a saddle point.
$E_2(0,0,1)$	$\lambda_1 = -\Delta R_2$ $\lambda_2 = C_2 + S_3$ $\lambda_3 = M - C_1 + S_1 + S_2 - \Delta R_1$	Due to $C_2 + S_3 > 0$, the equilibrium point $E_2(0,0,1)$ cannot be the ESS, but an unstable point or a saddle point.
$E_3(0,1,0)$	$\lambda_1 = \Delta R_2$ $\lambda_2 = -C_2$ $\lambda_3 = -C_1 - \Delta R_1$	Due to $\Delta R_2 > 0$, the equilibrium point $E_3(0,1,0)$ cannot be the ESS, but an unstable point or a saddle point.
$E_4(0,1,1)$	$\lambda_1 = C_2$ $\lambda_2 = \Delta R_2$ $\lambda_3 = -C_1 - \Delta R_1$	Due to $C_2 > 0$ and $\Delta R_2 > 0$, the equilibrium point $E_4(0,1,1)$ cannot be the ESS, but an unstable point or a saddle point.
$E_5(1,0,0)$	$\lambda_1 = M - \Delta R_2 - Ms$ $\lambda_2 = R_3 - C_2 + R_4$ $\lambda_3 = C_1 - M + \Delta R_1 + Ms$	The equilibrium point $E_5(1,0,0)$ is the ESS, if $M - \Delta R_2 - Ms < 0$, $R_3 - C_2 + R_4 < 0$, and $C_1 - M + \Delta R_1 + Ms < 0$. Otherwise, it is an unstable point or a saddle point.
$E_6(1,0,1)$	$\lambda_1 = M - \Delta R_2$ $\lambda_2 = C_2 - R_3 - R_4$ $\lambda_3 = C_1 - M - S_1 - S_2 + \Delta R_1$	The equilibrium point $E_6(1,0,1)$ is the ESS, if $M - \Delta R_2 < 0$, $C_2 - R_3 - R_4 < 0$, and $C_1 - M - S_1 - S_2 + \Delta R_1 < 0$. Otherwise, it is an unstable point or a saddle point.
$E_7(1,1,0)$	$\lambda_1 = C_1 + \Delta R_1$ $\lambda_2 = S_3 - C_2$ $\lambda_3 = \Delta R_2 - M + Ms$	Due to $C_1 + \Delta R_1 > 0$, the equilibrium point $E_7(1,1,0)$ cannot be the ESS, but an unstable point or a saddle point.
$E_8(1,1,1)$	$\lambda_1 = C_1 + \Delta R_1$ $\lambda_2 = C_2 - R_3$ $\lambda_3 = \Delta R_2 - M$	Due to $C_1 + \Delta R_1 > 0$, the equilibrium point $E_8(1,1,1)$ cannot be the ESS, but an unstable point or a saddle point.
For the matrix J' (the market with government regulations)		
$E_1(0,0,0)$	$\lambda_1 = R_6 - C_2 - S_3$ $\lambda_2 = P_2 v - \Delta R_2 - P_2 t v$	The equilibrium point $E_1(0,0,0)$ is the ESS, if $R_6 - C_2 - S_3 < 0$, $P_2 v - \Delta R_2 - P_2 t v < 0$, and $M -$

	$\lambda_3 = M - C_1 + R_5 - \Delta R_1 - Ms + P_1 w - P_1 tw$	$C_1 + R_5 - \Delta R_1 - Ms + P_1 w - P_1 tw < 0$. Otherwise, it is an unstable point or a saddle point.
$E_2(0,0,1)$	$\lambda_1 = C_2 - R_6 + S_3$ $\lambda_2 = P_2 uv - \Delta R_2 - P_2 tuv$ $\lambda_3 = \mathrm{M} - C_1 + R_5 + S_1 + S_2 - \Delta R_1 + P_1 uw - P_1 tuw$	The equilibrium point $E_2(0,0,1)$ is the ESS, if $C_2 - R_6 + S_3 < 0$, $P_2 uv - \Delta R_2 - P_2 tuv < 0$, and $\mathrm{M} - C_1 + R_5 + S_1 + S_2 - \Delta R_1 + P_1 uw - P_1 tuw < 0$. Otherwise, it is an unstable point or a saddle point.
$E_3(0,1,0)$	$\lambda_1 = R_6 - C_2$ $\lambda_2 = \Delta R_2 - P_2 v + P_2 tv$ $\lambda_3 = R_5 r - \Delta R_1 - C_1 + P_1 w - P_1 tw$	The equilibrium point $E_3(0,1,0)$ is the ESS, if $R_6 - C_2 < 0$, $\Delta R_2 - P_2 v + P_2 tv < 0$, and $R_5 r - \Delta R_1 - C_1 + P_1 w - P_1 tw < 0$. Otherwise, it is an unstable point or a saddle point.
$E_4(0,1,1)$	$\lambda_1 = C_2 - R_6$ $\lambda_2 = \Delta R_2 - P_2 uv + P_2 tuv$ $\lambda_3 = R_5 r - \Delta R_1 - C_1 + P_1 uw - P_1 tuw$	The equilibrium point $E_4(0,1,1)$ is the ESS, if $C_2 - R_6 < 0$, $\Delta R_2 - P_2 uv + P_2 tuv < 0$, and $R_5 r - \Delta R_1 - C_1 + P_1 uw - P_1 tuw < 0$. Otherwise, it is an unstable point or a saddle point.
$E_5(1,0,0)$	$\lambda_1 = R_3 - C_2 + R_4 + R_6$ $\lambda_2 = C_1 - M - R_5 + \Delta R_1 + Ms - P_1 w + P_1 tw$ $\lambda_3 = M + R_5 - \Delta R_2 - Ms - R_5 r + P_2 v - P_2 tv$	The equilibrium point $E_5(1,0,0)$ is the ESS, if $R_3 - C_2 + R_4 + R_6 < 0$, $C_1 - M - R_5 + \Delta R_1 + Ms - P_1 w + P_1 tw < 0$, and $M + R_5 - \Delta R_2 - Ms - R_5 r + P_2 v - P_2 tv < 0$. Otherwise, it is an unstable point or a saddle point.
$E_6(1,0,1)$	$\lambda_1 = C_2 - R_3 - R_4 - R_6$ $\lambda_2 = \mathrm{M} + R_5 - \Delta R_2 - R_5 r + P_2 uv - P_2 tuv$ $\lambda_3 = C_1 - M - R_5 - S_1 - S_2 + \Delta R_1 - P_1 uw + P_1 tuw$	The equilibrium point $E_6(1,0,1)$ is the ESS, if $C_2 - R_3 - R_4 - R_6 < 0$, $\mathrm{M} + R_5 - \Delta R_2 - R_5 r + P_2 uv - P_2 tuv < 0$, and $C_1 - M - R_5 - S_1 - S_2 + \Delta R_1 - P_1 uw + P_1 tuw < 0$. Otherwise, it is an unstable point or a saddle point.
$E_7(1,1,0)$	$\lambda_1 = R_3 - C_2$ $\lambda_2 = C_1 + \Delta R_1 - R_5 r - P_1 w + P_1 tw$ $\lambda_3 = \Delta R_2 - R_5 - M + Ms + R_5 r - P_2 v + P_2 tv$	The equilibrium point $E_7(1,1,0)$ is the ESS, if $R_3 - C_2 < 0$, $C_1 + \Delta R_1 - R_5 r - P_1 w + P_1 tw < 0$, and $\Delta R_2 - R_5 - M + Ms + R_5 r - P_2 v + P_2 tv < 0$. Otherwise, it is an unstable point or a saddle point.
$E_8(1,1,1)$	$\lambda_1 = C_2 - R_3$	The equilibrium point $E_8(1,1,1)$ is the ESS, if $C_2 - R_3 < 0$, $C_1 +$

	$\lambda_2 = C_1 + \Delta R_1 - R_5 r - P_1 uw + P_1 tuw$ $\lambda_3 = \Delta R_2 - R_5 - M + R_5 r - P_2 uv + P_2 tuv$	$\Delta R_1 - R_5 r - P_1 uw + P_1 tuw < 0$, and $\Delta R_2 - R_5 - M + R_5 r - P_2 uv + P_2 tuv < 0$. Otherwise, it is an unstable point or a saddle point.

The stability analysis of equilibrium points shows that the ESS of a single subject is not only affected by personal factors, but also affected by the strategies of other two subjects. It is difficult to reasonably customize the strategic choices of the players and identify the stable state of two evolutionary game systems. To achieve a better understanding of the stability of equilibrium points, we apply system dynamics to simulate and model the evolutionary game process.

System dynamics model of the evolutionary game

System dynamics contributes to the analysis of the complex dynamics of the evolutionary game model with multiple stakeholders (Sterman 2001). We adopt Vensim to conduct the system dynamics model of the evolutionary game of online ride-hailing regulations. Referring to the introduction of regulations in online ride-hailing market (Zhang 2019), we consider two scenarios. We first study the system dynamics model of three players, namely the online ride-hailing platforms, drivers, and passengers, when the government neglects regulations (as shown in Fig. 2), and then the system dynamics model with government regulations (as shown in Fig. 5).

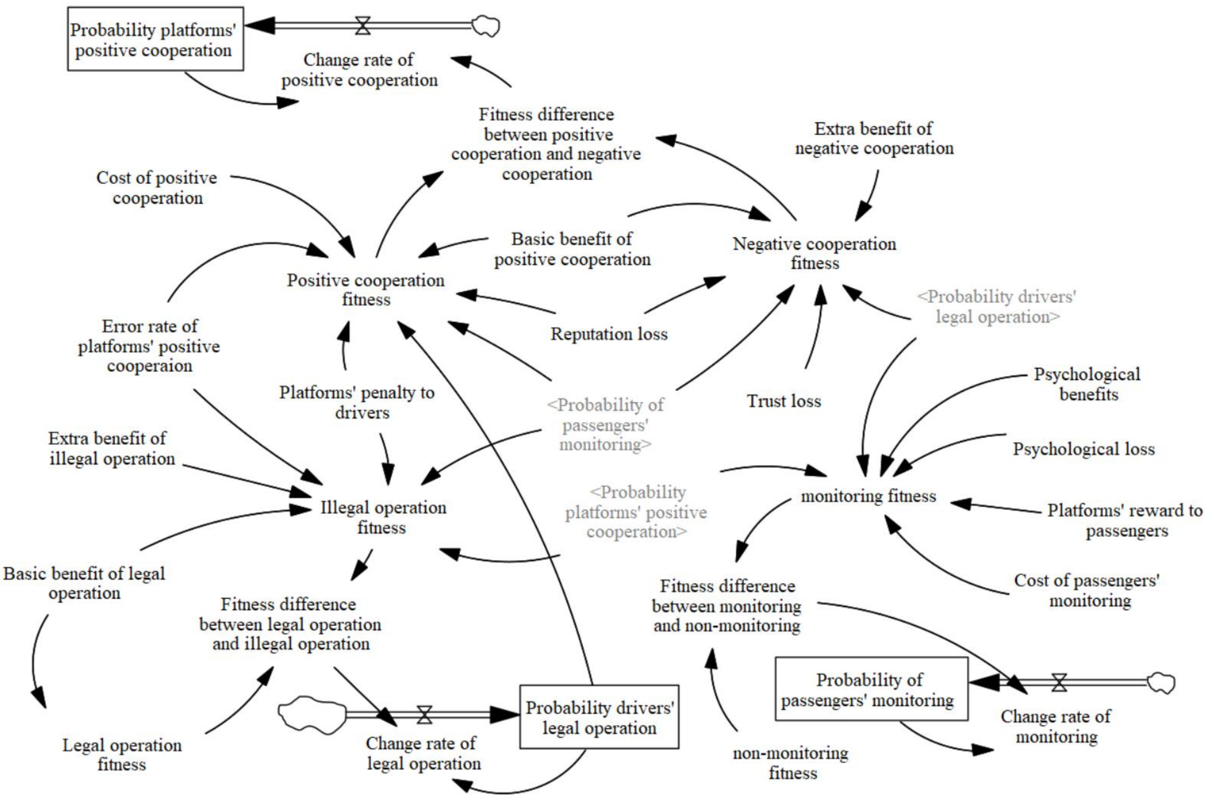

Figure 2. System dynamics model of evolutionary game among online ride-hailing platforms, drivers, and passengers when government neglects regulations

To analyze the system dynamics model without government regulations, it is necessary to assign the initial values of the external variables in the model. It should be noted that the system dynamics model focuses on revealing the dynamic change, variable assignment does not require accurate results but enables the model to reflect the trend of the system and the impact of regulation changes (Sterman 2001). Therefore, when setting the initial value of the external variables, we mainly consider the sensitivity of the variable changes to the players' strategy choices rather than precisely representing the benefits or costs of all parties. Referring to the relevant online ride-hailing news reports and related studies (Lei et al. 2020; Sun et al. 2019; Wang et al. 2020), the initial values of the external variables in the model are set as follows: $R_1 = 8, \Delta R_1 = 6, R_2 = 4, \Delta R_2 = 5, R_3 = 2, R_4 = 1, C_1 = 2, C_2 = 1.5, M =$

$3, S_1 = 2, S_2 = 2, S_3 = 3, s = 0{,}6$. We set the parameters in the system dynamics model as INITIAL TIME=0, FINAL TIME=100, TIME STEP=0.03125, and Units for TIME: Month.

The initial values of the external variables are introduced into the replicator dynamic equations (1-10), wherein eight pure strategy equilibrium points ($E_1 \sim E_8$) are satisfied. We simulate the dynamic process to analyze the stability of the pure strategy equilibrium points. The simulation results show that the three players do not actively change their initial strategies at pure strategy equilibrium points. However, the states of these equilibrium points are unstable and path-dependent. Taking $E_6 = (1,0,1)$ as an example, we simulate that a small number of passengers are mutated. When the probability of passengers choosing the monitoring strategy changes from $x = 1$ to $x = 0.99$, the results are shown in Fig. 3.

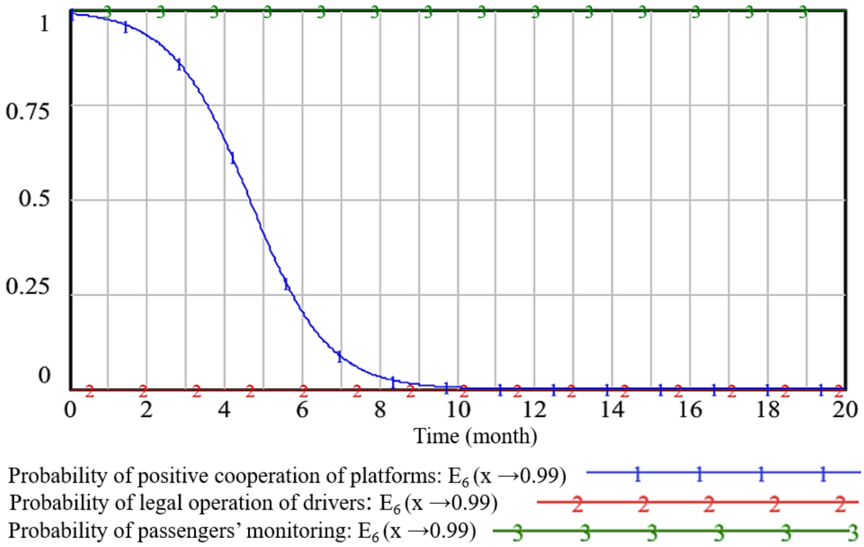

Figure 3. Game evolution of the initial pure strategy E_6 (x →0.99)

It is evident from Fig. 3 that the equilibrium state of pure strategy $E_6 = (1,0,1)$ is not stable. If a small number of passengers exit from monitoring, the overall strategy of the passengers will change to non-monitoring, and the game system will evolve from $E_6 =$

$(1,0,1)$ to $E_2(0,0,1)$. Similarly, we find that the other pure strategy equilibrium points are unstable. Regardless of the initial strategy of the game players, as time goes on, the equilibrium state eventually evolves to $E_1 = (0,0,0)$, as shown in Fig. 4.

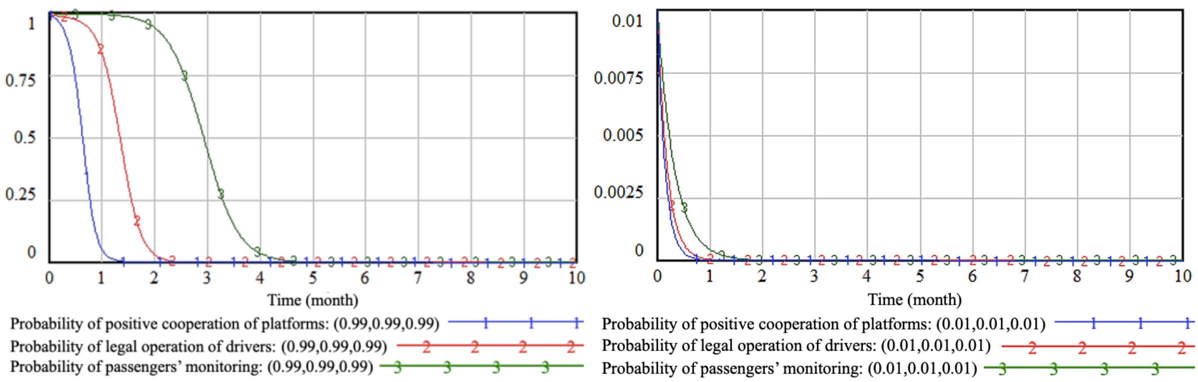

Figure 4. Game evolution of different initial strategies

In the absence of government regulations, the final evolutionary process of the online ride-hailing regulation system tends to be $E_1 = (0,0,0)$, indicating that online ride-hailing platforms are negatively cooperative, drivers operate illegally, and passengers do not participate in monitoring.

Based on the above system dynamics model of online ride-hailing platforms, drivers, and passengers, we further consider the role of government regulations from four aspects: penalty policy, incentive policy, policy adaptability, and public participation. The online ride-hailing system regulated by the government is modelled and simulated, as shown in Fig. 5.

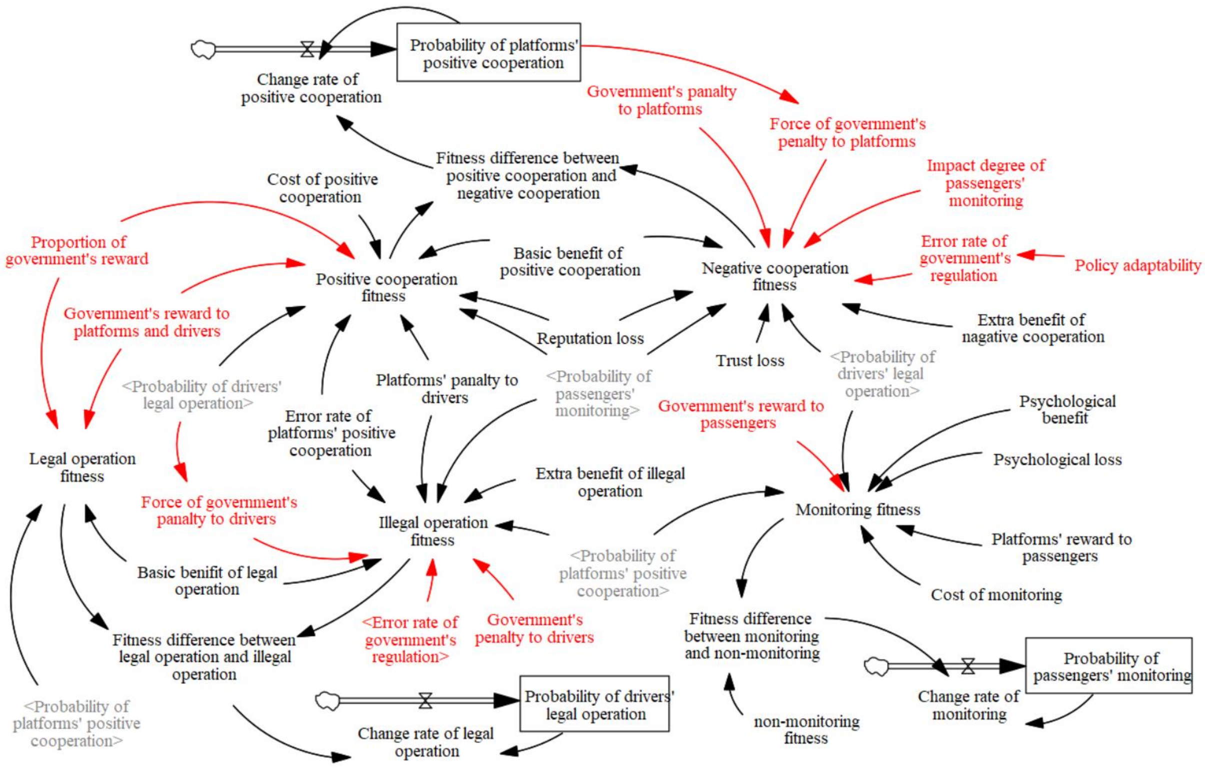

Figure 5. System dynamics model of evolutionary game among online ride-hailing platforms, drivers, and passengers with government regulations

As the case of online ride-hailing market in China, the government mainly regulates ride-hailing platforms and drivers by restrictive policy, and little or no incentives are introduced, which means that the government's penalties should be greater than its reward. With reference to reality and relevant research (Lei et al. 2020; Sun et al. 2019; Zhang 2019), the initial values of the other external variables in the model are assigned as follows: $R_5 = 4, r = 0.6, R_6 = 1.6, P_1 = 4, P_2 = 3.5, t = 0.4, u = 1.2, w = 1, v = 1$. We can also obtain eight pure strategy equilibrium points ($E_1 \sim E_8$) by solving the replicator dynamic equations (2-10) with above initial values. To analyze the stability of these equilibrium points, we consider the equilibrium point $E_8(1,1,1)$ as an example to simulate the game evolution process of the online ride-hailing regulation system. Simulating that a small number of online ride-hailing service platforms mutate from $x = 1$ to $x = 0.99$, the game system evolves from $E_8(1,1,1)$

to $E_4(0,1,1)$, as shown in Fig. 6. The simulation of other equilibrium points also indicates instability. In summary, no ESS exists during the game process.

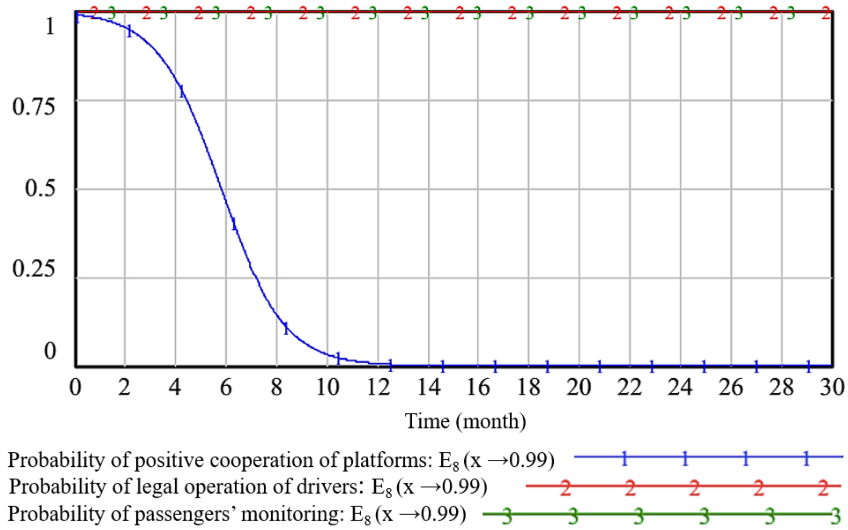

Figure 6. Game evolution of the initial mixed strategy E_8 (x→0.99)

Simulation experiments of stability control and optimization

The evolutionary game of the online ride-hailing regulation system with government regulations fluctuates unstably, posing challenges for government regulation strategies. Hence, it is necessary to optimize regulation strategies to control the volatility of the evolutionary game process to provide practical and effective guidance for government regulations.

Impact of penalty policy

General penalty strategy

The government usually imposes penalties in the form of fines to regulate the behavior of platforms and drivers. First, we examine the impact of the general penalty on online ride-hailing regulations. In terms of the platforms, the initial value of the government's penalty P_1

is assigned as 4, and we then simulate the evolution of online ride-hailing platforms when the government's penalty for platforms is increased to 6 and 8. Similarly, in addition to the initial government penalty for drivers (i.e., P_2=3.5), we consider the case in which the penalty value increases to 5 and 6.5. The simulation results are presented in Fig. 7.

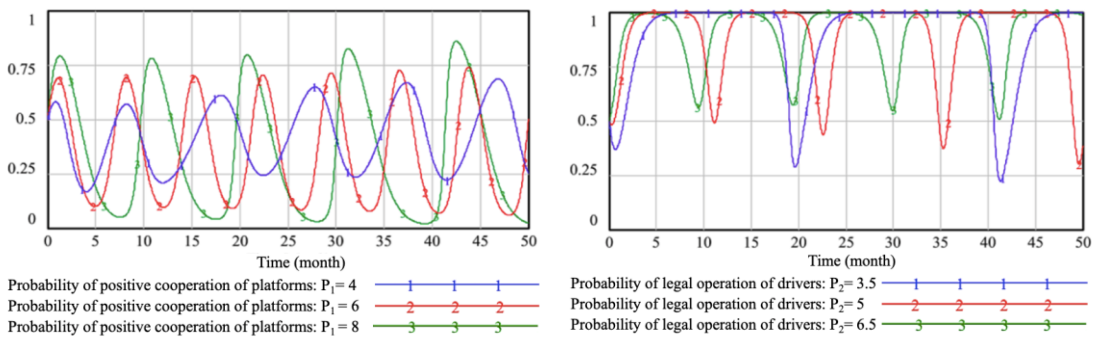

Figure 7. The impact of general penalty on platforms (left) and drivers (right)

As the government's penalty increased, the strategies of ride-hailing platforms and drivers did not change significantly. However, the amplitude and frequency of fluctuations in the evolutionary game process increased, causing greater volatility of the system. The behavior of online ride-hailing platforms and drivers becomes more difficult to predict and control during long-term games, which is an impediment to government regulations. From a long-term perspective, simply increasing the government's penalties for platforms and drivers is not conducive to online ride-hailing regulations.

Dynamic penalty strategy

To curb the volatility in the game of online ride-hailing regulations, scholars have proposed a dynamic penalty strategy (Wang et al. 2020), that is, the government dynamically regulates the behaviors of market entities according to their interactions. More specifically, the_government's penalty is adjusted dynamically based on the behavior of the penalized object. For example, the lower the probability of positive cooperation of platforms, the greater the government's penalty to the platforms.

The dynamic penalty mechanism contributes to restraining the fluctuation of the game among platforms, drivers, and passengers, and the evolution process roughly converged at x = 0.64, y = 0.57, and z = 0.69. For instance, regardless of the initial strategy set of online ride-hailing platforms, drivers and passengers are (0.1, 0.1, 0.1), (0.5, 0.5, 0.5), or (0.9, 0.9, 0.9), respectively, the process of the evolutionary game of online ride-hailing regulations always converges to (0.64, 0.57, 0.69). The results are shown in Fig. 8.

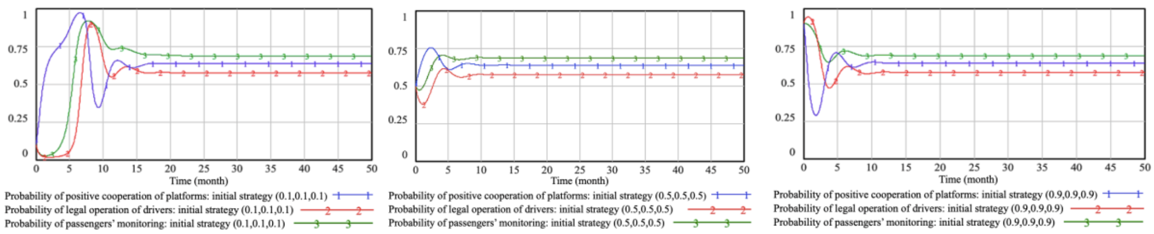

Figure 8. Game evolution of different initial strategies under dynamic penalty mechanism

Moreover, the government has an initial force for penalties in long-term regulations. We analyze the evolution paths of the platforms and drivers under different initial forces of government penalty in the dynamic penalty. The initial force of the government's penalty to platforms w is set as 1, 2, and 3, respectively, so is the initial force of the government's penalty to drivers v. The results are presented in Fig. 9.

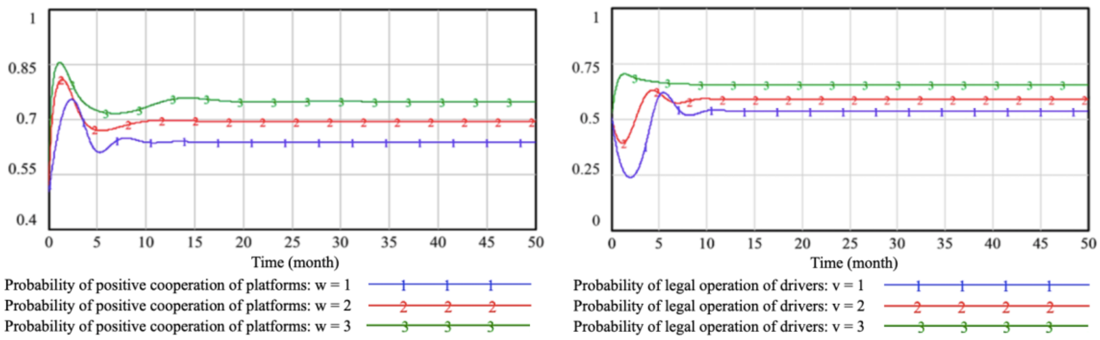

Figure 9. The impact of initial force of government penalty in dynamic penalty on platforms (left) and drivers (right)

Evidently, when the initial force of government penalty increases, the probability of positive cooperation of platforms as well as legal operation of drivers also increases. Improving the initial force of government's penalty results in a higher cost for violators. Hence, a dynamic penalty strategy with greater initial force benefits the regulation effect.

Impact of incentive policy

The government introduces a regulatory incentive mechanism to encourage ride-hailing platforms, drivers, and passengers to adopt strategies that benefit the overall market. First, the government rewards passengers to promote public participation. To simulate the incentive policy’s impact on passengers, we keep the other variables unchanged and set the government’s rewards to passengers R_6 as 1.6, 2.1, and 2.6. The simulation results are shown in Fig. 10.

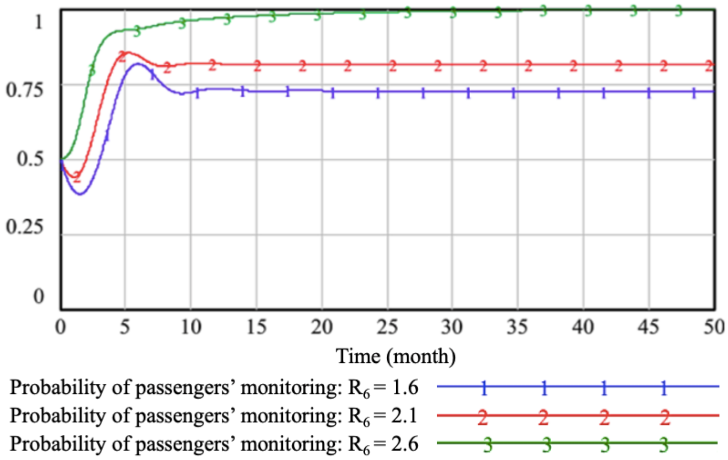

Figure 10. The impact of incentive policy on passengers

Government incentives increase the probability of public participation in monitoring activities. When the reward exceeds a certain amount, the proportion of passenger monitoring will reach 100%. Even if it is a general reward, passengers will be encouraged to monitor. Therefore, the incentive policy for passengers is better than that of no incentive policy.

Second, the government motivates platforms and drivers to behave lawfully through rewards. Additionally, the principal-agent cooperation between the government and platforms allows the platforms and drivers to share the government's rewards. To consider the incentive policy's impact on online ride-hailing platforms and drivers, we simulate the evolution process of online ride-hailing platforms and drivers with different government rewards, that is, R_5= 4, R_5= 5, R_5=6, while the other variables, including the proportion between platforms and drivers, remain the same. The results are shown in Fig. 11.

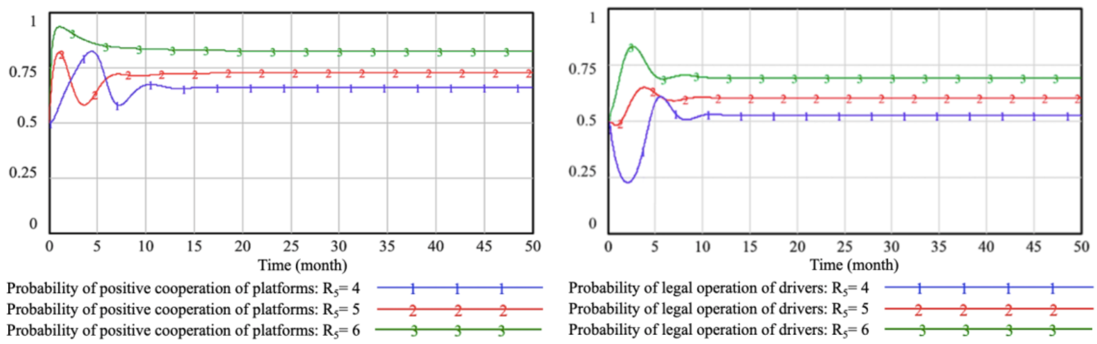

Figure 11. The impact of incentive policy on platforms (left) and drivers (right)

The results show that government rewards can improve the probability of positive platform cooperation, as well as the legal operation of drivers. Furthermore, the government needs to consider both the scale and allocation of rewards to optimize the regulatory result. In view of the principal-agent mechanism between government and platforms, we analyze the impact of the proportion of government rewards between platforms and drivers by simulating the evolution process of platforms and drivers under two different proportions, wherein the proportion of government rewards for platforms r is assigned as 0.6 and 0.8. The results are shown in Fig. 12.

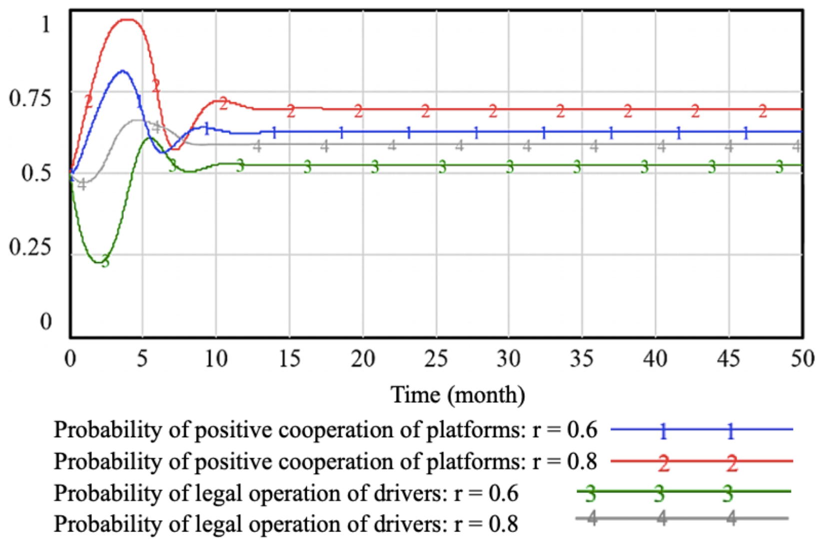

Figure 12. The impact of incentive policy that considers principal-agent mechanism

When the government rewards are inclined toward online ride-hailing platforms, both the probability of positive cooperation of platforms and the legal operation of drivers increase. The principal-agent relationship between the government and online ride-hailing platforms is conducive to market regulation. Drivers seem to prefer illegal operation strategies when the government rewards online ride-hailing platforms more, leading to lower benefits for drivers. Nevertheless, platforms are motivated by more rewards to enforce stricter regulations for drivers and monitor drivers to operate legally. Hence, the principal-agent cooperative regulation mechanism, in which a government–platform relationship is achieved, can play a better role in online ride-hailing market regulation. The overall effect of market regulation is better than that of the government's direct incentives for drivers.

Impact of policy adaptability

The enforcement of government regulations is affected by the adaptability of the online ride-hailing policy, including whether the policies and regulations of online ride-hailing are suitable for the development of online ride-hailing, whether the regulatory scope and contents are comprehensive and operable, and whether it is possible to mollify contradictions among multiple stakeholders in the online ride-hailing market. We employ the error rate of government regulations to reflect the probability of regulatory failure due to insufficient policy adaptation. To examine the impact of policy adaptability, the error rate of government regulations t is set to 0.4, 0.3, and 0.2, while keeping the other variables unchanged. A simulation analysis is conducted on the evolution of the probability of positive cooperation of platforms and the probability of the legal operation of drivers. The results are shown in Fig. 13.

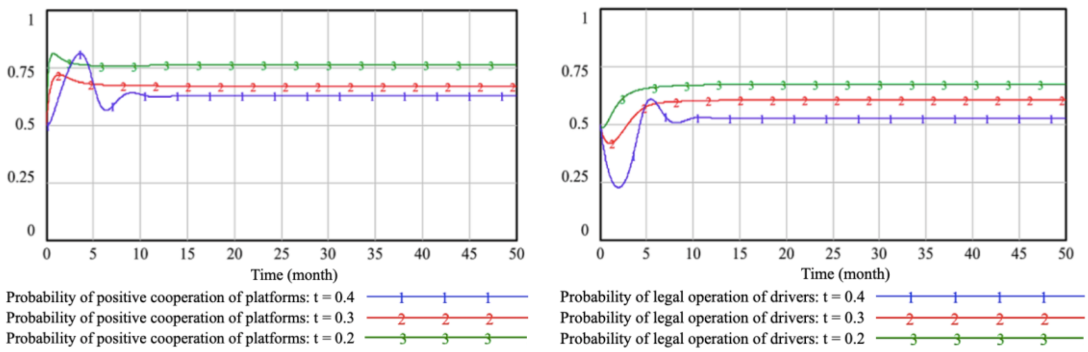

Figure 13. The impact of policy adaptability on platforms (left) and drivers (right)

As the error rate of government regulations declines, the probabilities of online ride-hailing platforms' positive cooperation and drivers' legal operation increase, indicating that improving policy adaptability has a positive effect on regulating the behavior of the main players in the online ride-hailing market. To adopt adaptive regulation in the emerging online ride-hailing market, the government needs to constantly adjust the regulatory strategy according to the feedback of the regulatory effect to improve the feasibility and effectiveness of regulations and make it more suitable for the sustainable development of the online ride-hailing market.

Impact of public participation

Passengers directly contact online ride-hailing platforms and drivers in the service process; therefore, they often experience the illegality of drivers or platforms, becoming an important force in online ride-hailing regulations. Here, public participation is considered as a complement to government regulations (Lee et al. 2017), and the degree of impact of passenger monitoring is introduced to estimate the effect. To analyze the impact of public participation in online ride-hailing regulations, we set the impact degree of passengers' monitoring u as 1.2, 2.4, and 3.6. The results for platforms and drivers are shown in Fig. 14.

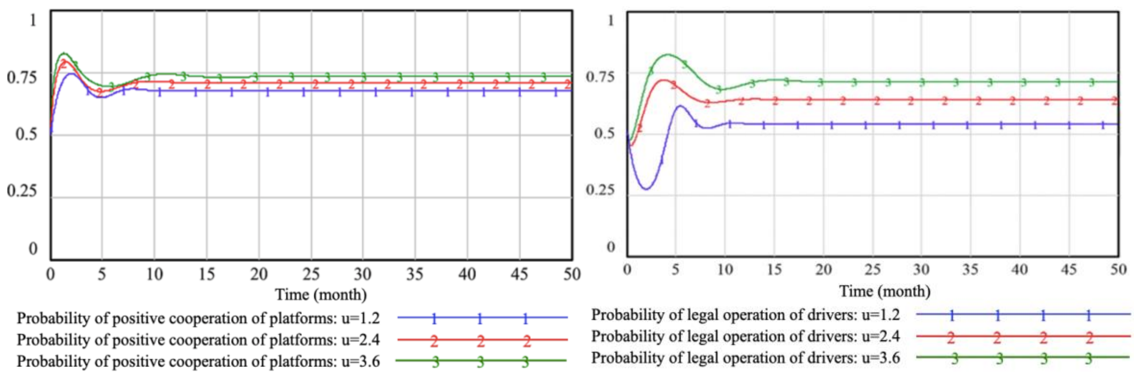

Figure 14. The impact of public participation on platforms (left) and drivers (right)

With an increase in the degree of impact, the probability of online ride-hailing platforms adopting a positive cooperation strategy slightly increases, and the probability of drivers operating legally significantly increases. In fact, as receivers of online ride-hailing services, passengers have direct contact with drivers in the process of service consumption. Whether drivers operate legally matters to the interests of passengers, so passengers often actively monitor their behavior. However, passengers connect with the platforms via a mobile application or an online client service, making it difficult to monitor the operation of the platforms. In brief, passengers can play a positive role in monitoring the operation of drivers, and it is difficult for passengers to significantly impact the regulation of online ride-hailing platforms.

Conclusion, implications, and limitations

Based on evolutionary game theory, this study builds gaming models that comprehensively consider the regulation strategies of government as well as three main players (i.e., online ride-hailing platforms, drivers, and passengers) in an online ride-hailing market context. Combining the idea of the evolutionary game with the simulation approach, we present the system dynamics of the evolutionary game and conduct simulation experiments to explore optimized regulatory measures from the aspects of penalty policy, incentive policy, policy adaptability, and public participation. The following conclusions and implications are drawn:

(1) Government regulations play an important role in restraining the lawbreaking of market entities, which is conducive to promoting sustainable development of the online ride-hailing market. The online ride-hailing market fluctuates in the absence of government regulations. Online ride-hailing platforms, drivers, and passengers, as bounded rational behaviorists in the online ride-hailing market, attempt to maximize their personal interests. The online ride-hailing market tends to stagnate when platforms cooperate negatively, drivers operate illegally, and passengers do not participate in regulation.

(2) Dynamic penalty can effectively suppress periodic fluctuations in the gaming process of the online ride-hailing market. Under the general penalty mechanism, no stable equilibrium state exists in the evolution game of the online ride-hailing regulation system. Conversely, the dynamic penalty mechanism effectively controls the fluctuation in the gaming process, resulting in an evolutionarily stable equilibrium. When ride-hailing accidents occur frequently, the government tends to tighten penalties. Furthermore, ride-hailing platforms and

drivers cope with strict regulations by operating in a friendly manner. As the ride-hailing market becomes orderly, the government eases its penalties. In summary, the government should be flexible, with a penalty mechanism to reduce game volatility in the online ride-hailing market.

(3) The indirect incentive mechanism of the principal-agent relationship between the government and ride-hailing platforms can achieve better regulatory effects than the government's direct driver supervision. Online ride-hailing platforms directly access the information of drivers and vehicles, but it is difficult for the government to obtain such first-hand information that is conducive to regulations. Hence, a principal-agent regulatory mode in which the government motivates ride-hailing platforms to regulate drivers is advantageous. Driven by the government’s incentives, ride-hailing platforms are willing to invest more resources in stricter regulation of drivers and explore more effective ways to motivate drivers’ legal operations.

(4) A regulation with greater adaptability results in better regulatory effects, whereas regulatory failure is linked to worse policy adaptation and a higher error rate in government regulations. This is reflected in the fact that with the improvement in policy adaptability, both the probability of positive cooperation of online ride-hailing platforms and the legal operation of drivers climbs. However, in the context of a sharing economy, traditional regulatory policies may no longer be applicable to the evolving ride-hailing market, failing to prevent accidents. To improve the adaptability and flexibility of regulatory policies, it is crucial for regulatory authorities to be aware of the actual needs of each player in the market and continuously adjust their policies.

(5) Public participation in monitoring drivers or platforms benefit government regulations. Our findings reveal that the positive impact of passenger monitoring on driver operations is significantly greater than their impact on online ride-hailing platforms. To achieve better effects of public participation on the regulation of the online ride-hailing market, both the government and online ride-hailing platforms should focus on providing convenient channels for passenger feedback. Additionally, incentives can greatly increase the proportion of the public involved in monitoring, regardless of the reward amount, an incentive policy to encourage public participation in monitoring is advocated.

This study has enriched online ride-hailing market regulation research by offering a systematic view of government regulations from four aspects, meanwhile, considering the major stakeholders of the entire online ride-hailing market. From a substantive standpoint, our findings provide regulatory authorities and online ride-hailing platforms with a better understanding of the gaming relationship and regulatory optimization in the ride-hailing market. Further, considering the limitations of this study, we merely examined the effectiveness of the regulations in four terms separately rather than their combined effect. The interaction between different regulatory strategies can be further explored. And researchers can build game models that better simulate reality by optimizing the assumptions and introducing factors (e.g., heterogeneity of drivers and passengers) that are more in line with the actual conditions of the regulation of the online ride-hailing market.

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