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Cooperative Vehicle Infrastructure System or Autonomous Driving System? From the Perspective of Evolutionary Game Theory

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Abstract: In this paper, we explore the trade-offs between public and private investment in autonomous driving technologies. Utilizing an evolutionary game model, we delve into the complex interaction mechanisms between governments and auto manufacturers, focusing on how strategic decisions impact overall outcomes. Specifically, we predict that governments may opt for strategies such as constructing and maintaining infrastructure for Roadside Infrastructure-based Vehicles (RIVs) or subsidizing high-level Autonomous Driving Vehicles (ADVs) without additional road infrastructure. Manufacturers' choices involve deciding whether to invest in RIVs or ADVs, depending on governmental policies and market conditions. Our simulation results, based on scenarios derived from existing economic data and forecasts on technology development costs, suggest that government subsidy policies need to dynamically adjust in response to manufacturers' shifting strategies and market behavior. This dynamic adjustment is crucial as it addresses the evolving economic environment and technological advancements, ensuring that subsidies effectively incentivize the desired outcomes in autonomous vehicle development. The findings of this paper could serve as valuable decision-making tools for governments and auto manufacturers, guiding investment strategies that align with the dynamic landscape of autonomous driving technology.

Keywords: autonomous driving system; cooperative vehicle infrastructure system; evolutionary game model; investment policy

MSC: 91A22

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1. Introduction

The technical roadmap for the development of autonomous driving has caused controversy in China and even the world. From the perspective of the individual vehicle, the Society of Automotive Engineers (SAE) divides the intelligence level of vehicles into 5 levels (from Level 0 to Level 5) according to the level of automatic driving function [1]. Manufacturers such as Tesla and Apollo in the United States, as well as Baidu and NIO in China have made vehicles more intelligent through continuous technological research. These manufacturers claim to be able to manufacture Level 3 to Level 4 intelligent vehicles. This kind of vehicle can be called Autonomous Driving-based Vehicles (ADVs). The intelligent functions of vehicles have gradually become one of the important gimmicks for manufacturers to compete for consumers. However, such vehicle-based technology roadmap relies heavily on expensive onboard intelligent devices. The price of a complete set of onboard intelligent devices may even exceed that of the vehicle itself. For example, Xiao Peng P5, as the first mass-produced intelligent vehicle in China, has a price difference of nearly 43.75% according to the level of vehicle intelligent [2]. Therefore, consumers need to bear high purchase costs to enjoy autonomous driving, which will seriously hinder the full deployment of autonomous driving. Moreover, for manufacturers, the cost of upgrading and maintenance of intelligent vehicles is also a relatively large expense.

In order to solve the shortcomings of the vehicle-based technology, the development path of Cooperative Vehicle Infrastructure System (CVIS) came into being. Its main motivation is to vigorously develop roadside intelligent devices to serve all vehicles, thereby reducing the demand for on-board equipment and lowering the popularization cost of autonomous driving. Unlike conventional autonomous driving system (ADS), where the individual vehicles are highly intelligent and can handle perception and decision-making on its own, CVIS allocates part of the work to roadside infrastructure. The equipment with a sensing function and computing storage unit is placed on the roadside. Thus, the sensing, data fusion, and decision processing functions are migrated to the roadside IRU (intelligent roadside unit) [3]. The vehicle only needs to retain a small part of the control receiver module to realize the vehicle's automatic driving function. In other words, this kind of vehicle with only a small part of intelligent functions can realize the functions of higher-level intelligent vehicles with the help of intelligent roadside infrastructure. And we can name this kind of vehicle as Roadside Infrastructure-based Vehicles (RIVs).

The emergence of CVIS addresses two obstacles that hinder the full deployment of vehicle automation at this stage: (1) the limitation of perception range, and (2) the high cost of vehicle equipment. With fixed roadside sensors, the range of the perception area can be significantly improved under any weather conditions. Additionally, the vehicle does not require a large amount of onboard computing and storage capacity required by the fully autonomous driving mode of the ADS system. CVIS provides consumers with the possibility to enjoy autonomous driving at a lower cost. In China, governments have promulgated a series of encouragement policies to promote the development of CVIS. By 2035, China will establish a comprehensive modern transport system, and CVIS will certainly play an important role in this process [4].

In CVIS, the government will pay for the construction, operation, and maintenance of intelligent roadside infrastructure. And CVIS will provide feedback to the government in terms of safety, efficiency, and energy consumption from the perspective of urban transportation network optimization. Auto manufacturers can also reduce the research and production costs of intelligent vehicles, but at the same time they will lose the competitive advantage of producing high-level Autonomous Driving Vehicles (ADVs). Therefore, automakers will confront two production strategies (i.e., producing RIVs or ADVs), while governments will also face an either-or policy choice (i.e., built the CVIS or not built). In other words, there is a game relationship between the profit maximization of auto manufacturers and the transportation system optimization of local governments. This relationship will dynamically change with the manufacturer's production strategy and the local government's policies. Therefore, in order to more effectively promote the development of autonomous driving, it is worth investigating how the different strategies formulated by local governments and auto manufacturers affect the development of CVIS, and how auto manufacturers choose between CVIS-compliant RIVs and ADS-compliant ADVs.

In addition, the advancement of autonomous driving technologies is at a critical juncture where significant decisions about the future direction of these systems must be made. Specifically, the industry faces a strategic dilemma: should the focus be on enhancing the intelligence capabilities of individual vehicles, or should there be a shift towards a cooperative approach that integrates vehicle and roadside infrastructure intelligence? Each strategy presents unique challenges and opportunities. As far as the current problem statement is concerned, it can be summarized as follows: Firstly, relying on vehicle intelligence involves high costs and complex technology requirements, which include expensive onboard sensors and computing devices that elevate the vehicle's price and limit market accessibility. Secondly, implementing CVIS requires significant infrastructure investments and faces hurdles in interoperability and standardization across various vehicle technologies and manufacturers. Finally, both approaches must navigate a complex regulatory landscape, addressing safety, liability, and the need for harmonized regulations to facilitate widespread adoption. These factors collectively influence the strategic direction toward the most viable, effective, and sustainable integration of autonomous driving technologies into the broader transportation and urban infrastructure.

To this end, this paper constructs an evolutionary game model between local governments and manufacturers decision-making, and the system evolution stability under different situations can be obtained from the replicator dynamic equation. On this basis, we can take numerical simulation analysis to investigate the influencing factors of different strategy choices.

This study helps establish strategic guidelines for auto manufacturers and governments to promote and develop autonomous driving in China. Major contributions of this paper are listed as follows:

(1) We develop an evolutionary game model to investigate the interaction mechanism of government and manufacturer's investment policies in autonomous driving.
(2) We estimate how investment decisions of governments and auto manufacturers in autonomous driving can ultimately shape the outcome.
(3) We investigate different scenarios that might occur depending on the starting conditions and the benefits/costs of each technology of autonomous driving.
(4) We predict the choices of government (whether or not to upgrade the road infrastructure) and auto manufacturers (whether to produce RIVs or ADVs).

The remainder of the paper can be organized as follows. Section 2 reviews related research. Section 3 develops the replicator evolutionary game model of the local governments and manufacturers and analyzes the evolutionary stability strategies and conditions. Section 4 executes numerical simulations to demonstrate the effectiveness of the proposed model, and Section 5 provides concluding remarks.

2. Literature Review

Currently, the academic research on CVIS mainly focuses on macro-framework research and micro-technology implementation methods [5–7]. At the macro level, scholars committed to improving the existing ITS architecture, using high-precision map technology and edge computing technology, etc. as the bottom of the system architecture [8,9]. At the same time, they penetrated intelligent communication technology into vehicles and roadside infrastructures. In terms of the technical approaches, scholars used the theories in the fields of traffic engineering, control optimization, and communication technology to explore ways to implement various functional modules of CVIS [10–12]. From the aforementioned studies, it is evident that CVIS has progressively matured at the technical level. Consequently, discussions about the economic implications of this emerging technology during its practical implementation become inevitable. Some current research has ventured into this arena, offering cutting-edge discussions on the topic. Shatanawi et al. found that road pricing strategies are essential for managing future CVIS, and the economic outcomes of these strategies are influenced by the penetration rates of different vehicle types [13]. Alonso Raposo et al. examined the socio-economic impacts of CVIS-enabled transportation systems, suggesting that policy-driven influences are the most profound [14]. This implies that the evolution of transportation systems needs rigorous monitoring to address potential future implications. Sindi and Woodman postulate that the primary factors influencing the commercialization of CVIS are the operational costs and transit efficiency of autonomous vehicles, especially for long-distance travel [15]. Tirachini and Antoniou discovered that the potential reduction in vehicle operational costs brought about by CVIS is beneficial both for operators (by decreasing operational expenses) and public transport users (by minimizing wait times and optimizing fare prices per trip) [16]. Berrada et al. explored the acceptance level of autonomous vehicles and, through economic analysis, identified that the key determinants affecting user choices are the policies set by governments [17]. Although these researches have discussed most scientific issues of CVIS deployment, there is still a lack of systematic research methods for the long-term development of CVIS from the aspect of local governments and automakers. How the government formulates reasonable and effective policies to promote the popularization of CVIS, and how manufacturers balance their production plans of RIVs or ADVs are all worth exploring.

The prevailing research on government investment in transportation reveals a concentrated focus on policies promoting the development of electric vehicles and analyzing road transportation costs. Within this sphere, scholars extensively examine various policy dimensions of electric vehicles, utilizing multi-category market information. Additionally, discussions on country-specific policies involve critical analysis of current shortcomings, with researchers offering tailored recommendations and solutions based on each country's unique conditions [18,19]. However, despite similarities between electric vehicles and the intelligent vehicles discussed in this paper, significant differences necessitate distinct policy approaches.

Electric vehicles are primarily characterized by their use of alternative energy sources, resembling conventional vehicles in most other aspects. In contrast, intelligent vehicles equipped with Cooperative Vehicle-Infrastructure Systems (CVIS) or Autonomous Driving Systems (ADS) significantly surpass traditional vehicles in terms of intelligence and automation levels. This disparity underscores the inability to directly transpose electric vehicle policies to intelligent vehicles. For the development of electric vehicles, governmental planning is essential, particularly in the strategic placement of charging stations. Similarly, the advancement of CVIS mandates a comprehensive and intelligent upgrade of existing road infrastructure to support these innovations. When it comes to policy design, current strategies for electric vehicles lean heavily towards subsidies and deregulation of license plates. Yet, policies for intelligent vehicles, which rely on varied systems, must be specifically crafted to reflect their unique functional characteristics, ensuring that the regulatory framework effectively fosters both technological innovation and practical integration.

In the calculation of road transportation costs, Anas introduced a general equilibrium framework addressing optimal allocation in urban traffic pricing, finance, and supply [20]. He discovered that time costs within the transportation system are influenced by the trade-offs between labor and leisure. Link et al. honed in on elements of highway freight cost and estimation methods, exploring the practical state of freight cost estimation across various modes of transport [21]. Through a comprehensive review of existing literature. Izadi et al. delineated those studies pertinent to road transportation costs can be broadly categorized into three segments: operational cost studies, value of time-saving research, and external cost investigations [22]. The most salient methods in estimation techniques and data collection model structures hinge on accounting and statistical modeling approaches. Schröder et al. proffered an integrative method to assess the external costs of diverse road traffic modes, encompassing public transportation, motorized individual transport, shared services, and active mobility [23].

In terms of investment decision-making research, evolutionary game theory has received extensive attention from scholars in recent years. It focuses on the interaction among different players or groups to find the frequencies of strategies adopted in the population during the evolutionary game process as the evaluation criterion in making decisions [24]. Benefit from the above characteristics of evolutionary game, many scholars see it as an effective and practical analytical theory for analyzing the interactive mechanism between two players [10,18,25–27]. Liu et al. applied the evolutionary game theory to explore the dynamic evolution game law of government and consumers in passive buildings demand incentives [25]. Chen et al. analyzed the evolutionary behavior of governments and manufacturers under various combinations of carbon taxes and subsidies [26]. Wang applied the evolutionary game theory to investigate the evolutionary game process between local government and developer group in the incentive and restriction of green building [28].

We have summarized the relevant literature as shown in Table 1.

Table 1. Summary of references.

References	Electric Vehicles	CVIS or ADS	Technical Research	Policy Research
[5–12]		√	√	
[13,14,17]				√
[15]			√	√
[18,19]	√			√
[20–28]			√	√

The table categorizes the existing studies into various segments: electric vehicles, CVIS or ADS, and others (which are not marked under the electric vehicles and CVIS or ADS categories). Furthermore, these studies are divided into technical research and policy research. It is evident from the table that there are currently few policy studies concerning CVIS or ADS, particularly those that utilize evolutionary game theory to explore the development of CVIS or ADS from the perspectives of local governments and manufacturers.

Therefore, in this paper, we try to use the idea of the evolutionary game to analyze the game process between governments and vehicle manufacturers on the development of CVIS. Firstly, we assume the strategic parameters of local governments and manufacturers according to the characteristics of CVIS and then construct the profit function of manufacturers under different production strategies. Finally, we analyze the stability under different strategy combinations by constructing an evolutionary game model and analyze the influence of model parameters by numerical simulation.

3. Methodology

3.1. Basic Assumptions

Scholars and local governments in the Chinese transportation sector have put forward many suggestions for the development of CVIS, including subsidies for RIVs manufacturers' research and development (R&D), construction of supporting facilities and infrastructure, cooperation with vehicle enterprises to purchase the computing power and storage unit of ADVs, and prioritizing RIVs license plate number.

There are two possible forms of autonomous driving: connected vehicles that communicate with and rely on sensors and devices in the road infrastructure, and autonomous vehicles that are fully independent but cost more due to the extra sensor technology installed on the vehicles. To allow the connected vehicles to work, government must install the necessary road infrastructure. Thus, the manufacturers that satisfying the production qualification of RIVs and ADVs will face two alternative production strategies: RIVs or ADVs. In this paper we suppose that there is no essential difference between RIVs and ADVs in terms of vehicle performance except for the intelligence level. ADVs can realize intelligent functions such as autonomous driving through the equipment on vehicles, while RIVs can realize the same intelligent functions as ADVs only with the support of roadside infrastructure. The unit production costs of RIVs and ADVs are p_1 and p_2, respectively. Due to the high cost of onboard equipment and high R&D costs, current ADVs are significantly more expensive than RIVs, thus in this paper we assume $p_1 < p_2$. The sales of RIVs and ADVs are s_1 and s_2, respectively. From the perspective of consumers, they are more willing to enjoy autonomous driving at a lower price, so in this paper we assume $s_1 < s_2$. The intelligence levels of RIVs and ADVs are i_1 and i_2, respectively. Compared with RIVs, ADVs have a great advantage in intelligence level when there is no CVIS, then we assume $i_2 > i_1 > 0$. Table 2 summarizes the meaning of the parameters and abbreviations used in this paper.

Table 2. Parameters and Descriptions.

Parameters	Description	Parameters	Description
s_1, s_2	selling prices of RIVs and ADVs	C_0	local government profits from the CVIS
p_1, p_2	manufacturing costs of RIVs and ADVs	C_1	subsidies for RIVs manufacturers from local governments
i_1, i_2	intelligent levels of RIVs and ADVs	C_2	benefits of ADVs manufacturers from computing power and storage unit trading
V_1, V_2	base values of RIVs and ADVs	C_3	cost of the building, developing and maintaining of roadside infrastructure
π_1, π_2	the profit of RIVs and ADVs	τ_1	the coverage ratio of roadside infrastructure
δ	consumer's intelligent preference	ε	user sensitivity to the roadside infrastructure coverage
U_1	net utility specification of RIVs consumers	T	travel cost
U_2	net utility specification of ADVs consumers	Ω	the evolutionary game domain
D	decision space matrix	ΔQ	the difference in fuel consumption per mile of a vehicle before and after the implementation of CVIS
B_c	driving cost benefit	Q_0	the fuel consumption of a car under conventional conditions
B_s	travel time cost benefit	α	the percentage of fuel efficiency savings when a vehicle operates within a CVIS environment
M	the annual mileage traveled	P_f	the average fuel price for that particular year
T_{save}	time saved in travel upon the utilization of CVIS	H	the number of vehicles of a specific model retained for that year
V	the societal value of an individual's unit of time	β	the percentage of time savings in a CVIS environment

3.2. Profit Function of RIVs and ADVs

The Hotelling model is often used in economics to study the impact of market structure on the efficiency of resource allocation. When different goods are similar substitutes, since each manufacturer wants to maximize its own interests, it is necessary to consider the behavior of other competitors. In this case, the manufacturer's pricing model is called the Hotelling model [27]. Under normal circumstances, the Hotelling model needs to meet the following three basic assumptions:

(1) The products have the same material properties or can be similar substitutes for each other;
(2) The sum of market percent rate of products is 1;
(3) Consumers are evenly distributed in the [0, 1] range and have unit demand.

Based on the description of RIVs and ADVs in Section 3.1, the Hotelling model can be used for the profit analysis of RIVs and ADVs. Figure 1 depicts the hoteling line of RIVs and ADVs. The RIVs and ADVs is located at 0 and 1, respectively. Consumers are evenly distributed from 0 to 1, RIVS and ADVs compete for marginal consumers. Each consumer is only willing to buy one type of vehicle. If consumers choose RIVs, then RIVs will bring them the utility value of U_1. Each consumer is faced with a travel cost (T) that will reduce the utility. And when consumers are located at $X \in [0,1]$, they will spend TX to meet their needs. In this case, net utility specification of RIVs consumers (U_1) and ADVs consumers (U_2) could be deduced:

$$U_1 = V_1 + \delta i_1 - s_1 - TX + \varepsilon\tau_1 \tag{1}$$

$$U_2 = V_2 + \delta i_2 - s_2 - T(1 - X) \tag{2}$$

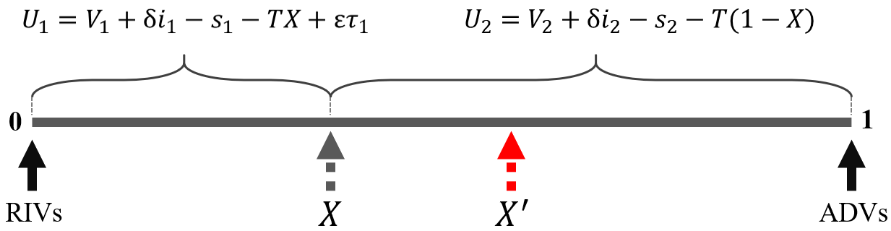


Figure 1. Hotelling line of RIVs and ADVs.

Suppose there is a marginal consumer located at X′ who does not care about buying any type of vehicle. In other words, for this kind of consumer, RIVs and ADVs bring the same utilities, then we have:

$$V_1 + \delta i_1 - s_1 - TX' + \varepsilon\tau_1 = V_2 + \delta i_2 - s_2 - T(1 - X') \tag{3}$$

By solving Equation (3), we can get $X' = [T - (V_2 - V_1) - \delta(i_2 - i_1) - (s_1 - s_2)]/2T$. Therefore, the market share of RIVs and ADVs could be clearly determined. Vehicle buyers distributed in $[0, X']$ are more inclined to buy RIVs, while customers in $[X', 1]$ will buy ADVs. Then, the profit functions of the manufacturers of RIVs and ADVs can be obtained as follows:

$$\pi_1 = (s_1 - p_1)X' \tag{4}$$

$$\pi_2 = (s_2 - p_2)(1 - X') \tag{5}$$

3.3. Establishment of Evolutionary Game Model

In this paper, we construct an evolutionary game model to discuss the tradeoffs between public and private investment in autonomous driving and investigate how investment decisions of government and manufacturer can ultimately shape the outcome. Thus, the investment policy strategy space of governments and manufacturers can be defined as $S_G = \{B, NB\}$ and $S_M = \{RIV, ADV\}$, respectively. B and NB indicate that the governments built or not built the CVIS, and RIV and ADV denote the production of RIVs or ADVs.

When governments started to build CVIS and vigorously construct the roadside infrastructure, government needs to bear the cost C_3 of the construction, development, and maintenance of roadside infrastructure while obtaining the benefit C_0 from CVIS. In this case, when manufacturers choose to produce RIVs, they can receive a certain subsidy C_1 from the government. On the contrary, if they choose to produce ADVs, they can also get income C_2 by selling the computing power and storage units to the governments.

In this paper we use $x(0 \le x \le 1)$ and $1 - x$ to represent the ratio of RIVs manufacturers and ADV manufacturers, respectively. Where, $x = 0$ indicates that no manufacturers are willing to produce RIVs, while $x = 1$ signifies that all manufacturers are inclined to produce RIVs. And we use $y(0 \le y \le 1)$ and $1 - y$ to denote the proportion of governments that choose to build (B) and not build (NB) CVIS, respectively. Similarly, $y = 0$ denotes that no government is willing to invest in the construction of CVIS, and $y = 1$ indicates full governmental investment in CVIS. The values of x and y are flexible and vary according to real-world circumstances. Next, we will separately establish the income matrix and replicator dynamic equation for the local governments and manufacturers, and then analyze their mutual strategies.

3.3.1. Investment Strategy Analysis of Manufacturers

The decision space matrix D_M contains the combination of different strategies of manufacturers and local governments. Thus the decision space matrix of manufacturers can be defined as D_M according to the investment policy decision space $S_G = \{B, NB\}$ and $S_M = \{RIV, ADV\}$:

$$D_M = \begin{pmatrix} RIV, B & ADV, B \\ RIV, NB & ADV, NB \end{pmatrix} \tag{6}$$

For each strategy combination, the income of manufacturers will be different, as shown in the income matrix A_M below:

$$A_M = \begin{pmatrix} \pi_1 + C_1 & \pi_2 + C_2 \\ \pi_1 & \pi_2 \end{pmatrix} \tag{7}$$

In the case that manufacturers decide to adopt RIV production strategy, their expected utility can be written as:

$$U_{M1} = \mathrm{e}A^T y = (10)\begin{pmatrix} \pi_1 + C_1 & \pi_1 \\ \pi_2 + C_2 & \pi_2 \end{pmatrix}\begin{pmatrix} y \\ 1-y \end{pmatrix} = y(\pi_1 + C_1) + (1-y)\pi_1 \tag{8}$$

Based on Equation (7), the average expected utility of manufacturers can be written as:

$$\begin{aligned} \overline{U}_M &= x^T A^T y = (x1-x)\begin{pmatrix} \pi_1 + C_1 & \pi_1 \\ \pi_2 + C_2 & \pi_2 \end{pmatrix}\begin{pmatrix} y \\ 1-y \end{pmatrix} \\ &= x[y(\pi_1 + C_1) + (1-y)\pi_1] + (1-x)[y(\pi_2 + C_2) + (1-y)\pi_2] \end{aligned} \tag{9}$$

According to the expression of replicator dynamic equation, the growth rate of RIV production by automakers is equal to the difference between U_{M1} and $\overline{U}_M$. Thus, we can get the replicator dynamic equation of manufactures:

$$F(x) = \frac{dx}{dt} = x\left[eA^T y - x^T A^T y\right] = x(1-x)[yC_1 + \pi_1 - \pi_2] \tag{10}$$

3.3.2. Investment Strategy Analysis of Governments

The decision space matrix of governments D_G can be expressed as follow:

$$D_G = \begin{pmatrix} B, RIV & B, ADV \\ NB, RIV & NB, ADV \end{pmatrix} \tag{11}$$

Same as the income matrix A_G of the manufacturers, the income matrix of government has the specific expression as below:

$$A_G = \begin{pmatrix} C_0 - C_1 - C_3 & C_0 - C_2 - C_3 \\ 0 & 0 \end{pmatrix} \tag{12}$$

And when local governments adopt strategy B, their expected utility can be defined as:

$$\begin{aligned} U_{G1} &= \mathrm{e}Bx = (10)\begin{pmatrix} C_0 - C_1 - C_3 & C_0 - C_2 - C_3 \\ 0 & 0 \end{pmatrix}\begin{pmatrix} x \\ 1-x \end{pmatrix} \\ &= x(C_0 - C_1 - C_3) + (1-x)C_0 - C_2 - C_3 \end{aligned} \tag{13}$$

The average expected utility of local governments can be denoted as the following:

$$\begin{aligned} \overline{U}_G &= y^T Bx = (y\,1-y)\begin{pmatrix} C_0 - C_1 - C_3 & C_0 - C_2 - C_3 \\ 0 & 0 \end{pmatrix}\begin{pmatrix} x \\ 1-x \end{pmatrix} \\ &= y[x(C_0 - C_1 - C_3) + (1-x)C_0 - C_2 - C_3] \end{aligned} \tag{14}$$

Similarly, the replicator dynamic equation of local governments can be shown as follows:

$$F(y) = \frac{dy}{dt} = y\left[eBx - y^T Bx\right] = y(1-y)[(C_1 + C_2)x + C_0 - C_3 - C_2] \tag{15}$$

3.4. System Stability Analysis

According to the description of Equations (10) and (15), we can calculate the equilibrium points of the bilateral evolutionary game, as shown in Equation (16).

$$\begin{cases} F(x) = \frac{dx}{dt} = x\left[eA^T y - x^T A^T y\right] = x(1-x)[yC_1 + \pi_1 - \pi_2] = 0 \\ F(y) = \frac{dy}{dt} = y\left[\mathrm{e}Bx - y^T Bx\right] = y(1-y)[(C_1+C_2)x + C_0 - C_3 - C_2] = 0 \end{cases} \tag{16}$$

According to Equation (16), it is easy to find that there are four balance points in the system (i.e., $(0,0), (0,1), (1,0), (1,1)$). These special points will form the boundaries of the evolutionary game domain $\Omega = \{(x,y)|0 \le x \le 1; 0 \le y \le 1\}$. In addition to these four obvious equilibrium points, there is another equilibrium point in the system according to Equation (16), which must satisfy the following equation:

$$\begin{cases} y^* C_1 + \pi_1 - C_2 = 0 \\ (C_1 + C_2)x^* + C_0 - C_3 - C_2 = 0 \end{cases} \tag{17}$$

As mentioned above, five balance points exists in the system, but it is worth noting that we cannot be sure whether these five equilibrium points are all evolutionary stable strategies of the system. To investigate the stability trend of the evolutionary game between local governments and automakers, according to Equation (16), the Jacobian matrix (J) can be deduced:

$$J = \begin{bmatrix} \partial F(x)/\partial x & \partial F(y)/\partial y \\ \partial F(y)/\partial x & \partial F(x)/\partial y \end{bmatrix} = \begin{bmatrix} (1-2x)(yC_1 + \pi_1 - \pi_2) & x(1-x)C_1 \\ y(1-y)(C_1+C_2) & (1-2y)[(C_1+C_2)x + C_0 - C_3 - C_2] \end{bmatrix} \tag{18}$$

On the basis of previous studies [24,29], the properties of the Jacobian matrix of the system will determine the stability performance of the equilibrium point. In other words, the stability is related to the values of the detersminant ($DetJ$) and trace (TrJ) of the matrix. An evolutionarily stable strategy (ESS) exists only when the value of $DetJ > 0$ and $TrJ < 0$. Based on Equation (18), $DetJ$ and trace TrJ on each equilibrium point can be obtained, as shown in Table 3.

Table 3. Determinant ***DetJ*** and trace ***TrJ*** on each equilibrium point.

Equilibrium Point	*DetJ*	*TrJ*
(0,0)	$(\pi_1 - \pi_2)(C_0 - C_3 - C_2)$	$(\pi_1 - \pi_2) + (C_0 - C_3 - C_2)$
(0,1)	$-(\pi_1 - \pi_2 + C_1)(C_0 - C_3 - C_2)$	$(\pi_1 - \pi_2 + C_1) - (C_0 - C_3 - C_2)$
(1,0)	$-(\pi_1 - \pi_2)(C_0 - C_3 - C_2)$	$-(\pi_1 - \pi_2) + (C_0 - C_3 - C_2)$
(1,1)	$(\pi_1 - \pi_2 + C_1)(C_0 - C_3 - C_2)$	$-(\pi_1 - \pi_2 + C_1) - (C_0 - C_3 - C_2)$

Where $N = \frac{(-C_0+C_3+C_2)(C_0-C_3+C_1)}{C_1+C_2} \frac{(\pi_1-\pi_2)(\pi_1-\pi_2+C_1)}{C_1}$.

Scenario 1: The primary goal of Scenario 1 is to explore how the construction of the CVIS can maximize benefits for local governments in terms of traffic congestion relief, accident prevention, and environmental improvements. Thus, the profit C_0 obtained by the local governments through the construction of CVIS is greater than the sum of the cost of the building, developing, and maintaining of roadside infrastructure (C_3), subsidiaries for RIVs manufacturers (C_1) and the purchase of ADVs computing power and storage unit (C_2). Namely, $C_0 > C_1 + C_2 + C_3$ in this scenario. At the same time, the profit of RIVs (π_1) is higher than that of ADVs (π_2). Under this premise, we can judge whether the determinant $DetJ$ and trace TrJ on each equilibrium point are greater than 0 or less than 0. Then, the stability performance of each equilibrium point can be obtained, as shown in Table 4. The symbol "+" represents ***DetJ*** or ***TrJ*** are positive (> 0), and "$-$" denotes the values are negative (< 0).

Table 4. Local stability analysis of scenario 1.

Equilibrium Point	*DetJ*	*TrJ*	Stability
(0,0)	+	+	Unstable
(0,1)	−	±	Saddle point
(1,0)	−	±	Saddle point
(1,1)	+	−	ESS
(x^*, y^*)	−	0	Saddle point

According to the determination method of the stable point described above, we can know that in this scenario, the final evolutionary stability point will appear at (1,1). In other words, the system will eventually reach an equilibrium state in which the manufacturer chooses RIV production strategy and the government adopts the strategy of building the CVIS (i.e., B strategy).

Scenario 2: Scenario 2 aims to assess the system's response to potential future shifts in the cost-effectiveness of onboard equipment, which might enhance the profitability of ADVs relative to RIVs. Compared with Scenario 1, the numerical relationship between π_1 and π_2 changes. With the development of technology, the cost of onboard equipment may be greatly reduced in the future, which will greatly increase the profitability of the manufacturers who produce ADVs. In this case, it is assumed that $\pi_2 < \pi_1 + C_1$. That is, for manufacturers, the profit of ADVs π_2 is much greater than that of RIVs π_1. However, the government's subsidies for RIVs can bridge the gap between them. Thus, the stability performance of the system at each equilibrium point in this scenario can be obtained, as shown in Table 5.

Table 5. Local stability analysis of scenario 2.

Equilibrium Point	*DetJ*	*TrJ*	Stability
(0,0)	−	±	Saddle point
(0,1)	−	±	Saddle point
(1,0)	+	+	Unstable
(1,1)	+	−	ESS
(x^*, y^*)	+	0	Non-system local equilibrium point

From the results in Table 4, we can find that this scenario is consistent with scenario 1, and the final stable point will also appear at the point (1,1) even if some conditional assumptions of model parameters change. The system will also eventually reach a steady state of "*RIV*" production strategy and "*B*" strategy. This is because both parties will choose the investment strategy that is most profitable for themselves.

Scenario 3: Different from the first two scenarios, Scenario 3 aims to understand the conditions under which the government and manufacturers might opt out of CVIS and RIV strategies due to economic constraints, predicting stability at a point where neither RIV production nor CVIS construction is pursued. That is, the cost of the building, developing, and maintaining of roadside infrastructure is higher than the dividend brought by CVIS to the local governments (i.e., $C_3 > C_0$). Meanwhile, the profit of RIVs (π_1) is smaller than that of ADVs (π_2), but government subsidies can fill this gap, that is, $\pi_1 - \pi_2 < 0$ and $\pi_1 - \pi_2 + C_1 > 0$. Table 6 presents the judgment results of the stability performance of the system at each equilibrium point.

Under the above premise, we can find that in this scenario the system will eventually reach stability at (0,0), that is, "*ADV*" production strategy for manufacturer and "*NB*" strategy for government will be the strategies that make the system stable.

To help local governments and manufacturers make strategic choices, we adopt the analysis method of phase diagram, which is presented in Figure 2. Figure 2a depicts the phase diagram of scenario 1 and 3, the area in this figure is cut into four parts by five different equilibrium points, and the point (x^*, y^*) is the saddle point of the evolutionary game. Equilibrium points are labeled as: $O(0,0)$, $A(0,1)$, $B(1,1)$, $C(1,0)$, and $D(x^*, y^*)$.

As described in scenarios 1 and 3, $O(0,0)$ and $B(1,1)$ are the stable points of these two scenarios, respectively. Therefore, in terms of these two scenarios, the system will continue to converge from an unstable initial state $D(x^*, y^*)$ to the final stable state $O(0,0)$ or $B(1,1)$, as shown by the black arrow in Figure 2a. For scenario 2, (x^*, y^*) is a non-system local equilibrium point, the phase diagram in this scenario is shown in Figure 2b, the evolutionary trend shows a convergence from point $O(0,0)$ to $B(1,1)$.

Table 6. Local stability analysis of scenario 3.

Equilibrium Point	*DetJ*	*TrJ*	Stability
(0,0)	+	−	ESS
(0,1)	+	+	Unstable
(1,0)	−	±	Saddle point
(1,1)	−	±	Saddle point
(x^*, y^*)	−	0	Saddle point

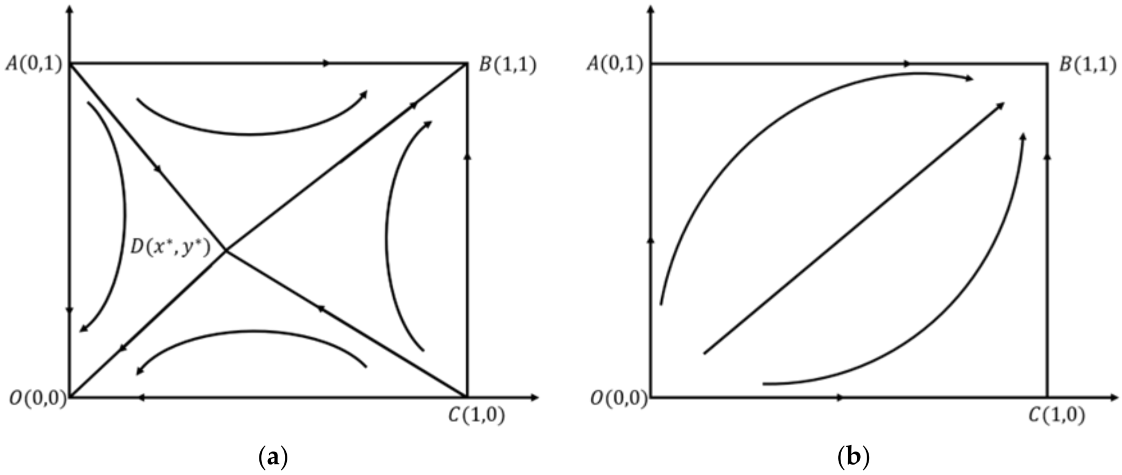


Figure 2. The phase diagram of the evolutionary game. (**a**) Scenario 1 and 3; (**b**) Scenario 2.

From the above analysis, it can be concluded that different assumptions about the model parameters will affect the final evolutionary process results. Therefore, in the next section, we will conduct a numerical simulation analysis for different parameters based on the current situation of China's transportation industry and the specific situation of China's domestic automobile manufacturers.

4. Numerical Simulation Analysis

Based on the current statistics of China's intelligent transportation construction and automobile industry investment, we propose a numerical study to simulate the behaviors of local governments and manufacturers under different mechanisms, respectively.

4.1. Data and Parameters

The Ministry of Industry and Information Technology (MIT) of China issued the "Draft Guidelines for the Management of Connected and Autonomous Vehicle Manufacturers and Product Access" on 7 April 2021, and solicited public comments [30]. According to statistics, among China's 34 provincial-level administrative regions, 20 local governments including Shanghai, Chongqing, Beijing, Zhejiang, Hubei, and Jiangsu have started the construction of CVIS demonstration areas. Thus, we set the initial value of y to 0.6.

With reference to the survey results of the automobile market in China, the basic cost and selling price of vehicles with similar performance will not fluctuate much between different brands. Therefore, for s_1, s_2, p_1 and p_2, we adopt the basic parameter values of vehicles of Xiao Peng, the leading brand of Chinese intelligent vehicles manufacturers, $s_1 = 160,000$ Yuan, $s_2 = 230,000$ Yuan, $p_1 = 11,000$ Yuan, $p_2 = 21,000$ Yuan.

According to the data in the literature [31], the Intelligent Transportation System in early period from 2008 to 2010 can bring a total benefit income of 3.58 billion *Yuan* to Beijing's urban transportation industry. However, the existing data is now somewhat outdated for the current context. Therefore, this study, while building upon the research foundation established by Huang, et al. [31], recalculates the results using more recent and updated data. This study assumes that the local government profits from CVIS C_0 include two components: driving cost benefit B_c and travel time cost benefit B_s. The estimation of driving cost benefit B_c is primarily based on econometric theory, simplifying the cost reduction to the amount of fuel saved in road transportation due to the application of CVIS. The calculation of travel time cost benefit B_s is mainly derived from the marginal productivity of labor theory, suggesting that the value of lost working time equates to the value of individual labor during that period, according to the human capital theory. This cost can be translated as the value created per unit of human time multiplied by the time saved in road transit. The expression for driving cost benefit B_c can be formulated as follows:

$$B_c = (\Delta Q) \times M \times P_f \times H \tag{19}$$

where, ΔQ represents the difference in fuel consumption per mile of a vehicle before and after the implementation of CVIS; M stands for the annual mileage traveled; P_f is the average fuel price for that particular year; and H indicates the number of vehicles of a specific model retained for that year.

To update the aforementioned parameters based on the most recent data available online, for Equation (19), $\Delta Q = Q_0 \times \alpha$, where $= Q_0$ denotes the fuel consumption of a car under conventional conditions and α represents the percentage of fuel efficiency savings when a vehicle operates within a CVIS environment. Drawing from data found on https://m.pcauto.com.cn/URL (accessed on 3 May 2024), an average compact car consumes approximately $7L/100$ km. According to the study by Qin, et al. [32], the value of α is around 40%. Referencing the data table from https://data.eastmoney.com, the value of M for 2021 is approximately 162,000 km, with P_f being 7.56 Yuan$/L$. As per the China Statistical Yearbook available at http://www.stats.gov.cn/URL (accessed on 3 May 2024), as of 2021, the value of H stands at 239.19 million vehicles.

The expression for B_s is presented as follows:

$$B_s = V \times T_{save} \tag{20}$$

where, V represents the societal value of an individual's unit of time, while T_{save} denotes the time saved in travel upon the utilization of CVIS.

For the variable V in Equation (20), the calculation is as follows: Given the 2021 Statistical Yearbook data, China's per capita GDP is 80,962.03 Yuan. If we subtract weekends and public holidays, and consider that on average a person works for 237 days per year at 8 h per day, the social value created per unit time by an individual is 42.70 Yuan/h. Where $T_{\text{save}} = T_0 \times \beta$, T_0 represents the average time individuals spend on transportation. According to certain reports, the average commute time for urban dwellers in China is about 40 min, which is equivalent to 0.67 h. β represents the percentage of time savings in a CVIS environment. Drawing from the research by Wadud, Z. [33], it's postulated that under baseline conditions, CVIS can lead to a 40% reduction in travel time (i.e., $\beta = 40\%$). Based on the expressions in Equations (19) and (20) and the values of the respective parameters, the final computation yields C_0 =1,666,917 Yuan/km.

According to the existing equipment cost and the required laying density, the cost of the building, developing, and maintaining of roadside infrastructure is 1,000,000 Yuan/km (i.e., C_3 =1,000,000 Yuan/km). Meanwhile, with reference to the national subsidy strategy for electric vehicles, we set the value of C_1 to 130,000 Yuan (i.e., C_1=130,000 Yuan). Since there is no reference case for the profits C_2 obtained by ADVs manufacturers from trading computing power and storage unit to the government, in this paper it is temporarily set to be the same as C_1 (i.e., $C_2 = C_1 = 130,000$ Yuan).

4.2. Simulation Results

In this section, MATLAB software is used for numerical simulations, and The MATLAB version used is R2018a. Based on the above data description, we further demonstrate the evolutionary trajectories of the above equilibrium points and the game players at different initial points. The initial values (x, y) of numerical simulation are set as (0.1,0.9), (0.3,0.7), (0.5,0.5), (0.7,0.3), (0.9,0.1), respectively. In order to better explore the evolution of the game process under the same value of x but different values of y, we added two sets of (0.5,0.4), (0.5,0.3) simulation experiments. The dynamic evolution process of game strategy selection is shown in Figure 3.

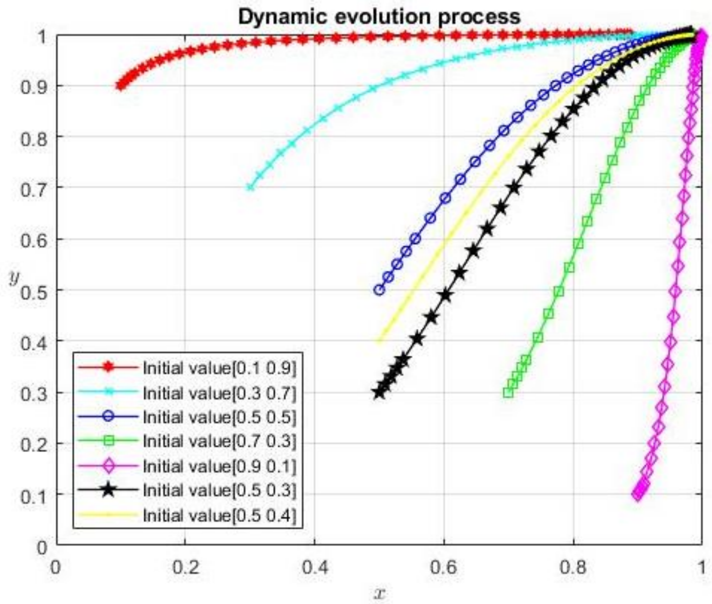
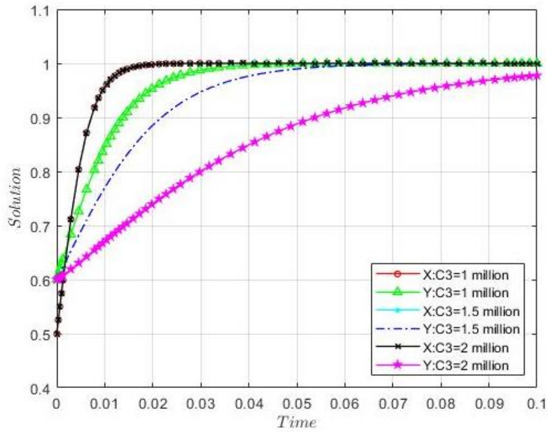


Figure 3. Dynamic evolution process of game strategy selection.

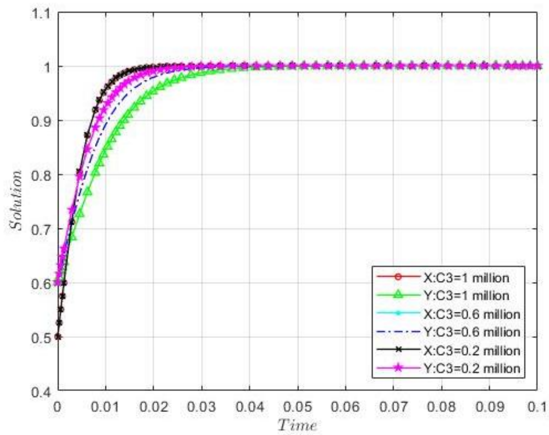
It can be seen from Figure 3 that when the probability (x, y) of the strategy adopted by the local governments and the manufacturers takes different initial values, the final game evolution results all converge to the same equilibrium point (1,1). That is, the manufacturers adopt the strategy *RIV* and the local governments adopt the strategy *B*, which is consistent with the ***Scenario 1*** in Section 3.4.

First, the initial values (x, y) of numerical simulation are randomly set as (0.5,0.6). Then we dynamically adjust the value of C_3 from the original 1,000,000 Yuan to 1,500,000 Yuan, 2,000,000 Yuan, 600,000 Yuan and 200,000 Yuan, respectively. The evolution results of the system corresponding to different values of C_3 are shown in Figure 4. Figure 4a,b depict the results of the gradual increase and decrease of the value of C_3, respectively.

Through the evolution results of game players in Figure 4, it can be found that with the increase of C_3, the convergence speed of the local governments (y) decreases. On the contrary, with the decrease of C_3, the convergence speed of the local governments (y) increases. These findings indicate that C_3 plays a negative correlation role in the dynamic evolution of the local governments. This is easy to understand, because with the reduction of C_3, the local governments are more willing to enjoy the benefit brought by CVIS at a lower cost. Additionally, it is worth noting that the change of the value of the parameter C_3 does not affect the evolution result of manufacturers (x). Since manufacturers do not need to bear the construction and maintenance cost of roadside infrastructure, the change of the value of C_3 has no impact on the strategy selection of manufacturers. In the bilateral evolutionary game described in Section 3, the local government's incentive policies for manufacturers will also ultimately affect the strategy evolution process. The incentive policies in this paper are mainly reflected in the subsidies for RIVs manufacturers from local governments C_1 and the benefits of ADVs manufacturers from computing power and storage' unit trading C_2. Therefore, next we will analyze the evolution of local governments and manufacturers by adjusting the values of C_1 and C_2. The evolution results are summarized in Figure 5. Figure 5a is the evolution result of only changing C_1 value, Figure 5b is the evolution result of only changing C_2 value and Figure 5c is the evolution result of changing C_1 and C_2 values at the same time.

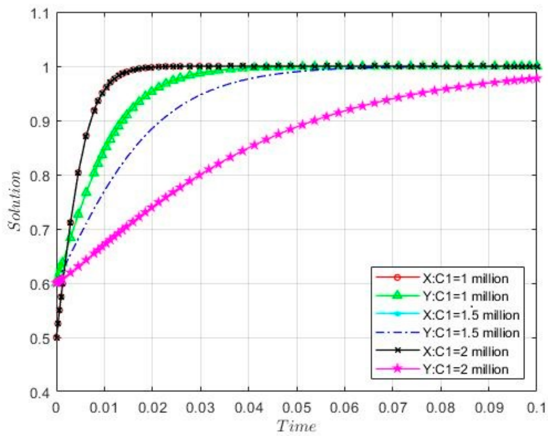


(a) The results of the gradual increase of the value of $\boldsymbol{C_3}$

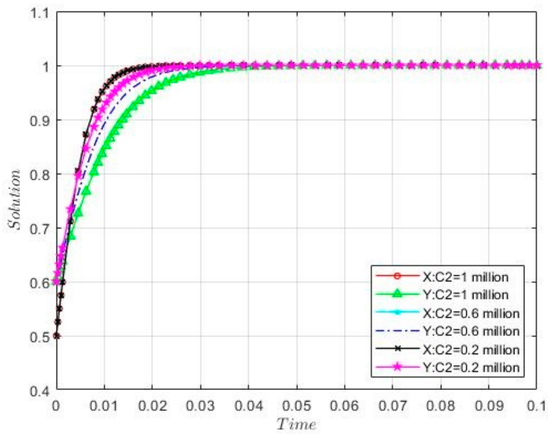


(b) The results of the gradual decrease of the value of $\boldsymbol{C_3}$

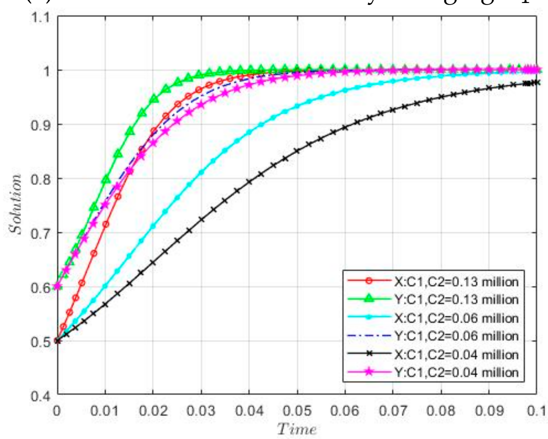
Figure 4. The evolution results of the system corresponding to different values of C_3.



(**a**) The evolution result of only changing C_1



(**b**) The evolution result of only changing C_2



(**c**) The evolution result of changing C_1 and C_2

Figure 5. Simulation of the parameters C_1 and C_2 in the evolutionary game.

In Figure 5a, we can find that reducing the subsidies to RIVs manufacturers can significantly affect manufacturers' production strategy for RIVs. As the value of C_1 parameter decreases, the convergence speed of manufacturer's RIV strategy is gradually delayed. It can also be found that the convergence speed of local governments for strategy B is also affected. Because the value of C_2 is not changed while reducing C_1, auto manufacturers are more willing to produce ADVs, which will reduce their desire to cooperate with the government, which in turn prompts the government to delay the choice of strategy B.

As shown in Figure 5b, the benefits that ADVs manufacturers obtain from computing power and storage unit trading C_2 has almost zero impact on manufacturer's *RIV* strategy selection. This is because for the strategy *RIV*, its production is not affected by the value of C_2. However, due to the reduction of C_2, the government's expenditure can be alleviated to a certain extent. Therefore, with the decrease of C_2, the government's convergence speed in strategy B will slightly improve.

In Figure 5c, the simultaneous change of C_1 and C_2 show a significant impact on the strategic choices of both local governments and manufacturers in the short term. It can be found that the reduction of C_1 will largely inhibit the convergence process of manufacturers in IRV strategy. If this inhibition is not controlled, when other factors change (such as the increase in the cost of roadside infrastructure increases or the decrease in the profit brought by CVIS), it will lead to a change in the evolution trend. Through the observation of C_2, it is shown that C_2 plays an opposite role in the evolution process of local government's choice of strategy B. Therefore, the government should avoid blindly increasing the subsidies for ADVs manufacturers from computing power and storage unit trading.

5. Conclusions

In the conclusion of our study, it is crucial to emphasize that while our economic model might suggest straightforward strategic choices between high-level ADVs and RIVs, our analysis, grounded in evolutionary game theory, unveils far deeper complexities. The study explores the interactive behaviors of manufacturers and local governments in promoting the development of autonomous driving and reveals the evolutionary process of the CVIS under diverse policy conditions. Our simulations, conducted using MATLAB, demonstrate that the dynamic strategic choices of local governments and manufacturers are significantly influenced by various factors, including subsidies for RIV manufacturers, the costs associated with building and operating CVIS, and the costs incurred by auto manufacturers in producing ADVs. Importantly, these parameters do not always correlate positively with the evolutionary process, suggesting the need for governments to carefully design incentive policies to steer the development of autonomous driving effectively.

Moreover, even minor changes in economic parameters such as subsidies and infrastructure costs can lead to significant and dynamic strategic adjustments over time. These adjustments are highly sensitive to evolving market conditions and technological advancements, which can unpredictably shift equilibrium points and strategic preferences. Therefore, the sophisticated analytical models used in our research provide crucial insights into the intricate interdependencies and dynamic nature of strategic decision-making, highlighting the practical challenges and considerations that influence the development of autonomous driving technologies. These insights substantiate the necessity of complex analyses to capture the nuanced dynamics that simple cost-benefit evaluations might overlook.

While this research has yielded intriguing findings, the limitations of our approach call for further investigation, particularly in future research addressing the challenges posed by information asymmetry, adverse selection, and moral hazard. Such factors include the government's limited knowledge of manufacturers' actual capacities and the potential for deception by auto manufacturers and their allies to secure greater subsidies. Exploring how governments can design optimal incentive contracts under these conditions will be critical for advancing the effective development of autonomous driving technologies.

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