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Evolutionary Game and Simulation Study on Collaborative Governance in Innovation Ecosystems: A Four-Party Analysis Involving Government, Core Enterprises, Supporting Enterprises, and S&T Service Institutions

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Abstract

Effective governance of innovation ecosystems depends on strategic coordination and dynamic adaptation among multiple heterogeneous actors. However, existing studies are yet to systematically unravel the endogenous evolutionary mechanisms underlying multi-agent strategic interactions. This paper constructs a four-player evolutionary game model encompassing local government, core enterprises, supporting enterprises, and S&T service institutions, and examines the dynamic evolutionary paths of collaborative governance in innovation ecosystems under the assumption of bounded rationality. The model integrates key mechanisms such as fiscal incentives, knowledge spillovers, free-riding benefits, and service innovation. By employing replicator dynamics equations, we analyze the evolutionary stability conditions of different strategy combinations, and we use numerical simulations to investigate the impact of core parameters on the system's evolutionary trajectories. The findings reveal that: (1) core enterprises' deep collaborative innovation plays a pivotal role in the system's evolution, with their strategic choices being jointly influenced by government subsidies and default penalties; (2) when the subsidy intensity is too low, the system converges slowly; when it is too high, fiscal sustainability constraints and strategic subsidy dependence may undermine the system's long-term stability—the optimal subsidy interval depends on the relative gap between the collaborative innovation benefits and costs of core enterprises; (3) supporting enterprises' free-riding behavior exerts an endogenous erosion effect on system collaboration, the intensity of which is jointly moderated by the degree of knowledge spillover and the relative benefits of free-riding; and (4) convergence to a high-level collaborative equilibrium requires the simultaneous satisfaction of incentive compatibility conditions for all agents—insufficient incentives for any single agent may cause the system to slide into a low-level collaborative trap.

Keywords: innovation ecosystem; collaborative governance; evolutionary game theory; multi-agent simulation; systems science

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1. Introduction

Before 2017, research on innovation ecosystems had already emphasized that innovation outcomes are not generated by isolated firms but emerge from interactions among governments, enterprises, research organizations, intermediary institutions, and other supporting actors. Early studies mainly focused on the structural composition of innovation networks, knowledge flows, and the division of functions among heterogeneous participants. However, as the number and diversity of actors increased, the ecosystem gradually exhibited stronger structural differentiation: governments were concerned with regional development and public value, core enterprises pursued technological leadership and market returns, supporting enterprises sought complementary business opportunities, and S&T service institutions aimed to obtain service revenues and enhance their professional influence. These differentiated interests may generate coordination difficulties, opportunistic behavior, and unequal distribution of innovation benefits. Therefore, understanding how heterogeneous actors adjust their strategies and form stable collaborative relationships became an important issue even before the policy shift after 2017.

Since Adner (2017) [1] proposed the actionable framework of "ecosystem as structure," the concept of innovation ecosystems has undergone a paradigm shift from structural description to dynamic mechanism analysis. Jacobides et al. (2018) [2] further theorized the ecosystem concept, emphasizing the central role of complementary assets and governance structures in value creation. Kapoor (2018) [3] extended the analytical boundaries of ecosystems, pointing out that the locus of value creation has transcended the boundaries of individual firms and extended to broader networks of actors. Nevertheless, the effective governance of innovation ecosystems continues to face formidable challenges [4].

The challenges arise first from the structural differentiation of actors' interest pursuits. Local governments focus on maximizing regional innovation performance and systemic positive externalities; core enterprises pursue the appropriable returns generated by technological innovation; supporting enterprises attempt to strategically arbitrage between collaborative investment and free-riding; and S&T service institutions weigh the trade-off between the high fixed costs of R&D services and the low marginal costs of routine intermediary services [5]. More fundamentally, the non-rivalry and partial excludability of knowledge in innovation activities render knowledge spillovers a double-edged sword: they constitute both the source of value co-creation in innovation ecosystems and the breeding ground for strategic free-riding behavior [6]. This "paradox of knowledge spillovers" makes the governance dilemma of innovation ecosystems endogenous to the system structure itself, rather than originating from external disturbances [7]. A critical theoretical and practical question thus emerges: In innovation ecosystems, how do the strategies of government, core enterprises, supporting enterprises, and S&T service institutions endogenously co-evolve? What combinations of conditions enable the system to converge to a high-level collaborative equilibrium, and what conditions instead lock the system into a low-level trap?

Academic research on innovation ecosystems has shifted from structural description toward dynamic mechanism analysis [8]. Zhang et al. (2025) [9] constructed an evolutionary game model of multi-agent knowledge sharing behavior in open innovation ecosystems, examining the behavioral and strategic evolution of core enterprises, small and medium-sized enterprises, and the government. Song et al. (2026) [10] employed a four-party evolutionary game approach to investigate the evolutionary dynamics of green collaborative innovation, revealing the strategic interaction mechanisms among government, core enterprises, supporting enterprises, and research institutions. Tian et al. (2025) [11] studied the collaborative governance mechanisms of cross-domain digital innovation ecosystems based on evolutionary game theory, finding that government penalty measures and internal

incentive mechanisms within the system exert positive effects on collaborative governance decisions. Dong and Jiang (2026) [12] established a four-party evolutionary game model of digital innovation ecosystems grounded in the quadruple helix theory, identified nine evolutionarily stable strategies, and explored the driving effects of subsidy and penalty mechanisms on the system's evolution toward the ideal equilibrium. Liu et al. (2022) [13] constructed an evolutionary game model encompassing core enterprises, research institutions, customers, and the government from the perspective of relational governance, revealing the facilitating role of reciprocity and trust in innovation ecosystem cooperation.

In recent years, evolutionary game methods have been increasingly introduced into innovation system research to address the dynamics and bounded rationality characteristics of multi-agent strategic interactions [14]. He et al. (2026) [15] constructed a three-party evolutionary game model of regional innovation ecosystems under digitalization, finding that government subsidies and penalties exert positive effects on system stability and the speed of evolutionary convergence. Shi and Wang (2026) [16] developed an evolutionary game model of value co-creation behavior between core enterprises and participating enterprises in innovation ecosystems, demonstrating that sufficient resource reserves, effective incentive policies, and appropriate regulatory measures are all conducive to high-quality value co-creation. Chen et al. (2024) [17] incorporated government regulation into a symbiotic evolutionary game model of digital innovation ecosystems, finding that under low-level subsidies and penalties, the system fails to enter a symbiotic state. Xu et al. (2019) [18] constructed an evolutionary game model of collaborative innovation networks incorporating government subsidies and supervision within the context of BA scale-free networks. Existing models have expanded from a bilateral government–enterprise framework to a tripartite government–enterprise–university framework, and some studies have begun to include financial institutions as fourth-party actors [19].

However, most existing models simplify S&T service institutions as exogenous parameters of knowledge supply, overlooking their independent strategic choices as proactive agents [20]. In fact, these institutions can actively influence knowledge flows and collaborative efficiency within innovation ecosystems by adjusting their R&D service directions, knowledge transformation channels, and service depth. Meanwhile, the endogenous drivers of supporting enterprises' free-riding behavior and its feedback effects are yet to be fully revealed. Free-riding is not merely opportunistic behavior but an attendant consequence of the properties of knowledge spillovers. Zhou and Ren (2021) [21] constructed an evolutionary model of low-carbon technology collaborative innovation based on a spatial public goods game and employed a social exclusion mechanism to curb R&D free-riding. When the innovative knowledge of core enterprises spills over to supporting enterprises, the latter face a strategic choice between proactively bearing collaborative costs to participate in innovation or passively absorbing knowledge at low cost; this choice further feeds back to affect the innovation incentives of core enterprises [22]. Other studies tend to default to a monotonic positive correlation between policy incentives and system performance, yet neglect the potentially nonlinear effects of fiscal subsidies. Therefore, the crux of policy lies not in whether to subsidize, but in how to affect the appropriate intensity of subsidies.

Although recent studies have applied four-party evolutionary game models to innovation ecosystems, the fourth actor in these studies is generally conceptualized as a research institution or a broad innovation participant. Such treatment does not fully capture the distinctive strategic role of S&T service institutions. Research institutions primarily focus on knowledge creation and scientific research, whereas S&T service institutions perform market-oriented and transaction-oriented functions, including technology transfer, R&D coordination, experimental testing, intellectual-property services, innovation-resource match-

ing, and commercialization support. These institutions do not merely generate knowledge; they actively connect knowledge suppliers, enterprises, and government support systems. Therefore, the present study differs from existing four-party models in both actor definition and mechanism design. It treats S&T service institutions as an independent strategic player that chooses between deep participation in R&D services and routine intermediary services. This distinction allows the model to capture an important but underexamined trade-off: deep participation requires specialized personnel, technical equipment, data platforms, and coordination resources, but it can generate higher service revenues, government R&D funding, collaborative subsidies, reputational benefits, and long-term ecosystem returns. By contrast, routine intermediary services involve lower costs and risks but produce relatively limited innovation contributions and service returns. This modeling approach explains how the behavior of S&T service institutions affects knowledge transfer, innovation-resource matching, collaboration efficiency, and the stability of the overall ecosystem. It also makes it possible to examine how government subsidies and R&D funding influence the transition from low-input intermediary services to substantive collaborative participation. Thus, the contribution of this study is not simply to add a fourth actor, but to identify and model the endogenous strategic incentives of an intermediary actor that connects scientific knowledge with enterprise innovation and commercialization.

This study constructs a four-player evolutionary game model involving local government, core enterprises, supporting enterprises, and S&T service institutions to investigate the dynamic mechanisms of collaborative governance in innovation ecosystems. The objectives are to identify the conditions under which a high-level collaborative equilibrium emerges, to analyze the influence of key parameters on evolutionary paths, and to provide theoretical references for innovation policy design. The theoretical contributions are threefold. First, by positioning S&T service institutions as agents with independent strategic choices, the model breaks from the conventional treatment of these institutions merely as exogenous parameters of knowledge supply, thereby offering a more complete representation of multi-agent interaction structures. Second, through parameterizing knowledge spillovers and embedding them into the payoff structure of supporting enterprises, we analyze the feedback effects of free-riding on core enterprises' innovation incentives and on system evolution, revealing the mechanism through which knowledge spillovers may induce collaboration erosion. Third, by employing parameter sensitivity analysis and joint scenario simulations, we examine the thresholds and boundary conditions of subsidy intensity, and demonstrate that low-subsidy scenarios are more likely to manifest as slow convergence rather than inevitable non-convergence, thereby providing a basis for differentiated and moderate subsidy policies.

2. Problem Description and Basic Assumptions

2.1. System Definition and Agent Strategy Space

Consider the innovation ecosystem composed of local government, core enterprises, supporting enterprises, and S&T service institutions. The four categories of actors exhibit significant heterogeneity and complementarity in their functional roles: local governments primarily provide institutional guarantees, infrastructure, and fiscal incentives; core enterprises undertake the responsibility for breakthrough technological innovation and industrialization leadership; supporting enterprises supply complementary technologies, products, and ancillary services; and S&T service institutions are responsible for knowledge creation, technology transfer, and R&D support. Under bounded rationality, the four parties find it difficult to accurately identify the optimal strategy at the initial stage of the game; instead, they continuously adjust their behavioral choices through ongoing interaction, observational learning, and payoff comparison. Accordingly, this paper con-

structs a four-party evolutionary game model to characterize the strategic choices and dynamic evolutionary processes of each actor within the innovation ecosystem. Replicator dynamics are adopted as the behavioral adjustment mechanism because they are consistent with the decision environment considered in this study. The four actors do not possess complete information or the capacity to identify a globally optimal strategy instantaneously. Instead, through repeated interaction, they compare the realized or expected payoff of a strategy with the average payoff obtainable within their relevant decision environment and gradually adjust the propensity to adopt that strategy. Under replicator dynamics, strategies that generate above-average payoffs increase in prevalence, whereas strategies associated with below-average payoffs decrease in prevalence. This mechanism provides a parsimonious representation of payoff-driven adaptation, observational learning, and imitation among boundedly rational actors.

The strategy spaces of the actors are specified as follows. The strategy space of the local government is $G = \{G_1, G_2\}$, where G_1 denotes "actively fostering the innovation ecosystem" and G_2 denotes "maintaining the traditional-industrial orientation." Let $x \in [0,1]$ be the probability that the local government chooses G_1, and the probability of choosing G_2 is $1-x$. The strategy space of the core enterprise is $E = \{E_1, E_2\}$, where E_1 denotes "deep collaborative innovation" and E_2 denotes "independent autonomous innovation." Let $y \in [0,1]$ be the probability that the core enterprise chooses E_1, and the probability of choosing E_2 is $1-y$. The strategy space of the supporting enterprise is $S = \{S_1, S_2\}$, where S_1 denotes "participating in collaborative supporting" and S_2 denotes "free-riding." Let $z \in [0,1]$ be the probability that the supporting enterprise chooses S_1, and the probability of choosing S_2 is $1-z$. The strategy space of the S&T service institution is $T = \{T_1, T_2\}$, where T_1 denotes "deep participation in R&D services" and T_2 denotes "providing routine intermediary services." Let $w \in [0,1]$ be the probability that the S&T service institution chooses T_1, and the probability of choosing T_2 is $1-w$.

2.2. Model Assumptions and Parameter System

To characterize the multi-agent strategic interactions and their dynamic evolutionary mechanisms within innovation ecosystems, this paper constructs a four-player evolutionary game model comprising local government, core enterprises, supporting enterprises, and S&T service institutions, under conditions of bounded rationality and incomplete information. Each agent dynamically adjusts its strategic choice based on a comparison of its own payoffs. The relevant parameters—including benefits, costs, subsidies, penalties, and knowledge spillovers—are specified as follows.

Assumption 1. *Payoff Structure of Local Governments.*

The strategic choices of local governments comprise "actively fostering the innovation ecosystem" and "maintaining the traditional-industrial orientation." When choosing active support, local governments are required to improve the innovation policy framework, establish public service platforms, coordinate relationships among participating actors, and implement incentive measures, thereby incurring a support cost of C_g. By contrast, when maintaining a traditional industry-oriented approach, governments primarily continue existing industrial governance practices, with routine governance costs denoted by C_{gl}, where $C_g > C_{gl}$. When the innovation ecosystem achieves a high level of collaborative development, local governments obtain macro-level innovation benefits, including economic growth, industrial upgrading, employment expansion, and enhanced regional innovation capacity, denoted by R_g. Conversely, if governments maintain a traditional orientation and fail to effectively promote ecosystem collaboration, they incur losses in innovation performance assessment, denoted by L_g, and face pressure from higher-level accountability mechanisms and public evaluation. In addition, local governments adopting active

support strategies provide subsidies S_e to core enterprises engaging in deep collaborative innovation and subsidies S_t to S&T service institutions that actively participate in R&D services, thereby reducing collaborative investment risks and strengthening incentives for multi-actor collaboration.

In addition, the local government is subject to a fiscal-budget constraint. Its expenditures on R&D subsidies, collaborative-service subsidies, supervision, and penalty enforcement cannot exceed its available fiscal capacity. Therefore, government support is not assumed to increase without limit. Excessive subsidy intensity may impose fiscal pressure, crowd out other public expenditures, and induce strategic dependence among enterprises. This setting helps explain why both insufficient and excessive incentives may hinder the long-term stability of collaborative governance.

Assumption 2. *Payoff Structure of the Core Enterprise.*

The core enterprise's strategic choices include "deep collaborative innovation" and "independent autonomous innovation." When the core enterprise chooses deep collaborative innovation, it needs to engage in joint R&D, technology sharing, and resource integration with supporting enterprises and S&T service institutions, and bears costs such as coordination, communication, knowledge protection, and commercialization; this collaboration cost is denoted as C_e. When choosing independent autonomous innovation, the enterprise mainly relies on its internal R&D resources for technological development, with its independent R&D cost denoted as C_{ei}, and it holds that $C_e > C_{ei}$. Deep collaborative innovation brings the core enterprise a collaborative revenue R_e, while independent autonomous innovation yields an independent revenue R_{ei}. When the local government chooses to actively foster the innovation ecosystem, it may provide innovation subsidies to the core enterprise, thereby reducing the pressure of collaborative investment and strengthening collaborative incentives. If the core enterprise, after receiving the subsidy, does not actually invest in collaborative innovation, this constitutes opportunistic behavior and the enterprise faces a default penalty P_e imposed by the government. The core enterprise dynamically adjusts its behavioral choices based on the expected net payoffs under different strategies.

Assumption 3. *Payoff Structure of the Supporting Enterprise.*

The supporting enterprise's strategic choices include "participating in collaborative supporting" and "free-riding." When choosing to participate in collaborative supporting, the supporting enterprise needs to carry out joint development, process adaptation, and resource input in line with the core enterprise's technical standards, R&D schedules, and production requirements, thereby incurring a collaborative supporting cost C_s. If it chooses free-riding, it merely obtains opportunistic gains through imitation, follow-along, or utilizing spillover information, with a maintenance cost C_{sf}, and it holds that $C_s > C_{sf}$. Participating in collaborative supporting brings the supporting enterprise a collaborative revenue R_s. Meanwhile, a knowledge spillover mechanism, parameterized by $k \in [0, 1]$, captures the intensity with which the core enterprise's innovative knowledge spills over to the supporting enterprise. Empirically, k represents the extent to which the technological knowledge, production know-how, technical standards, and innovation-related information generated by the core enterprise can be accessed, absorbed, and utilized by supporting enterprises. A higher value of k indicates a more open and effective knowledge diffusion environment, which may arise from frequent technical exchanges, joint R&D activities, shared digital platforms, personnel mobility, and close supply-chain linkages. Conversely, a lower value indicates that knowledge remains relatively protected or difficult for supporting enterprises to absorb because of technological complexity, intellectual-property protection, organizational barriers, or weak inter-firm interaction. In the present theoretical model, k is treated as a normalized exogenous parameter rather than a directly estimated

empirical variable. If the model is applied empirically, it may be proxied by indicators such as the frequency of joint R&D projects, patent citations or co-patents, technology-transfer intensity, R&D personnel exchanges, inter-firm collaborative-network density, or the degree of digital information sharing. When the core enterprise engages in deep collaborative innovation, if the supporting enterprise chooses to participate in collaborative supporting, it obtains a knowledge spillover benefit kR_e; if it chooses free-riding, the free-riding benefit R_{sf} itself already includes the passive benefits obtained from the core enterprise's knowledge spillovers. The supporting enterprise dynamically adjusts its behavioral choices based on the net payoff differential between the two strategies.

Assumption 4. *Strategy Set and Payoff Structure of S&T Service Institutions.*

S&T service institutions choose between two strategies: deep participation in R&D services and routine intermediary services. Deep participation refers to substantive involvement in the innovation process, including technology-demand identification, joint R&D coordination, experimental testing, intellectual-property services, technology transfer, digital-platform support, and commercialization assistance. This strategy requires investments in specialized personnel, technical equipment, data platforms, and project-management resources; therefore, it bears a higher service cost, denoted by C_t. Routine intermediary services refer to relatively low-input activities, such as information consultation, project matching, policy interpretation, basic training, and general technical services. The corresponding cost is denoted by C_{ti}, where $C_t > C_{ti}$. Deep participation yields service revenue R_t, whereas routine intermediary services yield service revenue R_{ti}. When the local government actively promotes collaborative innovation, it may provide the S&T service institution with government R&D funding G_t and collaborative-service subsidies S_t, thereby sharing part of the additional investment burden associated with deep participation. Accordingly, the payoff from deep participation in R&D services is $R_t + G_t + S_t - C_t$, whereas the payoff from routine intermediary services is $R_{ti} - C_{ti}$. The S&T service institution will tend to choose deep participation when:

$$R_t + G_t + S_t - C_t > R_{ti} - C_{ti}$$

Assumption 5. *Bounded Rationality, Resource Constraints, and Information Conditions.*

The local government, core enterprises, supporting enterprises, and S&T service institutions are assumed to be boundedly rational actors. Although each actor understands the basic game structure, relevant parameters, and available strategy sets, none can perfectly observe or accurately predict the contemporaneous decisions of the other actors. Instead of selecting a globally optimal strategy at once, actors continuously update their decisions through payoff comparison, observational learning, and repeated interaction. The bounded-rationality assumption also reflects the practical constraints faced by different actors. Local governments face limited fiscal budgets, administrative capacity, and performance-accountability pressures. Core enterprises are constrained by R&D expenditure, technological uncertainty, coordination costs, and market competition. Supporting enterprises face resource limitations, capability gaps, and uncertainty regarding the distribution of collaborative benefits. S&T service institutions are constrained by specialized personnel, technical facilities, data resources, service capacity, and the risk that high-input R&D services may not generate sufficient returns. These constraints prevent actors from making fully informed and perfectly optimized decisions and justify the use of an evolutionary-game framework. Based on the above payoff structures and strategy settings, we construct a four-player evolutionary game payoff matrix (for 16 strategy combinations) involving the local government, core enterprise, supporting enterprise, and S&T

service institution, as shown in Table 1. This payoff matrix systematically characterizes the strategic interactions among government fostering policies, core enterprise collaborative innovation, supporting enterprise participation or free-riding, and R&D service inputs of S&T service institutions. It also reflects the joint influence of factors such as subsidy incentives, knowledge spillovers, collaboration costs, and default penalties on the payoffs and strategic evolutionary directions of each actor.

Table 1. Payoff matrix of the four-player evolutionary game.

Strategy Combination	Local Government Payoff	Core Enterprise Payoff	Supporting Enterprise Payoff	S&T Service Institution Payoff
G_1, E_1, S_1, T_1	$R_g - C_g - S_e - S_t$	$R_g + S_e - C_e$	$R_s + kR_e - C_s$	$R_t + G_t + S_t - C_t$
G_1, E_1, S_1, T_2	$R_g - C_g - S_e$	$R_g + S_e - C_e$	$R_s + kR_e - C_s$	$R_{ti} + G_t - C_{ti}$
G_1, E_1, S_2, T_1	$R_g - C_g - S_e - S_t$	$R_g + S_e - C_e$	$R_{sf} - C_{sf}$	$R_t + G_t + S_t - C_t$
G_1, E_1, S_2, T_2	$R_g - C_g - S_e$	$R_g + S_e - C_e$	$R_{sf} - C_{sf}$	$R_{ti} + G_t - C_{ti}$
G_1, E_2, S_1, T_1	$-C_g - S_t + \alpha L_g$	$R_{ei} - P_e - C_{ei}$	$R_s - C_s$	$R_t + G_t + S_t - C_t$
G_1, E_2, S_1, T_2	$-C_g + \alpha L_g$	$R_{ei} - P_e - C_{ei}$	$R_s - C_s$	$R_{ti} + G_t - C_{ti}$
G_1, E_2, S_2, T_1	$-C_g - S_t + \alpha L_g$	$R_{ei} - P_e - C_{ei}$	$R_{sf} - C_{sf}$	$R_t + G_t + S_t - C_t$
G_1, E_2, S_2, T_2	$-C_g + \alpha L_g$	$R_{ei} - P_e - C_{ei}$	$R_{sf} - C_{sf}$	$R_{ti} + G_t - C_{ti}$
G_2, E_1, S_1, T_1	$-C_{gl}$	$R_e - C_e$	$R_s + kR_e - C_s$	$R_t - C_t$
G_2, E_1, S_1, T_2	$-C_{gl}$	$R_e - C_e$	$R_s + kR_e - C_s$	$R_{ti} - C_{ti}$
G_2, E_1, S_2, T_1	$-C_{gl}$	$R_e - C_e$	$R_{sf} - C_{sf}$	$R_t - C_t$
G_2, E_1, S_2, T_2	$-C_{gl}$	$R_e - C_e$	$R_{sf} - C_{sf}$	$R_{ti} - C_{ti}$
G_2, E_2, S_1, T_1	$-C_{gl} - (1-\alpha)L_g$	$R_{ei} - C_{ei}$	$R_s - C_s$	$R_t - C_t$
G_2, E_2, S_1, T_2	$-C_{gl} - (1-\alpha)L_g$	$R_{ei} - C_{ei}$	$R_s - C_s$	$R_{ti} - C_{ti}$
G_2, E_2, S_2, T_1	$-C_{gl} - (1-\alpha)L_g$	$R_{ei} - C_{ei}$	$R_{sf} - C_{sf}$	$R_t - C_t$
G_2, E_2, S_2, T_2	$-C_{gl} - (1-\alpha)L_g$	$R_{ei} - C_{ei}$	$R_{sf} - C_{sf}$	$R_{ti} - C_{ti}$

Note: When the core enterprise chooses E_2 but has previously received government subsidies, its payoff includes a term $-P_e$, representing the default penalty. In the table, $\alpha \in [0,1]$ denotes the performance assessment pressure coefficient, reflecting the intensity of innovation performance accountability faced by the local government. The free-riding benefit R_{sf} of the supporting enterprise already includes the passive benefits obtained from knowledge spillovers of the core enterprise; therefore, when the core enterprise chooses E_1, no additional term kR_e is added to the payoff of the free-riding supporting enterprise. λ represents the innovation performance accountability pressure coefficient of the local government.

For clarity, the payoff matrix explicitly distinguishes the two strategies of S&T service institutions. Under deep participation, the institution bears higher R&D-service costs but may obtain higher service revenue, government funding, and collaborative subsidies. Under routine intermediary services, it bears lower costs and receives relatively stable but lower service returns. This distinction enables the model to capture the institution's trade-off between high-input collaborative engagement and low-risk conventional service provision.

3. Construction of the Evolutionary Game Model

Based on the above assumptions and payoff structures, we derive the expected payoffs and replicator dynamics equations for the four actors in the following sections. For each actor, the replicator equation describes how the probability of adopting a strategy changes according to the difference between the expected payoff of that strategy and the actor's average expected payoff. Thus, the dynamic system represents gradual payoff-driven adaptation rather than one-shot optimal decision making.

3.1. Replicator Dynamics Equation of the Local Government

When the core enterprise chooses deep collaborative innovation, the local government's payoff is $R_g - S_e - wS_t - C_g$; when the core enterprise does not choose deep collaborative innovation, the local government's payoff is $\alpha L_g - C_g$. The expected payoff E_{11} for the local government when choosing the active fostering strategy G_1 is:

$$\begin{aligned} E_{11} &= y(R_g - S_e - wS_t - C_g) + (1-y)(\alpha L_g - C_g) \\ &= y(R_g - S_e) - wS_t - C_g + (1-y)\alpha L_g \end{aligned} \tag{1}$$

When the core enterprise does not choose deep collaborative innovation, the local government also bears the loss caused by collaboration failure, given by $(1-y)(1-\alpha)L_g$. Therefore, the expected payoff for the local government when choosing the traditional orientation strategy G_2, denoted E_{12}, is:

$$E_{12} = -C_{gl} - (1-y)(1-\alpha)L_g \tag{2}$$

The probability that the local government chooses the active fostering strategy is x, and the probability of choosing the traditional orientation strategy is $1-x$. Therefore, its average payoff is given by:

$$\overline{E}_1 = xE_{11} + (1-x)E_{12} \tag{3}$$

Substituting Equations (1) and (2) into Equation (3) yields:

$$\begin{aligned} \overline{E}_1 = \; & x\left[y(R_g - S_e) - wS_t - C_g + (1-y)\alpha L_g\right] \\ & +(1-x)\left[-C_{gl} - (1-y)(1-\alpha)L_g\right] \end{aligned}$$

According to replicator dynamics theory, the rate of change in the probability that the local government chooses the active fostering strategy is:

$$\dot{x} = x(E_{11} - \overline{E}_1) \tag{4}$$

Substituting Equation (3) into Equation (4) yields:

$$\dot{x} = x[E_{11} - xE_{11} - (1-x)E_{12}] = x(1-x)(E_{11} - E_{12})$$

The payoff difference between the two strategies can be expressed by the following formula:

$$\begin{aligned} E_{11} - E_{12} = \; & \left[y(R_g - S_e) - wS_t - C_g + (1-y)\alpha L_g\right] \\ & -\left[-C_{gl} - (1-y)(1-\alpha)L_g\right] \end{aligned}$$

Expanding yields:

$$\begin{aligned} E_{11} \; - \; & E_{12} = y(R_g - S_e) - wS_t - C_g + C_{gl} \\ & +(1-y)\alpha L_g + (1-y)(1-\alpha)\alpha L_g \end{aligned}$$

Since $\alpha + (1-\alpha) = 1$. Therefore,

$$(1-y)\alpha L_g + (1-y)(1-\alpha)\alpha L_g = (1-y)L_g$$

Hence,

$$E_{11} - E_{12} = y(R_g - S_e) - wS_t - C_g + C_{gl} + (1-y)L_g$$

Define the payoff difference between the two strategies of the local government as:

$$H(x) = yR_g - yS_e - wS_t - C_g - C_{gl} + (1-y)L_g \tag{5}$$

Then the replicator dynamics equation of the local government is:

$$F(x) = \dot{x} = x(1-x)\left[yR_g - yS_e - wS_t - C_g - C_{gl} + (1-y)L_g\right]$$

or

$$F(x) = \dot{x} = x(1-x)H(x) \tag{6}$$

Let $\dot{x} = 0$, then $x(1-x)H(x) = 0$. Therefore, there may exist two equilibrium states, namely $x^* = 0$ or $x^* = 1$.

Taking the first derivative of $F(x)$ with respect to x yields:

$$\frac{dF(x)}{dx} = (1-2x)H(x) \tag{7}$$

Substituting $x = 0$ into Equation (7), we obtain the derivative at the equilibrium point $x^* = 0$:

$$\frac{dF(x)}{dx}|_{x=0} = H(x) \tag{8}$$

From Equation (8), it can be seen that when $H(x) < 0$, we have $\frac{dF(x)}{dx}|_{x=0} < 0$; thus, $x^* = 0$ is a locally asymptotically stable equilibrium, meaning that the local government will ultimately tend to choose the traditional orientation strategy G_2.

Substituting $x = 1$ into Equation (7), we obtain the derivative at the equilibrium point $x^* = 1$:

$$\frac{dF(x)}{dx}|_{x=1} = -H(x) \tag{9}$$

From Equation (9), it can be seen that when $H(x) > 0$, we have $\frac{dF(x)}{dx}|_{x=1} < 0$; thus, $x^* = 1$ is a locally asymptotically stable equilibrium, meaning that the local government ultimately tends to choose the active fostering strategy G_1.

Let the payoffs of the two strategies be equal, i.e., $H(x) = 0$. Then:

$$y(R_g - S_e) - wS_t - C_g + C_{gl} + (1-y)L_g = 0$$

Expand and merge:

$$y(R_g - S_e - L_g) + L_g - wS_t - C_g + C_{gl} = 0$$

When $R_g - S_e - L_g \neq 0$, the critical value of the probability of deep collaborative innovation for core enterprises is obtained:

$$y^* = \frac{L_g - wS_t - C_g + C_{gl}}{R_g - S_e - L_g}$$

Proposition 1. *The probability of local governments adopting proactive support strategies is generally positively correlated with the probability of core enterprises opting for collaborative innovation strategies. However, this relationship is subject to the constraints of fiscal subsidy intensity and its associated marginal fiscal burden. Moderate subsidies can mitigate the costs and risks of collaborative innovation for core enterprises, thereby strengthening their willingness to collaborate. Nevertheless, when the subsidy level surpasses the local government's fiscal affordability, resulting in a negative net benefit from proactive support, the local government may shift to a passive strategy even if the core enterprise maintains a strong inclination for collaborative innovation. In*

other words, while government subsidies provide an incentive effect for collaborative innovation, their intensity should be confined to a reasonable range within the acceptable benefit threshold of the local government.

Proof. The local government's decision to adopt a proactive support strategy is contingent upon the net benefit difference $H(x)$ between the proactive support and traditional orientation strategies. Equations (8) and (9) indicate that when $H(x) > 0$, the proportion of local governments implementing the proactive support strategy increases progressively; conversely, when $H(x) < 0$, the system evolves toward the traditional orientation strategy. By solving for the partial derivative of the core enterprise's collaborative innovation probability y, we get:

$$\frac{\partial H(x)}{\partial y} = R_g - S_e - L_g \tag{10}$$

When $R_g > S_e + L_g$, it holds that $\frac{\partial H(x)}{\partial y} > 0$, which indicates that the higher the probability of collaborative innovation by core enterprises, the greater the benefits the government derives from collaborative governance, industrial upgrading, and improved innovation performance. Consequently, the relative advantage of the proactive support strategy becomes increasingly prominent. Therefore, provided that the subsidy intensity remains within a reasonable interval—specifically, under the condition where the synergistic benefit R_g is sufficient to offset the subsidy expenditure S_e and the loss L_g incurred due to non-collaboration by core enterprises—the evolutionary direction of the local government's proactive support strategy exhibits a positive correlation with the collaborative innovation probability of core enterprises.

However, subsidy S_e plays a dual role in shaping government decisions. Specifically, raising the subsidy reduces the core enterprise's collaborative costs, motivating it to elevate its collaborative probability y, which in turn indirectly increases the government's synergistic benefits via firm-level actions. Conversely, maintaining the core enterprise's collaborative innovation probability y unchanged and computing the partial derivative with respect to S_e yields:

$$\frac{\partial H(x)}{\partial S_e} = -y < 0 \tag{11}$$

Therefore, when $y > 0$, we have $\partial H(x)/\partial S_e < 0$; whereas when $y = 0$, this partial derivative equals 0. This indicates that, ceteris paribus, an increase in per-unit subsidies directly raises the local government's fiscal expenditure, thereby diminishing the relative net benefit of the proactive support strategy.

However, Equation (11) merely captures the direct fiscal cost effect of subsidies, and thus cannot be categorically inferred as the conclusive assertion that "higher subsidies necessarily make local governments less willing to adopt proactive support." An increase in subsidies may also reduce the costs and risks for core enterprises to engage in collaborative innovation, thereby driving an upward trend in their collaborative innovation probability y. When $R_g > S_e + L_g$, this rise in the collaborative innovation probability strengthens the payoff advantage for the local government in implementing a proactive support strategy. Therefore, subsidies exert two opposing effects on the local government's strategy selection: on the one hand, subsidies increase the fiscal burden; on the other hand, by enhancing the core enterprise's collaborative innovation probability, subsidies generate positive returns, including synergistic governance benefits, increased innovation output, and mitigated risk losses.

Therefore, under moderate subsidy conditions, the incremental revenue derived from synergistic incentives may surpass the incremental fiscal expenditure, leading the local government to remain inclined toward adopting a proactive support strategy. However,

when the subsidy intensity becomes excessively high, the fiscal burden may exceed the marginal benefits driven by improvements in collaborative innovation, causing $H(x)$ to shift from positive to negative. In this scenario, even if core enterprises exhibit a high willingness for collaborative innovation, the local government may reduce its probability of proactive support and gradually evolve toward a traditional orientation strategy. □

3.2. Replicator Dynamics Equation for Core Enterprises

When the local government provides active support, the core enterprise gains a collaborative innovation net benefit of $R_e + S_e - C_e$. Conversely, without active government support, the core enterprise receives a net benefit of $R_e - C_e$. Thus, the expected payoff for the core enterprise selecting deep collaborative innovation E_1 is derived as:

$$\begin{aligned} E_{21} &= x(R_e + S_e - C_e) + (1-x)(R_e - C_e) \\ &= x(R_e + S_e) + (1-x)R_e - C_e \\ &= R_e - C_e + xS_e \end{aligned} \tag{12}$$

Given that the local government implements an active support strategy whereas the core enterprise refrains from deep collaborative innovation, the enterprise incurs a breach penalty P_e, yielding a payoff of $R_{ei} - P_e - C_{ei}$. Conversely, in the absence of active government support, the enterprise's payoff is $R_{ei} - C_{ei}$. Thus, we have:

$$\begin{aligned} E_{22} &= x(R_{ei} - P_e - C_{ei}) + (1-x)(R_{ei} - C_{ei}) \\ &= x(R_{ei} - P_e) + (1-x)R_{ei} - C_{ei} \\ &= R_{ei} - C_{ei} - xP_e \end{aligned} \tag{13}$$

The average payoff of the core enterprise population is given by:

$$\overline{E}_2 = yE_{21} + (1-y)E_{22} \tag{14}$$

Substituting Equations (12) and (13) into Equation (14), we obtain:

$$\overline{E}_2 = y(R_e - C_e + xS_e) + (1-y)(R_{ei} - C_{ei} - xP_e)$$

The replicator dynamics equation for core enterprises adopting the deep collaborative innovation strategy is given by:

$$F(y) = \dot{y} = y\left(E_{21} - \overline{E}_2\right) \tag{15}$$

Substituting Equation (14) into Equation (15), we obtain:

$$\dot{y} = y[E_{21} - yE_{21} - (1-y)E_{22}] = y(1-y)(E_{21} - E_{22})$$

The payoff difference between the two strategies:

$$\begin{aligned} E_{21} - E_{22} &= (R_e - C_e + xS_e) - (R_{ei} - C_{ei} - xP_e) \\ &= x(S_e + P_e) + (R_e - C_e) - (R_{ei} - C_{ei}) \end{aligned}$$

Define the payoff difference for the core enterprise choosing deep collaborative innovation relative to independent innovation as:

$$H(y) = x(S_e + P_e) + (R_e - C_e) - (R_{ei} - C_{ei}) \tag{16}$$

Then, the replicator dynamics equation for the core enterprise can be expressed as:

$$\begin{aligned} F(y) = \dot{y} &= y(1-y)H(y) \\ &= y(1-y)(x(S_e + P_e) + (R_e - C_e) - (R_{ei} - C_{ei})) \end{aligned} \tag{17}$$

Setting $\dot{y} = 0$ yields $y(1-y)H(y) = 0$. Therefore, there exist two possible equilibrium states, namely $y^* = 0$ and $y^* = 1$.

The derivative of $F(y)$ with respect to y is given by:

$$\frac{dF(y)}{dy} = (1-2y)H(y) \tag{18}$$

Substituting $y = 0$ into Equation (18), we obtain the derivative at the equilibrium point $y^* = 0$:

$$\frac{dF(y)}{dy}\Big|_{y=0} = H \tag{19}$$

From Equation (19), when $H < 0$, we have $\frac{dF(y)}{dy}\Big|_{y=0} < 0$. Hence, $y^* = 0$ constitutes a locally asymptotically stable equilibrium, and the core enterprise will eventually select the independent innovation strategy E_2.

Substituting $y = 1$ into Equation (18) yields the derivative at the equilibrium point $y^* = 1$:

$$\frac{dF(y)}{dy}\Big|_{y=1} = -H \tag{20}$$

From Equation (20), we have $\frac{dF(y)}{dy}\Big|_{y=1} < 0$ when $H > 0$. Hence, $y^* = 1$ constitutes a locally asymptotically stable equilibrium, leading the core enterprise to eventually select the deep collaborative innovation strategy E_1.

Equating the payoffs of the two strategies, i.e., $H = 0$, yields:

$$x(S_e + P_e) + (R_e - C_e) - (R_{ei} - C_{ei}) = 0$$

When $S_e + P_e > 0$, the critical threshold of the local government's proactive support probability can be derived as:

$$x^* = \frac{R_{ei} - C_{ei} - R_e + C_e}{S_e + P_e}$$

Consequently, if the local government's proactive support probability surpasses the critical threshold, the deep collaborative innovation strategy of the core enterprise generates a higher relative payoff, prompting the system to converge to the equilibrium state $y = 1$. In contrast, when this probability remains below the threshold, the core enterprise tends to prefer independent innovation.

Proposition 2. *The core enterprise will opt for deep collaborative innovation provided that* $x(S_e + P_e) > (R_e - C_e) - (R_{ei} - C_{ei})$. *Upon meeting this condition, the expected net payoff of the collaborative innovation strategy exceeds that of the non-collaborative counterpart, leading the core enterprise to progressively migrate toward collaborative innovation. Under ceteris paribus conditions, both subsidies and breach penalties reinforce the incentives for deep collaborative innovation. There exists a substitutive relationship between them regarding incentive effects: raising the subsidy threshold alleviates the required penalty intensity, while enhancing the penalty intensity correspondingly reduces the required subsidy level. Nonetheless, only when the comprehensive incentives derived from both elements outweigh the net payoff differential arising from the core*

enterprise's strategic transition can the deep collaborative innovation strategy achieve a stable evolutionary superiority.

Proof. From Equations (19) and (20), it follows that the condition under which the core enterprise selects deep collaborative innovation is:

$$x(S_e + P_e) > (R_e - C_e) - (R_{ei} - C_{ei})$$

In the above equation, the RHS denotes the net payoff difference that the core enterprise must overcome when switching from independent to deep collaborative innovation, while the LHS specifies the collaborative incentive intensity generated jointly by the subsidy S_e and the breach penalty P_e given the local government's proactive support probability x.

Moreover, taking the partial derivatives of the net benefit difference function with respect to the respective variables yields:

$$\frac{\partial H}{\partial S_e} = x > 0, \frac{\partial H}{\partial P_e} = x > 0 \tag{21}$$

Equation (21) demonstrates that when $x > 0$, increases in either subsidies or breach penalties elevate the relative benefits of collaborative innovation. Moreover, given that both elements enter the incentive term jointly as $S_e + P_e$, they exhibit linear complementarity: as either component strengthens, the necessity for the other to meet the collaborative threshold diminishes correspondingly. Consequently, the government can affect an appropriate combination of subsidy incentives and default constraints, taking into account its fiscal capacity and regulatory expenditures. □

3.3. Replicator Dynamics Equation for Supporting Enterprises

When the supporting enterprise adopts the collaborative supporting strategy S_1, its expected payoff is:

$$E_{31} = y(R_s + kR_e) - C_s \tag{22}$$

When the supporting enterprise adopts the free-riding strategy S_2, its expected payoff is:

$$E_{32} = yR_{sf} - C_{sf} \tag{23}$$

From Equations (22) and (23), it can be seen that when the core enterprise chooses deep collaborative innovation ($y = 1$), if the supporting enterprise opts for free-riding, its payoff is R_{sf}; whereas if the core enterprise does not collaborate ($y = 0$), the supporting enterprise's free-riding payoff is 0. Here, R_{sf} is defined as the "total payoff obtained by the supporting enterprise through free-riding under the condition of core enterprise collaboration."

The average expected payoff of the supporting enterprise population is:

$$\overline{E}_3 = zE_{31} + (1 - z)E_{32} \tag{24}$$

Substituting Equations (22) and (23) into Equation (24), we obtain:

$$\overline{E}_3 = z[y(R_s + kR_e) - C_s] + (1 - z)\left(yR_{sf} - C_{sf}\right)$$

The replicator dynamics equation for the collaborative supporting strategy is:

$$\dot{z} = z\left(E_{31} - \overline{E}_3\right) \tag{25}$$

Substituting Equation (24) into Equation (25), we obtain:

$$\begin{aligned}\dot{z} &= z[E_{31} - zE_{31} - (1-z)E_{32}] \\ &= z[(1-z)E_{31} - (1-z)E_{32}] \\ &= z(1-z)[E_{31} - E_{32}]\end{aligned}$$

Hence,

$$F(z) = \dot{z} = z(1-z)\left[y\left(R_s + kR_e - R_{sf}\right) - C_s + C_{sf}\right]$$

The payoff difference between the two strategies is given by:

$$H(z) = y\left(R_s + kR_e - R_{sf}\right) - C_s + C_{sf} \tag{26}$$

Then, the replicator dynamics equation can be simplified as:

$$F(z) = \dot{z} = z(1-z)H(z) \tag{27}$$

Setting $\dot{z} = 0$, the equilibrium points of the system are given by $z^* = 0$ and $z^* = 1$. The derivative of $F(z)$ with respect to z is given by:

$$\frac{dF(z)}{dy} = (1-2z)H \tag{28}$$

Substituting $z = 0$ into Equation (28), we obtain the derivative at the equilibrium point $z^* = 0$:

$$\frac{dF(z)}{dz}|_{z=0} = H \tag{29}$$

From Equation (29), it can be seen that when $H < 0$, we have $\frac{dF(z)}{dz}|_{z=0} < 0$. Therefore, $z^* = 0$ is a locally asymptotically stable equilibrium, and the supporting enterprise will ultimately tend to adopt the free-riding strategy.

Substituting $z = 1$ into Equation (28), we obtain the derivative at the equilibrium point $z^* = 1$:

$$\frac{dF(z)}{dz}|_{z=1} = -H \tag{30}$$

From Equation (30), it can be seen that when $H > 0$, we have $\frac{dF(z)}{dz}|_{z=1} < 0$. Therefore, $z^* = 1$ is a locally asymptotically stable equilibrium, indicating that the supporting enterprise will ultimately adopt the collaborative supporting strategy.

Let the payoffs of the two strategies be equal, i.e., $H(z) = 0$, then $y\left(R_s + kR_e - R_{sf}\right) = C_s - C_{sf}$. When $R_s + kR_e - R_{sf} > 0$, we can solve for the critical threshold of the core enterprise's deep collaborative innovation probability:

$$y^* = \frac{C_s - C_{sf}}{R_s + kR_e - R_{sf}}$$

Therefore, reducing the collaborative supporting cost C_s, enhancing the collaborative payoff R_s, and increasing the sharing ratio k of the core enterprise's payoff all facilitate the supporting enterprise's shift from free-riding to collaborative supporting. Conversely, an excessively high free-riding payoff R_{sf} will weaken the supporting enterprise's incentive to participate in collaborative supporting.

Proposition 3. *The knowledge-spillover intensity k exerts a dual effect on the collaborative supporting strategy of supporting enterprises. Ceteris paribus, an increase in k can enhance the innovation payoff spillover kR_e accrued by supporting enterprises from participating in collaborative*

supporting, thereby bolstering their collaborative willingness. However, higher knowledge spillovers may also elevate the payoff R_{sf} associated with the free-riding strategy adopted by supporting enterprises. Therefore, whether knowledge spillovers facilitate collaborative supporting hinges on the relative variations between kR_e and R_{sf}. If the increase in kR_e exceeds the increase in R_{sf}, knowledge spillovers augment the payoff advantage of supporting enterprises engaging in collaborative supporting. Conversely, if the increase in R_{sf} surpasses that of kR_e, knowledge spillovers may reinforce the free-riding incentive and consequently inhibit collaborative supporting.

Proof. By taking the partial derivative of Equation (26) with respect to the knowledge - spillover intensity k, we obtain $\partial H/\partial k = yR_e$. When the core enterprise possesses a positive collaborative innovation payoff $R_e > 0$ and its probability of adopting deep collaborative innovation is $y > 0$, we have $\partial H/\partial k > 0$. This indicates that, *ceteris paribus*, an increase in knowledge-spillover intensity can enhance the relative net payoff of supporting enterprises participating in collaborative supporting.

Furthermore, the collaborative incentive generated by knowledge spillovers depends on the relative variations between kR_e and the free-riding payoff R_{sf}. If R_{sf} changes synchronously with k, we have $dH/dk = y\left(R_e - dR_{sf}/dk\right)$. Evidently, when $dR_{sf}/dk < R_e$, knowledge spillovers still enhance the relative payoff of collaborative supporting; however, when $dR_{sf}/dk > R_e$, the free-riding payoff grows faster than the collaborative payoff. In this case, $dH/dk < 0$, indicating that knowledge spillovers instead weaken the incentive for supporting enterprises to participate in collaborative supporting. □

Corollary 1. *Whether supporting enterprises choose to participate in collaborative supporting depends on the payoff advantage and cost differentials of collaborative supporting relative to the free-riding strategy. When the core enterprise definitively adopts the deep collaborative innovation strategy, i.e., $y = 1$, if the condition $R_s + kR_e - R_{sf} > C_s - C_{sf}$ is satisfied, the net payoff for the supporting enterprise opting for the collaborative supporting strategy exceeds that of the free-riding strategy, prompting the supporting enterprise to progressively gravitate toward collaborative supporting. Conversely, if the aforementioned inequality fails to hold, the supporting enterprise will be more inclined to opt for the free-riding strategy. Therefore, only when the sum of the direct benefits derived from collaborative supporting and the innovation payoff spillover from core enterprises is sufficient to offset the additional costs relative to the free-riding strategy can the participation in collaborative supporting maintain a stable evolutionary advantage.*

Corollary 2. *When the core enterprise adopts the deep collaborative innovation strategy, i.e., $y = 1$, even if the direct payoff obtained by the supporting enterprise from participating in collaborative supporting exceeds that of adopting the free-riding strategy, i.e., $R_s > R_{sf}$, provided that the cost of collaborative supporting is relatively high and the condition $R_s + kR_e - R_{sf} < C_s - C_{sf}$ is met, then the net payoff difference for the supporting enterprise to participate in collaborative supporting relative to adopting the free-riding strategy is $R_s + kR_e - R_{sf} - \left(C_s - C_{sf}\right) < 0$. Consequently, the expected net payoff from collaborative supporting is lower than that from free-riding, and the supporting enterprise will still tend to choose the free-riding strategy.*

3.4. Replicator Dynamics Equation for S&T Service Institutions

When the S&T service institutions choose the deep participation in research service strategy T_1, their expected payoff is given by:

$$\begin{aligned} E_{41} &= x(R_t + G_t + S_t) + (1 - x)R_t - C_t \\ &= R_t - C_t + x(G_t + S_t) \end{aligned} \tag{31}$$

When the S&T service institution chooses the regular intermediary service strategy T_2, its expected payoff is given by:

$$\begin{aligned} E_{42} &= x(R_{ti} + G_t) + (1 - x)R_{ti} - C_{ti} \\ &= R_{ti} - C_{ti} + xG_t \end{aligned} \tag{32}$$

The average expected payoff of the S&T service institution population is given by:

$$\overline{E}_4 = wE_{41} + (1 - w)E_{42} \tag{33}$$

That is,

$$\overline{E}_4 = w[R_t - C_t + x(G_t + S_t)] + (1 - w)[R_{ti} - C_{ti} + xG_t]$$

The replicator dynamics equation for the proportion w of S&T service institutions adopting the deep participation in research service strategy T_1 is given by:

$$\dot{w} = w\left(E_{41} - \overline{E}_4\right) \tag{34}$$

Substituting Equation (33) into Equation (34), we obtain:

$$\begin{aligned} \dot{w} &= w[E_{41} - wE_{41} - (1 - w)E_{42}] \\ &= w(1 - w)(E_{41} - E_{42}) \end{aligned} \tag{35}$$

The payoff difference between the two strategies is given by:

$$\begin{aligned} H(w) &= E_{41} - E_{42} \\ &= [R_t - C_t + x(G_t + S_t)] - [R_{ti} - C_{ti} + xG_t] \\ &= xS_t + (R_t - C_t) - (R_{ti} - C_{ti}) \end{aligned} \tag{36}$$

Therefore, the replicator dynamics equation for the S&T service institutions is given by:

$$F(w) = \dot{w} = w(1 - w)H(w) \tag{37}$$

Setting $\dot{w} = 0$, we obtain two equilibrium scenarios, namely $w^* = 0$ and $w^* = 1$.

Taking the derivative of Equation (37) with respect to w:

$$\frac{\partial F(w)}{\partial w} = (1 - 2w)H(w) \tag{38}$$

Thus, we obtain two boundary equilibrium points, $w = 0$ and $w = 1$. Next, we examine their stability respectively:

Substituting $w = 0$ into Equation (38), we obtain the derivative at the equilibrium point $w^* = 0$:

$$\frac{dF(w)}{dw}|_{w=0} = H \tag{39}$$

From Equation (39), it can be seen that when $H < 0$, we have $\frac{dF(w)}{dw}|_{w=0} < 0$. Therefore, $w^* = 0$ is a locally asymptotically stable equilibrium, and the S&T service institutions will ultimately tend to choose the regular intermediary service.

Substituting $w = 1$ into Equation (38), we obtain the derivative at the equilibrium point $w^* = 1$:

$$\frac{dF(w)}{dw}|_{w=1} = -H \tag{40}$$

From Equation (40), it can be seen that when $H > 0$, we have $\frac{dF(w)}{dw}|_{w=1} < 0$. Therefore, $w^* = 1$ is a locally asymptotically stable equilibrium, and the S&T service institutions will ultimately tend to adopt the deep participation in research service strategy.

Let the expected payoffs of the two strategies for the S&T service institutions be equal, i.e., $H(w) = 0$, then we have:

$$H(w) = xS_t + (R_t - C_t) - (R_{ti} - C_{ti}) = 0$$

That is,

$$xS_t + (R_t - C_t) - (R_{ti} - C_{ti}) = 0$$

When $S_t > 0$, the critical threshold of the local government's proactive support probability is given by:

$$x^* = \frac{(R_{ti} - C_{ti}) - (R_t - C_t)}{S_t}$$

This threshold indicates that the higher the local government's proactive support probability and its subsidy level S_t, the more likely the S&T service institutions are to shift from regular intermediary services to deep participation in research services.

Proposition 4. *When the net payoff for S&T service institutions choosing deep participation in R&D services exceeds that of choosing regular intermediary services, i.e., when* $xS_t > (R_{ti} - C_{ti}) - (R_t - C_t)$ *holds, the S&T service institutions will tend to adopt the deep participation strategy; conversely, they will tend to choose the regular intermediary service strategy. Moreover, the sensitivity of S&T service institutions to government subsidies hinges upon the net payoff difference between deep participation and regular services. When the relative net payoff from deep participation is insufficient to compensate for its additional input costs, government subsidies will serve as a critical incentive factor driving the transition from regular services to deep participation; furthermore, the required subsidy intensity increases with the magnitude of the net payoff difference.*

Proof. From Equations (31) and (32), it can be seen that when $H > 0$, we have $xS_t > (R_{ti} - C_{ti}) - (R_t - C_t)$. For any $w \in (0,1)$, we have $F(w) > 0$. Therefore, the proportion of S&T service institutions choosing deep participation will continuously increase, and the system eventually converges to $w = 1$. At this point, $w = 1$ is an evolutionary stable strategy (ESS), and the S&T service institutions will ultimately tend to choose deep participation in R&D services. When $H < 0$, for any $w \in (0,1)$, we have $F(w) < 0$. In this case, the proportion of deep participation continuously decreases, and the system eventually converges to $w = 0$. Consequently, $w = 0$ is an ESS, and the S&T service institutions will ultimately tend to provide regular services. When $H = 0$, the expected payoffs of deep participation and regular services are equal, resulting in $F(w) = 0$. At this stage, there is no clear incentive for the S&T service institutions to adjust their strategies, and the system is in a neutrally stable state.

Furthermore, differentiating the subsidy intensity S_t with respect to H yields. When $x > 0$, $\partial H/\partial S_t > 0$. An increase in government subsidy intensity therefore enlarges the payoff advantage of deep participation over routine service provision, thereby increasing both the probability and rate at which S&T service institutions choose deep participation. The critical subsidy threshold S_t^* is obtained by setting $H = 0$. That is $S_t^* = [(R_t - C_t) - (R_{ti} - C_{ti})]/x$. When $S_t > S_t^*$, $H > 0$, and S&T service institutions will ultimately choose deep participation; when $S_t < S_t^*$, $H < 0$, and they will ultimately choose routine service provision. Therefore, the larger the payoff advantage of deep participation relative to routine service provision, namely $(R_{ti} - C_{ti}) - (R_t - C_t)$, the more readily S&T service institutions can achieve deep participation in R&D activities. Conversely, when the

government subsidy reaches or exceeds this threshold, a relatively low level of subsidy is sufficient to induce S&T service institutions to shift toward deep participation. □

3.5. System Equilibrium and Stability Conditions

The four-player evolutionary game system consists of the replicator dynamic equations of local governments, core enterprises, supporting enterprises, and S&T service institutions. The system equilibrium points satisfy:

$$F(x) = F(y) = F(z) = F(w) = 0$$

Since each agent has two pure strategies, the system has $2^4 = 16$ pure-strategy boundary points, namely:

$$E_{ijkl} = (i, j, k, l), i, j, k, l \in \{0, 1\}$$

In addition, when the expected payoffs of the two strategies for each agent are equal, the system may also have mixed-strategy equilibria. This paper focuses on analyzing the local stability of the high-level collaborative equilibrium $E_{16} = (1, 1, 1, 1)$ and the low-level non-collaborative equilibrium $E_0 = (0, 0, 0, 0)$.

For analytical convenience, the payoff differences in the four stakeholders when adopting the positive strategy relative to the passive strategy are defined as Equations (5), (16), (26) and (35). Accordingly, the four-agent replicator dynamic equations can be uniformly written as Equations (6), (17), (27), and (36). To judge the local stability of equilibrium points, the Jacobian matrix is constructed as follows:

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

From the replicator dynamic equations, we obtain:

$$J = \begin{bmatrix} (1-2x)H(x) & x(1-x)(R_g - S_e - L_g) & 0 & -x(1-x)S_t \\ y(1-y)(S_e + P_e) & (1-2y)H(y) & 0 & 0 \\ 0 & z(1-z)\left(R_s + kR_e - R_{sf}\right) & (1-2z)H(z) & 0 \\ w(1-w)S_t & 0 & 0 & (1-2w)H(w) \end{bmatrix}$$

At the pure-strategy boundary equilibrium point E_{ijkl}, since $x, y, z, w \in \{0, 1\}$, we have

$$x(1-x) = y(1-y) = z(1-z) = w(1-w) = 0$$

Therefore, all off-diagonal elements in the Jacobian matrix are zero, and the matrix degenerates into a diagonal matrix.

$$J\left(E_{ijkl}\right) = \text{diag}[(1-2i)H(x), (1-2j)H(y), (1-2k)H(z), (1-2l)H(w)]$$

where each function H is evaluated at the strategy values corresponding to equilibrium point E_{ijkl}. According to Lyapunov's indirect method, if all eigenvalues of $J\left(E_{ijkl}\right)$ are negative, the equilibrium point is locally asymptotically stable; if at least one eigenvalue is positive, the equilibrium point is unstable. Since the Jacobian matrix at boundary equilibrium points is a diagonal matrix, its eigenvalues are exactly the diagonal elements.

Therefore, the local stability of an equilibrium point can be affected solely by examining the sign of the payoff-difference function for each agent under the corresponding strategy profile.

Theorem 1. *Local stability conditions for the high-level synergistic equilibrium. The system's high-level synergistic state* $E_{16}(1,1,1,1)$ *is a locally asymptotically stable equilibrium if and only if the following four conditions hold simultaneously:*

$$R_g - S_e - L_g > 0 \tag{41}$$

$$S_e + P_e > (R_{ei} - C_{ei}) - (R_e - C_e) \tag{42}$$

$$R_s + kR_e - R_{sf} > C_s - C_{sf} \tag{43}$$

$$S_t > (R_t - C_t) - (R_{ti} - C_{ti}) \tag{44}$$

Proof. At equilibrium point $E_{16}(1,1,1,1)$, all four agents adopt positive strategies, i.e., $x = z = w = 1$. Substitute this point into the Jacobian matrix. Since each replicate dynamic equation takes the form of $q(1-q)$, the cross-partial derivative terms contain $x(1-x)$, $y(1-y)$, $z(1-z)$ or $w(1-w)$. These terms all equal zero at the boundary point E_{16}. Accordingly, the Jacobian matrix degenerates into a diagonal matrix, whose eigenvalues are:

$$\lambda_1 = -\left(R_g - S_e - L_g\right)$$

$$\lambda_2 = -[S_e + P_e + (R_e - C_e) - (R_{ei} - C_{ei})]$$

$$\lambda_3 = -\left(R_s + kR_e - R_{sf} - C_s + C_{sf}\right)$$

$$\lambda_4 = -[S_t + (R_{ti} - C_{ti}) - (R_t - C_t)]$$

Based on the Lyapunov linearization method, the equilibrium point E_{16} is locally asymptotically stable if and only if all eigenvalues of the Jacobian matrix are negative. Accordingly, $\lambda_1 < 0$, $\lambda_2 < 0$, $\lambda_3 < 0$, $\lambda_4 < 0$ correspond to conditions (41)–(44), respectively. When these four conditions are satisfied simultaneously, the relative payoffs for the four agents adopting positive strategies are all positive, and the system locally converges to the high-level synergistic equilibrium $E_{16}(1,1,1,1)$. Conversely, if any condition fails to hold, at least one eigenvalue is non-negative. Specifically, a positive eigenvalue implies instability of this equilibrium point, whereas a zero eigenvalue means the linearization method cannot affect its local asymptotic stability. □

Theorem 1 indicates that the formation of a high-level collaborative equilibrium depends on the simultaneous incentive compatibility of the four agents. The synergy dividends for local governments must cover the extra costs of active support as well as subsidy expenditures for core enterprises and S&T service institutions. For core enterprises, the combined benefits of subsidies, default penalty constraints and net synergy gains ought to offset the opportunity cost of abandoning independent innovation. For supporting enterprises, synergy returns and knowledge spillover benefits should exceed free-riding gains and additional matching costs. For S&T service institutions, subsidies plus the net-profit advantages from routine services need to outweigh the relative net returns of their in-depth R&D services. Insufficient incentives in any link may be associated with the system away from the high-level synergistic state. This reveals a "short-board effect" in the collaborative governance of innovation ecosystems: system stability is constrained by the weakest incentive link.

Theorem 2. *Local Stability Conditions for the Low-Level Non-Synergistic Equilibrium. If and only if the following four conditions hold simultaneously, the low-level non-synergistic state* $E_0 = (0, 0, 0, 0)$ *of the system is a locally asymptotically stable equilibrium:*

$$L_g - C_g + C_{gl} < 0 \tag{45}$$

$$(R_e - C_e) - (R_{ei} - C_{ei}) < 0 \tag{46}$$

$$C_{sf} - C_s < 0 \tag{47}$$

$$(R_t - C_t) - (R_{ti} - C_{ti}) < 0 \tag{48}$$

In other words, under the low-level non-synergistic state, if the relative payoffs for local governments implementing active governance, core enterprises carrying out in-depth collaboration, supporting enterprises participating actively, and S&T service institutions engaging deeply are all negative, then the low-level non-collaborative equilibrium is locally asymptotically stable. That is, for initial strategy profiles sufficiently close to this equilibrium, the evolutionary trajectories converge to it.

Proof. At equilibrium point $E_0 = (0, 0, 0, 0)$, the local government, core enterprises, supporting enterprises, and S&T service agencies all adopt passive strategies, i.e., $x = y = z = w = 0$. Substituting this point into the payoff-difference function of each agent yields:

$$H(x) = L_g - C_g + C_{gl}$$

$$H(y) = (R_e - C_e) - (R_{ei} - C_{ei})$$

$$H(z) = C_{sf} - C_s$$

$$H(w) = (R_{ti} - C_{ti}) - (R_t - C_t)$$

Since each replicate dynamic equation contains terms of the form $q(1 - q)$, and the off-diagonal entries of the Jacobian matrix all involve $x(1 - x)$, $y(1 - y)$, $z(1 - z)$ or $w(1 - w)$, the off-diagonal entries of the Jacobian matrix are all zero at the boundary point E_0. Consequently, the Jacobian matrix degenerates into a diagonal matrix. Its eigenvalues are given by:

$$\lambda_1 = L_g - C_g + C_{gl}$$

$$\lambda_2 = (R_e - C_e) - (R_{ei} - C_{ei})$$

$$\lambda_3 = C_{sf} - C_s$$

$$\lambda_4 = (R_{ti} - C_{ti}) - (R_t - C_t)$$

Based on the Lyapunov linearization method, the equilibrium point E_0 is locally asymptotically stable if all eigenvalues of the Jacobian matrix are negative. Therefore, when conditions (45)–(48) hold simultaneously, the low-level non-collaborative equilibrium is locally asymptotically stable. This result characterizes stability in a neighborhood of the equilibrium and does not, by itself, establish convergence from all possible initial strategy profiles. Conversely, if at least one eigenvalue is positive, E_0 is unstable. If any eigenvalue equals zero, the linearization method cannot affect the local asymptotic stability of this point. □

Theorem 2 reveals the most severe governance risk within the innovation ecosystem: when the gains obtained by supporting enterprises through free-riding exceed their net benefits from collaborative participation, free-riding becomes a dominant strategy. This not only directly erodes supporting enterprises' willingness to participate, but also indi-

rectly dampens core enterprises' incentives for collaborative innovation by lowering their expected returns from collaboration. Once such a vicious cycle of "free-riding–low-level collaboration" emerges, the system may move toward, or remain in, a low-level lock-in state, particularly when its initial strategy profile lies within the basin of attraction of the low-level equilibrium. The local stability analysis does not exclude the possibility of alternative evolutionary outcomes under different initial conditions, an important contributing factor.

The preceding analysis identifies two focal boundary equilibria of the four-player evolutionary system. The first is the high-level collaborative equilibrium, in which local governments actively foster the innovation ecosystem, core enterprises undertake deep collaborative innovation, supporting enterprises participate in collaborative supporting, and S&T service institutions engage deeply in R&D services. The second is the low-level non-collaborative equilibrium, in which local governments maintain the traditional-industrial orientation, core enterprises adopt independent autonomous innovation, supporting enterprises choose free-riding behavior, and S&T service institutions provide routine intermediary services. The local stability conditions for these two equilibria are reported in Theorems 1 and 2, respectively. Their comparison indicates that the evolution toward high-level collaboration requires simultaneous incentive compatibility among all four actors, whereas insufficient incentives for one or more actors may lead the system toward the low-level non-collaborative state.

4. Numerical Simulation

4.1. Parameter Sources, Setting Principles, and Baseline Scenario

This study employs numerical simulation to investigate the evolutionary implications and operating mechanisms of the proposed four-player evolutionary game model, rather than to estimate the behavior of a particular region using a single empirical dataset. Therefore, the baseline parameter values are not directly calibrated from one observed sample. Instead, they are determined by integrating: (1) the economic logic embedded in the payoff structure; (2) the relative parameter relationships commonly reported in the evolutionary game, innovation policy, and collaborative innovation literature; and (3) normalization procedures that ensure comparability among heterogeneous costs, benefits, subsidies, penalties, and knowledge-spillover effects. More specifically, the parameter settings follow several theoretically and practically grounded principles. First, the costs of active and deep collaborative behavior are assumed to exceed those of conventional or low-input behavior. Accordingly, the cost of deep collaborative innovation undertaken by core enterprises is set higher than that of independent innovation, the cost of collaborative supporting undertaken by supporting enterprises is set higher than that of free riding, and the cost of deep R&D service participation by S&T service institutions is set higher than that of routine intermediary services. Second, active collaboration is assumed to generate greater potential long-term returns than passive, independent, or opportunistic behavior under an effective incentive and constraint mechanism. Third, government subsidies, R&D funding, and default penalties are assigned moderate baseline levels, so that their incentive effects and possible nonlinear or threshold effects can be examined.

The baseline values reported in Table 2 are normalized scenario values. For clarity, the detailed definitions and descriptions of all model variables and parameters are provided in Table A1. They do not represent exact empirical estimates for a specific city or region; rather, they reflect economically plausible relative magnitudes and are used to test the internal consistency and dynamic implications of the theoretical model. For example, the baseline setting assumes that the benefits from collaborative innovation exceed those from independent innovation, while the associated costs are also higher. Similarly, deep participation by S&T service institutions yields higher service revenues but requires greater

inputs in specialized personnel, technical equipment, data platforms, and project coordination. Accordingly, the numerical results should be interpreted as mechanism-based scenario simulations rather than direct empirical predictions. Future research may improve the external validity of the model by calibrating the parameters with regional panel data, enterprise survey data, innovation-policy program data, or micro-level data on S&T service institutions.

Table 2. Baseline parameter settings.

Parameter	Economic Meaning	Baseline Value	Setting Basis
R_g	Innovation dividend of local government	50	Reflects the comprehensive contribution of collaborative innovation to regional economy
C_g/C_{gl}	Cost of active support/traditional governance	20/5	Active support incurs additional policy-coordination costs
L_g	Performance-assessment loss for innovation	15	Reflects superior-level accountability and public pressure
α	Pressure coefficient of performance assessment	0.6	Local governments face moderate innovation-performance pressure
S_e	Subsidy for core enterprises	12	Moderate intensity of fiscal incentives
P_e	Default penalty for core enterprises	10	Moderate intensity of institutional constraints
R_e/R_{ei}	Benefit of collaborative/independent innovation	35/20	Collaborative innovation yields significant excess returns
C_e/C_{ei}	Cost of collaborative/independent innovation	25/12	Collaboration requires deeper-level inputs
R_s/R_{sf}	Benefit of collaborative supporting/free-riding	22/10	Collaborative supporting yields higher returns; free-riding benefits include knowledge spillovers
C_s/C_{sf}	Cost of collaborative supporting/free-riding	8/3	Collaborative supporting requires certain inputs, while free-riding has markedly lower costs
k	Intensity of knowledge spillovers	0.4	Moderate diffusion of innovation knowledge
R_t/R_{ti}	Benefit of in-depth/conventional services	20/10	In-depth services bring higher returns
C_t/C_{ti}	Cost of in-depth/conventional services	15/5	In-depth services demand more resource inputs
S_t	Subsidy for S&T service institutions	8	Government support for R&D services
G_t	Government research funding	6	Baseline of public R&D investment

The parameter values in Table 2 are specified according to the relative payoff relationships required by the model. The benefits and costs of collaborative innovation, collaborative supporting, and R&D service participation are normalized to reflect the fact that deeper collaboration involves both higher expected returns and greater resource commitments. Government subsidies and R&D funding represent fiscal support for firms and S&T service institutions, whereas default penalties capture the institutional constraints imposed on opportunistic or non-cooperative behavior. The knowledge-spillover coefficient is set at a moderate level to represent an environment in which innovation knowledge can diffuse among ecosystem participants but is not fully and costlessly transferred.

The initial strategy probabilities are set as $x_0 = y_0 = z_0 = w_0 = 0.5$, representing a neutral condition in which the four agents have no prior strategic advantage. The simulation is implemented on the MATLAB R2017b platform. The fourth-order Runge–Kutta (RK4) is adopted to solve the system of differential equations, with the step size

$dt = 0.01$ and simulation period $T = 15$. In all simulation figures, the horizontal axis represents evolutionary time, whereas the vertical axis denotes the probability that the corresponding agent adopts the collaborative strategy. Unless otherwise specified, only one focal parameter is varied in each sensitivity-analysis scenario, while all remaining parameters are maintained at their baseline values reported in Table 2. Accordingly, the relative positions and slopes of the curves indicate the direction of strategy evolution and the speed at which the system approaches a stable equilibrium.

4.2. Baseline Scenario Simulation

As shown in Figure 1, the horizontal axis denotes the evolution period, and the vertical axis represents the probability that each agent adopts the collaborative strategy. By examining the four-party strategy evolution curves, we can identify the system's convergence direction, agents' response speed, and the formation process of high-level collaborative equilibrium under the baseline scenario. Starting from the initial neutral state $(0.5, 0.5, 0.5, 0.5)$, the system gradually evolves toward the high-level collaborative equilibrium $E_{16}(1, 1, 1, 1)$. Among all agents, core enterprises exhibit the fastest response, reaching $y = 0.95$ at approximately period 3. This indicates that the combined incentives of subsidies and default penalties can strengthen their willingness for in-depth collaboration. Supporting enterprises reach $z = 0.95$ at about period 5.5, which reflects a prolonged strategic trade-off between collaborative participation and free-riding. Local governments show slight fluctuations during periods 4–7 before converging to stability. S&T service institutions evolve relatively slowly and attain $w = 0.95$ around period 5. The simulation results reveal that when baseline parameters satisfy the incentive compatibility condition, the system can converge stably to the high-level collaborative equilibrium. This pattern is consistent with the replicator-dynamic mechanism. When the expected payoff from collaborative behavior exceeds that from the alternative strategy, the probability of adopting collaboration increases over time. The relatively rapid convergence of core enterprises indicates that, under the baseline setting, the combined effects of collaborative innovation returns, government subsidies, and default penalties generate a sufficiently strong payoff advantage for collaborative innovation. By contrast, the slower adjustment of supporting enterprises and S&T service institutions reflects their more gradual evaluation of collaboration costs, knowledge-spillover benefits, service returns, and potential free-riding opportunities.

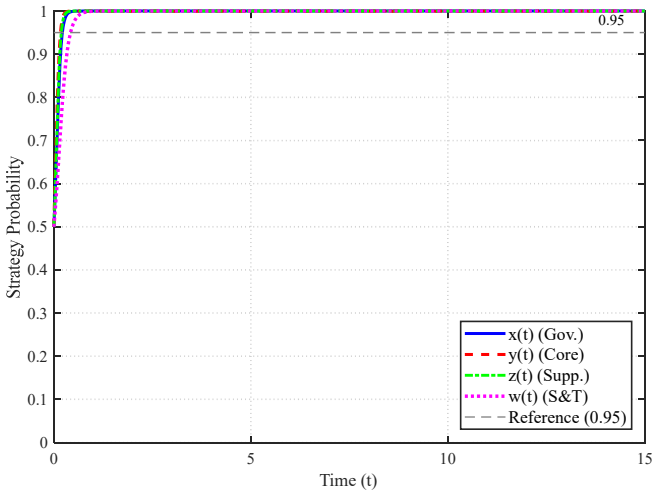


Figure 1. Evolutionary trajectories of the strategy probabilities of local governments, core enterprises, supporting enterprises, and S&T service institutions under the baseline scenario. The horizontal axis represents evolutionary time t, and the vertical axis represents the probability of adopting the collaborative strategy.

4.3. Sensitivity Analysis of Key Parameters

On the basis that the system converges to a high-level collaborative equilibrium under the baseline scenario, this paper conducts a sensitivity analysis. By adjusting government subsidies, default penalties, the knowledge spillover coefficient, and free-riding benefits respectively, we compare the evolutionary differences in the collaborative-strategy probabilities of the four agents, so as to reveal the impacts of policy instruments and benefit structures on the system's convergence speed, steady-state outcomes, and agent responses.

4.3.1. Non-Monotonic Effect of Government Subsidy Intensity

The subsidy for core enterprises S_e is scanned over the interval [0, 30] with a step size of 2 to investigate its influence on the system's evolutionary equilibrium and convergence speed (Figure 2). The results reveal a pronounced nonlinear subsidy effect. Within the low-subsidy range ($S_e < 6$), the system fails to converge to the high-level collaborative equilibrium within 15 periods. When $S_e = 4$, the probability of in-depth collaborative innovation for core enterprises is merely 0.38, and the participation probability of supporting enterprises is 0.25; the system falls into a low-level mixed state. Within the moderate-subsidy interval ($6 \leq S_e < 18$), the system can converge to E_{16} within 15 periods, and higher subsidies accelerate convergence. When $S_e = 12$, core enterprises reach the probability of 0.95 at approximately period 3; when S_e rises to 18, the convergence time is shortened to about 2.5 periods. Nevertheless, for $S_e > 18$, the marginal incentive effect diminishes evidently. Further raising subsidies improves convergence speed by less than 0.5 periods. Meanwhile, the local government's net payment $R_g - C_g - S_e - S_t$ keeps declining. When $S_e > 22$, its net payment turns negative. Although the system may still converge to E_{16}, the fiscal sustainability and policy stability of the equilibrium are undermined. Accordingly, subsidy design should balance incentive intensity and fiscal constraints to avoid the policy misconception that "higher subsidies always bring better outcomes".

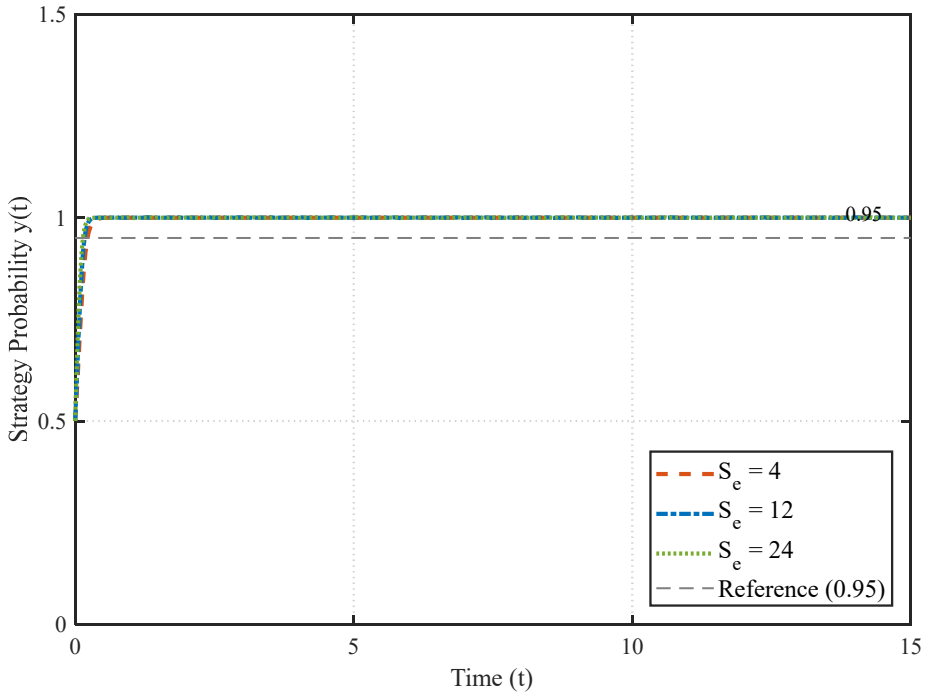


Figure 2. Evolution trajectories of core enterprises under different subsidy intensities. The three curves correspond to $S_e = 4, 12$, and 24, respectively.

4.3.2. Substitution and Complementarity Between Subsidies and Penalties

Figure 3 illustrates the joint effects of government subsidies S_e and default penalties P_e on system convergence time, as well as their prominent nonlinear characteristics. The horizontal axis denotes subsidy intensity, and the vertical axis represents the periods required for the system to reach a stable collaborative state. The three curves correspond to P_e = 6, 10, and 14, respectively. On the whole, convergence time declines as subsidies rise, yet heterogeneous mechanisms emerge across different intervals. When $S_e < 6$, subsidies and penalties exhibit strong complementarity: raising penalties can substantially shorten convergence time. This suggests that under insufficient-incentive conditions, default constraints can effectively offset the low willingness of core enterprises for collaborative innovation. For $6 < S_e < 18$, subsidies and penalties show partial substitutability. Increasing subsidies becomes the major driver for shortening convergence time, while the marginal effect of higher penalties gradually diminishes. Especially when S_e approaches 18, system convergence time drops rapidly to a low level, indicating that moderate subsidies can significantly strengthen multi-agent collaborative incentives. When $S_e \geq 18$, all curves remain within a short convergence-time range. Further raising subsidies or penalties yields limited improvements, revealing redundant effects of policy instruments. Excessive policy tightening at this stage can hardly boost collaboration efficiency notably; instead, it may increase fiscal expenditure and enterprises' constraint costs. Therefore, policy design should flexibly adjust penalty intensity according to subsidy intervals: strengthen constraints under low-subsidy conditions, prioritize incentives in the moderate-subsidy interval, and avoid policy superposition under high-subsidy scenarios.

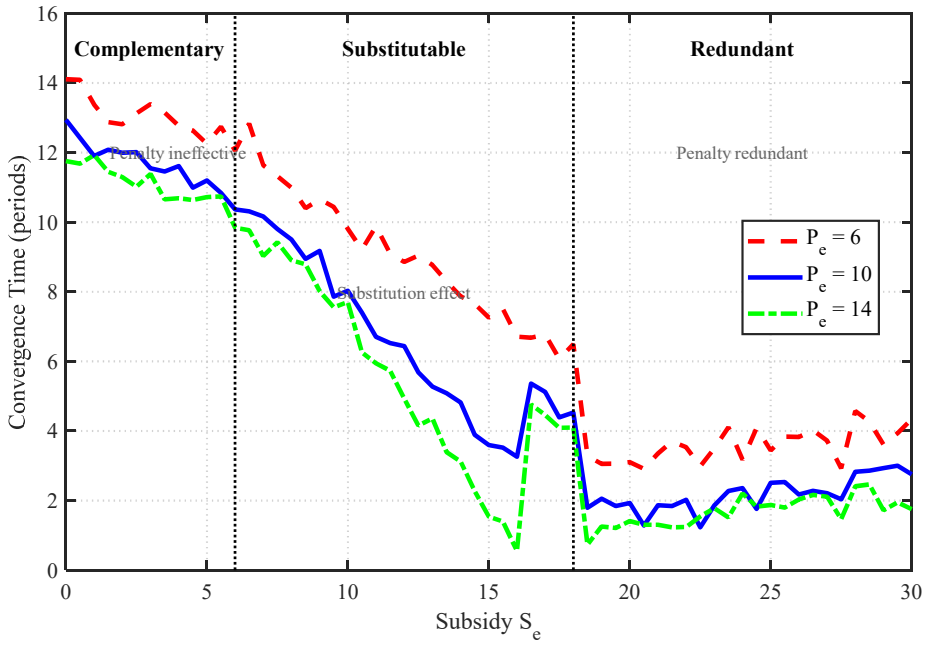


Figure 3. Nonlinear variation in system convergence time under the linkage of government subsidies and default penalties. The vertical axis denotes convergence time, and the horizontal axis represents subsidy intensity.

4.3.3. Interaction Effect of Free-Riding Benefits and Knowledge Spillovers

Figure 4 presents the joint impacts of the knowledge spillover coefficient k and supporting-enterprise free-riding benefits R_{sf} on the evolution of collaborative strategies for core enterprises $y(t)$ and supporting enterprises $z(t)$. The four subplots correspond to combinations of k = 0.2, 0.6 and R_{sf} = 8, 16, respectively. The dashed line denotes the 0.95 convergence threshold. Under all scenarios, both $y(t)$ and $z(t)$ rise rapidly from 0.5

to near 1 and cross the 0.95 threshold within a short period. This indicates that under given parameter settings, the system can stably converge to a high-level collaborative state featuring in-depth collaborative innovation by core enterprises and active participation of supporting enterprises. Horizontal comparison reveals that, for a fixed knowledge-spillover level, raising R_{sf} from 8 to 16 does not alter the final steady state of the two types of enterprises. Nevertheless, the early-stage rise in the curve for supporting enterprises slows down slightly, which suggests that higher free-riding benefits weaken the relative appeal of voluntary collaboration. However, this negative effect is not strong enough to break the constraints formed by collaborative returns and policy incentives, and thus it only produces mild disturbances to convergence speed. Vertical comparison shows that when k increases from 0.2 to 0.6, the incentives for supporting enterprises to participate in collaboration are strengthened. $z(t)$ converges more quickly toward the steady state, and drives the synchronous rise in core-enterprise strategy probability through industrial-chain linkages. Overall, knowledge spillovers exert positive incentive effects, whereas free-riding benefits carry potential inhibitory effects. Within the current parameter ranges, knowledge spillovers and systemic collaborative incentives dominate. Accordingly, all four combinations achieve high-level collaborative convergence.

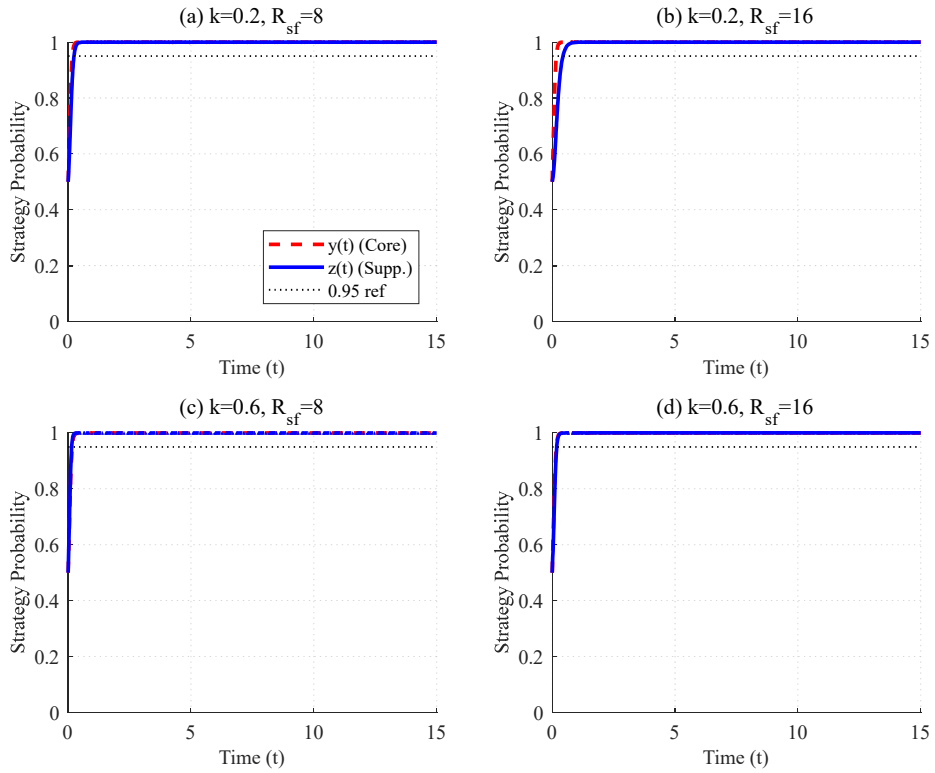


Figure 4. Evolution trajectories of supporting enterprises and core enterprises under different combinations of k and R_{sf}. This is a 2 × 2 matrix plot corresponding to the combinations of k = 0.2, 0.6 and R_{sf} = 8, 16, respectively.

4.3.4. Path Dependence of Initial Conditions

As shown in Figure 5, system evolution exhibits significant path-dependent characteristics with respect to initial conditions. The initial collaboration willingness of core enterprises acts as the critical threshold determining whether the system can initiate high-level collaborative evolution, while the initial support willingness of local governments mainly affects the startup speed and evolutionary stability of the system.

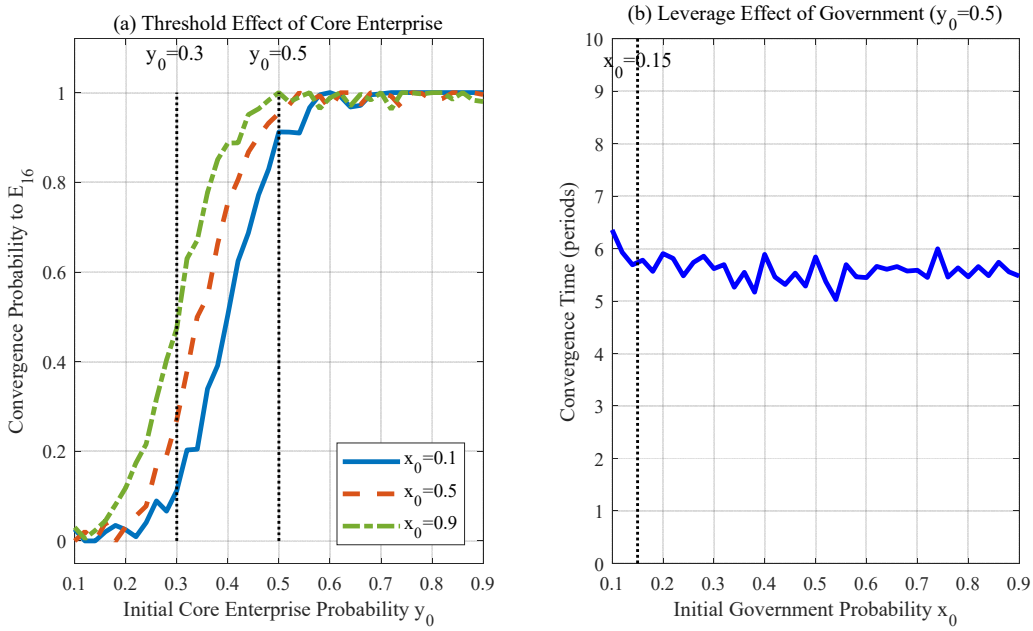


Figure 5. Threshold of initial collaboration willingness and the leverage effect of government support. In subplot (**a**), the horizontal axis denotes the initial collaborative-strategy probability of core enterprises y_0, and the vertical axis represents the probability that the system converges to the high-level collaborative equilibrium E_{16}. The blue, orange, and green curves correspond to government initial active-support probabilities x_0 = 0.1, 0.5, and 0.9, respectively. Two vertical dashed lines mark the critical thresholds at y_0 = 0.3 and y_0 = 0.5. In subplot (**b**), y_0 is fixed at 0.5. The horizontal axis is the government initial active-support probability x_0, and the vertical axis is system convergence time. The blue curve illustrates convergence cycles under different x_0, and the vertical dashed line indicates the critical value of government support x_0 = 0.15.

Figure 5a examines how the initial collaboration willingness of core enterprises affects the simulated likelihood that the evolutionary trajectories approach the high-level collaborative equilibrium under the specified parameter settings and simulation horizon. The three curves correspond to different government initial-support-willingness values x_0 = 0.1, 0.5, and 0.9. The results show a distinct "S-shaped threshold" feature. When $y_0 < 0.3$, the probability of the system converging to E_{16} is close to zero regardless of the level of government initial support willingness. This occurs because insufficient collaborative willingness among core enterprises prevents supporting enterprises from forming stable collaboration expectations; S&T service institutions also lack sustained demand for R&D services, and governments may weaken proactive support strategies due to low subsidy efficiency. Consequently, a self-reinforcing cycle emerges: "low collaboration expectation–low collaboration input–low collaboration output". When $y_0 > 0.5$, the proportion of simulated trajectories that approach the high-level collaborative equilibrium rises rapidly and approaches 1 under the specified initial-condition grid, parameter settings, convergence criterion, and simulation horizon. Even if other agents hold low initial willingness, core enterprises can may be associated with supporting enterprises, S&T service institutions and governments toward collaborative strategies via demonstration effects and knowledge spillovers. Within the transition interval $0.3 < y_0 < 0.5$, higher government initial support willingness can partially lower the core-enterprise willingness threshold required for the system to enter a high-level collaborative state, yet it cannot substitute for the leading role of core enterprises.

Figure 5b further investigates the effect of government initial support willingness x_0 on system convergence time when core-enterprise initial collaboration willingness remains at a relatively high fixed level y_0 = 0.5. The results indicate that when $x_0 < 0.15$ (this critical

value corresponds to the inflection point of the convergence-time curve in Figure 5b), system convergence time extends from approximately 5.5 cycles to more than 8.5 cycles. By contrast, when $x_0 > 0.15$, convergence time stabilizes at roughly 5.5 cycles. This reveals the evident "leverage effect" of government support: insufficient initial government input generally does not completely block system evolution toward E_{16}, but it considerably prolongs the collaboration startup process and raises uncertainty over evolutionary paths.

4.4. Robustness Checks

Three types of robustness checks are performed to verify the robustness of model conclusions under parameter perturbations.

First, stochastic-perturbation test for parameters. As shown in Figure 6a, uniform random perturbations of $\pm 20\%$ are imposed on the baseline parameters. The simulation is repeated 500 times, and the frequency at which the system converges to E_{16} within 15 cycles is recorded. The results yield a convergence frequency of 91.8%. Non-convergent cases mainly occur under extreme combinations where subsidy S_e and free-riding benefit R_{sf} fluctuate simultaneously in unfavorable directions (probability $\approx 8.2\%$). The 91.8% convergence rate should be interpreted conditionally rather than as unconditional evidence of global parameter robustness. Specifically, it represents the proportion of Monte Carlo realizations that converged to the high-level collaboration equilibrium under the assumed parameter-sampling distribution, perturbation range, initial conditions, simulation horizon, and convergence criterion. Because a Monte Carlo convergence rate is a distribution-weighted result, it may change when the parameter range, the assumed distribution, or the dependence structure among parameters changes. Moreover, the remaining non-convergent cases indicate that the high-level equilibrium is not recovered under every admissible parameter combination. Therefore, the result supports the relative robustness of the high-level collaboration equilibrium within the tested parameter neighborhood, rather than a claim of unconditional robustness over the entire parameter space. The reported convergence-time statistics further complement the convergence proportion by indicating whether the system reaches the target equilibrium consistently and within a practically meaningful adjustment period.

Second, extreme-parameter test. As shown in Figure 6b, each parameter is pushed toward its economically meaningful extreme value (e.g., $k \to 1$, $S_e \to 0$, $R_{sf} \gg R_s$) to examine system behaviors under diverse extreme conditions. The extreme-parameter test further validates the conclusions of Theorem 2: when free-riding benefits and knowledge-spillover intensity rise to sufficiently high levels, the system does undergo a catastrophic shift from the high-level collaborative equilibrium to a locked-in low-level equilibrium. This catastrophe is irreversible—even if parameters revert to baseline values, the system remains trapped in the low-level equilibrium. The discovery of this hysteresis effect reveals the "prevention-over-remediation" principle for innovation ecosystem governance. Once the system becomes locked into a low-level equilibrium, the intervention intensity required for unlocking is far higher than that needed to avert lock-in.

Third, structural-robustness test. As shown in Figure 6c, the four-player game model is degenerated into a three-player model (removing S&T service institutions) and a two-player model (retaining only government and core enterprises) for comparative simulation. Results show that the four-player model imposes stricter conditions for high-level collaborative convergence than the three-player model (an extra incentive-compatibility condition for S&T service institutions must be satisfied), alongside slightly higher volatility along convergence paths, as strategic adjustments from additional agents introduce greater feedback delays. This difference aligns with theoretical expectations: greater system complexity and a larger number of agents raise collaboration difficulty and impose more constraints for con-

vergence. Neither degenerated model refutes the core findings derived from the four-player model, which demonstrates acceptable structural robustness of the proposed model.

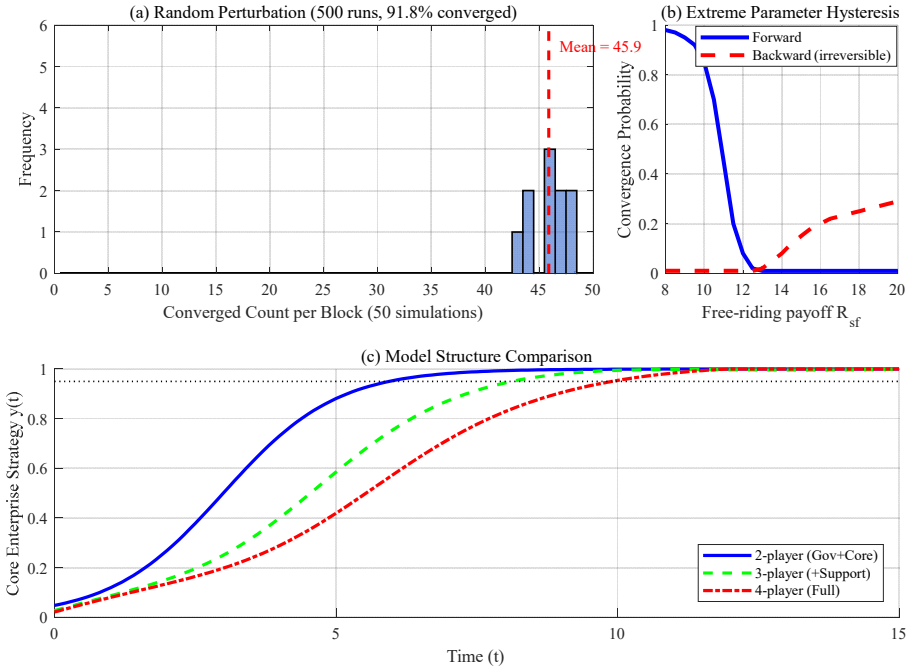


Figure 6. Results of robustness checks. The three subplots respectively present the convergence-frequency histogram for the stochastic parameter-perturbation test, the catastrophic-shift path plot for the extreme-parameter test, and the evolutionary-trajectory plot for model-structure comparison.

5. Conclusions

This study constructs a four-player evolutionary game model comprising local governments, core enterprises, supporting enterprises, and S&T service institutions, and systematically investigates the dynamic evolutionary mechanism of collaborative governance within innovation ecosystems. The main findings are as follows. First, the realization of high-level system collaboration depends on satisfied incentives for all four agents. Insufficient collaborative returns for any single agent may trigger strategic shifts and trap the system in a low-collaboration state, reflecting an evident "short-board effect". Second, core enterprises play an important coordinating role for collaborative evolution. Their collaboration willingness not only directly affects the system-wide collaboration level but also fosters participation of other agents through knowledge spillovers, demonstration effects, and transmission of R&D demand. Accordingly, core enterprises should be prioritized for targeted governance. Third, government subsidies exert a non-monotonic effect on system evolution. Insufficient subsidies fail to initiate collaboration effectively, while excessively high subsidies may reduce fiscal efficiency and induce reliance. Moderate, dynamic and differentiated incentives should be implemented according to firms' collaborative performance and the evolutionary stage of the system. Fourth, knowledge spillovers do not necessarily boost collaboration. Excessively high free-riding benefits will dampen supporting enterprises' willingness for proactive investment. Therefore, it is necessary to coordinate intellectual-property protection, benefit-sharing arrangements, default constraints and subsidy incentives according to industrial knowledge characteristics, so as to build a multi-agent incentive-compatible mechanism for collaborative governance.

Drawing on the theoretical analysis and simulation results, the following policy implications are summarized. First, policymakers should emphasize the collaborative initiation role of core enterprises. The simulations indicate that the initial willingness of core enter-

prises to engage in collaborative innovation is an important condition for the system to evolve toward a high-level collaborative state. Local governments may therefore identify core enterprises with collaborative potential and provide targeted support to alleviate their initial collaboration costs, rather than relying exclusively on universal subsidies. Increased collaboration by core enterprises may, in turn, encourage supporting enterprises and S&T service institutions through the modeled mechanisms of knowledge spillovers and demand for R&D-related services. Second, policymakers should reduce incentives for free-riding and enhance the relative returns to collaborative participation by supporting enterprises. Within the model, this can be achieved through an appropriate combination of penalties for opportunistic behavior, collaboration-related incentives, and measures that increase the expected benefits of active participation. Although intellectual-property protection and benefit-sharing arrangements may be relevant practical instruments for achieving these objectives, they are not modeled as independent policy variables in this study. Therefore, they should be interpreted as potential institutional mechanisms consistent with, rather than directly tested by, the model's incentive structure. Third, subsidies should be designed dynamically and linked to collaborative-innovation performance. The simulation results suggest that insufficient incentives may delay the emergence of collaboration, whereas excessively high subsidies may create fiscal burdens and increase reliance on external support. Local governments should therefore calibrate subsidy intensity to firms' collaboration costs and expected returns, and consider gradually reducing subsidies once collaborative activities become self-sustaining. Fourth, policy design should aim to improve incentive compatibility among local governments, core enterprises, supporting enterprises, and S&T service institutions. The model indicates that high-level collaboration is more likely when the payoff conditions for active participation are simultaneously satisfied across the four actors. Accordingly, policy interventions should focus on the modeled levers—such as fiscal incentives, penalties for free-riding, and support for R&D-related services—and identify the actor whose insufficient incentive most constrains the evolution of system-wide collaboration.

Policy design should prioritize incentive compatibility among all actors rather than focusing exclusively on enterprise subsidies. For local governments, fiscal support should be linked to measurable collaborative outcomes and budget sustainability. For core enterprises, subsidies and penalties should jointly encourage genuine collaborative innovation rather than symbolic participation. For supporting enterprises, benefit-sharing arrangements, knowledge-access mechanisms, and contractual safeguards should reduce the attractiveness of free riding. For S&T service institutions, targeted R&D-service subsidies, performance-based remuneration, and intellectual-property protection can compensate for the higher risks and costs of deep participation. A coordinated incentive system that aligns the expected benefits of all four actors is essential for avoiding low-level equilibrium traps. Nevertheless, several limitations of the present study should be acknowledged. It should be emphasized that the findings of this study are theoretical results derived from the assumptions and parameter settings of the evolutionary game model. The numerical simulations illustrate possible dynamic patterns and parameter effects rather than provide direct empirical validation. Therefore, the policy implications should be interpreted as conditional theoretical propositions. Future research should employ empirical data to calibrate the model and test the mechanisms proposed in this study.

Building on this caveat, several specific limitations of the current model and corresponding directions for future research can be identified. First, parameter settings are mainly derived from theoretical relationships and economic implications, without calibration against field-collected data. Future research may estimate parameters and validate model conclusions using firm-level microdata, innovation surveys or patent data. Second,

the model assumes homogeneous costs, benefits and strategic preferences for agents of the same type, and does not fully account for the heterogeneity of core enterprises in terms of technical capacity and market position, as well as the collaborative-capacity heterogeneity of supporting enterprises. Heterogeneous agents can be incorporated in follow-up work to analyze the evolutionary impacts of capability discrepancies. Third, policy parameters including subsidies, penalties and R&D grants are set as static in this paper. Future studies may construct adaptive policy rules that are dynamically adjusted and gradually phased out alongside evolutionary stages. Fourth, the model adopts deterministic replicator dynamics and excludes stochastic shocks such as technological breakthroughs, market fluctuations and policy adjustments. Stochastic differential equations or Markov-switching models can be adopted in further research to investigate system resilience and recovery capacity.

This model is primarily developed for the local-government level, where governments can directly influence regional innovation ecosystems through localized fiscal incentives, regulatory arrangements, public-service provision, and performance assessment. Its direct application to the national level should be made with caution. National governments usually face more heterogeneous regions, multiple administrative layers, broader fiscal responsibilities, and more complex policy-transmission mechanisms. Therefore, extending the model to the national level would require incorporating interregional heterogeneity, central–local fiscal relations, multilevel governance, and differentiated industrial structures. These issues provide important directions for future research.

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Appendix A

Table A1. Definitions of model variables and description of parameters.

Variables/Parameters	Symbol	Type	Definition
Probability of active support by local government	x	State variables	$x \in [0, 1]$, Probability that local government chooses to actively support the innovation ecosystem
Probability of in-depth collaboration for core enterprises	y	State variables	$y \in [0, 1]$, Probability that core enterprises choose in-depth collaborative innovation
Probability of collaborative participation for supporting enterprises	z	State variables	$z \in [0, 1]$, Probability that supporting enterprises choose to participate in collaborative supporting
Probability of in-depth participation for S&T service institutions	w	State variables	$w \in [0, 1]$, Probability that S&T service institutions choose in-depth participation in R&D services

Table A1. *Cont.*

Variables/Parameters	Symbol	Type	Definition
Innovation dividend of local government	R_g	Exogenous parameters	Regional-innovation performance and industrial-upgrading benefits brought by high-level collaboration
Support cost of local government	C_g	Exogenous parameters	Expenditure on policy formulation, coordination and management for actively supporting the innovation ecosystem
Traditional governance cost of local government	C_{gl}	Exogenous parameters	Routine administrative expenditure for maintaining the traditional-industry orientation
Loss from innovation-performance assessment	L_g	Exogenous parameters	Loss from superior accountability and public pressure under the traditional orientation
Pressure coefficient of performance assessment	α	Exogenous parameters	$\alpha \in [0, 1]$, Intensity of innovation-performance accountability faced by local government
Subsidy for core enterprises	S_e	Policy parameters	Fiscal subsidies provided by the government for enterprises adopting in-depth collaborative innovation
Penalty for breach of contract of core enterprises	P_e	Policy parameters	Institutional penalty for core enterprises' breach (obtaining subsidies without collaboration)
Collaborative-innovation benefit of core enterprises	R_e	Exogenous parameters	Returns such as technological breakthroughs and market expansion brought by in-depth collaborative innovation
Independent-innovation benefit of core enterprises	R_{ei}	Exogenous parameters	Market and technological returns obtained from independent innovation
Collaborative-innovation cost of core enterprises	C_e	Exogenous parameters	R&D investment and coordination cost of in-depth collaborative innovation
Independent-innovation cost of core enterprises	C_{ei}	Exogenous parameters	R&D investment cost of independent innovation
Collaborative-supporting benefit of supporting enterprises	R_s	Exogenous parameters	Benefits including stable cooperation and technology spillovers from participating in collaborative supporting
Free-riding benefit of supporting enterprises	R_{sf}	Exogenous parameters	Total benefits of the free-riding strategy when core enterprises implement collaboration
Collaborative supporting cost of supporting enterprises	C_s	Exogenous parameters	Technology adaptation and collaboration investment cost for participating in collaborative supporting

Table A1. *Cont.*

Variables/Parameters	Symbol	Type	Definition
Free-riding cost of supporting enterprises	C_{sf}	Exogenous parameters	Maintenance cost of the free-riding strategy
Intensity of knowledge spillover	k	Exogenous parameters	$k \in [0, 1]$, Degree of innovation-knowledge spillover from core enterprises to supporting enterprises
In-depth service benefit of S&T service institutions	R_t	Exogenous parameters	Returns from technology transfer and cooperative R&D for in-depth participation in R&D services
Routine service benefit of S&T service institutions	R_{ti}	Exogenous parameters	Service benefits from routine intermediary services
In-depth service cost of S&T service institutions	C_t	Exogenous parameters	Expenditure on scientific-research investment and knowledge creation for in-depth participation in R&D services
Routine service cost of S&T service institutions	C_{ti}	Exogenous parameters	Operating cost of routine intermediary services
Subsidy for S&T service institutions	S_t	Policy parameters	Fiscal subsidies for institutions with in-depth participation in R&D services
Government research grant	G_t	Policy parameters	Public R&D investment of local government in S&T service institutions

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