

Article

Formation Mechanism of Innovation Chain: How Do Innovation Subjects and Support Subjects Cooperate?

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Abstract

Despite extensive research on knowledge spillovers, existing literature has paid limited attention to the formation mechanism of innovation chains. To address this gap, this paper constructs a multi-party evolutionary game model including two innovators and one supporter, incorporating knowledge spillover effects, and empirically tests the theoretical predictions using data from Chinese listed companies (2016–2025). The results show that the final equilibrium is (cooperation, cooperation, support). Empirically, we find a non-linear relationship between knowledge spillover and the formation mechanism of an innovation chain with a double threshold effect of absorptive capacity: the positive impact of spillover increases as capacity moves from low to moderate, but diminishes-while remaining positive-when capacity becomes excessively high, revealing an S-shaped pattern. The originality lies in two aspects. Theoretically, our multi-player model extends the conventional bilateral framework to better reflect real-world parallel collaboration. Empirically, our firm-level analysis of Chinese listed companies is among the first to identify a double threshold effect, moving beyond regional-level or single-threshold studies. Practically, our findings suggest that governments should tailor subsidy intensities to firms' absorptive capacity levels—allocating more to moderate-capacity firms where spillover gains are maximized—offering a more precise strategy for promoting sustainable innovation chain development.

Keywords: innovation chain; knowledge spillover; evolutionary game theory; double-threshold model

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1. Introduction

In an increasingly complex and competitive global economy, innovation has become a core driver for enhancing the competitiveness of nations and firms. According to resource dependence theory, organizations cannot be fully self-sufficient; their survival depends on resources from the external environment [1]. This theoretical lens highlights that firms form inter-organizational linkages to manage environmental interdependence and secure critical resources [2]. Recent studies have applied this perspective to explain why firms engage in R&D cooperation and value co-creation under conditions of uncertainty and resource constraints [3,4]. Consistent with this logic, it is difficult for enterprises to achieve technological breakthroughs relying solely on their own capabilities and resources; they therefore seek cooperative innovation to compensate for their innovation

deficiencies and to integrate internal resources with absorbed external knowledge, giving rise to the innovation chain.

The innovation chain is a link structure for the transfer and transformation of innovation elements, starting from the source of innovation, with the innovation subject as the core and the division of labor among multiple subjects [5,6]. It is a collection of the whole innovation process from basic research to industrialization, reflecting the flow, transformation and value realization process of innovation elements in the whole innovation activity and embodying the value link and innovation synergy relationship of innovation subjects in the process of innovation activity. This dynamic chain serves as the backbone of technological advancements, knowledge dissemination, and market evolution, fostering synergistic interactions among diverse stakeholders in driving innovation and economic growth. The innovation chain, as a systematic and comprehensive framework for innovation activities, encompasses the entire innovation process from basic research to industrialization [7]. It not only reflects the flow and transformation of innovation elements at different stages but also emphasizes the synergistic relationships and value connections among innovation entities. By optimizing the innovation chain, it is possible to enhance innovation efficiency, promote the transformation of scientific and technological achievements, and maximize economic and social value [8].

As a complex system, the successful operation of the innovation chain depends on the close cooperation and reasonable division of labor among each innovation subject. However, although scholars have affirmed the important role of knowledge in the innovation chain, the understanding of innovation chains in current research mostly remains at the level of static description and linear analysis, neglecting the complex interaction mechanisms in its formation process. Contrary to being a static representation of a given structure, the innovation chain is a dynamic emergent outcome that arises from strategic interactions, learning, and adaptation among multiple actors, all propelled by knowledge flows. Without a thorough examination of the underlying mechanisms governing participants' game-theoretic decisions, knowledge spillovers, and the absorption and transformation of knowledge, it remains challenging to uncover the evolutionary trajectory through which fragmented collaboration coalesces into systematic integration. Given that knowledge permeates every stage of the innovation process, a critical gap persists in current theoretical accounts: it is unclear whether knowledge functions as a linear driver or manifests threshold effects and nonlinearities during formation. Therefore, this study aims to answer two core questions. First, how is the innovation chain formed? Second, what is the effect of knowledge on the formation of the innovation chain?

In order to solve these problems, this study aims to build an evolutionary game model of innovation chain and conduct simulation analysis from the perspective of knowledge. The innovation chain essentially reflects the establishment of collaborative innovation relationships among various entities in the innovation process. Generally, these collaborative innovation relationships are typically formed through continuous bargaining, learning, and adjustment among innovation entities with "bounded rationality" in the environment created by the government and the market. Based on the interaction between the participants in the innovation chain, this paper constructs an evolutionary game model that includes the innovation subjects and the supporting subjects to analyze the interaction mechanism among the participants in the innovation chain. Then, a simulation model is built to simulate the influence of exogenous variables on strategy selection, and the formation mechanism of innovation chain is discussed. Finally, this paper uses empirical method to further test the important role of knowledge in the formation mechanism of innovation chain.

The research contributions of this paper are as follows. First, theoretically, this paper explores the interaction mechanisms among participants in the innovation chain by constructing a multi-party evolutionary game model that includes two innovators and one supporter. Unlike previous studies that have predominantly focused on bilateral relationships or single-threshold effects, our model captures the complex evolution of collaboration and support behavior among multiple entities, thereby enhancing our understanding of how innovation chains emerge from strategic interactions. Second, empirically, this paper identifies the nonlinear relationship between knowledge spillover and the formation mechanism of the innovation chain, with absorptive capacity exhibiting a double threshold effect. Specifically, we uncover an S-shaped pattern: the positive impact of spillovers increases as absorptive capacity moves from low to moderate levels, but diminishes—while remaining positive—when capacity becomes excessively high. This finding moves beyond linear or single-threshold assumptions in prior work and extends the literature on absorptive capacity [9]. Third, from a practical standpoint, understanding this mechanism can provide a more accurate and comprehensive foundation for innovation-chain-related policy, which is critical for creating a conducive environment for innovation-driven cooperation. Specifically, our findings suggest that governments and financial institutions, as supporting subjects, should design differentiated innovation subsidy intensities according to firms' heterogeneous knowledge absorptive capacity levels, thereby improving the efficiency of policy support and accelerating the overall formation of innovation chains.

The remainder of this paper is arranged as follows: The Section 2 is the literature review, the Section 3 describes the model establishment, the Section 4 describes the analysis of the evolutionary game, the Section 5 describes the simulation analysis of the evolutionary game, the Section 6 describes the empirical analysis, and the Section 7 presents the conclusions and suggestions.

2. Literature Review

Marshall first defined the concept of the innovation chain in 1992, and he believed that the innovation chain is a chain formed by the interaction of multiple subjects, such as suppliers, manufacturers, and sellers, including different stages in the innovation process [5]. Lin et al. (2001) defined the innovation chain from the perspective of industry through the concept of the technology chain and suggested that the innovation chain embodies the process of industrialization of technological achievements and is the product of the mutual integration of innovative technology and the sales market [10]. The innovation chain largely receives the influence of the external environment [11]; the general environment of the market indicates the innovation direction of the innovation chain, and the participants in the innovation chain clarify the innovation goal according to the innovation direction, thus promoting the sustainable development of the innovation chain [12]. From the perspective of economics, the goal of technological innovation is to achieve economic benefits; from the perspective of knowledge form, the innovation chain embodies the transformation of knowledge to technology. From the perspective of knowledge, Roper et al. (2008) noted that the innovation chain is a segment of the process in which knowledge is sourced, transferred and then completed [13]. Li et al. (2018) proposed that the innovation chain is essentially a process in which different knowledge is coupled with each other in the innovation process [14]. Liu et al. (2012) and Xie and Zhang (2014) suggested that the innovation chain embodies the transformation process from knowledge to technology [15,16]. Xia et al. (2026) established an analytical framework for the integration of industrial chains and innovation chains driven by knowledge spillovers of high-value patents, and verified that regional absorptive capacity serves as an important moderating variable [17]. Shi and Jiang (2020)'s study indicated that scholars have established some theoretical frameworks for the innovation chain, these frameworks mainly focus on the operational

aspect, and neglect the analysis of the construction and operation [18]. Therefore, the existing research on innovation chains is still in the conceptual stage, and scholars have affirmed the important role of knowledge in innovation chains.

Previous studies have focused mainly on the concept, definition and connotation of innovation chains, neglecting the complex interaction mechanisms in its formation process. This deficiency is reflected in the following aspects: (1) Lack of in-depth analysis of the interaction mechanisms among participants: existing studies mainly focus on the functions and roles of each link in the innovation chain, but lack systematic analysis of the strategic interactions and choices among innovation subjects [18]. (2) Neglect of the complexity of the formation mechanism: existing studies pay little attention to the formation mechanisms of innovation chains across different stages of development, and lack systematic investigation of the participation motives of different subjects. Innovation subjects include government, research institutions, enterprises and markets, and their behavior is characterized by uncertainty and strategic decision-making. How to analyze the interaction mechanisms among these subjects through game-theoretic models remains an important gap in current research [19]. (3) Limited dynamic perspective: the innovation chain is not only a linear process but also a dynamically evolving system. The behavior and decisions of different subjects change over time, affecting the overall efficiency and stability of the innovation chain [20].

3. Model Establishment

The basic idea of evolutionary game theory is that in a game group of a certain size, the game players carry out repeated game activities [21,22]. In this paper, we adopt evolutionary game theory to investigate the cooperation relationships among multiple players in an innovation chain. The reasons for using this method are as follows: (1) The behavioral choices of different subjects affect whether the innovation chain can be formed, and the process can be regarded as a multiparty game [23,24]; (2) the research object of the evolutionary game is the process of choosing strategies for the players, and the results of the analysis are universal [25,26]. (3) The results of an evolutionary game, that is, an evolutionarily stable strategy, can well reflect the long-term stable results of multiparty games, which can essentially explain the evolutionary direction of the innovation chain [27]. Therefore, evolutionary game theory is suitable for this paper. This paper constructs an evolutionary game model with participants whose goal is to maximize their own interests. During the game, they continuously adjust and improve their strategic choices based on their own benefits.

To construct a more reasonable research model, the following assumptions are made in this study:

(1) This study involved two types of participant entities: innovation subjects of the innovation chain, namely, enterprises, universities and research institutes, and support subjects of the innovation chain, namely, the government and financial institutes. The main functions of innovation subjects in the innovation chain are to perform different parts of the innovation activity, and the main function of the support subjects in the innovation chain is to provide financial and other kinds of support for the innovation activities of the innovation subjects. We assume that there are two innovation subjects in the innovation chain, innovator₁ and innovator₂, and that the innovator could be an enterprise or university and research institute. Innovation subjects have two possible strategies: cooperating (I1) or not cooperating (I2). When one innovative subject chooses the I1 strategy, the innovative subject participates in the innovation chain and shares its own knowledge resources with other participants. The I2 strategy means that the innovative subject chooses to innovate independently. The probabilities of innovator₁ choosing I1 or I2 are denoted as x and $1 - x$, respectively ($0 \leq x \leq 1$). Similarly, the probabilities of innovator₂

choosing I1 and I2 are denoted as y and $1 - y$, respectively ($0 \leq y \leq 1$). Support subjects, which are denoted as supporter, can provide innovation subsidies to incentivize innovation for innovation subjects by formulating relevant policies or providing funding. Therefore, the strategies of the supporter in the innovation chain are to support (S1) or not to support (S2). The probabilities of the supporter choosing S1 or S2 are denoted as z and $1 - z$, respectively ($0 \leq z \leq 1$).

(2) The knowledge stocks of innovator₁ and innovator₂ are denoted as k_1 and k_2 , respectively. In the collaborative process, both innovator₁ and innovator₂ engage in knowledge sharing. When one of them selects the I1 strategy, they will acquire benefits directly derived from the knowledge sharing of the other innovation subject, denoted as $a_i k_j$ (where $i = 1, 2$), in which a_i ($0 < a_i < 1$) denotes the absorptive capacity of innovator_i and k_j represents the knowledge stock of innovator j .

(3) There are significant differences between innovation subjects in terms of knowledge stock and knowledge structure. When one of them chooses the I1 strategy, its own knowledge is transmitted interactively among innovation subjects. The dissemination and interaction of knowledge between innovators can be categorized into two types: knowledge spillover and knowledge diffusion. Knowledge diffusion predominantly involves explicit knowledge; whereas, knowledge spillover mainly involves tacit knowledge [28]. The learning of tacit knowledge is challenging and can be disseminated only if both innovation subjects actively collaborate, resulting in a synergistic “ $1 + 1 > 2$ ” benefit. Therefore, if both innovation subjects choose the I1 strategy, they will obtain additional benefits. Due to the complementary nature of their knowledge, a Cobb–Douglas production function [29–31] is employed to reflect the additional knowledge generated through collaboration, denoted as $ck_1^m k_2^n$. Here, c represents the knowledge spillover coefficient ($c > 1$), and m and n ($0 < m < n < 1, = 1$) denote the elasticity coefficients. Under this circumstance, innovator₁ gains additional benefits from $a_1 ck_1^m k_2^n$, while innovator₂ acquires additional benefits from $a_2 ck_1^m k_2^n$.

(4) The choice of the I1 strategy is accompanied by certain costs, which are denoted as C_1 and C_2 for each innovative subject. Zhang (2016) demonstrated that collaborative research can reduce transaction costs and research and development expenses [32]. Additionally, Chen (2020) noted that knowledge spillover resulting from cooperation between innovative entities can effectively lower the investment costs of technological activities [28]. Consequently, when both innovation subjects simultaneously choose the I1 strategy, the collaboration cost is correspondingly reduced [33]. In this case, the ultimate cost incurred by innovator₁ is represented as $\frac{1}{c} C_1$, while the ultimate cost for innovator₂ is represented as $\frac{1}{c} C_2$.

(5) Since cooperation can bring additional benefit, in the establishment of collaborative relationships in an innovation chain, to mitigate free-riding behavior, when one innovative subject chooses to cooperate while the other does not, the non-cooperating partner is required to penalize. The penalization is denoted as P .

(6) The baseline returns for innovation subjects and support subjects are denoted as R_1 , R_2 , and R_3 , respectively. When the supporter chooses the S1 strategy, a cost of implementation is needed, denoted as F . When innovator₁ chooses the I1 strategy, the supporter gains a benefit $\lambda_1 F$ from the support. Otherwise, they gain a benefit $\lambda_2 F$, ($\lambda_1 > \lambda_2$). Similarly, when innovator₂ chooses the I1 strategy, it gains a benefit $\gamma_1 F$ from the support. Otherwise, it gains a benefit $\gamma_2 F$, ($\gamma_1 > \gamma_2$). When the supporter chooses the S1 strategy, it can acquire economic and social benefits generated by innovative individuals. The economic and social benefits brought by innovator₁ and innovator₂ are represented by αR_1 and βR_2 , respectively ($0 < \alpha < 1$; $0 < \beta < 1$).

The variables and definitions proposed in this paper are presented in Table 1.

Table 1. Model variable setting and meaning.

Participants	Variables	Connotation
Innovator ₁	x	The probability of the innovator ₁ that chooses the I1 strategy. ($0 \leq x \leq 1$)
	R_1	The base revenue of the innovator ₁ .
	k_1	Knowledge stock of the innovator ₁ .
	a_1	The ability of the innovator ₁ to absorb external knowledge. ($0 < a_1 < 1$)
	C_1	The cost to the innovator ₁ of choosing I1 strategy.
	α	The proportion of economic and social benefits brought to the supporter by innovator ₁ receiving dividends to their own base revenue. ($0 < \alpha < 1$)
Innovator ₂	y	The probability of innovator ₂ that chooses the I1 strategy. ($0 \leq y \leq 1$)
	R_2	The base revenue of the innovator ₂ .
	k_2	Knowledge stock of the innovator ₂ .
	a_2	The ability of the innovator ₂ to absorb external knowledge. ($0 < a_2 < 1$)
	C_2	The cost to the innovator ₂ of choosing I1 strategy.
	β	The proportion of economic and social benefits brought to the supporter by the innovator ₂ receiving dividends to their own base income. ($0 < \beta < 1$)
Supporter	z	The probability of the supporter that chooses the S1 strategy. ($0 \leq z \leq 1$)
	R_3	The base revenue of the supporter.
	F	The cost to the supporter of choosing S1 strategy.
	λ_1	The ratio of the dividends received by the supporter to the costs paid by the supporter choosing S1 strategy when the innovator ₁ chooses I1 strategy. ($0 < \lambda_1 < 1$)
	λ_2	The ratio of the dividends received by the supporter to the costs paid by the supporter choosing S1 strategy when innovator ₁ chooses I2 strategy. ($0 < \lambda_1 < 1, \lambda_1 > \lambda_2$)
	γ_1	The ratio of the dividends received by the supporter to the costs paid by the supporter choosing S1 strategy when the innovator ₂ chooses I1 strategy. ($0 < \gamma_1 < 1$)
	γ_2	The ratio of the dividends received by the supporter to the costs paid by the supporter choosing S1 strategy when the innovator ₂ chooses I2 strategy. ($0 < \gamma_2 < 1, \gamma_1 > \gamma_2$)
Others	P	The penalty paid by the non-cooperating entity when one of the innovation subjects chooses to cooperate and the other chooses not to cooperate.
	c	The degree of knowledge spillover between innovation subjects when they both choose the “cooperate” strategy. ($c > 1$) $\frac{1}{c}$ is the cost reduction factor caused by the knowledge spillover.
	m, n	When both the innovation subjects choose the “cooperate” strategy, both entities gain additional elasticity coefficients of knowledge (Cobb–Douglas production function). ($0 < m, n < 1, m + n = 1$)

To clarify the logical connection among model parameters, all variables in Table 1 can be categorized into four groups: revenue-type, cost-type, capability-type, and policy-type parameters, with supplementary explanations for strategy probability and penalty variables. First, revenue-type parameters (R_1, R_2, R_3) denote the baseline inherent income of innovator₁, innovator₂ and the supporter without collaborative innovation or policy intervention, forming the benchmark of the game payoff function. Second, cost-type parameters include direct input costs C_1, C_2, F and implicit penalty cost P ; C_1, C_2 are the cooperation costs of two innovators, F represents the policy implementation cost of the supporter, and P is the penalty for non-cooperative free-riding behavior. Third, capability-type parameters ($a_1, a_2, k_1, k_2, c, m, n$) reflect the knowledge endowment and knowledge transformation efficiency of innovation subjects: a_1, a_2 measure knowledge absorptive capacity, k_1, k_2 represent original knowledge stock, c captures knowledge spillover intensity, and m, n are output elasticity coefficients of the Cobb–Douglas knowledge production function under constant returns to scale. Fourth, policy-type parameters ($\alpha, \beta, \lambda_1, \lambda_2, \gamma_1, \gamma_2$) are proportional coefficients related to subsidy benefit distribution, quantifying the transmission rule of economic and social dividends brought by supporting policies. In addition, x, y, z are evolutionary strategy probability variables ranging from 0 to 1, which are used to construct the replicator dynamic equations to describe the long-term stable evolution of players' strategies.

According to the model assumptions and parameter settings, the results of innovation subjects and support subjects choosing different strategies are combined, and the payment matrix of the multi-entity evolutionary game is shown in Table 2.

Table 2. The revenue payment matrix.

		Innovator ₁			
		Innovator ₂		Supporter	
		I1	I2	I1	I2
Innovator ₂		x		$1 - x$	
		I1	I2	I1	I2
		y	$1 - y$	y	$1 - y$
Supporter	S1	$(1 - \alpha)R_1 + a_1ck_1^mk_2^n - \frac{1}{c}C_1 + \lambda_1F$	$(1 - \alpha)R_1 - C_1 + \lambda_1F + P$	$R_1 + a_1k_2 + \lambda_2F - P$	$R_1 + \lambda_2F$
	z	$(1 - \beta)R_2 + a_2ck_1^mk_2^n - \frac{1}{c}C_2 + \gamma_1F$	$R_2 + a_2k_1 + \gamma_1F - P$	$(1 - \beta)R_2 - C_2 + \gamma_1F + P$	$R_2 + \gamma_2F$
		$R_3 + \alpha R_1 + \beta R_2 - F$	$R_3 + \alpha R_1 - F$	$R_3 + \beta R_2 - F$	$R_3 - F$
	S2	$R_1 + a_1ck_1^mk_2^n - \frac{1}{c}C_1$	$R_1 - C_1 + P$	$R_1 + a_1k_2 - P$	R_1
	$1 - z$	$R_2 + a_2ck_1^mk_2^n - \frac{1}{c}C_2$	$R_2 + a_2k_1 - P$	$R_2 - C_2 + P$	R_2
		R_3	R_3	R_3	R_3

4. Evolutionary Game Analysis

4.1. Comprehensive Analysis of Innovator₁ and Innovator₂

U_{11} and U_1 are used to represent the expected return of innovator₁, when the I1 strategy is chosen and the average return of innovator₁ respectively. U_{11} is calculated as shown in Equation (1), and U_1 is calculated as shown in Equation (2).

$$\begin{aligned}
 U_{11} = & yz \left[(1 - \alpha)R_1 + a_1ck_1^mk_2^n - \frac{1}{c}C_1 + \lambda_1F \right] \\
 & + (1 - y)z \left[(1 - \alpha)R_1 - C_1 + \lambda_1F + P \right] + y(1 - z) \left(R_1 + a_1ck_1^mk_2^n - \frac{1}{c}C_1 \right) \\
 & + (1 - y)(1 - z)(R_1 - C_1 + P)
 \end{aligned} \tag{1}$$

$$\begin{aligned}
 U_1 = & xyz \left[(1 - \alpha)R_1 + a_1ck_1^mk_2^n - \frac{1}{c}C_1 + \lambda_1F \right] \\
 & + x(1 - y)z[(1 - \alpha)R_1 - C_1 + \lambda_1F + P] + xy(1 - z) \left(R_1 + a_1ck_1^mk_2^n - \frac{1}{c}C_1 \right) \\
 & + x(1 - y)(1 - z)(R_1 - C_1 + P) + (1 - x)yz(R_1 + a_1k_2 + \lambda_2F - P) \\
 & + (1 - x)(1 - y)z(R_1 + \lambda_2F) + (1 - x)y(1 - z)(R_1 + a_1k_2 - P) \\
 & + (1 - x)(1 - y)(1 - z)R_1
 \end{aligned} \tag{2}$$

The replica dynamic equation for innovator₁ when choosing the I1 strategy is shown in Equation (3).

$$\begin{aligned}
 F(x) = \frac{dx}{dt} &= x(U_{11} - U_1) \\
 &= x(1 - x) \left\{ y \left[a_1ck_1^mk_2^n - a_1k_2 + \left(1 - \frac{1}{c} \right) C_1 \right] + z[(\lambda_1F - \alpha R_1) - \lambda_2F] - C_1 + P \right\}
 \end{aligned} \tag{3}$$

When $z = A = \frac{C_1 - P - y[a_1ck_1^mk_2^n - a_1k_2 + (1 - \frac{1}{c})C_1]}{(\lambda_1F - \alpha R_1) - \lambda_2F}$, then $F(x) \equiv 0$, which means that the replica dynamic equation of innovator₁ is stable for any x ($0 < x < 1$); when $z \neq A$, let $F(x) = 0$; then, $x = 0$ and $x = 1$ are two equilibrium points. Since the evolutionary equilibrium point also has the property of making $F'(x) < 0$, $F'(x)$ is shown in Equation (4).

$$\frac{dF(x)}{dx} = (1 - 2x) \left\{ y \left[a_1ck_1^mk_2^n - a_1k_2 + \left(1 - \frac{1}{c} \right) C_1 \right] + z[(\lambda_1F - \alpha R_1) - \lambda_2F] - C_1 + P \right\} \tag{4}$$

where $0 \leq x, y, z \leq 1$, $0 < \alpha, \beta, \lambda_1, \lambda_2 < 1$, $c, k_1, k_2, R_1, F > 0$, and $(\lambda_1F - \alpha R_1) - \lambda_2F > 0$, which indicates the additional benefit from supporter when the innovator₁ I1 strategy is greater than the additional benefit from the supporter when the I2 strategy is chosen; thus:

(1) When $y[a_1ck_1^mk_2^n - a_1k_2 + (1 - \frac{1}{c})C_1] > C_1 - P$, then $A < 0$ and $z > A$. When $x = 1$, $\frac{dF(x)}{dx} < 0$, and $x = 1$ is the equilibrium point.

(2) When $C_1 - P - y[a_1ck_1^mk_2^n - a_1k_2 + (1 - \frac{1}{c})C_1] > (\lambda_1F - \alpha R_1) - \lambda_2F > 0$, then $A > 1$ and $z < A$. When $x = 0$, $\frac{dF(x)}{dx} < 0$, and $x = 0$ is the equilibrium point.

(3) When $0 < C_1 - P - y[a_1ck_1^mk_2^n - a_1k_2 + (1 - \frac{1}{c})C_1] < (\lambda_1F - \alpha R_1) - \lambda_2F$, then $0 < A < 1$, which can be divided into two cases:

a. For $z > A$, when $x = 1$, $\frac{dF(x)}{dx} < 0$; thus, $x = 1$ is the equilibrium point.

b. For $z < A$, when $x = 0$, $\frac{dF(x)}{dx} < 0$; thus, $x = 0$ is the equilibrium point.

According to the analysis above, the evolutionary phase diagram of innovator₁'s strategy is shown in Figure 1.

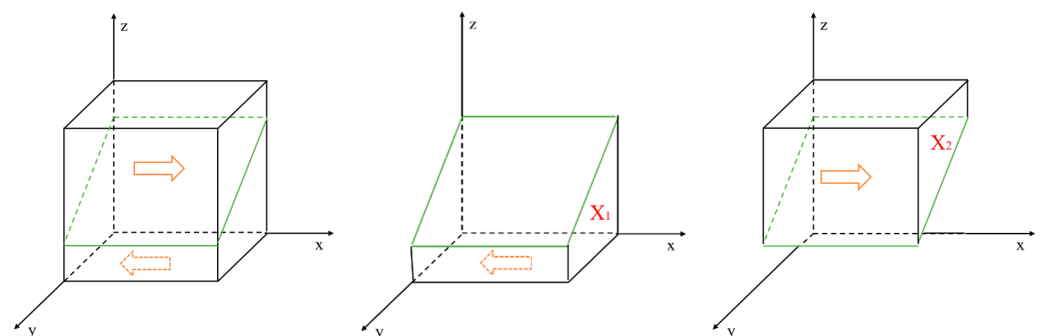


Figure 1. Evolutionary phase diagram of the innovator₁.

Figure 1 shows that the probability of choosing the I1 strategy x is the volume of X_1 , represented as V_{X_1} , and the probability of choosing the I2 strategy $1 - x$ is the volume of X_2 , represented as V_{X_2} . V_{X_2} is calculated as shown in Equation (5):

$$V_{X_2} = 1 - V_{X_1} = 1 - \int_0^1 \int_0^1 \frac{C_1 - P - y \left[a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c} \right) C_1 \right]}{(\lambda_1 F - \alpha R_1) - \lambda_2 F} dy dz \quad (5)$$

$$= \frac{2[(\lambda_1 F - \alpha R_1) - \lambda_2 F] - 2C_1 + 2P + a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c} \right) C_1}{2[(\lambda_1 F - \alpha R_1) - \lambda_2 F]}$$

Corollary 1. *The probability of innovator₁ choosing the I1 strategy is positively related to the knowledge absorption ability of innovator₁ a_1 , the degree of knowledge spillover between the two innovators c , the penalty of “free-riding” P , and the subsidy F granted by the supporter to innovators and negatively related to the cost C_1 paid by innovator₁ when choosing the I1 strategy (under the model assumptions set forth in this paper).*

Proof. According to the expression V_{X_2} , the first-order partial derivatives of each element are obtained: $\frac{\partial V_{X_2}}{\partial a_1} > 0$, $\frac{\partial V_{X_2}}{\partial c} > 0$, $\frac{\partial V_{X_2}}{\partial P} > 0$, $\frac{\partial V_{X_2}}{\partial F} > 0$, and $\frac{\partial V_{X_2}}{\partial C_1} < 0$. Therefore, an increase in a_1 , c , P , or F or a decrease in C_1 will increase the probability that innovator₁ will choose the I1 strategy. $\square$

Corollary 2. *The probability of innovator₁ choosing the I1 strategy x increases as the probability of innovator₂ choosing the I1 strategy y increases, and decreases as the probability of the supporter choosing the S1 strategy z increases (under the model assumptions set forth in this paper).*

Proof. From the analysis of innovator₁'s strategy, we know that when $y < \frac{C_1 - P - z[(\lambda_1 F - \alpha R_1) - \lambda_2 F]}{a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c} \right) C_1}$, $z < \frac{C_1 - P - y[a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c} \right) C_1]}{(\lambda_1 F - \alpha R_1) - \lambda_2 F}$, we have $\frac{dF(x)}{dx} < 0$, and $x = 0$ is the evolutionary equilibrium strategy; conversely, $x = 1$ is the evolutionary equilibrium strategy. Therefore, as y and z gradually increase, innovator₁'s equilibrium strategy increases from $x = 0$ (E2) to $x = 1$ (E1). $\square$

4.2. Comprehensive Analysis of Innovator₂

U_{21} and U_2 are used to represent the expected return of innovator₂ when the I1 strategy is chosen and the average return of innovator₂, respectively. U_{21} is calculated as shown in Equation (6), and U_2 is calculated as shown in Equation (7).

$$U_{21} = xz \left[(1 - \beta)R_2 + a_2 c k_1^m k_2^n - \frac{1}{c} C_2 + \gamma_1 F \right] + (1 - x)z \left[(1 - \beta)R_2 - C_2 + \gamma_1 F + P \right] + x(1 - z) \left(R_2 + a_2 c k_1^m k_2^n - \frac{1}{c} C_2 \right) + (1 - x)(1 - z)(R_2 - C_2 + P) \quad (6)$$

$$U_2 = xyz \left[(1 - \beta)R_2 + a_2 c k_1^m k_2^n - \frac{1}{c} C_2 + \gamma_1 F \right] + (1 - x)yz \left[(1 - \beta)R_2 - C_2 + \gamma_1 F + P \right] + xy(1 - z) \left(R_2 + a_2 c k_1^m k_2^n - \frac{1}{c} C_2 \right) + (1 - x)y(1 - z)(R_2 - C_2 + P) + x(1 - y)z(R_2 + a_2 k_1 + \gamma_2 F - P) + (1 - x)(1 - y)z(R_2 + \gamma_2 F) + x(1 - y)(1 - z)(R_2 + a_2 k_1 - P) + (1 - x)(1 - y)(1 - z)R_2 \quad (7)$$

The replica dynamic equation for the innovator₂ choosing the I1 strategy is shown in Equation (8).

$$F(y) = \frac{dy}{dt} = y(U_{21} - U_2) \quad (8)$$

$$= y(1-y) \left\{ x \left[a_2 c k_1^m k_2^n - a_2 k_1 + \left(1 - \frac{1}{c}\right) C_2 \right] + z[(\gamma_1 F - \beta R_2) - \gamma_2 F] - C_2 + P \right\}$$

When $z = B = \frac{C_2 - P - x[a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2]}{(\gamma_1 F - \beta R_2) - \gamma_2 F}$, then $F(y) \equiv 0$, which means that the replica dynamic equation of innovator₂ is stable for any $y(0 < y < 1)$; if $z \neq B$, let $F(y) = 0$; then, $y = 0$ and $y = 1$ are two equilibrium points. Since the evolutionary equilibrium point also has the property of making $F'(y) < 0$, $F'(y)$ is shown in Equation (9).

$$\frac{dF(y)}{dy} = (1-2y) \left\{ x \left[a_2 c k_1^m k_2^n - a_2 k_1 + \left(1 - \frac{1}{c}\right) C_2 \right] + z[(\gamma_1 F - \beta R_2) - \gamma_2 F] - C_2 + P \right\} \quad (9)$$

where $0 \leq x, y, z \leq 1$, $0 < a, \beta, \lambda_1, \lambda_2 < 1$, $c, k_1, k_2, R_1, F > 0$, and $\beta R_2 > 0$; thus,

(1) When $x[a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2] > C_2 - P$, then $B < 0$ and $z > B$. When $y = 0$, $\frac{dF(y)}{dy} < 0$, and $y = 0$ is the equilibrium point.

(2) When $C_2 - P - x[a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2] > (\gamma_1 F - \beta R_2) - \gamma_2 F > 0$, then $B > 1$ and $z < B$. When $y = 1$, $\frac{dF(y)}{dy} < 0$, and $y = 1$ is the equilibrium point.

(3) When $(\gamma_1 F - \beta R_2) - \gamma_2 F > C_2 - P - x[a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2] > 0$, then $0 < B < 1$, which can be divided into two cases:

a. For $z > B$, when $y = 0$, $\frac{dF(y)}{dy} < 0$; thus, $y = 0$ is the equilibrium point.

b. For $z < B$, when $y = 1$, $\frac{dF(y)}{dy} < 0$; thus, $y = 1$ is the equilibrium point.

Based on the analysis above, the evolutionary phase diagram of the research strategies of innovator₂ is illustrated in Figure 2.

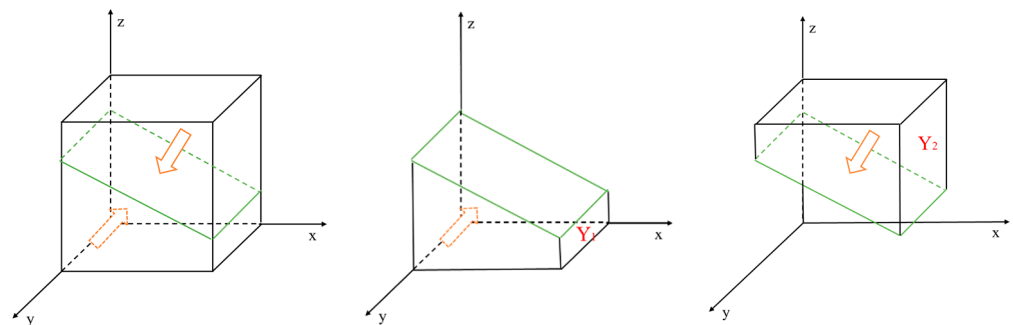


Figure 2. Evolutionary phase diagram of innovator₂.

Figure 2 illustrates that the probability of choosing the I1 strategy y is the volume of Y_1 , represented as V_{Y_1} , while the probability of choosing the I2 strategy $1 - y$ is the volume of Y_2 , represented as V_{Y_2} . The calculation of V_{Y_2} is shown in Equation (10).

$$\begin{aligned} V_{Y_2} &= 1 - V_{Y_1} = 1 - \int_0^1 \int_0^1 \frac{C_2 - P - x[a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2]}{(\gamma_1 F - \beta R_2) - \gamma_2 F} dx dz \\ &= \frac{2[(\gamma_1 F - \beta R_2) - \gamma_2 F] - 2C_2 + 2P + a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2}{2[(\gamma_1 F - \beta R_2) - \gamma_2 F]} \end{aligned} \quad (10)$$

Corollary 3. The probability of innovator₂ choosing the I1 strategy y is positively correlated with the knowledge absorption ability of universities and research institutions a_2 , the degree of knowledge spillover between the two entities c , the penalty of “free-riding” denoted as P , and the

subsidies F granted by the supporter to the innovator₂. On the other hand, it is negatively correlated with the cost C_2 incurred by innovator₂ when choosing the I1 strategy (under the model assumptions set forth in this paper).

Proof. According to the expression V_{Y_2} , the first-order partial derivatives of each element are obtained: $\frac{\partial V_{Y_2}}{\partial a_2} > 0$, $\frac{\partial V_{Y_2}}{\partial c} > 0$, $\frac{\partial V_{Y_2}}{\partial P} > 0$, $\frac{\partial V_{Y_2}}{\partial F} > 0$, and $\frac{\partial V_{Y_2}}{\partial C_2} < 0$. Therefore, an increase in a_2 , c , P , or F or a decrease in C_2 will increase the probability that innovator₂ will choose the I1 strategy. $\square$

Corollary 4. The probability of innovator₂ choosing the I1 strategy y increases with the increasing probability of innovator₁ choosing the I1 strategy x . Conversely, it decreases with the increasing probability of the supporter choosing the S1 strategy z (under the model assumptions set forth in this paper).

Proof. From the analysis of innovator₂'s strategy, we know that when $x < \frac{C_2 - P - z[(Y_1 F - \beta R_2) - Y_2 F]}{a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2}$, $z < \frac{C_2 - P - x[a_2 c k_1^m k_2^n - a_2 k_1 + (1 - \frac{1}{c})C_2]}{(Y_1 F - \beta R_2) - Y_2 F}$, we have $\frac{dF(y)}{dy} < 0$, and $y = 0$ is the evolutionary equilibrium strategy; conversely, $y = 1$ is the evolutionary equilibrium strategy. Therefore, as x and z gradually increase, innovator₂'s equilibrium strategy increases from $y = 0$ (I2) to $y = 1$ (I1). $\square$

4.3. Comprehensive Analysis of the Supporter

U_{31} and U_3 are used to represent the expected return of the supporter's choice of the S1 strategy and the average return of the supporter. U_{31} is calculated as shown in Equation (11), and the average return U_3 is calculated as shown in Equation (12).

$$U_{31} = xy(R_3 + \alpha R_1 + \beta R_2 - F) + x(1 - y)(R_3 + \alpha R_1 - F) + (1 - x)y(R_3 + \beta R_2 - F) + (1 - x)(1 - y)(R_3 - F) \quad (11)$$

$$U_3 = xyz(R_3 + \alpha R_1 + \beta R_2 - F) + x(1 - y)z(R_3 + \alpha R_1 - F) + (1 - x)yz(R_3 + \beta R_2 - F) + xy(1 - z)(R_3 - F) + x(1 - y)(1 - z)R_3 + (1 - x)y(1 - z)R_3 + (1 - x)(1 - y)(1 - z)R_3 \quad (12)$$

The replica dynamic equation for the supporter's choice of S1 strategy is Equation (13):

$$F(z) = \frac{dz}{dt} = z(U_{31} - U_3) = z(1 - z)(x\alpha R_1 + y\beta R_2 + R_3 - F) \quad (13)$$

When $x = C = \frac{F - R_3 - y\beta R_2}{\alpha R_1}$, then $F(z) \equiv 0$, indicating that the replica dynamic equation of the supporter is stable for any $z(0 < z < 1)$; if $x \neq C$, let $F(z) = 0$; then, $z = 0$ and $z = 1$ are two equilibrium points. Since the evolutionary equilibrium point also has the property of making $F'(z) < 0$, $F'(z)$ is represented by Equation (14).

$$\frac{dF(z)}{dz} = (1 - 2z)(x\alpha R_1 + y\beta R_2 + R_3 - F) \quad (14)$$

where $0 \leq x, y, z \leq 1$, $0 < \alpha, \beta, \lambda_1, \lambda_2 < 1$, $c, k_1, k_2, R_1, F > 0$, and $\alpha R_1 > 0$; thus,

(1) When $R_3 + y\beta R_2 > F$, then $C < 0$, $x > C$. When $z = 1$, $\frac{dF(z)}{dz} < 0$, and $z = 1$ is the equilibrium point.

(2) When $F - R_3 + y\beta R_2 > \alpha R_1 > 0$, then $C > 1$, $x < C$. When $z = 0$, $\frac{dF(z)}{dz} < 0$, and $z = 0$ is the equilibrium point.

(3) When $\alpha R_1 > F - R_3 + y\beta R_2 > 0$, $0 < C < 1$, which can be divided into two cases:

a. For $x > C$, when $z = 1$, $\frac{dF(z)}{dz} < 0$; thus, $z = 1$ is the stable point.

b. For $x < C$, when $z = 0$, $\frac{dF(z)}{dz} < 0$; thus, $z = 0$ is the stable point.

According to the analysis above, the evolution phase diagram of supporter's strategy is shown in Figure 3.

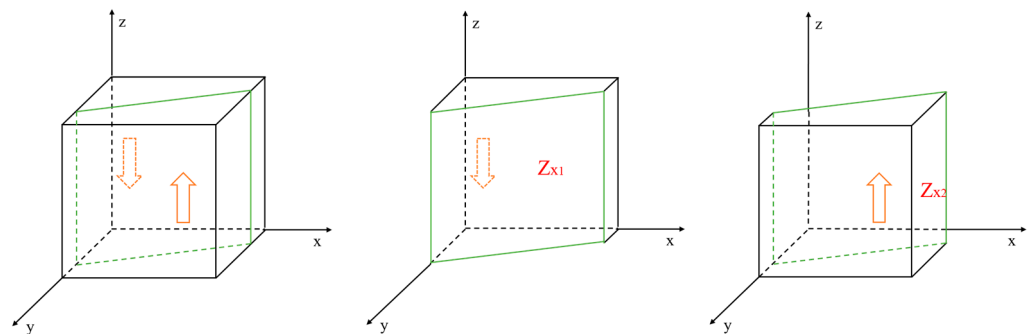


Figure 3. Evolutionary phase diagram of the supporter.

Figure 3 shows that the probability of the supporter choosing the S1 strategy z is the volume of Z_{x_1} , represented as V_{z_1} , and the probability of choosing the S2 strategy $1 - z$ is the volume of Z_{x_1} , which is represented as V_{z_2} . V_{z_2} is calculated as shown in Equation (15).

$$V_{z_2} = 1 - V_{z_1} = 1 - \int_0^1 \int_0^1 \frac{F - R_3 - y\beta R_2}{\alpha R_1} dx dz = \frac{2\alpha R_1 - 2F + 2R_3 + \beta R_2}{2\alpha R_1} \quad (15)$$

Corollary 5. The probability that the supporter chooses the S1 strategy z is positively related to the economic and social benefits αR_1 brought to the supporter by innovator₁, βR_2 brought to the supporter by innovator₂, and the supporter's own benefits R_3 and negatively related to the subsidy cost F (under the model assumptions set forth in this paper).

Proof. Based on the expression of V_{z_2} for the probability of supporter choosing the S1 strategy, the first-order partial derivatives of each element are obtained as follows: $\frac{\partial V_{z_2}}{\partial \alpha R_1} > 0$, $\frac{\partial V_{z_2}}{\partial \beta R_2} > 0$, $\frac{\partial V_{z_2}}{\partial R_3} > 0$, and $\frac{\partial V_{z_2}}{\partial F} < 0$. Therefore, an increase in αR_1 , βR_2 , or R_3 or a decrease in F will increase the probability that the supporter will choose the S1 strategy. $\square$

Corollary 6. The probability of the supporter choosing the S1 strategy z increases with the probability of innovator₁ choosing the I1 strategy and the probability of innovator₂ choosing the I1 strategy (under the model assumptions set forth in this paper).

Proof. From the analysis of the supporter's strategy, we know that when $x < \frac{F - R_3 - y\beta R_2}{\alpha R_1}$, $y < \frac{F - R_3 - x\alpha R_1}{\beta R_2}$, we have $\frac{dF(z)}{dz} < 0$, and $z = 0$ is the evolutionary equilibrium strategy; conversely, $z = 1$ is the evolutionary equilibrium strategy. Thus, as x and y gradually increase, the supporter's equilibrium strategy increases from $z = 0$ (S2) to $z = 1$ (S1). $\square$

4.4. Comprehensive Analysis of the Evolutionary Game Model

The replication dynamics equations in 4.1–4.3 are combined to obtain Equation (16), which is denoted as follows:

$$\begin{cases} F(x) = x(1-x) \left\{ y \left[a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c}\right) C_1 \right] + z[(\lambda_1 F - \alpha R_1) - \lambda_2 F] - C_1 \right\} \\ F(y) = y(1-y) \left\{ x \left[a_2 c k_1^m k_2^n - a_2 k_1 + \left(1 - \frac{1}{c}\right) C_2 \right] + z[(\gamma_1 F - \beta R_2) - \gamma_2 F] - C_2 \right\} \\ F(z) = z(1-z)(x\alpha R_1 + y\beta R_2 + R_3 - F) \end{cases} \quad (16)$$

According to the previous analysis, the system satisfies $F(x) = F(y) = F(z) = 0$ at equilibrium, so the local Nash equilibrium points include $E_1(0,0,0)$, $E_2(0,0,1)$, $E_3(0,1,0)$, $E_4(0,1,1)$, $E_5(1,0,0)$, $E_6(1,0,1)$, $E_7(1,1,0)$, and $E_8(1,1,1)$. The Jacobian matrix is adopted to judge the stability of the local equilibrium point, thereby obtaining the evolutionary stability strategy (ESS) of the replica dynamical system, which is denoted as J .

$$J = \begin{bmatrix} J_{11} & J_{12} & J_{13} \\ J_{21} & J_{22} & J_{23} \\ J_{31} & J_{32} & J_{33} \end{bmatrix}$$

where $J_{11} = (1 - 2x) \left\{ y \left[a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c} \right) C_1 \right] + z[(\lambda_1 F - \alpha R_1) - \lambda_2 F] - C_1 + P \right\}$,
 $J_{12} = x(1 - x) \left[a_1 c k_1^m k_2^n - a_1 k_2 + \left(1 - \frac{1}{c} \right) C_1 \right]$, $J_{13} = x(1 - x)[(\lambda_1 F - \alpha R_1) - \lambda_2 F]$, $J_{21} =$
 $y(1 - y) \left[a_2 c k_1^m k_2^n - a_2 k_1 + \left(1 - \frac{1}{c} \right) C_2 \right]$, $J_{22} = (1 - 2y) \left\{ x \left[a_2 c k_1^m k_2^n - a_2 k_1 + \left(1 - \frac{1}{c} \right) C_2 \right] + \right.$
 $\left. z[(\gamma_1 F - \beta R_2) - \gamma_2 F] - C_2 + P \right\}$, $J_{23} = y(1 - y)[(\gamma_1 F - \beta R_2) - \gamma_2 F]$, $J_{31} = z(1 - z)\alpha R_1$,
 $J_{32} = (1 - z)\beta R_2$, and $J_{33} = (1 - 2z)(x\alpha R_1 + y\beta R_2 + R_3 - F)$.

If all the characteristic roots of the equilibrium point are less than or equal to zero, the point is considered to be an ESS. By bringing the eight local equilibria into the Jacobian matrix, the characteristic roots of the Jacobian matrix corresponding to each equilibrium point can be obtained, as shown in Table 3.

Table 3. Eigenvalues of Jacobi matrix.

Local Stability Point	λ_1	λ_2	λ_3
$E_1(0,0,0)$	$P - C_1$	$P - C_2$	$R_3 - F$
$E_2(0,0,1)$	$P - C_1 + [(\lambda_1 F - \alpha R_1) - \lambda_2 F]$	$P - C_2 + [(\gamma_1 F - \beta R_2) - \gamma_2 F]$	$F - R_3$
$E_3(0,1,0)$	$a_1 c k_1^m k_2^n - a_1 k_2 - \frac{1}{c} C_1 + P$	$C_2 - P$	$\beta R_2 + R_3 - F$
$E_4(0,1,1)$	$a_1 c k_1^m k_2^n - a_1 k_2 - \frac{1}{c} C_1 + P + [(\lambda_1 F - \alpha R_1) - \lambda_2 F]$	$C_2 - P - [(\gamma_1 F - \beta R_2) - \gamma_2 F]$	$F - \beta R_2 - R_3$
$E_5(1,0,0)$	$C_1 - P$	$a_2 c k_1^m k_2^n - a_2 k_1 - \frac{1}{c} C_2 + P$	$\alpha R_1 + R_3 - F$
$E_6(1,0,1)$	$C_1 - P - [(\lambda_1 F - \alpha R_1) - \lambda_2 F]$	$a_2 c k_1^m k_2^n - a_2 k_1 - \frac{1}{c} C_2 + P + [(\gamma_1 F - \beta R_2) - \gamma_2 F]$	$F - \alpha R_1 - R_3$
$E_7(1,1,0)$	$\frac{1}{c} C_1 - a_1 c k_1^m k_2^n + a_1 k_2 - P$	$\frac{1}{c} C_2 - a_2 c k_1^m k_2^n + a_2 k_1 - P$	$\alpha R_1 + \beta R_2 + R_3 - F$
$E_8(1,1,1)$	$\frac{1}{c} C_1 - a_1 c k_1^m k_2^n + a_1 k_2 - P - [(\lambda_1 F - \alpha R_1) - \lambda_2 F]$	$\frac{1}{c} C_2 - a_2 c k_1^m k_2^n + a_2 k_1 - P - [(\gamma_1 F - \beta R_2) - \gamma_2 F]$	$F - \alpha R_1 - \beta R_2 - R_3$

Since the sign of the characteristic root depends on the magnitude of many parameter values, that is, the equilibrium points to reach a stable state cannot be determined, only the system that reaches a stable equilibrium under certain conditions can be analyzed. Based on the previous analysis, the following assumptions are proposed.

(1) $\lambda_1 F - \alpha R_1 > \lambda_2 F$ and $\gamma_1 F - \beta R_2 < \gamma_2 F$. For innovator₁, the net benefit from supporter when I1 is chosen is greater than the net benefit from supporter when I2 is chosen; for innovator₂, the net benefit from supporter when I1 is chosen is greater than the net benefit from supporter when I2 is chosen.

(2) $C_1 > P$, $a_1 c k_1^m k_2^n - a_1 k_2 - \frac{1}{c} C_1 > 0$, $C_2 > P$, and $a_2 c k_1^m k_2^n - a_2 k_1 - \frac{1}{c} C_2 > 0$. For innovator₁, the cost of choosing I1 is greater than the penalty of choosing I2, and when both entities choose I1, the additional benefits brought to innovator₁ are greater than the cost. For innovator₂, the cost of choosing I1 is greater than the penalty of choosing I2, and when both entities choose I1, the additional benefits brought to innovator₂ are greater than the cost.

(3) $R_3 > F$. For the supporter, the cost of supporter choosing S1 is less than the supporter's basic benefit.

According to the assumptions and Table 4, the evolutionary stability point of the system is $E_8(1,1,1)$, at which innovator₁ chooses I1, innovator₂ chooses I1, and the supporter chooses S1.

Table 4. Local stability of equilibrium points.

Local Stability Point	λ_1	λ_2	λ_3	Stability
$E_1(0,0,0)$	−	−	+	Unstable point
$E_2(0,0,1)$	+, −	+, −	−	Saddle point
$E_3(0,1,0)$	+	+	+, −	Unstable point
$E_4(0,1,1)$	+	+, −	+, −	Unstable point
$E_5(1,0,0)$	+	+	+, −	Unstable point
$E_6(1,0,1)$	+, −	+	+, −	Unstable point
$E_7(1,1,0)$	−	−	+	Unstable point
$E_8(1,1,1)$	−	−	−	ESS

5. Simulation Analysis

5.1. Simulation Analysis of Evolutionary Stabilization Strategies

To more intuitively illustrate the evolutionary process of the evolutionary game among innovators and supporters, MATLAB R2025a is adopted to simulate the formation mechanism in Section 4.4. The initial value of each parameter is assigned based on the simulation process considering the realistic cooperation among innovators and supporters, with reference to existing studies [30,33,34]. The specific values do not represent the actual amounts and indicate only the relative magnitudes among the parameters. The initial values of the parameters were set as follows: $R_1 = 10$, $k_1 = 5$, $C_1 = 2$, $a_1 = 0.7$, $\alpha = 0.3$, $\lambda_1 = 0.7$, $\lambda_2 = 0.7$, $R_2 = 10$, $k_2 = 5$, $C_2 = 2$, $a_2 = 0.7$, $\beta = 0.3$, $\gamma_1 = 0.7$, $\gamma_2 = 0.$, $R_3 = 10$, $F = 6$, $P = 1$, $c = 5$, $\delta = 0.5$, and $n = 0.5$. The evolutionary trajectory of the ESS is shown in Figure 4.

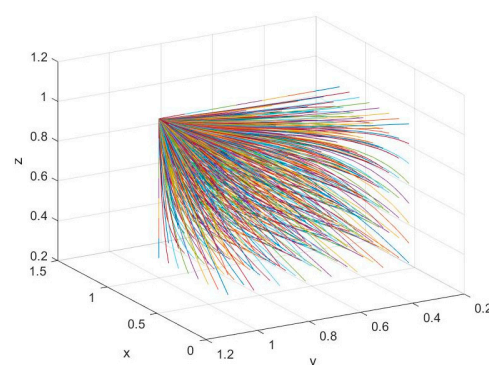


Figure 4. Evolutionary trajectory diagram.

5.2. The Impact of Knowledge Spillover on Evolutionary Stabilization Strategies

According to the results above, this paper further analyses the influence of knowledge spillover on the simulation results from the perspectives of the knowledge absorption ability of innovators and the degree of knowledge spillover.

Initially, to reflect the evolutionary trajectory of the system more accurately, probabilities of 0.3, 0.6 and 0.9 are set for innovators and supporters, respectively, to choose different behavioral decisions.

The influence of the knowledge absorption capacity of innovator₁ is shown in Figure 5. Figure 5a shows the trajectory of change in x . Figure 5b shows the trajectory of change in y , and Figure 5c shows the trajectory of change in z . The influence of the knowledge absorption capacity of innovator₂ is shown in Figure 6. Figure 6a shows the trajectory of change in x . Figure 6b shows the trajectory of change in y , and Figure 6c shows the trajectory of change in z .

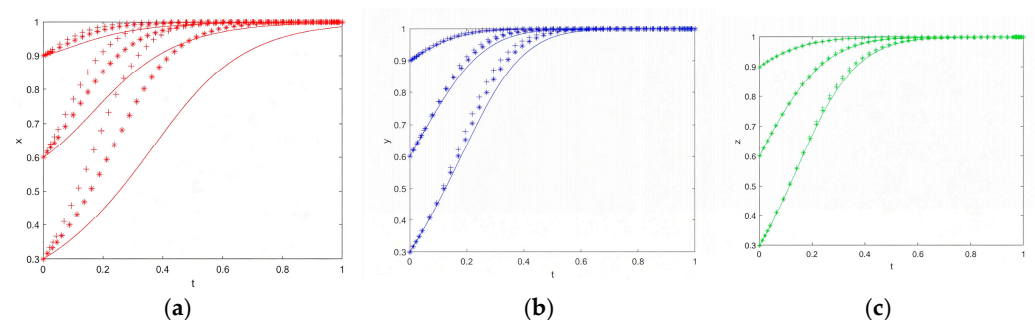


Figure 5. Effect of changes in the innovator₁'s knowledge absorption capacity on x , y , z . (a) Description of the process of change in x when a_1 changes. (b) Description of the process of change in y when a_1 changes. (c) Description of the process of change in z when a_1 changes.

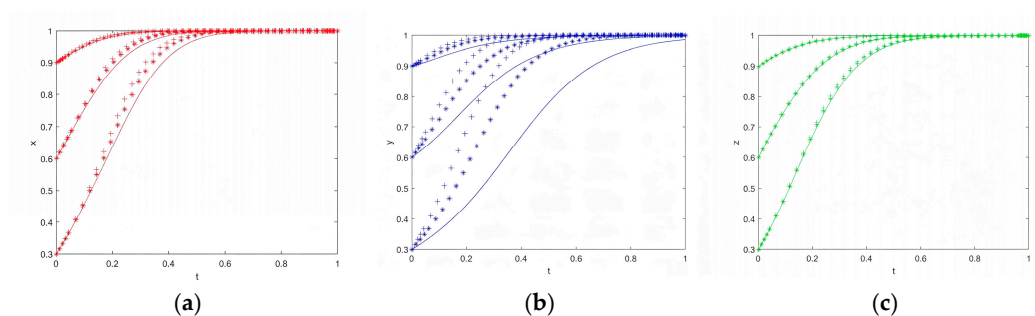


Figure 6. Effect of changes in knowledge absorption capacity of innovator₂ on x , y , z . (a) Description of the process of change in x when a_2 changes. (b) Description of the process of change in y when a_2 changes. (c) Description of the process of change in z when a_2 changes.

Combined with the simulation analysis in Section 4.1, when the knowledge absorption capacities a_1 and a_2 of innovators are taken as 0.3, 0.5 and 0.7, respectively (the values of the remaining parameters in the model are consistent with those in Section 4.1), the value of 0.3 corresponds to the “---” curve, 0.5 corresponds to the “***” curve, and 0.7 corresponds to the “+++” curve. Figures 5 and 6 show that the participants of the game still choose (I1, I1, S1) as the final strategy as the knowledge absorption capacity of the innovators increases. In addition, the trajectories of the three curves in Figures 5a,b and 6a,b are significantly different, indicating that a higher knowledge absorption capacity increases the speed at which innovators choose a cooperation strategy. The trajectories of the three curves in Figures 5c and 6c basically overlap, indicating that supporter makes decisions at basically the same speed under different knowledge absorption capacities.

Conclusion 1. *The knowledge absorption capacity of innovators does not affect the evolutionary stability strategy in the game; a higher knowledge absorption capacity is conducive to helping innovators make cooperative decisions but has a weak influence on the decision-making speed of the supporter.*

Combined with the numerical simulation analysis in Section 4.1, when the knowledge overflow degree is set to 5, 7 and 9 (the values of the remaining parameters in the model are consistent with those in Section 4.1), the value of 5 corresponds to the “---” curve, the value of 7 corresponds to the “***” curve, and the value of 9 corresponds to the “+++” curve. Figure 7 shows that as the degree of social knowledge spillover increases, the participants of the game still choose (I1, I1, S1) as the final strategy. There are weak differences in the trajectories of the three curves in Figure 7a, indicating that a higher degree of knowledge spillover increases the speed at which innovator₁ chooses the cooperation strategy. There are also weak differences in the trajectories of the three curves in Figure 7b, indicating that a higher degree of knowledge spillover also increases the speed of choosing I1 by innovator₂. The trajectories of the three curves in Figure 7c basically overlap, indicating that supporter makes decisions at basically the same speed under different degrees of knowledge spillover.

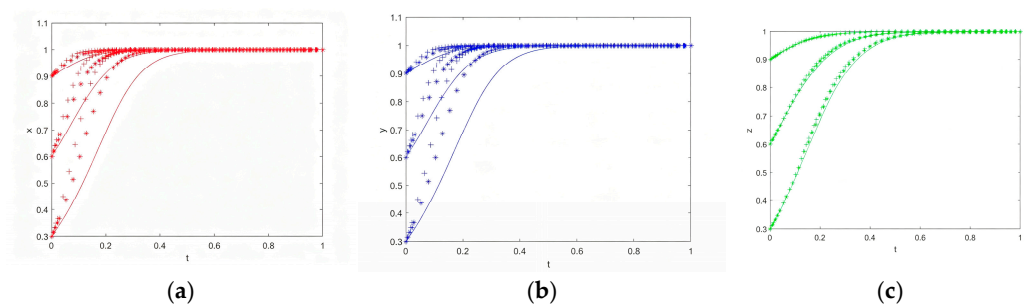


Figure 7. Effects of changes in the degree of knowledge spillover from both sides on x , y , z . (a) Description of the process of change in x when c changes. (b) Description of the process of change in y when c changes. (c) Description of the process of change in z when c changes.

Conclusion 2. *The degree of knowledge spillover between innovators does not affect the evolutionary stabilization strategies of the game; a higher degree of knowledge spillover helps innovators make cooperative decisions faster and has a weaker effect on the speed of supporter decisions.*

6. Empirical Analysis

To further verify the influence of knowledge spillover on the formation mechanism of innovation chain, this paper conducts empirical tests and comparative analysis.

6.1. Sample Selection

Considering the availability and authenticity of the data, this paper selects Chinese listed enterprises as the research sample. The sample selection criteria are as follows: (1) exclude the sample of enterprises marked as ST, *ST, etc., in the sample period; (2) exclude the sample with missing key variables; and (3) exclude the sample with significant changes in control in the sample period [35]. As the threshold regression model requires balanced panel data, after screening, a total of 25,676 sample data points of 1834 enterprises were obtained. The operation and R&D data of the listed enterprises for the period 2016–2025 were obtained from the Wind database, and the patent data were obtained from the IncoPat patent database.

6.2. Model Settings and Variable Descriptions

6.2.1. Model Construction

Based on the results of the evolutionary game, this paper hypothesizes that the impact of knowledge spillover on the formation mechanism of innovation chain is subject to knowledge absorption capacity, which implies that there is a nonlinear relationship between knowledge spillover and the formation mechanism of the innovation chain. Therefore, adopting a linear regression model will lead to bias in the final estimation results. In this paper, we use the panel threshold regression model proposed by Hansen (1999), with knowledge absorptive capacity as the threshold variable [36]; the threshold regression model is shown in Equation (17):

$$c_{i,t} = \mu + \beta_1 k_{s,i,t} (a_{b,i,t} \leq \omega) + \beta_2 k_{s,i,t} (a_{b,i,t} > \omega) + \beta_0 Z_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t} \quad (17)$$

where i denotes different enterprises and t denotes time. The dependent variable of the model, $c_{i,t}$, denotes the formation of innovation chain, measured by enterprises' willingness to cooperate. k_s is the independent variable and represents knowledge spillover. a_b is the threshold variable, representing knowledge absorption capacity, and ω is the threshold value that changes the relationship between knowledge spillover and the formation mechanism of the innovation chain. Z denotes a series of control variables. In addition, the model controls for dual individual and time fixed effects. γ_i denotes individual fixed effects, η_t denotes time fixed effects, and $\varepsilon_{i,t}$ is the residual term.

On the basis of the single threshold model, this paper further considers the case where there are multiple thresholds in the model, taking the two-threshold model as an example, as shown in Equation (18):

$$c_{i,t} = \mu + \beta_1 k_{s,i,t} (a_{b,i,t} \leq \omega_1) + \beta_2 k_{s,i,t} (\omega_1 < a_{b,i,t} \leq \omega_2) + \beta_3 k_{s,i,t} (a_{b,i,t} > \omega_2) + \beta_4 Z_{i,t} + \gamma_i + \eta_t + \varepsilon_{i,t} \quad (18)$$

where ω_1 and ω_2 are the double threshold values that change the relationship between knowledge spillover and the formation mechanism of the innovation chain, and the rest of the variables have the same meanings as in Equation (17).

6.2.2. Variables

1. Dependent variable: enterprises' willingness to cooperate (c_i).

According to the evolutionary game model of the formation mechanism of the innovation chain, enterprises are the core participants in the innovation chain. Enterprises are both developers of innovation results and producers of innovative products throughout the innovation chain. Therefore, this paper uses enterprises' willingness to cooperate to measure the formation mechanism of innovation chain. According to Lv et al. (2021) and Belderbos et al. (2014), the number of patents filed by enterprises in collaboration as a percentage of total patent applications is used to measure enterprises' willingness to collaborate, and information on the patent ownership structure is used to distinguish between individually owned and collaboratively owned patents [37,38].

2. Independent variable: knowledge spillover (k_s).

Referring to Yi et al. (2021), this paper uses the number of cited corporate patents to measure the knowledge spillover generated by cooperation among participants [39]. To distinguish patent citations from inventor citations and patent citations from patent examiners, this paper uses a three-year window to calculate the number of corporate patent citations.

3. Threshold variable: knowledge absorption capacity (a_b).

Knowledge absorptive capacity includes knowledge recognition ability, comprehension and digestion ability, and knowledge transformation ability [39]. Many scholars in

recent years have measured human capital as an important indicator of knowledge absorptive capacity [40–42]. Therefore, this paper uses the logarithm of the number of R&D personnel of an enterprise plus one to measure the knowledge absorptive capacity of an enterprise.

4. Control variables.

The control variables at the enterprise level include enterprise age ($age_{i,t}$), enterprise size ($size_{i,t}$), return on assets ($roe_{i,t}$), and the gearing ratio ($lev_{i,t}$). By further considering the driving role of support subjects in the formation mechanism of innovation chain, support from the government and financial institutes ($sup_{i,t}$) is also controlled.

The results of the descriptive statistics for each variable are shown in Table 5.

Table 5. Descriptive statistics of variables.

Variables	Mean	Std	Min	Max	N
c_i	0.074619	0.230179	0	1	25,676
k_s	64.47764	900.9154	0	54,704	25,676
a_s	1.539455	2.597472	0	15.17749	25,676
age	17.1318	7.287289	0	63	25,676
size	3317.179	18,500.31	0	552,810	25,676
roe	9.369218	122.3592	−18592	4571.41	25,676
sup	19,609.42	141,671.6	−6885.94	8,605,000	25,676
lev	39.69927	199.5528	0	17,834.55	25,676

6.3. Panel Threshold Regression

6.3.1. Threshold Effects

First, the number of thresholds that exist between the independent and dependent variables needs to be determined before conducting a panel threshold regression [43,44]. Therefore, the hypothesis of the existence of different threshold values for the threshold variables needs to be tested. This paper conducts LM tests for the presence of threshold effects in the model [45,46]. In this paper, Hansen's (1999) self-help sampling method is used to test whether there is a threshold effect between knowledge spillover and the formation mechanism of innovation chain [36]. Using Stata 16.0, the P values of the test statistics were derived by repeating the sampling tests 500 times, and the results are shown in Table 6.

Table 6. Significance tests for threshold effects.

Model	Threshold	F	P	BS	Critical Value		
					10%	5%	1%
Single	0	10.78 **	0.03	500	4.9552	8.6451	22.9159
Double	1.7918	36.21 ***	0.01	500	17.4167	21.7523	35.1358
	2.8904						
Tripe	6.4831	8.84 *	0.552	500	39.5057	49.4257	73.078

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As shown in Table 6, when knowledge absorptive capacity is used as the threshold variable, the self-sampling p value corresponding to the triple threshold is 0.5520, which does not pass the significance test at the 10% level, while the self-sampling p values corresponding to the single and double thresholds are 0.0300 and 0.0100, respectively, which pass the significance tests at the 5% and 1% levels, respectively. Therefore, according to the conclusion of Hansen's threshold regression, it can be concluded that the impact of knowledge spillover on the formation mechanism of innovation chain is characterized by nonlinearity and has two significant thresholds of knowledge absorption capacity [34,35].

Moreover, the two estimates of the double threshold are 1.7918 and 2.8904, respectively. Therefore, the double threshold model is chosen for the subsequent analysis in this paper.

Corresponding to Table 6, to further test the accuracy of the double threshold, this paper tests it using the Likelihood ratio (LR) statistic of least squares, and the threshold estimate is the value of ω corresponding to when the LR tends to zero [36]. The test results are shown in Figure 8.

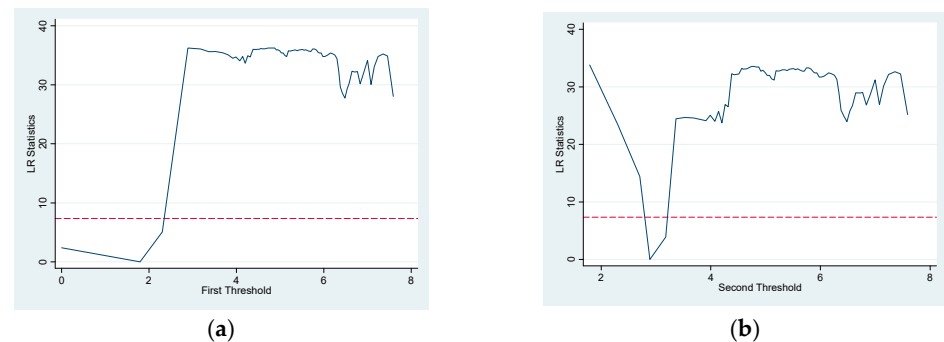


Figure 8. Dual threshold estimation results. (a) Description of the Likelihood ratio function for the threshold value of 1.7918. (b) Description of the Likelihood ratio function for the threshold value of 2.8904.

As shown in Figure 8, when the LR is equal to 0, the parameters corresponding to the two thresholds are 1.7918 and 2.8904, and the dashed line in the figure represents the 95% confidence interval for the threshold value in the LR test [47]. Therefore, the impact of knowledge spillover on the formation mechanism of innovation chain has two significant thresholds of knowledge absorption capacity.

6.3.2. Panel Threshold Regression Results

After determining the threshold values, the panel threshold model is estimated in this paper, and the results are shown in Table 7.

Table 7. Threshold regression of knowledge spillover and the formation mechanism of innovation chain.

	c_i	c_i
$k_s (a_b \leq 1.7918)$	0.00000501 ** (2.48)	0.00000656 *** (3.28)
$k_s(1.7918 < a_b < 2.8904)$	0.0118 *** (5.92)	0.0115 *** (5.82)
$k_s (a_b \geq 2.8904)$	0.0000132 *** (3.93)	0.0000105 *** (3.17)
Constant	0.0740 *** (66.27)	0.384 ** (2.37)
Control variables	No	Yes
Time-fixed effect	Yes	Yes
Individual-fixed effect	Yes	Yes
R ²	0.00276	0.0259
N	25,676	25,676
F	21.97	30.21

The t statistics are in parentheses, = “** $p < 0.05$, *** $p < 0.01$ ”.

The results in Table 7 show that the effect of knowledge spillover on the formation mechanism of innovation chain is always positive with the change in knowledge absorption capacity; only the specific magnitude of the effect varies with the size of knowledge absorption capacity. When the threshold variable is knowledge absorption capacity, there are large differences in the formation mechanism of innovation chains with different degrees of knowledge spillover. When the knowledge absorption capacity is low ($a_b \leq 1.7918$), the coefficient is 0.00000656; when the knowledge absorption capacity is high ($1.7918 < a_b < 2.8904$), the coefficient becomes larger, which is 0.0115. When the knowledge absorption capacity further increases ($a_b \geq 2.8904$), the impact of knowledge spillover on the formation mechanism innovation chain decreases, the coefficient is 0.0000105, and the above three regression coefficients are significant at the 1% level.

By comparing the estimated coefficients of knowledge spillover in the three threshold intervals, which are 0.00000501, 0.0118 and 0.0000132, we find that the positive influence of knowledge spillover on the formation mechanism of innovation chain has a nonlinear characteristic, showing the characteristic of flattening first, then increasing and finally flattening again. This nonlinearity can be interpreted through the lens of absorptive capacity dynamics: (1) At low absorption capacity, the receiving firms lack the ability to effectively utilize the incoming knowledge. Although spillover still exerts a positive effect, its magnitude is severely constrained because knowledge cannot be properly absorbed and applied, limiting its practical value. (2) At moderate absorption capacity, firms achieve a better matching between external knowledge and their internal needs. They are able to filter out redundant information, assimilate relevant insights, and translate them into innovative actions. This is the stage where the promoting effect of knowledge spillover reaches its maximum. (3) At high absorption capacity, however, a potential "absorption capacity trap" emerges. Firms may become overly focused on acquiring and digesting new knowledge, continuously updating their knowledge stocks at the expense of actually applying what they have already learned. This over-investment in acquisition, coupled with rising maintenance costs and reduced resource allocation for utilization, diminishes the marginal benefit of additional spillover. As a result, the positive effect decreases compared with the moderate stage—although it remains significantly positive overall, as the coefficient still exceeds the low-capacity level.

The underlying reason is that knowledge spillover is a dynamic transfer process, influenced by environmental, network, organizational, and knowledge-related factors. When absorption capacity is low, the bottleneck is the inability to utilize knowledge effectively. As capacity improves, firms can better screen and integrate external knowledge, maximizing the spillover benefit. But beyond a certain point, excessive emphasis on absorption may lead to diminishing returns, as firms incur increasing acquisition costs without commensurate gains from application—consistent with the findings in prior studies [48,49]. Thus, the overall relationship remains positive, but its intensity fluctuates in an S-shaped manner, reflecting the trade-offs inherent in knowledge management strategies.

6.4. Robustness Tests

To avoid estimation bias in the model setting, the results in Section 6.3.2 are tested for robustness using both the mixed panel and the robust standard error response model in this paper [50,51], and the results are shown in Table 8. The regression results in Table 8 are similar to those in Table 7, which proves the robustness of the conclusions in this paper.

Table 8. Results of robustness test.

	OLS	fe_robust
k_s ($a_b \leq 1.7918$)	0.0000135 *** (7.63)	0.00000656 * (1.87)
$k_s(1.7918 < a_b < 2.8904)$	0.0160 *** (6.50)	0.0115 *** (3.00)
k_s ($a_b \geq 2.8904$)	0.0000194 *** (4.99)	0.0000105 * (1.70)
Constant	0.112 *** (14.60)	0.384 ** (1.97)
Control variables	Yes	Yes
Time-fixed effect	Yes	Yes
Individual-fixed effect	Yes	Yes
R ²	0.0215	0.0259
N	25,676	25,676
F	26.81	12.17

The t statistics are in parentheses, = “* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ ”.

7. Conclusions

Addressing the first research question—“How is the innovation chain formed?”—this paper, from a knowledge perspective, builds a multi-party evolutionary game model that includes two innovators and one supporter, based on evolutionary game theory. The model incorporates the knowledge spillover effect, and, by analyzing the replicator dynamics system, we derive the final equilibrium point (I1, I1, S1). Meanwhile, a simulation system is constructed according to the evolutionary game model to examine how different degrees of knowledge spillover affect the strategy choices of the agents. The results indicate that due to the presence of knowledge spillovers, innovators will eventually choose strategy I1 to reduce R&D costs and obtain additional benefits, while the supporter’s subsidy policy accelerates the speed at which innovators make cooperative decisions, thereby speeding up the formation of the innovation chain. This finding corroborates the general proposition of resource dependence theory that organizations establish inter-organizational linkages to secure critical resources under conditions of uncertainty [2], and is consistent with recent empirical evidence on the enabling role of subsidies in R&D cooperation [52]. Compared with previous studies [53], our model extends the analysis to a multi-player setting with two innovators and one supporter, better capturing the parallel collaboration among multiple innovation actors that characterizes real-world innovation chains, and provides a quantitative simulation that dynamically verifies the equilibrium conditions derived from the replicator dynamics, thereby reinforcing the theoretical robustness of our findings.

Turning to the second research question—“What is the effect of knowledge on the formation of the innovation chain?”—we further conduct an empirical analysis using data from Chinese listed companies to test the influence of knowledge spillover on the innovation-chain formation mechanism. The empirical findings show that there is a nonlinear relationship between knowledge spillover and the formation mechanism, and that knowledge absorption capacity has a double threshold effect. When knowledge absorption capacity is below the first threshold, knowledge spillover exerts a significantly positive effect on innovation-chain formation; when it lies between the two thresholds, this positive effect increases; and when it exceeds the second threshold, the effect diminishes compared with the previous stage, but remains larger than when absorption capacity is below the first threshold. Overall, as knowledge absorption capacity changes, the effect of knowledge spillover on innovation-chain formation remains consistently positive, which

corroborates the conclusions drawn from the evolutionary game. This S-shaped pattern extends prior work on absorptive capacity, which has primarily identified linear or single-threshold relationships [20], and offers a more nuanced explanation for the diminishing returns of knowledge absorption observed in some contexts [54]. This study therefore provides clear answers to both core questions: how the innovation chain is formed and how knowledge influences its formation. Compared with previous studies [55], our study moves the analysis to the firm level and focuses specifically on the innovation chain formation mechanism, revealing an S-shaped nonlinear pattern (flattening, then increasing, then flattening again) that provides a more nuanced understanding of how knowledge spillovers operate within innovation networks, thereby complementing and refining the existing understanding of absorptive capacity's role in knowledge transfer.

Based on these results, some suggestions are obtained.

First, innovation subjects should strengthen the establishment of knowledge strategic partnerships. Firms play a key role in innovation chains because they are usually market oriented and possess market insights and knowledge. To promote the development of the innovation chain, enterprises should actively search for suitable partners from universities and research institutes to establish long-term and stable strategic partnerships. Through in-depth cooperation with research institutions and universities, enterprises can better access cutting-edge scientific and technological knowledge and innovative ideas to improve their competitiveness. This aligns with the view that inter-organizational knowledge partnerships serve as critical channels for external knowledge acquisition, particularly when firms face resource constraints in turbulent environments [56]. Universities and research institutes should strengthen the collaboration between industry, academia and research. Universities and research institutes play the role of knowledge suppliers in the innovation chain, so they should actively seek opportunities for cooperation with enterprises and supporters. To promote the construction and development of the innovation chain, universities and research institutes can take the following steps: (1) Establish an industry–university–research knowledge sharing platform: create a specialized cooperation platform to promote information sharing and collaborative research among universities, enterprises and supporters. This approach can help innovation subjects absorb knowledge efficiently. (2) Provide technical consulting and training: Universities and research institutes can provide technical consulting and training services to enterprises to help them better apply new technologies and knowledge. (3) Promotion of knowledge spillover: universities and research institutes should encourage their faculty and staff to actively participate in industrial projects to promote knowledge spillover and technology transfer.

Second, support subjects should provide support and incentive policies for the formation mechanism of innovation chains. The government plays a regulatory and supportive role in the innovation chain; therefore, it should take active measures to promote the development of the innovation chain. Drawing on our empirical findings regarding the nonlinear effects of knowledge absorption capacity, we propose the following differentiated policy recommendations: (1) Provide innovation financial support: The government should design innovation subsidy schemes that are tailored to firms' heterogeneous knowledge absorption capacity levels. Specifically, for firms with low absorption capacity, subsidies should focus on capacity-building and basic R&D to help them overcome the initial bottleneck of knowledge utilization; for firms with moderate absorption capacity, subsidy intensity should be increased to maximize the spillover-induced innovation gains; and for firms with high absorption capacity, subsidies should be more targeted toward application-oriented and collaborative innovation projects, avoiding the potential "absorption trap" where excessive acquisition crowds out effective utilization. This dif-

ferentiated approach is consistent with the argument that one-size-fits-all innovation policies are less effective than targeted interventions calibrated to firms' heterogeneity in capabilities [57], and echoes recent calls for more nuanced policy designs that account for non-linearities in innovation processes [58]. Such differentiated subsidy intensities can significantly improve the efficiency of policy support and accelerate the overall formation of innovation chains. (2) Strengthening intellectual property rights protection: The government should strengthen intellectual property rights protection to encourage enterprises, universities, and research institutes to share knowledge and technology while protecting their innovations. Additionally, as the main source of funds in the innovation chain, financial institutions can also take corresponding measures to promote the evolution of the innovation chain: (1) Develop a value assessment and rating mechanism for innovation entities to screen out the worthiest individuals for funding. (2) Provide customized financial products and services that are sensitive to firms' absorptive capacity stages, offering more flexible financing terms to those with proven capacity to translate external knowledge into commercial applications, thereby reinforcing the positive spillover effect while mitigating the risk of over-investment in pure knowledge acquisition.

This paper has certain limitations. Firstly, to simplify the analysis of the multi-participant game model, this paper only studies the game process of the entities' interest strategy selection. Therefore, the model may not fully reflect the multi-party game process. Secondly, the factors selected for analysis in this article only include the ability to absorb knowledge, while ignoring the influence of other factors such as the ecological environment. In the future, we will conduct further studies. First, follow-up research can add technology intermediaries and industrial service platforms to expand our simplified three-agent evolutionary game model. Second, scholars can integrate digital, institutional and ecological factors beyond knowledge to enrich the theoretical framework of innovation chain formation. Third, researchers can expand samples to SMEs and unlisted institutions or carry out cross-country comparisons to improve external validity.

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