Journal of Engineering and Technology Management 77 (2025) 101903

Contents lists available at ScienceDirect

Journal of Engineering and Technology Management

journal homepage: www.elsevier.com/locate/jengtecman

# Order out of chaos: Analyzing strategic research and development cooperation decision of young technology-based firms under multiple factors

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ARTICLE INFO

*Keywords:*
R&D cooperation
Stochastic evolutionary game
Attention allocation

ABSTRACT

We develop a decision-making model utilizing stochastic evolutionary game theory to explore research and development (R&D) cooperation dynamics between firms with varying levels of R&D intensity. The model incorporates five key factors pivotal to strategic R&D cooperation: R&D subsidies, synergy effects, knowledge spillovers, R&D coordination costs, and absorptive capacity. An empirical analysis on 383 Chinese young technology-based firms validates the model. We find divergence between theoretical predictions and practical applications in how managerial attention is allocated in the strategic cooperation decision. Excessive managerial attention to subsidies and coordination costs constrains cooperation, while absorptive capacity and knowledge spillovers are undervalued.

## 1. Introduction

Young technology-based firms are core to economic development by means of regional scientific technological innovation and to promote independent innovative capability which increasingly is aimed at both in emerging and in developed economies (Draghi, 2024; Soetanto and Jack, 2018). However, resource scarcity, enterprise scale, and rapidly changing environments bring along high risks for the R&D activities of these firms and form an important stimulus for R&D cooperation (Link and Scott, 2018), which is considered a common way to learn about knowledge produced by other innovative firms (Belderbos et al., 2004). In view of knowledge spillovers, which are assumed essential for more economic growth and an improved performance of the innovation system, this R&D cooperation also ranks high in public funding policies for R&D (Guisado-González et al., 2018).

As highlighted by López (2008), the determinants of R&D cooperation can be situated in three domains: cost and risk sharing, skill-sharing or complementarities, and factors related to the firms' absorptive capacity. However, potential downsides of R&D collaboration in terms of cost of coordination and monitoring (transaction cost economics and incomplete R&D cooperation contracts given the highly intangible assets – Deeds and Hill, 1996), and risk of knowledge disclosure and opportunistic behavior (Hottenrott and Lopes-bento, 2016) should not be ignored. Especially smaller and younger firms can benefit from R&D collaboration through access to more diversified and broader knowledge and cost sharing (Becker, 2015), but their resource constraints put limits on managerial attention and available internal resources, resulting in limitations for bearing this cost and risk.

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https://doi.org/10.1016/j.jengtecman.2025.101903
Received 27 August 2024; Received in revised form 16 July 2025; Accepted 30 July 2025
Available online 8 August 2025
0923-4748/

Despite the insights in the importance of the three board domains of drivers for R&D cooperation and the downside aspect of monitoring and coordination, most studies about R&D cooperation fail to consider these determinants conjointly and take a partial focus (for younger and smaller firms – e.g., Okamuro et al. (2011) for Japanese start-ups; Chun and Mun (2012) for Korean SMEs; Badillo and Moreno (2016) for Spanish firms). We address this gap and develop a conceptual model based on a stochastic evolutionary game model (EGT) and a simulation system to better understand the drivers for deciding or not to engage in strategic R&D cooperation. Without being exhaustive in terms of all potential determinants for strategic R&D cooperation, we take into account five factors (synergy effects, R&D subsidies, knowledge spillovers, R&D coordination costs, and absorptive capacity) that are commonly relied upon when dealing with strategic R&D cooperation and which cover the three categories of determinants as formulated by López (2008).

Building upon insights regarding the role of heterogeneity in R&D intensity in the context of strategic R&D cooperation (Belderbos et al., 2004), our emphasis is on modeling of firm-level strategic decisions to either promote or refrain from promoting strategic R&D cooperation between firms with varying R&D intensity. We focus on the potential benefits associated with strategic R&D cooperation rather than actual collaboration. By testing this model on young technology-based firms, we – as far as we know for the first time in the literature – integrate the direction of managerial attention in the decision-making process for strategic R&D cooperation (a theoretical link already hinted at by e.g., Hottenrott and Lopes-Bento (2016)). In line with the focus on strategic decision making in the conceptual model and its link with the literature on managerial attention (Ocasio, 2011, 1997), we explore the role of managers rather than solely focusing on the possession of resources (as primarily emphasized and considered a limitation of the resource-based view, e.g., Andersén, 2022; Helfat and Peteraf, 2015; Lockett et al., 2009; Yang et al., 2020). We also contribute to the literature by taking an alternative (non-survey based) measurement of R&D cooperation by assessing how firms perceive the strategic importance of R&D collaboration to avoid limitations of self-reporting bias in surveys and to move beyond cross-sectional survey data commonly used to measure R&D collaboration (Lu and Chesbrough, 2022; Schäper et al., 2023).

The paper is organized as follows: Section 2 reviews the relevant literature. Section 3 presents our decision-making model for strategic R&D cooperation based on the five factors. In Section 4, we investigate the framework for attention allocation in strategic R&D cooperation. The final section encapsulates the discussion and conclusions, including theoretical contributions, managerial implications, limitations, and avenues for further research.

## 2. Literature review

We tackle the coordination of multiple factors in decision-making within the context of strategic R&D cooperation, draw connections to attention allocation in R&D decisions. In our literature review, we specifically focus on the "situational" intricacies pertinent to young technology-based firms.

### 2.1. *Five factors influencing strategic R&D cooperation decision making*

We start from the three primary categories of motivations for firms to engage in strategic R&D cooperation, as outlined by López (2008): cost and risk sharing, complementarities or skill sharing, and absorptive capacity. As shown in Table 1, we follow this framework of determining factors for R&D cooperation and summarize representative literature in recent years based on samples of firms from different countries. Some studies suggest that public subsidies and synergy effects can help firms reduce cost and share risks, thereby significantly influencing R&D cooperation of firms (e.g., Busom and Fernández-Ribas, 2008; Martinez-Noya and Garcia-Canal, 2024; Ono and Sekozawa, 2016). Other studies argue that spillover effects between firms can bring complementary knowledge to collaborators, without ignoring a concern about higher coordination costs (e.g., Bernal et al., 2022; Chun and Mun, 2012; Falvey et al., 2013). A third group of studies emphasizes the effects of absorptive capacity in determining R&D cooperation (e.g., Clausen, 2013; Roy, 2018).

First, R&D subsidies and the synergy effect play a pivotal role in the domain of cost and risk sharing for firms. Governments adopt a cost and risk-sharing approach by providing R&D subsidies. While private firms seek to minimize the outflow of knowledge spillovers, policymakers aim to maximize their effect. To reconcile this divergence in objectives, governments extend grants to firms as a supplementary source of financing (Guisado-González et al., 2018). While R&D cooperation is not invariably a precondition for firms to obtain R&D subsidies, these subsidies have substantially increased firms' inclination to seek R&D collaborators or share expertise (Busom and Fernández-Ribas, 2008; Guisado-González et al., 2016; Piga and Vivarelli, 2004). Governments encourage the dissemination of R&D knowledge among firms, and while R&D cooperation is not mandatory for obtaining R&D subsidies, except for specific cooperation projects such as the Intergovernmental International Cooperation on Scientific and Technological Innovation Programs,[1] engaging in R&D collaboration substantially enhances the likelihood of securing R&D subsidies (Scherngell and Barber, 2011).

It is noteworthy that R&D cooperation involving subsidies tends to yield superior results compared to collaborations without such udioort (Cabon-Dhersin and Gibert, 2018). Examining seven European countries as an illustrative case, Franco and Gussoni (2014) discern that firms benefiting from R&D subsidies are more inclined to engage in cooperative endeavors. In the context of China, firms encounter heightened financial constraints during the ongoing economic transition (He et al. 2019; Li et al. 2019), prompting them to actively seek R&D subsidies or establish partnerships for R&D.

[1] Ministry of Science and Technology, 2022, The Announcement of Intergovernmental International Cooperation on Scientific and Technological Innovation Programs (2023). Available at https://service.most.gov.cn/kjjh_tztg_all/20221109/5137.html

**Table 1**
Review of previous studies on the three categories of determinants of R&D cooperation identified by López (2008).

| Category | Paper | Major significant determinants | Sample | Method |
|---|---|---|---|---|
| Cost and risk sharing | Martinez-Noya and Garcia-Canal, 2024 | Public R&D support | Spain, survey data, more than 6500 firms | Negative binomial model |
| | Cantabene and Grassi, 2019 | Public subsidies and orders | Italy, survey data, 6505 firms | Probit approach |
| | Lee et al., 2020 | Synergy effects | Korean, survey data, 2319 firms | Stochastic frontier analysis and Meta-frontier analysis |
| | Dawid et al., 2013 | Synergy effects | None | Dynamic oligopoly model |
| | Ono and Sekozawa, 2016 | Synergy effects | None | Game-theoretic real options approach |
| Complementarities or skill sharing | Bernal et al., 2022 | Incoming knowledge spillovers | Spain, survey data, 12849 firms | Multivariate probit model |
| | Chun and Mun, 2012 | Knowledge spillovers | Korean, survey data, 3775 firms | Bivariate probit model |
| | Aristei et al., 2016 | Knowledge spillover | European survey data, 7545 firms | Multivariate binary choice (probit) model |
| | Bönte and Keilbach, 2005 | Knowledge spillover | Germany, survey data, 730 firms | Multinomial logit (MNL) model |
| | Falvey et al., 2013 | Coordination costs | None | Oligopoly model |
| Absorptive capacity | Melnychuk et al., 2021 | Absorptive capacity | Global, unique panel data, 56 global pharmaceutical and biotech firms | Negative binomial model |
| | Roud and Vlasova, 2020 | Absorptive capacity; competition regime, technological opportunities | Russia, survey data, 805 manufacturing firms | Bivariate probit model |
| | Roy, 2018 | Absorptive capacity | Germany, survey data, 1200 firms | Structural model |

The synergy effect predominantly elucidates the effect of R&D on profitability. It denotes heightened innovation productivity achieved by eliminating redundant R&DD efforts within the scope of cooperation (Bolli and Woerter, 2013). Complementary resources and capacities among collaborating partners constitute a vital impetus for seeking synergy in R&D cooperation (Lee et al., 2020, 2010), leading to reduced R&D expenditures and amplified profits. The synergy effect enhances immediate returns by reducing the anticipated time until the introduction of a new product (Dawid et al., 2013), rendering R&D cooperation more appealing. Leveraging economies of scale and scope in the generation and dissemination of R&D, participating firms can harness the synergistic advantages of exchanging and sharing information and expertise (Falvey et al., 2013). For firms constrained by limited R&D resources, the synergy effect of R&D cooperation facilitates the distribution of greater R&D benefits with fewer resources (Chun and Mun, 2012; Rese and Baier, 2011).

Second, within the context of complementarities or skill sharing, two significant underlying factors are knowledge spillovers and coordination costs. Knowledge spillovers serve as a fundamental means of skill sharing, as they involve the transfer of knowledge from one entity to another, providing access to external knowledge (Yang et al. 2010). Scholars such as Belderbos et al. (2004) and Audretsch and Belitski (2020) argue that the presence of effective knowledge spillovers between firms can serve as an incentive for R&D cooperation. Firms can optimize their benefits from R&D collaboration by maximizing incoming spillovers and minimizing outgoing spillovers through effective measures, such as knowledge protection and well-structured R&D agreements (Belderbos et al. 2004, Cassiman et al. 2002, Ding and Huang, 2010, Kesteloot and Veugelers, 1995). It is worth noting that Chinese innovative firms, in comparison to their counterparts in developed economies, face a higher proprietary cost associated with disclosing information (Chen et al. 2017; Li et al. 2019), which makes these firms more cautious about R&D cooperation due to concerns regarding outgoing spillovers.

While sharing information or know-how in collaboration can be beneficial, the act of coordination also incurs coordination costs (Cassiman and Veugelers, 2002). Coordination costs in the context of R&D cooperation with external partners refer to the expenses arising from increased management burden, which often acts as a significant deterrent for firms considering engagement in R&D collaborations (Hottenrott and Lopes-bento, 2016). These coordination costs not only reduce profits but also alter a firm's expectations regarding the benefits of R&D cooperation (Falvey et al., 2013). Hottenrott and Lopes-Bento (2016) contend that transaction costs stemming from coordination efforts need to be carefully weighed against the advantages derived from R&D partnerships. As external R&D intensity, complexity, heterogeneity, and the number of member firms increase, firms encounter higher coordination costs (Carboni and Medda, 2021; Okamuro, 2007).

The final factor we address regarding the benefits of R&D cooperation is absorptive capacity. The utilization of knowledge flows largely depends on a firm's absorptive capacity (Guisado-González et al., 2018; Melnychuk et al., 2021), which refers to a firm's ability to recognize the value of new external knowledge and effectively apply it for commercial purposes (Cohen and Levinthal, 1990). Firms with high levels of absorptive capacity are better equipped to adapt to rapidly changing market conditions and reconfigure their resource bases to gain a competitive edge (Knockaert et al., 2014). Such firms are more inclined to engage in R&D cooperation because they can extract more value from R&D alliances (Lin et al., 2012). Additionally, when the potential for knowledge spillovers in cooperation is higher, firms invest in enhancing their absorptive capacity through internal R&D, training, and cultivating an educated workforce core elements of absorptive capacity (Clausen, 2013; Hammerschmidt, 2009). Developing absorptive capacity can serve as a potential mechanism for small and young firms to enhance their performance and contribute to the success of the alliance (Emden et al., 2005; Flatten et al., 2011), although further research in this area is warranted (Flatten et al., 2011).

It is noteworthy that some of the factors described above (R&D subsidies, synergy effects, knowledge spillovers, R&D coordination costs, and absorptive capacity) have been considered in previous studies (Bae and Woo, 2020; Bernal et al., 2022; Bolli and Woerter, 2013; Cassiman and Veugelers, 2002; Cohen and Levinthal, 1990; Veugelers, 1998). However, thus far, limited attention has been devoted to examining these five factors within a unified analytical framework or from a coordinated perspective. Hence, the theoretical and empirical literature on the relationship between the three dimensions (cost and risk sharing, complementarities or skill sharing, and absorptive capacity) for R&D cooperation as outlined by López (2008) are limited and inconclusive. For example, Guisado-González et al. (2018) advocate for the inclusion of absorptive capacity in models analyzing the influence of R&D subsidies and spillovers on R&D cooperation. To offer a decision-making framework for R&D cooperation in young technology-based firms - related to the resource constraints these firms generally are confronted with - an integrated perspective on the combined effects of the different drivers for decision making in the field of R&D is needed (as demonstrated by Teirlinck, 2022, 2017). Therefore, in our approach, we expand upon the existing paradigm by considering the interplay between all five factors. Consequently, our first research question is: *How to model the multifactor influence of R&D subsidies, synergy effects, knowledge spillovers, R&D coordination costs, and absorptive capacity on the decision of promotion or non-promotion of R&D cooperation between high- and low R&D intensive firms?* Answering this question will furnish a decision-making framework for R&D cooperation that can guide managers in their strategic choices.

### 2.2. *Attention allocation of R&D decisions*

Attention is defined as the process including the noticing, encoding, interpretation, and dedicated allocation of time and effort by organizational decision-makers to particular issues and solutions (Ocasio, 1997). Decision-makers confront a plethora of factors vying for their attention, yet their bounded rationality imposes limitations on their ability to give equal attention to all these factors (Stevens et al., 2015). This challenge is particularly pronounced for firms operating within emerging markets, characterized by a dearth of formal institutions and stable regulations (Ernst et al. 2015, Wang et al. 2020). Decision-makers must make judicious choices about where to direct their attention, thereby enhancing the speed and accuracy of their information processing and actions (Ocasio, 1997). Attention allocation significantly shapes decision making by influencing the decision maker's perception and selection of information (Ocasio et al., 2018).

According to the attention-based view, effective management of attention resources within the constraints of cognitive limitations is pivotal for fostering innovation (Ridge et al., 2017; Yadav et al., 2007). However, the domain of R&D cooperation, a critical facet of technology decisions, has yet to be scrutinized from an attention-based perspective (Palmié et al., 2016). Thus far, the management literature has predominantly analyzed cooperation through the lenses of transaction costs and resource-based frameworks (Tyler and Steensma, 1995), with limited attention given to the theoretical examination of attention allocation in R&D cooperation. A selective managerial focus, for instance, on R&D subsidies, may lead to a potential oversight of pertinent options, information, and decision alternatives (Barnett, 2008; Palmié et al., 2016). It has been observed that firms often engage in R&D cooperation even when their absorptive capacity is insufficient (Guisado-González et al., 2018). When considering the promotion of R&D cooperation within the context of attention allocation, the five factors can be perceived as guiding the attention and action of organizations, effectively controlling, distributing, and monitoring organizational attention and resources.

In pursuit of effective decision making within the framework of attention allocation, our second research question is: *How do multiple coordinating factors jointly shape firms' strategic R&D cooperation decisions, as interpreted through a game simulation framework?* This question seeks to offer a decision-making framework. Its relevance can be linked to the concept of an attention structure, which includes specialized attention within specific units and integrated attention across units (Joseph and Wilson, 2018). Ocasio (1997) proposes four factors for assessing attention structure: rules of the game, players, structural positions, and resources. Attention structure not only shapes the design and operation of communication channels but also molds the focus of attention (Kleinknecht et al., 2020). We draw upon the concept of attention structure to craft an analytical framework that conceptualizes the attention allocation across four dimensions: players, procedures and rules, goals, and decision-making.

First, *players* exert influence by regulating firms' attention through their unique skills and values (Stevens et al., 2015). Within the context of firms' strategic R&D cooperation, we identify R&D managers as the key players responsible for attention allocation. R&D managers grapple with challenges related to managing attention in strategic R&D cooperation, particularly the allocation of limited attention resources (Bianchi et al., 2019).

Second, game rules represent the guiding principles that underpin the achievement of firms' goals, including a set of assumptions, norms, values, and incentives dictating how success can be attained (Stevens et al., 2015). In our study, *procedures and rules* establish a fundamental framework that structures the five factors for promoting strategic R&D cooperation, thus directing firms' choices in innovative actions.

Third, the *goal* signifies the optimal allocation of attention across the five factors for promoting strategic R&D cooperation in our study, alleviating the competing demands on players' attention (Stevens et al., 2015). The goal serves as the determinant of where players channel and concentrate their attention, thereby regulating prioritization with immediate attention.

Last, the *decision-making* aspect of attention allocation pertains to the means employed to approach the goal of attention allocation, involving a comparison of the effectiveness of various allocation alternatives.

## 3. Development of a conceptual model

Classical game theory relies on two crucial assumptions (Gu et al., 2019). First, it assumes that players are entirely rational and are solely motivated by maximizing their self-interests. Second, it presupposes that all players possess common knowledge, meaning that each player knows that all other players are rational, and this knowledge extends indefinitely. In contrast, EGT departs from these assumptions of perfect rationality (Friedman, 1998). In EGT, players are bounded by their rationality. They are prone to making errors, engage in repeated trials, and learn from their mistakes, signifying that they cannot achieve optimal results in economic activities instantaneously. Consequently, time assumes a pivotal role in EGT. As time progresses, firms have the opportunity to continuously modify and enhance their behavioral strategies and approaches (Encarnação et al., 2018). Therefore, EGT provides a valuable framework for examining cooperation, competition, and interaction in social and business decision making processes (Cai and Kock, 2009; Requejo and Camacho, 2011). In recent years, EGT has found application in decision-making related to innovation collaboration, including the analysis of synergy effects within patents alliances and enterprise-university-government networks (Shen and Shang, 2014; Song et al. 2020).

To address the first research question, we have developed a decision-making model for strategic R&D cooperation based on the five factors within the framework of stochastic EGT. This section outlines the process of developing the stochastic evolutionary game model, including fundamental assumptions, the payoff matrix, and the simulation system. Additionally, it introduces methods relied upon for acquiring data and measuring variables for simulation.

### 3.1. Basic assumptions and model parameters

We begin with the standard Cobb—Douglas production function for two primary reasons. First, it serves as a widely adopted framework, offering a foundation for modeling firms' growth or productivity (Hall and Mairesse, 1995). This, in turn, facilitates the evaluation of firms' profits. Second, total factor productivity can be dissected into R&D stock and other factors (Cin et al., 2017), establishing a structured approach for the analysis of the five factors associated with strategic R&D cooperation among firms characterized by varying levels of R&D intensity.

The typical Cobb—Douglas production function can be expressed as follows:

$$Q = A(t)L^{\alpha}K^{\beta} \tag{1}$$

where $Q$ is the total production, $A(t)$ is the total factor productivity, $L$ is the labor input, $K$ is the level of capital stock, $\alpha$ and $\beta$ are the total output elasticity of labor and capital. Total factor productivity is usually assumed to include factors that affect the efficiency of production, such as R&D and technology transfer. Therefore, total factor productivity is specified by Nemethova et al. (Nemethova et al., 2019):

$$A(t) = C(R\&D)^{\omega}H^{\delta} \tag{2}$$

where $C$ is a constant term, $R\&D$ represents the R&D stock, and $H$ refers to other factors that can affect the utilization of inputs in production (Nemethova et al., 2019). $\omega$ and $\delta$ are respective elasticities. Following Nemethova et al. (Nemethova et al., 2019) and Cin et al. (Cin et al., 2017), we consider the effect of public R&D subsidies in the following way:

$$A(t) = C(R\&D)^{\omega+\theta}H^{\delta} \tag{3}$$

where $\theta$is the effect of R&D subsidies on total factor productivity. Combining (1) and (3), we obtain the following production function:

$$Q = C(R\&D)^{\omega+\theta}H^{\delta}L^{\alpha}K^{\beta} \tag{4}$$

In response to Conti and Marini's (Conti and Marini, 2019) call for further research on the connection between decisions and the inclination toward strategic R&D cooperation, as well as the existing disparities between firms, we consider a simplified scenario in which the market comprises two distinct groups of firms characterized by varying levels of R&D intensity in the market ($i = 1,2$). The profit ($\pi_i$) of these two groups can be mathematically represented as an adjusted production function:

$$\pi_i = C_i(R\&D)_i^{\omega_i+\theta_i}H_i^{\delta_i}L_i^{\alpha_i}K_i^{\beta_i}, i = 1,2 \tag{5}$$

To address market failures arising from spillovers or imperfect appropriability conditions of innovations, governments extend R&D subsidies to innovative firms (David et al., 2000; Meuleman and Maeseneire, 2012). Knowledge spillovers play a pivotal role in this context, as they enable competitors or partners to enhance their productivity performance while reducing R&D expenditures (Aldieri and Cincera, 2009). For the sake of simplicity, our focus remains on knowledge spillovers within the domain of strategic R&D cooperation. On the one hand, firms tend to safeguard their innovation benefits by exerting control over outbound knowledge spillovers (Belderbos et al., 2004). On the other hand, they implement measures to facilitate the influx of external knowledge, commonly referred to as incoming knowledge spillovers, recognizing that profitability is contingent upon a firm's capacity to absorb spillovers from competitors or partners (Leahy and Neary, 2007). Therefore, we take a spillover effect ($\gamma_i$) and an absorptive capacity effect ($\mu_i$) into account.

When heterogeneous firms cooperate, their profits are expressed in the following way:

$$\pi_1 = C_1(R\&D)_1^{\omega_1+\mu_1\gamma_2+\theta_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1} \tag{6}$$

$$\pi_2 = C_2(R\&D)_2^{\omega_2+\mu_2\gamma_1+\theta_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2} \tag{7}$$

where $\gamma_i$ and $\mu_i$ represent the spillover and absorptive capacity effects on total factor productivity, respectively. Taking group 1 as an example, the decision of strategic R&D cooperation is affected not only by incoming spillovers ($\gamma_2$) from group 2 but also by outgoing spillovers ($\gamma_1$) to group 2 (Ishikawa and Shibata, 2021).

Firms opting for R&D collaboration stand to reap the advantages of the synergy effect by pooling technical information, know-how, cost-sharing, and risk mitigation (Carboni, 2013). The synergy effect ($\sigma$) of strategic R&D cooperation is anticipated to exert an influence on firms' production processes. Consequently, the profitability associated with the decision to engage in R&D collaboration can be represented by the following model:

$$\pi_1 = C_1(R\&D)_1^{\omega_1+\mu_1\gamma_2+\theta_1+\sigma}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1} \tag{8}$$

$$\pi_2 = C_2(R\&D)_2^{\omega_2+\mu_2\gamma_1+\theta_2+\sigma}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2} \tag{9}$$

We consider the scenario in which group 1 promotes strategic R&D cooperation while group 2 refrains from doing so, with group 1 incurring a coordination cost ($\sigma_1$) due to opportunistic behavior and implementation of monitoring mechanisms (Belderbos et al. 2010; Mazzola et al. 2012). Conversely, in the opposite scenario, the coordination cost ($\sigma_2$) is borne by group 2.

### *3.2. Payoff matrix and evolutionary dynamics of the model*

The concept of inherently unstable cooperation has been extensively discussed in the literature (e.g., Lhuillery and Pfister, 2009, Reuer and Zollo, 2005). This cleads us to consider two strategies that can be adopted by two distinct groups: "promoting strategic R&D cooperation" (referred to as cooperator, C) and "not promoting strategic R&D cooperation" (referred to as non-cooperator, D) (Encarnação et al., 2018).

Since each group has two strategies, there are four distinct game scenarios that warrant examination. We analyze these scenarios based on firms' decisions and focus on the potential benefits associated with strategic R&D cooperation rather than actual collaboration. These benefits serve as guiding for firms' subsequent decisions regarding strategic R&D cooperation.

In the first scenario, firms from both groups opt for the strategy of promoting strategic R&D cooperation, representing the most favorable scenario. In this case, firms can harness the advantages of absorbing knowledge spillovers from their partners, as well as reaping profits from the synergy effect and R&D subsidies.

The second scenario involves firms from both groups choosing the strategy of not promoting strategic R&D cooperation, representing the least favorable scenario. In this scenario, firms miss out on the profits from the synergy effect, R&D subsidies, and knowledge spillovers from potential partners.

Scenarios three and four are similar, so we will discuss one of them. For instance, in scenario three, firms in group 1 opt to promote strategic R&D cooperation, while firms in group 2 choose not to promote strategic R&D cooperation. In this scenario, firms in group 1 incur R&D coordination costs $\sigma_1$. Collaborative R&D activities often lead to increased coordination costs due to opportunistic behavior and the implementation of monitoring mechanisms (Belderbos et al. 2010; Mazzola et al. 2012). Such opportunistic behavior, characterized by "self-interest seeking with guile" behavior (Williamson, 1975), can manifest in various forms, including cheating, shirking, distorting information, misleading partners, providing substandard products/services, and appropriating partners' critical resources (Das and Teng, 1998), Consequently, collaborators who seek to foster cooperation often need to bear the costs of R&D coordination costs.

Simultaneously, collaborators continue to share their skills or knowledge, but non-cooperators have effectively "taken a free ride" (Lhuillery and Pfister, 2009; Walter et al., 2015). Firms in group 2 can obtain the spillover benefit from partners ($\mu_2\gamma_1$). Even if only collaborators unilaterally promote strategic R&D cooperation, it remains beneficial for firms in both groups to secure R&D subsidies. In this scenario, firms can derive profits from R&D subsidies, although there will be no synergistic effect ($\sigma$).

The individual payoffs of the two groups with different scenarios are given in Table 2.

In group 1, the fractions of non-cooperators and cooperators are $x$ and $1 - x$, respectively. In group 2, the fractions of non-cooperators and cooperators are $y$ and $1 - y$, respectively. As such, we can obtain the replicator dynamic functions as follows (Friedman, 1998):

$$F(x) = x(1-x)(U_{11} - U_{12}) \tag{10}$$

$$F(y) = y(1-y)(U_{21} - U_{22}) \tag{11}$$

**Table 2**
Payoff between group 1 and group 2, where C indicates cooperators and D non-cooperators.

| Strategies | Payoffs accruing to each group | |
|---|---|---|
| (Group1, Group 2) | Group 1 | Group 2 |
| C, C | $C_1(R\&D)_1^{\omega_1+\mu_1\gamma_2+\theta_1+\sigma}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1}$ | $C_2(R\&D)_2^{\omega_2+\mu_2\gamma_1+\theta_2+\sigma}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2}$ |
| C, D | $C_1(R\&D)_1^{\omega_1+\theta_1-\sigma_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1}$ | $C_2(R\&D)_2^{\omega_2+\mu_2\gamma_1+\theta_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2}$ |
| D, C | $C_1(R\&D)_1^{\omega_1+\mu_1\gamma_2+\theta_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1}$ | $C_2(R\&D)_2^{\omega_2+\theta_2-\sigma_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2}$ |
| D, D | $C_1(R\&D)_1^{\omega_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1}$ | $C_2(R\&D)_2^{\omega_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2}$ |

where $1-x$ and $1-y$ are non-negative and will not affect the outcome of evolutionary strategies. Therefore, functions (10) and (11) can be rewritten in the following ways:

$$F(x) = x(U_{11} - U_{12}) \tag{12}$$

$$F(y) = y(U_{21} - U_{22}) \tag{13}$$

Each firm within the game selects either a cooperative strategy (C) or a non-cooperative strategy (D) based on its earnings ($U$). The replicator dynamic system relies on dynamic differential equations and characterizes the frequency of a particular strategy (C or D) employed within a population (Friedman, 1991). Consequently, we can track the evolutionary progression of the fraction of firms embracing cooperative or non-cooperative strategies (C or D) within the two groups as time advances. In this context, the replicator dynamic equations governing the adoption of a non-cooperative strategy by the two groups are expressed as follows (detailed steps of the process are available in Appendix A: Calculation of expected earnings):

$$\begin{aligned} F(x) = x[&C_1 H_1^{\delta_1} L_1^{\alpha_1} K_1^{\beta_1} (R\&D)_1^{\omega_1-\sigma_1} (-(-1+y)(R\&D)_1^{\mu_1\gamma_2+\theta_1+\sigma_1} + (-1+y)(R\&D)_1^{\mu_1\gamma_2+\theta_1+\sigma+\sigma_1} - \\ &y(R\&D)_1^{\theta_1} + y(R\&D)_1^{\sigma_1})] \end{aligned} \tag{14}$$

$$\begin{aligned} F(y) = y[&C_2 H_2^{\delta_2} L_2^{\alpha_2} K_2^{\beta_2} (R\&D)_2^{\omega_2-\sigma_2} (-(-1+x)(R\&D)_2^{\mu_2\gamma_1+\theta_2+\sigma_2} + (-1+x)(R\&D)_2^{\mu_2\gamma_1+\theta_2+\sigma+\sigma_2} - \\ &x(R\&D)_2^{\theta_2} + x(R\&D)_2^{\sigma_2})] \end{aligned} \tag{15}$$

### 3.3. Stochastic evolutionary game model and simulation system

The decision-making environment is marked by a substantial degree of uncertainty and information asymmetry, exerting an effect on firms' participation in strategic R&D cooperation (Mukherjee et al., 2013). To account for this uncertainty, we incorporate a random interference system into the evolutionary game model utilizing the Wiener process. The Wiener process is frequently employed to depict the effects of uncertainty or random variables, such as in simulating stock price processes (Buckdahn and Hu, 1998).

A stochastic process $W_t$, $t \in [0, +\infty)$, is named the Wiener process (or Brownian motion). $W_t$ satisfies the following conditions: (1)$W_o = 0$; (2)$W_{t+h} - W_t \sim N(0,h) \forall t, h > 0$; (3) the increments $W_{t1} - W_{t0}, \ldots, W_{tn} - W_{tn-1}$ are independent for $t_0 < t_1 < \cdots < t_n$,$N$ is the normal distribution.

Consider a one-dimensional $It\hat{o}$ stochastic differential equation (SDE) (Higham, 2001):

$$dP_t = f(P_t)dt + g(P_t)dW_t, \qquad P_0 = p_0 \tag{16}$$

where $W$ is an m-dimensional standard Wiener process. It is necessary to solve the systems numerically because many SDE systems do not have an analytic solution. Therefore, we use the Euler-Maruyama method for the stochastic numerical approximation, simulating the distribution of a random process $W_t$ at a certain moment. It is a common and convenient method for numerical simulation of SDE. Considering the $It\hat{o}$ SDE (16) on $[t_0, T]$, for a given discretization $t_0 < t_1 < \cdots < t_n < \cdots t_N = T$ of $[t_0, T]$, an Euler-Maruyama approximation is a continuous-time stochastic process satisfying the iterative scheme:

$$q_{n+1} = q_n + h_n f(q_n) + g(q_n)\Delta W_n \qquad q_0 = p_0, \quad n = 0, 1, \ldots, N-1 \tag{17}$$

where $q_n = q(t_n)$, the step size is $h_n = t_{n+1} - t_n$, $\Delta W_n = W(t_{n+1}) - W(t_n) \sim N(0, h_n)$, and $W(t_0) = 0$, $N$ is the normal distribution.

We consider the simplified SDE of (16) in the MATLAB simulation system as follows:

$$dP_t = f(P_t)dt + \xi dW_t, \qquad P_0 = p_0 \tag{18}$$

where $\xi$ represents the intensity of stochastic disturbance. The fractions of non-cooperators in group 1 and group 2 at time $t$ are labeled $X_t$ and $Y_t$, respectively. The replicator dynamic equations can be rewritten in the following ways:

$$\begin{aligned} dX_t = X_t[&C_1 H_1^{\delta_1} L_1^{\alpha_1} K_1^{\beta_1} (R\&D)_1^{\omega_1-\sigma_1} (-(-1+Y_t)(R\&D)_1^{\mu_1\gamma_2+\theta_1+\sigma_1} + (-1+Y_t)(R\&D)_1^{\mu_1\gamma_2+\theta_1+\sigma+\sigma_1} - \\ &Y_t(R\&D)_1^{\theta_1} + Y_t(R\&D)_1^{\sigma_1})]dt \end{aligned} \tag{19}$$

$$\begin{aligned} dY_t = Y_t[&C_2 H_2^{\delta_2} L_2^{\alpha_2} K_2^{\beta_2} (R\&D)_2^{\omega_2-\sigma_2} (-(-1+X_t)(R\&D)_2^{\mu_2\gamma_1+\theta_2+\sigma_2} + (-1+X_t)(R\&D)_2^{\mu_2\gamma_1+\theta_2+\sigma+\sigma_2} - \\ &X_t(R\&D)_2^{\theta_2} + X_t(R\&D)_2^{\sigma_2})]dt \end{aligned} \tag{20}$$

The production function (3) incorporates $H$ as an additional factor influencing input utilization. Given that the stochastic evolutionary game model has already accounted for the stochastic disturbance factor (Xu et al., 2015), to avoid redundancy, we have omitted the term $H$ in the production function. Consequently, the replicator equations presented in (19) and (20) can be expressed as follows:

$$\begin{aligned} dX_t = X_t[&C_1 L_1^{\alpha_1} K_1^{\beta_1} (R\&D)_1^{\omega_1-\sigma_1} (-(-1+Y_t)(R\&D)_1^{\mu_1\gamma_2+\theta_1+\sigma_1} + (-1+Y_t)(R\&D)_1^{\mu_1\gamma_2+\theta_1+\sigma+\sigma_1} - \\ &Y_t(R\&D)_1^{\theta_1} + Y_t(R\&D)_1^{\sigma_1})]dt + g(X_t)dW_t \end{aligned} \tag{21}$$

$$dY_t = Y_t[C_2 L_2^{\alpha_2} K_2^{\beta_2} (R\&D)_2^{\omega_2 - \sigma_2} (-(-1 + X_t)(R\&D)_2^{\mu_2\gamma_1 + \theta_2 + \sigma_2} + (-1 + X_t)(R\&D)_2^{\mu_2\gamma_1 + \theta_2 + \sigma + \sigma_2} - X_t(R\&D)_2^{\theta_2} + X_t(R\&D)_2^{\sigma_2})]dt + g(Y_t)dW_t \tag{22}$$

### 3.4. *Test base: population and data*

As a test of the conceptual model, our focus is on firms listed on China's ChiNext[2] Board (Growth Enterprise Board) during the period from 2015 to 2019. The ChiNext Board serves as a fundraising platform primarily for young small- and medium-sized technology-based enterprises with substantial growth potential (Luo and Ouyang, 2014). These firms have predominantly gained a competitive edge through their R&D endeavors (Kong and Su, 2021). We have an unbalanced panel dataset comprising 387 firms. Fundamental information about these firms, such as their age, employment, fixed assets, and R&D investment, has been collected from the China Stock Market and Accounting Research (CSMAR) database. CSMAR offers comprehensive data on listed companies, including information from annual reports and additional data from publicly available sources (Wei and Zuo, 2018).

After excluding four firms with missing data, our final sample consists of 383 firms. To categorize these young technology-based firms on R&D intensity[3] (R&D investment as a percentage of operating revenue), we divide them into two groups: the "high R&D intensive group" ("HIG") with R&D intensity above or equal the median value of 5.6 %, and the "low R&D intensive group" ("LIG") with R&D intensity below the median value of 5.6 %. On the one hand, the 5.6 % threshold for classifying firms in the high R&D intensive group can be justified by the OECD classification of firms in industries earmarked as highly R&D intensive (Galindo-Rueda and Verger, 2016). In terms of R&D expenses on gross output, an intensity of around 7 percent leads to a classification as high R&D intensity industry (Galindo-Rueda and Verger, 2016, p. 14). Based on this classification, Nunes et al. (2012) compared the R&D intensity of non-high-tech versus high-tech SMEs in Iberian manufacturing industries. They measured R&D intensity by the ratio of R&D investment to total sales. Based on 827 observations, the average intensity amounted to 4.7 % for high-tech SMEs, compared to 0.08 % for non-high-tech SMEs. On the other hand, the 5.6 % threshold also is close to the (worldwide) 6.3 percent R&D-to-sales-ratio for young leading innovative firms (regardless of being classified in high-tech industries or not) as reported by Cincera and Veugelers (2013), with marked differences between the EU (4.4 %) and the US (10.2 %). The median value of 5.6 % R&D intensity reported for Chinese high-tech firms also indicates relatively small differences between the R&D intensities of Chinese young technology-based firms compared to similar firms in other parts of the world, providing no indication of potential bias due to selection of a sample of Chinese firms as a basis for testing the theoretical model. There are 617 years of observations in the HIG and 645 years of observations in the LIG.[4] Notably, R&D activities in the low R&D intensive group of young technology-based firms still play an integral role in obtaining competitive advantage (Kong and Su, 2021).

We identify firms' strategic R&D cooperation strategies by examining company announcement documents available on the official website of the Shenzhen Stock Exchange (ChiNext) website (https://www.szse.cn/index/index.html). Information about strategic R&D cooperation is extracted from these announcements. If a company's announcement states that it is engaged in strategic R&D cooperation with partners on products or technology between 2015 and 2019, we classify it as pursuing a strategy of promoting R&D cooperation. Conversely, if a company has no announcements regarding R&D cooperation during the same period, we consider it to have a strategy of not promoting R&D cooperation.

Our approach to the construct of the dependent variable is based on analysis of R&D cooperation announcements and reveals how organizations signal the importance of interorganizational R&D collaborations. These public cooperation signals reflect firms' strategic choices regarding engagement in R&D collaboration, and the publicly available signals provide a unique perspective on organizations R&D collaboration activities (e.g., Lu and Chesbrough, 2022). In other words, rather than relying on R&D surveys, the way we construct the dependent variable allows us to assess how firms perceive the strategic importance of R&D collaboration. This way of measurement has advantages in quality concerns and avoids limitations of self-reporting bias in surveys and allows to move beyond cross-sectional survey data commonly used to measure R&D collaboration (e.g., Lu and Chesbrough, 2022; Schäper et al., 2023).

The approach is in line with insights on the importance of the depth of R&D cooperation (Laursen and Salter, 2006) and allows inclusion of both formal and informal forms of R&D cooperation. It avoids focusing on commonly applied binary measurement of often less important R&D cooperation and is in line with where managerial attention is focusing on. In other words, if the target population of young technology-based firms mention R&D cooperation, we can suppose the importance is high in view of their R&D strategy.

Among the firms in the "HIG," thirty firms engaged in at least one strategic R&D cooperation, while in the "LIG," twenty-three firms did the same. Further details are provided in the subsequent section and in Tables 3 and 4, which present the definitions of the main variables and provide descriptive statistics. Additionally, we include return on assets and firm age as control variables. It is worth noting that the companies in the sample are relatively young with an average age of approximately 15 years (minimum of around 5 years and maximum of around 25 years), and are experiencing rapid growth. For consistency with prior research (Cin et al., 2017;

[2] ChiNext was launched on October 30 2009 alongside the Shenzhen Stock Exchange. As an independent market, ChiNext is an important component of China's multitier capital market system and mainly for Chinese growing and high-tech firms. ChiNext provides a new capital platform tailor-made for the needs of enterprises engaged in independent innovation and for other growing venture enterprises (Yu and Si, 2012).

[3] We consider the median value of R&D intensity as classification criteria for two reasons. First, firms listed on the ChiNext focus on some specific industries, such as manufacture of computer, electronic and optical products. Thus, it is not suitable to use classification based on industries (e.g., OECD taxonomy). Second, the target population are R&D active firms.

[4] Each year the firms were divided into two groups based on annual R&D intensity. A firm may be classified as HIG or LIG in different years.

**Table 3**
Definition of variables.

| Variables | Definition (Firm-level) | Unit |
|---|---|---|
| $\pi/L$ | Operating revenue per employee | CNY/person |
| $K/L$ | Fixed assets per employee | CNY/person |
| $R\&D$ | R&D investment | CNY |
| $L$ | Number of employees | Person |
| $ROA$ | Return on assets | CNY |
| $age$ | Firm age | Number of years |

**Table 4**
Dataset characteristics.

| Variables of HIG | No. of obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| $Ln(\pi/L)$ | 617 | 13.40 | 0.54 | 12.01 | 15.76 |
| $Ln(K/L)$ | 617 | 11.72 | 1.24 | 6.45 | 14.10 |
| $Ln(R\&D)$ | 617 | 17.77 | 0.89 | 15.60 | 21.82 |
| $Ln(L)$ | 617 | 6.68 | 0.84 | 4.89 | 11.46 |
| $Ln(ROA)$ | 617 | 1.81 | 0.70 | −1.13 | 3.30 |
| $Ln(age)$ | 617 | 2.65 | 0.30 | 1.79 | 3.30 |
| Variables of LIG | No. of obs | Mean | SD | Min | Max |
| $Ln(\pi/L)$ | 645 | 13.63 | 0.65 | 11.93 | 16.40 |
| $Ln(K/L)$ | 645 | 12.01 | 1.10 | 6.85 | 15.02 |
| $Ln(R\&D)$ | 645 | 17.09 | 0.85 | 13.44 | 21.22 |
| $Ln(L)$ | 645 | 6.86 | 0.94 | 4.57 | 11.55 |
| $Ln(ROA)$ | 645 | 1.79 | 0.67 | −2.12 | 3.46 |
| $Ln(age)$ | 645 | 2.72 | 0.34 | 1.79 | 3.53 |

Hottenrott et al., 2017), we take the natural logarithm of these variables.

### *3.5. Variable values in the stochastic evolutionary game model*

To perform the simulation analysis, we must acquire initial values for the variables in the stochastic evolutionary game model. This process involves several steps. First, we commence by investigating the parameters of the adjusted production function (Eq. 5) through empirical analysis using the database. The results of this analysis are presented in Table 7. Second, based on the results obtained from the adjusted production function, we proceed to calculate the values needed for the replicator dynamic equations (Eqs. 21 and 22). Third, we proceed with conducting simulations utilizing replicator dynamic equations.

Following the approach outlined by Cin et al. (2017), we initiate by dividing both sides of the improved production function (Eq. 5) by the labor stock and subsequently take logarithms. This allows us to formulate the productivity model for the two heterogeneous groups, denoted as "HIG" and "LIG" as follows:

$$\ln(\pi/L) = \ln(C) + \omega \ln(R\&D) + \beta \ln(K/L) + (\alpha + \beta - 1)\ln(L) + \delta_1 \ln(ROA) + \delta_2 \ln(age) + \varepsilon \tag{23}$$

Based on the unbalanced panel of 383 firms, the empirical results of the fixed effect model are presented in Table 5. The coefficients of all variables (both for HIG and LIG) are significant ($p < 0.01$).

In the period from 2015 to 2019, a total of 53 companies within our sample entered in 76 agreements for strategic R&D

**Table 5**
Results of regressions for the production function, coefficient (standard error).

| Variable | HIG | LIG |
|---|---|---|
| $\ln(K/L)$ | 0.041** | 0.096** |
| | (0.014) | (0.024) |
| $\ln(R\&D)$ | 0.405** | 0.486** |
| | (0.040) | (0.035) |
| $\ln(L)$ | −0.581** | −0.597** |
| | (0.051) | (0.040) |
| $\ln(ROA)$ | 0.137** | 0.118** |
| | (0.016) | (0.019) |
| $\ln(age)$ | 0.856** | 0.738** |
| | (0.131) | (0.158) |
| Constant | 7.097 | 6.030 |
| | (0.394) | (0.382) |
| $R^2$ | 0.51 | 0.59 |

Note: *denotes significance at the 5 percent level, **denotes significance at the 1 percent level.

cooperation. The percentage of HIG firms promoting strategic R&D cooperation stands at 15.1 %, while for LIG firms, it amounts to 12.5 %. These values serve as the initial fractions of cooperators in the respective groups (as shown in Table 6). Consequently, we can deduce the initial fractions of non-cooperators in HIG ($x = 84.9$ %) and LIG ($y = 87.5$ %), representing firms that do not engage in promoting strategic R&D cooperation.

Based on the results of Table 5 and Table 6, we obtain the initial values of the parameters of the production function (Table 7), except $\mu_i$,$\gamma_i$,$\theta_i$,$\sigma_i$ and $\sigma$. $R\&D_i$ is measured by R&D investment (Cin et al., 2017). $K_i$ and $L_i$ are the net value of fixed assets and the number of employees, respectively. For the parameters $\mu_i$,$\gamma_i$,$\theta_i$,$\sigma_i$ and $\sigma$, it is difficult to investigate the values by empirical analysis. Therefore, we set a group of values (0.001, 0.005, 0.009) for comparison.

To explore the effect of parameter values and assess the sensitivity of the evolutionary dynamic to variations, we conduct a robustness check by considering scenarios in which the parameters $x$ and $y$ vary within a range of 10 % and 5 %, respectively. Additional details and results of this sensitivity are provided in Appendix B.

## 4. Framework for attention allocation to strategic R&D cooperation

Regarding the second research question, this study investigates the framework of attention allocation, including players, procedures and rules, goals, and decision making. These insights offer valuable guidance for R&D managers to effectively allocate their attention to promote strategic R&D cooperation. The procedures and rules governing attention allocation are detailed in Section 4.1, with a three-stage analysis as an illustrative example, to explore how the five factors influence strategic R&D cooperation. Subsequently, in Section 4.2, we define the coordination of these five factors as the goal of attention allocation. Section 4.3 then evaluates the decision-making and attention allocation process aimed at promoting strategic R&D cooperation while regulating these five factors.

### *4.1. Procedures and rules of attention allocation: a three-stage analysis as an example*

Through simulations, the three-stage analysis elucidates the complex connections between the allocation of attention to the five factors and managerial decisions regarding strategic R&D cooperation. To attain the goal of attention allocation, it becomes crucial to establish precise procedures and rules governing the allocation process. These procedures and rules play a pivotal role in sifting out the determining factors. The investigation into the evolutionary dynamics of strategic R&D cooperation among firms in HIG and LIG under various scenarios characterized by different combinations ($\mu_i$,$\gamma_i$,$\theta_i$,$\sigma_i$and$\sigma$) is carried out through a progressive three-stage analysis process depicted in Fig. 1. Each successive stage incorporates a broader array of variables compared to the preceding stage, offering a comprehensive perspective on the subject.

We present the three-stage analysis not to suggest that managers must follow this operational process, but to illustrate how we capture the net effect of individual factors on strategic R&D cooperation. The stages are defined based on the stepwise introduction of key influencing factors - coordination costs, synergy effects, and R&D subsidies - which correspond to distinct theoretical mechanisms affecting firms' collaborative decisions. For example, comparing panel A and panel B of Fig. 1, the only difference is the intervention of the synergy effect ($\sigma$), which shifts the evolutionary dynamics from one state to another. This implies that the synergy effect ($\sigma$) plays a causal role in this shift. Therefore, the three-stage analysis serves merely as a demonstrative case to help clarify how each factor contributes to the evolution of R&D cooperation strategies.

The coefficient interval is in line with, e.g., the approach used for the coefficients of R&D subsidies on firm performance in China (Wang et al. 2020) and the coefficients of knowledge spillovers on firm productivity (Mitze and Makkonen, 2020). This setting will not change the simulation conclusion because all coefficients are compared at the same level.

In Fig. 1, as an illustrative example, we investigate the intricacies of coordination costs in the first stage. Moving to the second stage, we introduce the concept of the synergy effect in conjunction with coordination costs in strategic R&D cooperation. Finally, in the third stage, we incorporate R&D subsidies into the analysis. Each stage builds upon the insights gained from the previous stage, offering a progressively comprehensive perspective.

In the first stage (panel A of Fig. 1), when coordination costs ($\sigma_1$and$\sigma_2$) in strategic R&D cooperation are set a low value of 0.001, the fraction of non-cooperators in both HIG and LIG experiences significant fluctuations. Although there is a temporary downward trend during a specific period (i.e.,$Time \in [2, 2.5]$), the fraction of non-cooperators ultimately converges to 100 % in the long run. This implies that the fraction of non-cooperators surpasses the initial values (84.9 % for HIG and 87.5 % for LIG), resulting in a lock-in state when the coordination costs of strategic R&D cooperation are low ($\sigma_1$and$\sigma_2$ equal 0.001).

Moving to the second stage (panel B of Fig. 1), we introduce the influence of the synergy effect ($\sigma$) of strategic R&D cooperation while retaining the coordination costs from the first stage. In the initial phase (i.e., $Time \in [0, 0.5]$), similar to panel A, the fraction of non-cooperators in both the HIG and LIG experience a rapid rise, reaching 100 %. However, as time progresses, the fraction of non-cooperators gradually converges to zero. In other words, the short-term effect of enhancing the synergy effect is not readily apparent, as firms may exhibit instability by repeatedly shifting between cooperative and non-cooperative strategies. Nevertheless, this effect becomes evident in the long run. When the fraction of non-cooperators converges to zero, signifying 100 % cooperative firms in either HIG or LIG, the objectives are achieved. The efficiency of reaching this goal can be gauged by evolutionary time, where shorter evolutionary times indicate faster promotion of strategic R&D cooperation.

In the third stage (panel C of Fig. 1), we further enhance the coefficient of R&D subsidies ($\theta_1$, $\theta_2$) from 0 to 0.001, including a new incentive mechanism. R&D subsidies begin to influence the adoption of strategies (C or D) in both HIG and LIG. Two notable conditions

**Table 6**
Strategic R&D cooperation and initial fraction of non-cooperators in HIG and LIG during the period 2015-2019.

| Groups (R&D intensity) | Number of R&D cooperative firms | Number of ChiNext listed firms | Initial fraction of cooperative firms * | Initial fraction of non-cooperative firms |
|---|---|---|---|---|
| HIG (≥5.6 %) | 30 | 199 | 0.151 | $x = 0.849$ |
| LIG (<5.6 %) | 23 | 184 | 0.125 | $y = 0.875$ |

Note: R&D intensity equals R&D investment in operating revenue. The R&D intensity of firms varies from year to year. To consider the current situation, we use the data on the R&D intensity of firms in 2019 as the basis for grouping. *R&D cooperative firms /ChiNext listed firms.

**Table 7**
Values of variables in the stochastic evolutionary game model.

| Variables | $C_1$ | $R\&D_1$ | $L_1$ | $K_1$ | $\omega_1$ | $\beta_1$ | $\alpha_1$ | $x$ |
|---|---|---|---|---|---|---|---|---|
| Values | 7.097 | 233.777 | 27.568 | 650.28 | 0.405 | 0.041 | 0.378 | 0.849 |
| Variables | $C_2$ | $R\&D_2$ | $L_2$ | $K_2$ | $\omega_2$ | $\beta_2$ | $\alpha_2$ | $y$ |
| Values | 6.030 | 111.131 | 46.709 | 1159.388 | 0.486 | 0.096 | 0.307 | 0.875 |

Note: The value of $R\&D_i$,$L_i$,$K_i$ is the total value of firms in the two groups. The units of currency and employees are 100 million yuan and 10,000 people, respectively. In line with the basis of R&D intensity, we select the values of $R\&D_i$,$L_i$, and $K_i$ in 2019.

emerge in this stage. First, greater stability is observed in the time evolution of strategy adoption. The worst-case scenario (HIG: Time=0.74, $Y_{max}$=0.8002; LIG: Time=0.34, $Y_{max}$=0.7234) indicates that the fraction of non-cooperators falls below the initial values. If there is a regression from cooperation to non-cooperation, the situation does not deteriorate beyond the initial state. Second, efficiency improves. The evolutionary time to reach the state of 100 % cooperators is reduced compared to the second stage. Specifically, in the third stage, the evolutionary time for achieving this goal is 2.48 (HIG) and 2.24 (LIG), representing a reduction of 44.14 % for HIG and 49.55 % for LIG compared to the second stage.

Throughout the transition from the first stage to the third stage, a progressively expanding set of factors has been taken into account in the game. These factors have demonstrated a notable ability to significantly enhance the proportion of cooperators in both HIG and LIG. In comparison to the results derived from considering individual factors in isolation, the results from the multifactor coordination approach have proven to be more effective in promoting strategic R&D cooperation among firms.

In support of the three-stage analysis, we conducted sensitivity analyses, which are elaborated upon in Appendix B. The results presented in Figures B1 and B2 show minimal variations in the fraction of non-cooperators during specific time periods (e.g.,$Time \in [0, 0.2]$ in Figure B1. (a) and $Time \in [2.5, 3.8]$ in Figure B2. (b)). The different values of $x$ and $y$ do not alter the overarching of the evolutionary dynamic of the fraction of non-cooperators. The fraction of non-cooperators still converges to 100 % in the long run. Compared with the original value ($\sigma_i = 0.001$), we investigate the evolutionary dynamics when $\sigma_i = 0.002$and $\sigma_i = 0.003$ (Figure B3), and we find that the fraction of non-cooperators ultimately reaches 100 %, despite occasional fluctuations during specific periods (e.g., $Time \in [2, 4]$). Furthermore, we discuss different scenarios of $\sigma$ ($\sigma = 0.004$ and $\sigma = 0.006$ in Figure B4). A comparison between the evolutionary dynamics in Figure B4 and panel B of Fig. 1 reveals striking similarity. A similar comparison between Figure B5 ($\theta_i = 0.002$ and $\theta_i = 0.003$ in Figure B5) and panel C of Fig. 1 also corroborates this trend. Consequently, we can confidently assert that variations in variable values do not alter the final evolutionary dynamics of the fraction of non-cooperators. The conclusions drawn from the three-stage analysis remain robust even when considering changes in variable values within the examined range.

### *4.2. Goal of attention allocation: coordination of five factors of strategic R&D cooperation*

Within the context of the fundamental framework for analyzing multifactor coordination via the three-stage analysis, we systematically examine 19,683 combinations of the five factors. Through this rigorous exploration, we have identified specific combinations of attention allocation strategies favored by managers to promote strategic R&D cooperation. Furthermore, in pursuit of a more comprehensive analysis, we have considered three sets of values (0.001,0.005,0.009) for each parameter ($\mu_1$,$\mu_2$,$\gamma_1$,$\gamma_2$,$\theta_1$,$\theta_2$,$\sigma_1$,$\sigma_2$and$\sigma$). These three sets of values are used to represent three distinct scenarios: high value (0.009), median value (0.005), and low value (0.001). The results, showcasing the ten most strategic R&D cooperation favorable ("optimal") and the ten least favorable ("worst") combinations, are presented separately for HIG and LIG groups: Tables 8 and 9 report the optimal and worst combinations for the HIG group, respectively, while Tables 10 and 11 present the corresponding results for the LIG group. More details on the five-factor combinations can be found in Tables E1 and E2 in Appendix E.

The fraction of non-cooperators in HIG is expressed with $x$. The top ten and worst ten combinations are selected from 19,683 combinations for HIG. Evolutionary time represents the time needed for the fraction of non-cooperators to converge to zero.

To gain a deeper understanding of how managers prioritize the five factors when aiming to promote strategic R&D cooperation between firms, we have examined the actual attention allocated to these factors. Based on the literature review, we propose that the optimal combination for promoting strategic R&D cooperation consists of sufficient R&D subsidies ($\theta_i = 0.009$) and incoming knowledge spillovers ($\gamma_i = 0.009$), strong absorptive capacity ($\mu_i = 0.009$), a significant R&D synergy effect ($\sigma = 0.009$), and low coordination costs of strategic R&D cooperation ($\sigma_i = 0.001$).

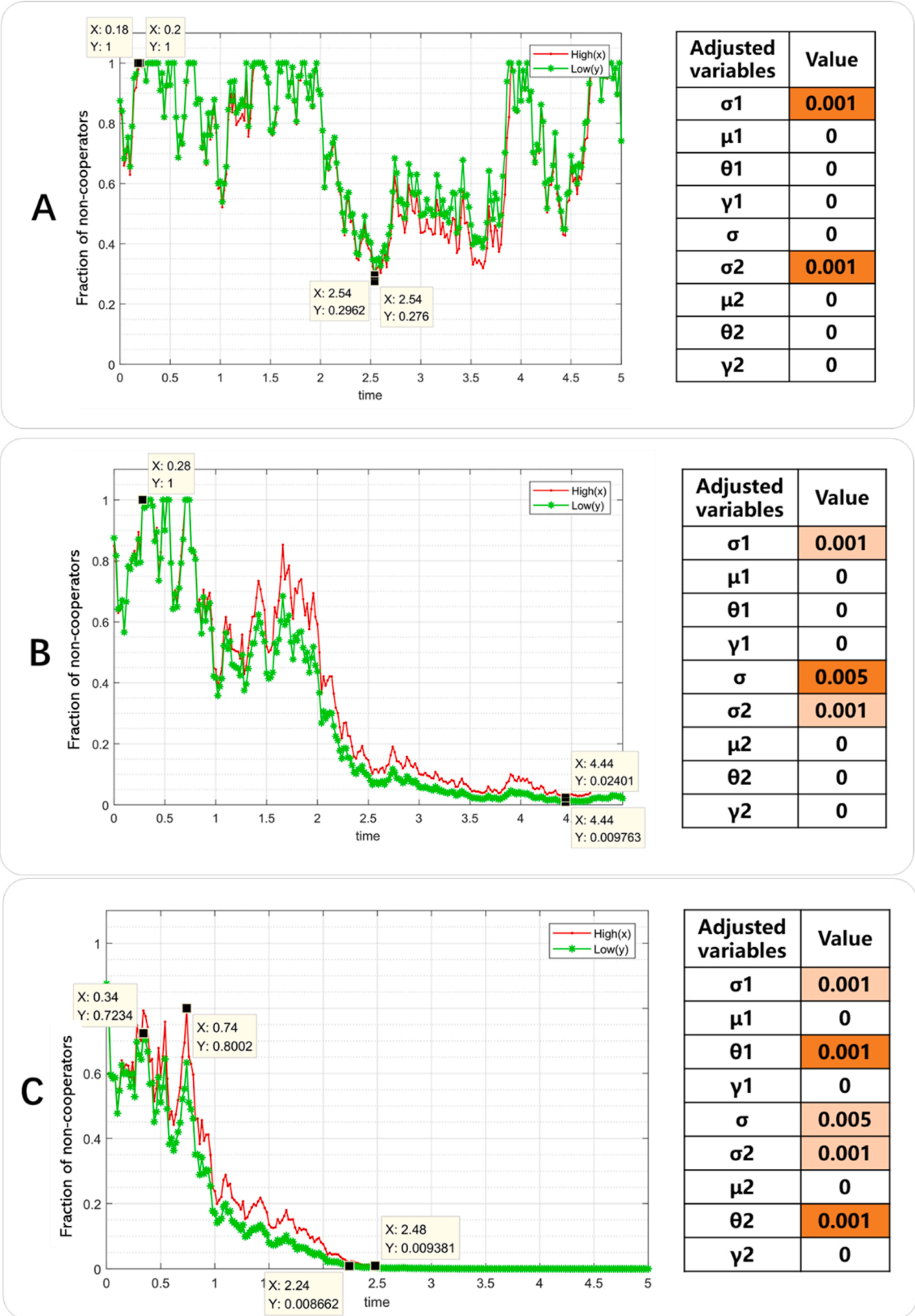


**Fig. 1.** The evolutionary dynamics of strategic R&D cooperation between HIG and LIG. Note: Intensity of stochastic disturbance $\xi = 1$, step size $h = 0.02$, time-interval $[T_0, T] = [0, 5]$. We use a seed equal to 0.5 for the generation of pseudorandom Wiener increments. Time is a virtual concept in simulation and does not indicate a specific year (Encarnação et al., 2018; Gao et al., 2014). Time (X-axis) refers to evolutionary time and consists of time steps. The time step size is the minimum division of the time on which the maximum iteration given is going to perform. For example, for a 1000-day simulation, the time steps will be 1000 when the time granularity is 1 day. The fraction of non-cooperators (Y-axis) refers to the fraction of non-cooperative firms in each group (HIG or LIG). Each panel (A, B, C) consists of two parts. (1) Left of panels. The evolutionary dynamics of HIG (red line) and LIG (green line). (2) Right of panels are variables' values. To compare and show the best simulation dynamics more intuitively, and for simplicity, in the simulation, we choose three sets of values: 0.001(low), 0.005 (median), and 0.009 (high).

**Table 8**
Optimal multifactor combinations for strategic decisions in R&D cooperation of HIG.

| Optimal combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time ($x$ first reaches zero) |
|---|---|---|---|---|---|---|
| No.1 | High | High | Low | High | High | 0.30 |
| No.2 | Middle | High | Low | High | High | |
| No.3 | High | High | Low | High | Middle | |
| No.4 | Middle | High | Low | High | Middle | |
| No.5 | Low | High | Low | High | High | |
| No.6 | High | High | Low | High | Low | |
| No.7 | Low | High | Low | High | Middle | |
| No.8 | Middle | High | Low | High | Low | |
| No.9 | Low | High | Low | High | Low | |
| No.10 | High | High | Low | Middle | High | 0.32 |

High Middle Low

Note: "High", "Middle", and "Low" refer to parameter values of 0.009, 0.005, and 0.001, respectively.

**Table 9**
Worst multifactor combinations for strategic decisions in R&D cooperation of HIG.

| Worst combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time ($x$ first reaches one) |
|---|---|---|---|---|---|---|
| No.1 | Low | Low | High | Low | Low | 0.06 |
| No.2 | Low | Low | High | Low | Middle | |
| No.3 | Middle | Low | High | Low | Low | |
| No.4 | Low | Low | High | Low | High | |
| No.5 | High | Low | High | Low | Low | |
| No.6 | Middle | Low | High | Low | Middle | |
| No.7 | Middle | Low | High | Low | High | |
| No.8 | High | Low | High | Low | Middle | |
| No.9 | High | Low | High | Low | High | |
| No.10 | Low | Low | High | Middle | Low | |

High Middle Low

Note: "High", "Middle", and "Low" refer to parameter values of 0.009, 0.005, and 0.001, respectively.

Comparing the combinations for strategic decisions in R&D cooperation for HIG (Tables 8,9) and LIG (Tables 10,11), it is evident that high R&D subsidies ($\theta_i = 0.009$) and low R&D coordination costs ($\sigma_i = 0.001$) are stable factors, regardless of variations in the other factors. This implies that before addressing the effects of incoming knowledge spillovers ($\gamma_i$), absorptive capacity ($\mu_i$) and R&D synergy ($\sigma$), decision-makers prioritize R&D subsidies ($\theta_i$) and minimize the coordination costs of strategic R&D cooperation ($\sigma_i$). Note that the value of the synergy effect becomes less critical in the tenth position of combinations ($\sigma$ decreased from 0.009 to 0.005), provided that significant attention is devoted to incoming knowledge spillovers ($\gamma_i = 0.009$) and absorptive capacity ($\mu_i = 0.009$). In this scenario, the incoming knowledge spillovers and absorptive capacity of both HIG and LIG firms serve as supplements to compensate for the relatively weak synergistic effect of strategic R&D cooperation.

On the opposite end of spectrum, the worst combinations reflect inadequate government R&D subsidies ($\theta_i = 0.001$) and incoming knowledge spillovers ($\gamma_i = 0.001$), weak absorptive capacity ($\mu_i = 0.001$), weak R&D synergy effect ($\sigma = 0.001$), and high coordination costs of strategic R&D cooperation ($\sigma_i = 0.009$). Although the variable values in the best and worst combinations are symmetrical (i.e., maximum $\mu_i(\mu_i = 0.009)$, $\theta_i(\theta_i = 0.009)$ in the best combination and minimum $\mu_i(\mu_i = 0.001)$, $\theta_i(\theta_i = 0.001)$ in the worst combination), it is intriguing to observe the asymmetry in the time needed to converge to a stable state (100 % cooperators or non-cooperators). In the scenarios of optimal combinations in Tables 8–11, the fraction of non-cooperators in HIG and LIG converges to zero when Time= 0.30 and Time= 0.26, respectively. However, for the worst combinations, the fraction of non-cooperators reaches 100 % at Time= 0.06 (HIG) and Time= 0.02 (LIG). Adjusting the variable values in factor combinations can make it challenging to promote 100 % cooperative firms within a short time. However, in the case of the worst combination, strategic R&D cooperation breaks down instantly.

**Table 10**
Optimal multifactor combinations for strategic decisions in R&D cooperation of LIG.

| Optimal combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time ($y$ first reaches zero) |
|---|---|---|---|---|---|---|
| No.1 | High | High | Low | High | High | 0.26 |
| No.2 | High | High | Low | High | Middle | |
| No.3 | Middle | High | Low | High | High | |
| No.4 | Middle | High | Low | High | Middle | |
| No.5 | High | High | Low | High | Low | |
| No.6 | Low | High | Low | High | High | |
| No.7 | Middle | High | Low | High | Low | |
| No.8 | Low | High | Low | High | Middle | |
| No.9 | Low | High | Low | High | Low | |
| No.10 | High | High | Low | Middle | High | 0.3 |

High
Middle
Low

Note: "High", "Middle", and "Low" refer to parameter values of 0.009, 0.005, and 0.001, respectively. The top ten and worst ten combinations are selected from 19,683 combinations for LIG. The fraction of non-cooperators in LIG is expressed with $y$.

**Table 11**
Worst multifactor combinations for strategic decisions in R&D cooperation of LIG.

| Worst combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time ($y$ first reaches one) |
|---|---|---|---|---|---|---|
| No.1 | Low | Low | High | Low | Low | 0.02 |
| No.2 | Middle | Low | High | Low | Low | |
| No.3 | Low | Low | High | Low | Middle | |
| No.4 | High | Low | High | Low | Low | |
| No.5 | Low | Low | High | Low | High | |
| No.6 | Middle | Low | High | Low | Middle | |
| No.7 | High | Low | High | Low | Middle | |
| No.8 | Middle | Low | High | Low | High | |
| No.9 | High | Low | High | Low | High | |
| No.10 | Low | Low | High | Middle | Low | 0.06 |

High
Middle
Low

Note: "High", "Middle", and "Low" refer to parameter values of 0.009, 0.005, and 0.001, respectively. The top ten and worst ten combinations are selected from 19,683 combinations for LIG. The fraction of non-cooperators in LIG is expressed with $y$.

### *4.3. Decision making of attention allocation: effect of factors on strategic R&D cooperation*

Given managers' limited cognitive abilities and finite attention resources, it is crucial for them to prioritize specific factors (Ocasio, 1997). To explore this further, we employ a comparative experimental approach by establishing a baseline group and a control group to assess the attention allocation toward each factor.

Taking Table 12 as an example, the evolutionary time required to reach zero non-cooperators in the HIG group is obtained from the simulation system described in Section 3.3. Both the baseline and control groups in the simulation use the same set of sample firms; the only difference lies in the assignment of the five key factors. This design enables us to isolate the net effect of these five factors on strategic R&D cooperation, while minimizing potential confounding influences from other variables.

In Table 12 and Table 13 we focus on R&D subsidies and take a baseline group as the reference point to examine how changes in the other five factors influence strategic R&D cooperation. The evolutionary time required to reach 100 % cooperators serves as a key indicator in our analysis. This metric allows us to capture the extent to which managerial attention to each of the five factors affects the dynamics of strategic R&D cooperation.

The baseline group shows the optimal value of R&D subsidies ($\theta_i$) and the worst values of other variables ($\mu_i$,$\sigma_i$,$\sigma$,$\gamma_i$).

The results regarding R&D subsidies are presented in Tables 12 and 13. We examine scenarios where R&D subsidies receive significant managerial attention. The findings suggest that diminishing the focus on R&D subsidies can result in the collapse of strategic

**Table 12**
Decision making of R&D subsidies for firms of HIG.

| Groups | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | Low | High | High | Low | Low | 3.5 |
| Control groups | Low | Low | High | Low | Low | - |
| | High | Low | High | Low | Low | - |
| | Low | Low | Low | Low | Low | 3.5 |
| | Low | Low | High | High | Low | - |
| | Low | Low | High | Low | High | - |

Note: Evolutionary time represents the time that the fraction of non-cooperation converges to zero (that is 100 % cooperators). "-" indicates that the fraction of cooperation converges to zero. In this case, no firm is willing to engage in strategic R&D cooperation.

**Table 13**
Decision making of R&D subsidies for firms of LIG.

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | Low | High | High | Low | Low | 3.36 |
| Control groups | Low | Low | High | Low | Low | - |
| | High | Low | High | Low | Low | - |
| | Low | Low | Low | Low | Low | 3.36 |
| | Low | Low | High | High | Low | - |
| | Low | Low | High | Low | High | - |

R&D cooperation among firms, assuming that other variables remain constant. For instance, in Table 12, when the parameter for R&D subsidies ($\theta_1$) decreases from 0.009 to 0.001, no firms participate in strategic R&D cooperation compared to the baseline group. A high technology start-up's founder insightfully observed, "Government-sponsored research projects are like a drug. (After receiving them) many companies never grow-up. They become reliant on them"(Yi et al., 2021). This situation can only be altered by reducing R&D coordination costs ($\sigma_i$), regardless of changes in other variables. From another perspective, our analysis indirectly reveals that coordination costs disproportionately attract managerial attention - a pattern likely driven by the elevated governance burdens inherent in interfirm cooperation among young technology-based firms (Xie et al., 2023).

The results concerning absorptive capacity are presented in Tables 14 and 15. We compare the baseline group with control groups characterized by low R&D absorptive capacity[5] ($\mu_i$). The results indicate that absorptive capacity is not the primary factor influencing firms' participation in strategic R&D cooperation, suggesting that managers pay limited attention to their firms' own absorptive capabilities when making collaboration-related decisions. This finding is consistent with the study by Guan et al. (2006), who argue that Chinese firms generally neglect the development of absorptive capacity. As a result, even when firms acquire key equipment and apparatus from abroad, such acquisitions often fail to translate into substantive innovation. High levels of R&D subsidies ($\theta_i$) and low R&D coordination costs ($\sigma_i$) can also stimulate strategic R&D cooperation among firms with low absorptive capacity. Similar results are observed for incoming knowledge spillovers (Appendix C: Tables C1 and C2). These results suggest that attention to knowledge spillovers and absorptive capacity in the decision-making process of strategic R&D cooperation among SMEs is rather limited.

As shown in Tables 16 and 17, compared to the baseline group, reducing attention to coordination costs ($\sigma_i$) from 0.009 to 0.001 leads to a dramatic shift in firms' strategic behavior - from complete non-cooperation to full cooperation, with the fraction of cooperating firms converging from zero to one. Notably, such a sharp transition is not observed in the analysis of any other variable, underscoring the uniquely pivotal role that coordination costs play in shaping cooperative outcomes. High coordination costs,

[5] The firms listed on ChiNext Board are R&D active and young high-tech companies. Thus, low R&D absorptive capacity is relative for the firms in the database.

**Table 14**
Decision making of absorptive capacity for firms of HIG.

| Groups | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | High | Low | High | Low | Low | - |
| Control groups | Low | Low | High | Low | Low | - |
| | Low | High | High | Low | Low | 3.5 |
| | Low | Low | Low | Low | Low | 3.5 |
| | Low | Low | High | High | Low | - |
| | Low | Low | High | Low | High | - |

High / Low

Note: Baseline group shows the optimal value of absorptive capacity ($\mu_i$) and the worst values of other variables ($\theta_i$,$\sigma_i$,$\sigma$,$\gamma_i$).

**Table 15**
Decision making of absorptive capacity for firms of LIG.

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | High | Low | High | Low | Low | - |
| Control groups | Low | Low | High | Low | Low | - |
| | Low | High | High | Low | Low | 3.36 |
| | Low | Low | Low | Low | Low | 3.36 |
| | Low | Low | High | High | Low | - |
| | Low | Low | High | Low | High | - |

High / Low

exacerbated by resource constraints and organizational immaturity (Hottenrott and Lopes-bento, 2016), have emerged as a critical impediment to the participation of young technology-based firms in R&D collaboration. This also helps explain why coordination costs command disproportionate managerial attention. A reduction in these costs significantly enhances managerial willingness to engage in cooperative innovation activities. Additionally, a combination of high attention to R&D subsidies ($\theta_i = 0.009$) and high attention to (low) coordination costs ($\sigma_i = 0.001$) can expedite firms' strategic R&D cooperation the most (evolutionary time equals 0.36 in Table 16 and 0.32 in Table 17). The results of the R&D synergy effect are presented in Appendix Tables C3 and C4.

**Table 16**
Decision making of coordination costs for firms of HIG.

| Groups | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | Low | Low | High | Low | Low | - |
| Control groups | Low | Low | Low | Low | Low | 3.5 |
| | High | Low | Low | Low | Low | 3.5 |
| | Low | High | Low | Low | Low | 0.36 |
| | Low | Low | Low | High | Low | 2.04 |
| | Low | Low | Low | Low | High | 3.5 |

High / Low

Note: Baseline group shows the worst value of coordination costs ($\sigma_i$) and the worst values of other variables ($\mu_i$,$\theta_i$,$\sigma$,$\gamma_i$).

**Table 17**
Decision making of coordination costs for firms of LIG.

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | Low | Low | High | Low | Low | - |
| Control groups | Low | Low | Low | Low | Low | 3.36 |
| | High | Low | Low | Low | Low | 3.36 |
| | Low | High | Low | Low | Low | 0.32 |
| | Low | Low | Low | High | Low | 1.74 |
| | Low | Low | Low | Low | High | 3.36 |

## 5. Discussion and conclusions

### 5.1. Theoretical contributions and management implications

This paper makes valuable contributions to two distinct research areas within the domain of strategic R&D cooperation.

First, it introduces a novel theoretical analysis grounded in EGT to investigate the collective effect of five factors (knowledge spillovers, absorptive capacity, R&D subsidies, R&D synergy effects, and coordination costs) on strategic R&D cooperation between "high" and "low" R&D intensive firms. This contribution aligns with the literature that examines the efficacy of determinants or firm-specific factors that influence the formation of R&D cooperation (e.g., Falvey et al. 2013, Franco and Gussoni, 2014, Guisado-González et al. 2018, López, 2008).

Second, the study enriches the literature on the attention-based view of technology decisions (Palmié et al., 2016) by presenting a framework for understanding attention allocation in the context of strategic R&D cooperation. The focus is directed toward how managers allocate their attention to coordination factors to foster strategic R&D cooperation. This is accomplished through a comprehensive simulation experiment involving 19,683 combinations of the five factors, shedding light on the extent to which managers allocate "multifactor" attention to these variables. In the context of young technology-based firms in China, the research suggests that multifactor-coordinated attention by managers is not prevalent. Instead, there appears to be a pronounced emphasis on subsidies and coordination costs in the decision-making process related to strategic R&D cooperation. These findings substantiate existing studies that underscore the influence of R&D subsidies on strategic R&D cooperation (e.g., Cantabene and Grassi, 2019) and align with Falvey et al. (2013) who emphasized that coordination costs are key factors influencing the success research joint ventures. Moreover, the study aligns with research that indicates limited attention to absorptive capacity in strategic R&D cooperation decisions (e.g., Guisado-González et al. 2018), suggesting that managerial attention to absorptive capacity plays a relatively minor role in the decision making process. Additionally, the research suggests that managerial attention to incoming knowledge spillovers in strategic R&D cooperation decisions is limited, offering fresh insights into the actual effect of outgoing and incoming spillovers on strategic R&D cooperation (contributing to the work of, e.g., Belderbos et al. 2004).

Our paper’s core theoretical contribution is evident in the identification of a discrepancy between theoretical insights concerning vital determinants of strategic R&D cooperation and an attention-based view that explains engagement in R&D collaboration. We present a framework that illuminates the lack of attention given by R&D managers to multifactor coordination as a means to promote strategic R&D cooperation. Our findings underscore the opportunity for policymakers and managers to mitigate bounded rationality in their decision-making process, particularly in the context of young technology-based firms. It becomes apparent that there is a need for greater emphasis on absorptive capacity and knowledge spillovers (both outgoing and incoming spillovers) as opposed to an exclusive focus on R&D subsidies and coordination costs when striving to promote strategic R&D cooperation.

Our research also carries significant managerial implications. First, the findings highlight the crucial need for managers to of young technology-based firms balance their attention between R&D subsidies and absorptive capacity. Firms tend to enter cooperation agreements that pose more disadvantages than benefits solely to secure R&D subsidies, without fully considering their own absorptive capacity to effectively utilize the knowledge flows generated by other firms (Guisado-González et al., 2018). Second, high coordination costs have emerged as a critical challenge in R&D collaborations among young technology-based firms (Soh and Subramanian, 2014). For these firms, constrained managerial attention renders the coordination costs of collaboration particularly burdensome (Hottenrott and Lopes-bento, 2016). Such costs are tangible and salient, often dominating managerial focus and crowding out attention to longer-term strategic considerations. To address this issue, both policymakers and corporate managers are advised to adopt a variety of strategies to reduce coordination costs and alleviate their negative impact on strategic R&D cooperation, including prioritizing clear contracts and cooperation agreements to minimize uncertainty and misalignment, as well as establishing a flexible decision-making mechanism for quick adjustments to market changes and technological advancements (Vivona et al., 2023).

### 5.2. Limitations and further research

The theoretical model proposed in our paper for decision-making in strategic R&D cooperation is grounded in five widely accepted determinants for R&D collaboration. However, it is worth considering the potential for extending or adapting the model by incorporating additional, strategic R&D cooperation-specific determinants. Future research could investigate how the flow of tacit and explicit knowledge among partners influences strategic R&D cooperation. While explicit knowledge is easier to transfer, tacit knowledge requires deeper interaction and stronger trust between partners (Park et al., 2022). Understanding this dynamic could provide valuable insights into how different types of knowledge impact cooperation and long-term collaboration success. Additionally, given that heterogeneous partners (e.g., firms, universities, and other institutions) often have different goals, future studies could use a multi-party evolutionary game model (Hu et al., 2025) to analyze how different types of partners (or partners with differing objectives) influence resource allocation and strategy adoption in R&D partnerships. Another key factor for future research is the geographical proximity of partners (Sarpong and Teirlinck, 2018). Research could examine how proximity affects cooperation by reducing communication costs and enhancing the frequency of interactions, which in turn facilitates better knowledge sharing. However, cross-border collaborations introduce challenges such as cultural differences, regulatory issues, and communication barriers. Investigating these factors could provide a deeper understanding of the stability and effectiveness of strategic R&D cooperation in diverse geographical contexts. Furthermore, it is important to contextualize our empirical results within the specific context of young technology-based firms in China during the period 2015–2019. Testing the theoretical model in different (other than Chinese) contexts could yield valuable insights into the influence of situational factors and the generalizability of our findings to various industries, economic and political environments, and different types of firms beyond just fast-growing ones.

Besides, a promising direction for future research is incorporating Stochastic Evolutionary Stability (SES) and Stochastic Convergence Stability (SCS) (Feng; et al., 2022; Zheng et al., 2017) into the study of corporate strategic R&D cooperation. While our stochastic EGT model simulates evolutionary dynamics, SES and SCS provide deeper insights into long-term equilibrium selection and cooperation stability under perturbations. Future studies could explore how firm heterogeneity influences cooperation stability, the role of path dependence in locking firms into suboptimal partnerships, and the impact of asymmetric information on cooperation breakdowns. Additionally, SES and SCS could help analyze the influence of geographical and institutional factors on R&D collaboration resilience and assess how external shocks, such as policy changes or technological disruptions, affect long-term cooperative behaviors. Extending these stability concepts would enhance our understanding of how firms sustain R&D partnerships, adapt to uncertainty, and navigate dynamic competitive environments.

## CRediT authorship contribution statement

**Junqiang Li:** Writing – original draft, Methodology, Formal analysis, Data curation. **Peter Teirlinck:** Writing – review & editing, Supervision, Project administration, Formal analysis, Conceptualization.

## Acknowledgements

The authors thank the editor and three anynomous reviewers for their valuable feedback. This work was supported by the China National Office for Philosophy and Social Sciences - Grant number: 24CGL016.

## Appendix A. Calculation of expected earning

Let $U_{11}$ and $U_{12}$ represent respectively the expected earning of "not promoting strategic R&D cooperation" and "promoting strategic R&D cooperation" for group 1:

$$U_{11} = (1-y)(C_1(R\&D)_1^{\omega_1+\mu_1\gamma_2+\theta_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1}) + y(C_1(R\&D)_1^{\omega_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1})$$

$$U_{12} = (1-y)(C_1(R\&D)_1^{\omega_1+\mu_1\gamma_2+\theta_1+\sigma}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1}) + y(C_1(R\&D)_1^{\omega_1+\theta_1-\sigma_1}H_1^{\delta_1}L_1^{\alpha_1}K_1^{\beta_1})$$

Let $U_{21}$ and $U_{22}$ represent respectively the expected earning of "not promoting strategic R&D cooperation" and "promoting strategic R&D cooperation" for group 2:

$$U_{21} = (1-x)(C_2(R\&D)_2^{\omega_2+\mu_2\gamma_1+\theta_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2}) + x(C_2(R\&D)_2^{\omega_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2})$$

$$U_{22} = (1-x)(C_2(R\&D)_2^{\omega_2+\mu_2\gamma_1+\theta_2+\sigma}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2}) + x(C_2(R\&D)_2^{\omega_2+\theta_2-\sigma_2}H_2^{\delta_2}L_2^{\alpha_2}K_2^{\beta_2})$$

## Appendix B. : Sensitivity analysis

To investigate the influence of setting values of parameters on the evolutionary dynamic, we use several sets of values for new simulations. The details are below:

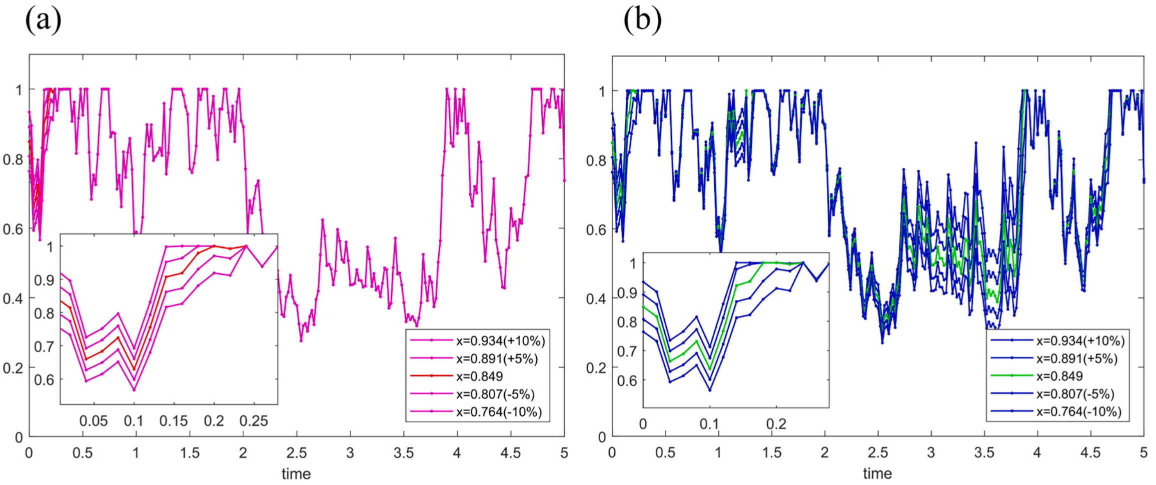


**Figure B1.** Evolutionary dynamic with four sets values of $x$ (+10 %, +5 %, −5 %, −10 % compared with the initial value $x = 0.849$), (a) shows the effect of different initial values of $x$ on HIG. (b) shows the effect of different initial values of $x$ on LIG. $x = 0.849$ is the original value

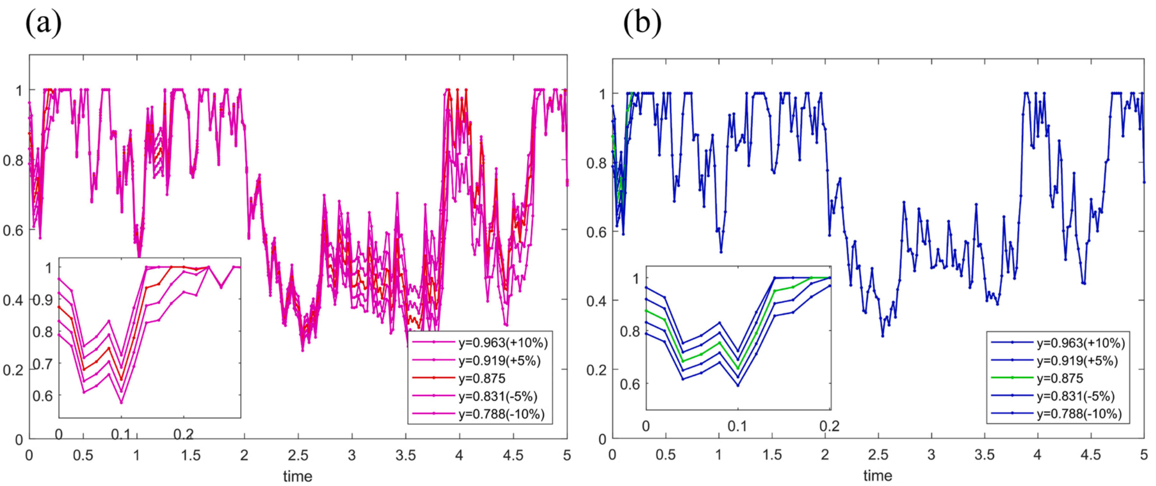


**Figure B2.** Evolutionary dynamic with four sets values of $y$ (+10 %, +5 %, −5 %, −10 % compared with the initial value $y = 0.875$). (a) shows the effect of different initial values of $y$ on HIG. (b) shows the effect of different initial values of $y$ on LIG. $y = 0.875$ is the original value

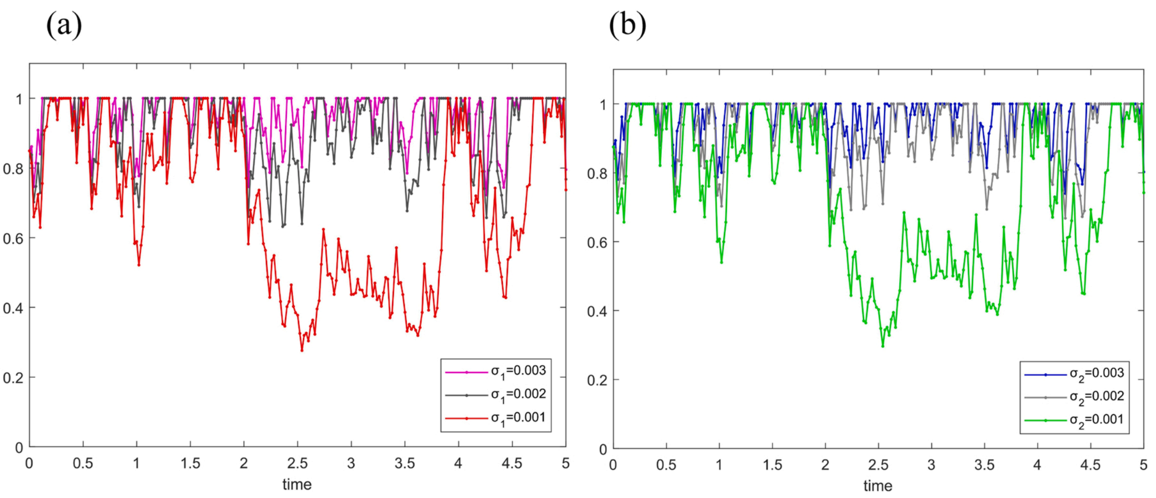


**Figure B3.** Evolutionary dynamic with three sets values of $\sigma_1$ and $\sigma_2$ (0.001, 0.002, 0.003). (a) shows the effect of different values of $\sigma_1$ on HIG. (b) shows the effect of different values of $\sigma_2$ on LIG. $\sigma_1 = 0.001$ and $\sigma_2 = 0.001$ are the original values

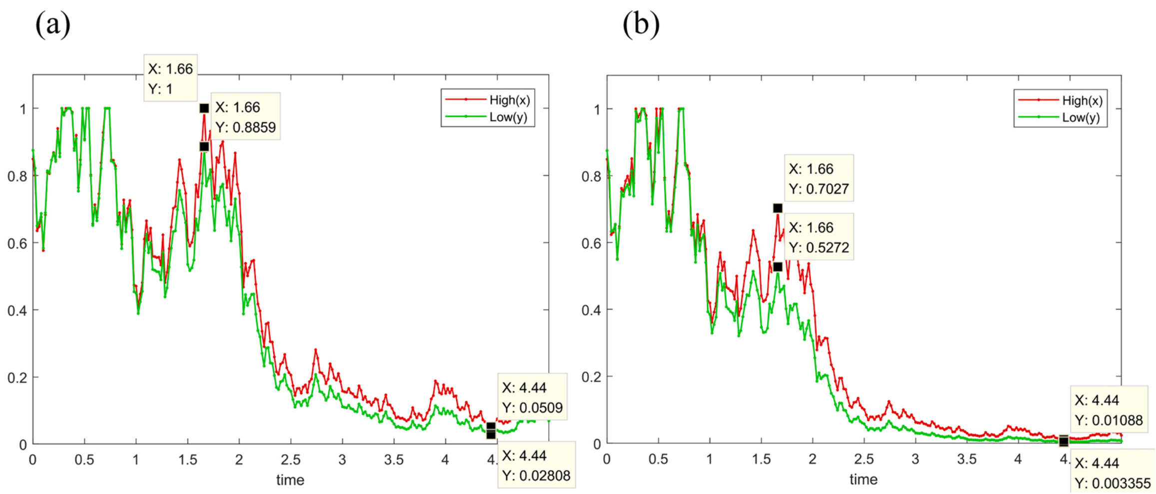


**Figure B4.** Evolutionary dynamic with two sets values of $\sigma$ (0.004, 0.006). (a) shows the effect of $\sigma = 0.004$ on HIG and LIG. (b) shows the effect of $\sigma = 0.006$ on HIG and LIG. $\sigma = 0.005$ is the original value

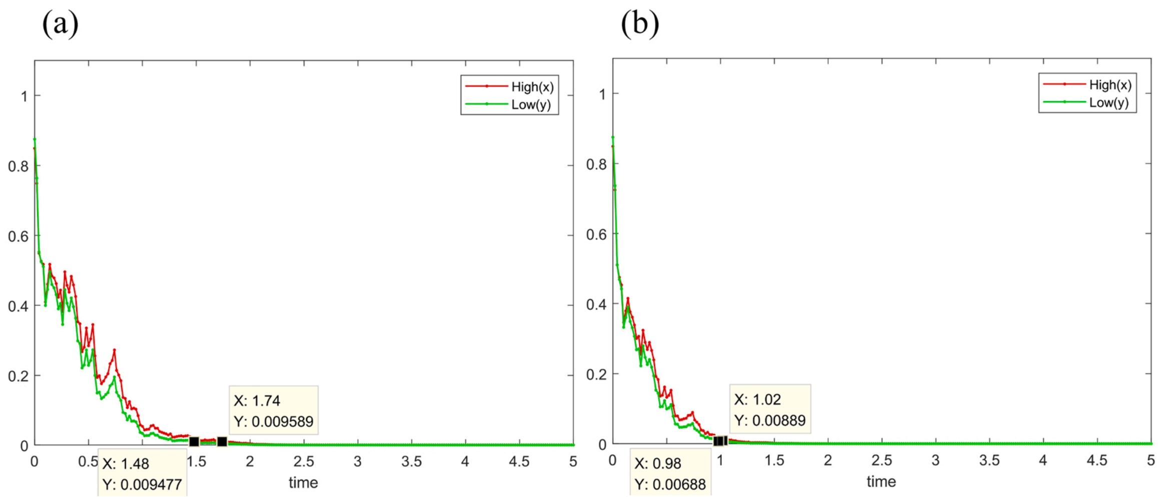


**Figure B5.** Evolutionary dynamic with two sets values of $\theta_1$ and $\theta_2$ (0.002, 0.003). (a) shows the effect of $\theta_1 = 0.002$ and $\theta_2 = 0.002$ on HIG and LIG. (b) shows the effect of $\theta_1 = 0.003$ and $\theta_2 = 0.003$ on HIG and LIG. $\theta_1 = 0.001$ and $\theta_2 = 0.001$ are the original values

## Appendix C. : Decision making results

**Table C1**
Decision making of (incoming) knowledge spillovers for firms of HIG

| Groups | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |
| | 0.009 | 0.001 | 0.009 | 0.001 | 0.009 | - |
| | 0.001 | 0.009 | 0.009 | 0.001 | 0.009 | 3.5 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.009 | 3.5 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.009 | - |

Note: Baseline group shows the worst value of knowledge spillovers ($\gamma_i$) and the worst values of other variables ($\mu_i$,$\theta_i$,$\sigma_i$,$\sigma$).

**Table C2**
Decision making of (incoming) knowledge spillovers for firms of LIG

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |
| | 0.009 | 0.001 | 0.009 | 0.001 | 0.009 | - |
| | 0.001 | 0.009 | 0.009 | 0.001 | 0.009 | 3.36 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.009 | 3.36 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.009 | - |

**Table C3**
Decision making of R&D synergy effect for firms of HIG

| Groups | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.009 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.001 | 0.009 | 0.009 | 0.009 | 0.001 | 2.02 |
| | 0.001 | 0.001 | 0.001 | 0.009 | 0.001 | 2.04 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.009 | - |

Note: Baseline group shows the worst value of R&D synergy effect ($\sigma$) and the worst values of other variables ($\mu_i$,$\theta_i$,$\sigma_i$,$\gamma_i$).

**Table C4**
Decision making of R&D synergy effect for firms of LIG

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.009 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.001 | 0.009 | 0.009 | 0.009 | 0.001 | 1.56 |
| | 0.001 | 0.001 | 0.001 | 0.009 | 0.001 | 1.74 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.009 | - |

## Appendix D. Robustness check with new database

New database for simulations

We provide a new theoretical model to look at strategic R&D cooperation behavior. For emphasizing the repeatability of the model, we test a new sample of China's STAR market (officially known as the Science and Technology Innovation Board). To support the development of high-tech industries, the Shanghai Stock Exchange STAR market was launched on 22 July 2019. Unlike the Main Board and ChiNext Board, the STAR market changes the previous requirements profitability and corporate governance of IPOs, which provides a flexible platform for innovative firms going public (Yan et al., 2022).

We get an unbalanced panel dataset with a sample of 374 firms (2019–2021). The basic information of firms is gathered form the China Stock Market and Accounting Research (CSMAR) database. The cooperation details are collected manually according to the announcements on the websites of Shanghai Stock Exchange. If a company states in the announcement that it is cooperating with other firms from 2019 to 2021, we consider this to be a strategy for promoting strategic R&D cooperation. According to the median value of R&D intensity, we classify these firms into two groups. HIG includes firms with above-median R&D intensity (Firms' R&D intensity≥8.69 %). LIG includes firms with below-median R&D intensity (Firms' R&D intensity <8.69 %). More details about the dataset are provided in Table D1.

**Table D1**
Dataset characteristics

| Variables of HIG | No. of obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| $Ln(\pi/L)$ | 340 | 13.646 | 0.609 | 12.276 | 15.500 |
| $Ln(K/L)$ | 340 | 11.789 | 1.290 | 8.192 | 15.123 |
| $Ln(R\&D)$ | 340 | 9.063 | 0.926 | 7.323 | 13.054 |
| $Ln(L)$ | 340 | 6.500 | 0.810 | 4.605 | 9.780 |
| $Ln(ROA)$ | 340 | 1.809 | 0.702 | −2.303 | 3.273 |
| $Ln(age)$ | 340 | 2.699 | 0.314 | 1.792 | 3.401 |
| Variables of LIG | No. of obs | Mean | SD | Min | Max |

(continued on next page)

**Table D1** (*continued*)

| Variables of HIG | No. of obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| $Ln(\pi/L)$ | 338 | 14.062 | 0.681 | 12.473 | 16.358 |
| $Ln(K/L)$ | 338 | 12.468 | 0.978 | 8.184 | 14.749 |
| $Ln(R\&D)$ | 338 | 8.734 | 1.040 | 6.897 | 12.483 |
| $Ln(L)$ | 338 | 6.810 | 0.965 | 4.317 | 10.342 |
| $Ln(ROA)$ | 338 | 1.938 | 0.716 | −1.204 | 4.101 |
| $Ln(age)$ | 338 | 2.771 | 0.354 | 1.792 | 3.714 |

Following the same model (23), we can get the empirical results of the fixed effect model in Table D2.Table D3 summaries the strategic R&D cooperation details. In 2021, 35 firms in our samples signed agreements for strategic R&D cooperation. The share of HIG and LIG firms promoting the strategic R&D cooperation is 9.8 % and 9.7 %. Then, we can get the initial fraction of non-cooperators in HIG ($x = 90.2$ %) and LIG ($y = 90.3$ %).

**Table D2**
Results of regressions for the production function, coefficient (standard error)

| Variable | HIG | LIG |
|---|---|---|
| $\ln(K/L)$ | 0.014 | −0.041 |
| | (0.016) | (0.041) |
| $\ln(R\&D)$ | 0.402** | 0.849** |
| | (0.056) | (0.069) |
| $\ln(L)$ | −0.468** | −0.892** |
| | (0.083) | (0.108) |
| $\ln(ROA)$ | 0.144** | 0.129** |
| | (0.019) | (0.028) |
| $\ln(age)$ | 0.130 | 0.020 |
| | 0.314 | (0.311) |
| Constant | 12.271 | 12.938 |
| $R^2$ | 0.465 | 0.665 |

Note:
*denotes significance at 5 percent level,
**denotes significance at 1 percent level.

**Table D3**
Strategic R&D cooperation and the initial fraction of non-cooperators in HIG and LIG in 2021

| Groups (R&D intensity) | Number of R&D cooperative firms | Number of ChiNext listed firms | Initial fraction of cooperative firms * | Initial fraction of non-cooperative firms |
|---|---|---|---|---|
| HIG (≥5.72 %) | 17 | 173 | 0.098 | $x = 0.902$ |
| LIG (<5.72 %) | 18 | 185 | 0.097 | $y = 0.903$ |

Note: R&D intensity equals R&D investment on operating revenue.
*R&D cooperative firms /STAR Market listed firms.

We get the initial value of parameters of production function in Table D4.

**Table D4**
Values of variables in stochastic evolutionary game model

| Variables | $C_1$ | $R\&D_1$ | $L_1$ | $K_1$ | $\omega_1$ | $\beta_1$ | $\alpha_1$ | $x$ |
|---|---|---|---|---|---|---|---|---|
| Values | 12.271 | 316.328 | 20.034 | 1050.697 | 0.402 | 0.014 | 0.518 | 0.902 |
| Variables | $C_2$ | $R\&D_2$ | $L_2$ | $K_2$ | $\omega_2$ | $\beta_2$ | $\alpha_2$ | $y$ |
| Values | 12.938 | 285.314 | 33.416 | 1353.921 | 0.849 | −0.041 | 0.149 | 0.903 |

Note: The value of $R\&D_i$,$L_i$,$K_i$ is the total value of firms in the two groups. The unit of currency and employees are respectively 100 million yuan and 10,000 persons. In line with the basis of R&D intensity, we select the values of $R\&D_i$,$L_i$,$K_i$ in 2021.

The robustness test of decision making

For testing the robustness of simulation, we investigate the evolutionary dynamics with new database (the STAR market). As the results shown in Figure D1, LIG can still be considered as the first movers. Comparing to HIG, the dynamics of LIG are always closer to the direction of convergence in three scenarios. Hence, our results are robust.

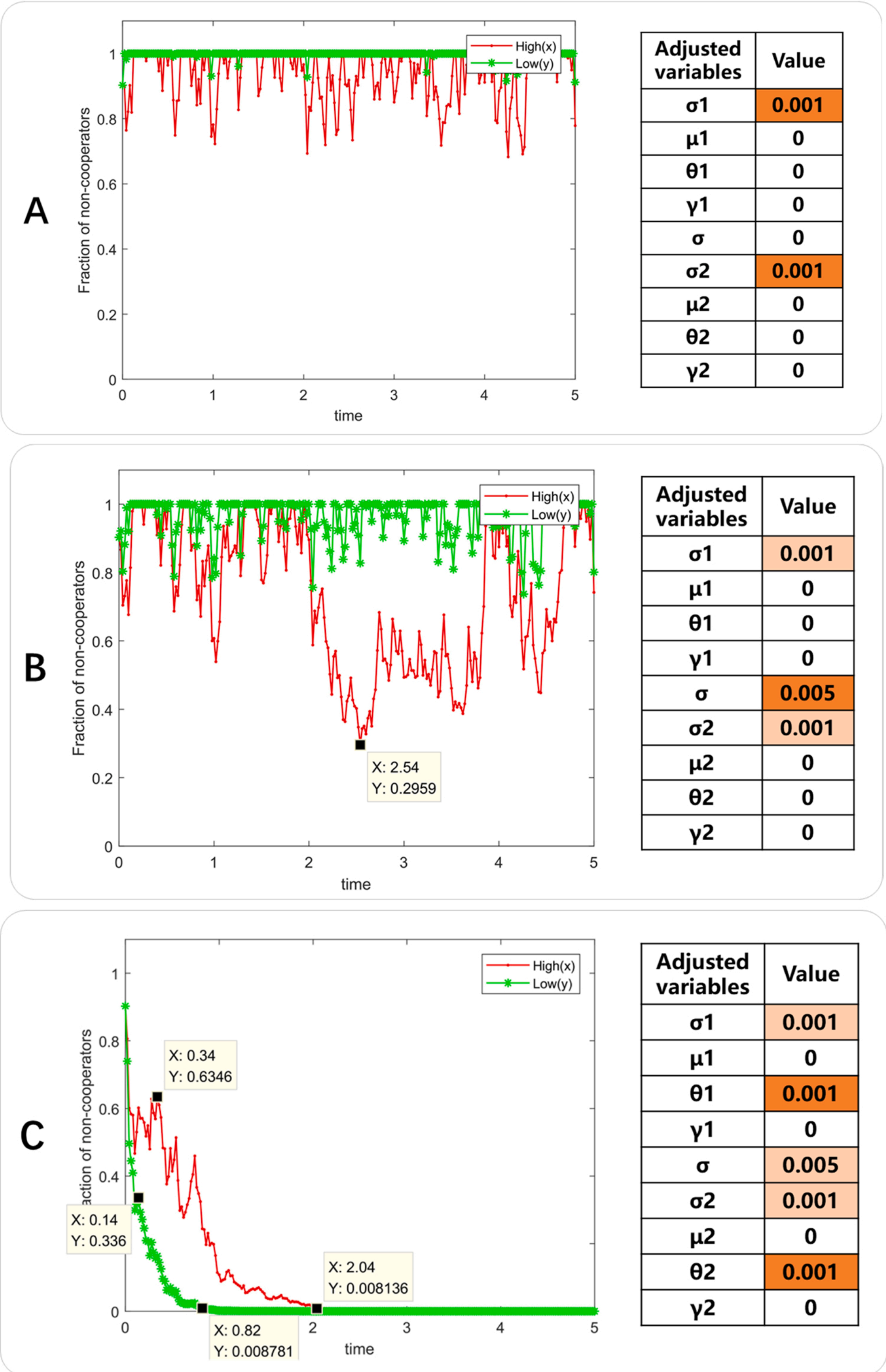


**Figure D1.** The evolutionary dynamic of strategic R&D cooperation between HIG and LIG. Note: Intensity of stochastic disturbance $\xi = 1$, step size $h = 0.02$, time-interval $[T_0, T] = [0,5]$. We use a seed equal to 0.5 for the generation of pseudo-random Wiener increments. Time is a virtual concept in simulation and does not indicate a specific year (Encarnação et al., 2018; Gao et al., 2014). Time (X-axis) refers to evolutionary time and consists of time steps. Time step size is the minimum division of the time on which the maximum iteration given is going to perform. For example, for a 1000 days simulation, the time steps will be 1000 when the time granularity is 1 day. The fraction of non-cooperators (Y-axis) refers to the fraction of non-cooperative firms in each group (HIG or LIG)

Each panel (A, B, C) consists of two parts. (1) Left of panels. The evolutionary dynamic of HIG (red line) and LIG (green line). (2)

Right of panels are variables' values. To compare and show the best simulation dynamics more intuitively, and for simplicity, in the simulation, we choose three sets of values: 0.001(low), 0.005 (median), 0.009 (high).

The coefficient interval is in line with e.g. the approach used for the coefficients of R&D subsidies on firm performance in China (Wang et al. 2020) and the coefficients of knowledge spillovers on firm productivity (Mitze and Makkonen, 2020). This setting will not change the simulation conclusion because all the coefficients are compared at the same level.

Comparing with the Tables D5, D6 and Tables 7,8, the ten most optimal and the ten worst combinations are the same. The results are robust.

**Table D5**
Results of multi-factor combinations for strategic decisions in strategic R&D cooperation of HIG

| Optimal combinations | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | $a$ | Evolutionary time ($x$ first reaches zero) |
|---|---|---|---|---|---|---|---|
| 1 | 0.009 | 0.009 | 0.001 | 0.009 | 0.009 | −31.0272 | 0.08 |
| 2 | 0.005 | 0.009 | 0.001 | 0.009 | 0.009 | −31.02647 | 0.08 |
| 3 | 0.009 | 0.009 | 0.001 | 0.009 | 0.005 | −31.02647 | 0.08 |
| 4 | 0.005 | 0.009 | 0.001 | 0.009 | 0.005 | −31.02607 | 0.08 |
| 5 | 0.001 | 0.009 | 0.001 | 0.009 | 0.009 | −31.02574 | 0.08 |
| 6 | 0.009 | 0.009 | 0.001 | 0.009 | 0.001 | −31.02574 | 0.08 |
| 7 | 0.001 | 0.009 | 0.001 | 0.009 | 0.005 | −31.02566 | 0.08 |
| 8 | 0.005 | 0.009 | 0.001 | 0.009 | 0.001 | −31.02566 | 0.08 |
| 9 | 0.001 | 0.009 | 0.001 | 0.009 | 0.001 | −31.02558 | 0.08 |
| 10 | 0.009 | 0.009 | 0.001 | 0.005 | 0.009 | −29.44312 | 0.1 |
| Worst combinations | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | $a$ | Evolutionary time ($x$ first reaches one) |
| 1 | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | 25.91112 | 0.02 |
| 2 | 0.001 | 0.001 | 0.009 | 0.001 | 0.005 | 25.91111 | 0.02 |
| 3 | 0.005 | 0.001 | 0.009 | 0.001 | 0.001 | 25.91111 | 0.02 |
| 4 | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | 25.91111 | 0.02 |
| 5 | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | 25.91111 | 0.02 |
| 6 | 0.005 | 0.001 | 0.009 | 0.001 | 0.005 | 25.91107 | 0.02 |
| 7 | 0.005 | 0.001 | 0.009 | 0.001 | 0.009 | 25.91102 | 0.02 |
| 8 | 0.009 | 0.001 | 0.009 | 0.001 | 0.005 | 25.91102 | 0.02 |
| 9 | 0.009 | 0.001 | 0.009 | 0.001 | 0.009 | 25.91095 | 0.02 |
| 10 | 0.001 | 0.001 | 0.009 | 0.005 | 0.001 | 24.43345 | 0.02 |

Note: The stochastic differential equation of HIG is $dX_t = f(X_t)dt + \xi dW_t = aX_t dt + \xi dW_t$. The intensity of stochastic disturbance $\xi = 1$, step size $h = 0.02$, and time-interval $[T_0, T] = [0,5]$. The fraction of non-cooperators in HIG is expressed with $x$. The top ten and worst ten combinations are selected from 19,683 combinations for HIG. Evolutionary time represents the time that the fraction of non-cooperators converges zero.

**Table D6**
Results of multi-factor combinations for strategic decisions in strategic R&D cooperation of LIG

| Optimal combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | $b$ | Evolutionary time ($y$ first reaches zero) |
|---|---|---|---|---|---|---|---|
| 1 | 0.009 | 0.009 | 0.001 | 0.009 | 0.009 | −92.96014 | 0.02 |
| 2 | 0.009 | 0.009 | 0.001 | 0.009 | 0.005 | −92.95798 | 0.02 |
| 3 | 0.005 | 0.009 | 0.001 | 0.009 | 0.009 | −92.95798 | 0.02 |
| 4 | 0.005 | 0.009 | 0.001 | 0.009 | 0.005 | −92.95798 | 0.02 |
| 5 | 0.009 | 0.009 | 0.001 | 0.009 | 0.001 | −92.95582 | 0.02 |
| 6 | 0.001 | 0.009 | 0.001 | 0.009 | 0.009 | −92.95582 | 0.02 |
| 7 | 0.005 | 0.009 | 0.001 | 0.009 | 0.001 | −92.95558 | 0.02 |
| 8 | 0.001 | 0.009 | 0.001 | 0.009 | 0.005 | −92.95558 | 0.02 |
| 9 | 0.001 | 0.009 | 0.001 | 0.009 | 0.001 | −92.95534 | 0.02 |
| 10 | 0.009 | 0.009 | 0.001 | 0.005 | 0.009 | −88.17148 | 0.02 |
| Worst combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | $b$ | Evolutionary time ($y$ first reaches one) |
| 1 | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | 77.59254 | 0.02 |
| 2 | 0.005 | 0.001 | 0.009 | 0.001 | 0.001 | 77.59252 | 0.02 |
| 3 | 0.001 | 0.001 | 0.009 | 0.001 | 0.005 | 77.59252 | 0.02 |
| 4 | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | 77.59249 | 0.02 |
| 5 | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | 77.59249 | 0.02 |
| 6 | 0.005 | 0.001 | 0.009 | 0.001 | 0.005 | 77.59239 | 0.02 |
| 7 | 0.009 | 0.001 | 0.009 | 0.001 | 0.005 | 77.59227 | 0.02 |
| 8 | 0.005 | 0.001 | 0.009 | 0.001 | 0.009 | 77.59227 | 0.02 |
| 9 | 0.009 | 0.001 | 0.009 | 0.001 | 0.009 | 77.59204 | 0.02 |
| 10 | 0.001 | 0.001 | 0.009 | 0.005 | 0.001 | 73.12001 | 0.02 |

Note: The stochastic differential equation of HIG is $dY_t = f(Y_t)dt + \xi dW_t = bY_t dt + \xi dW_t$. The intensity of stochastic disturbance $\xi = 1$, step size $h = 0.02$, and time-interval $[T_0, T] = [0,5]$. The top ten and worst ten combinations are selected from 19,683 combinations for LIG. The fraction of non-cooperators in LIG is expressed with $y$.

The results provided in Tables D7 to D12 can well prove our findings. According to the results in Tables D7 and D8, even if R&D subsidies are reduced, firms will engage in the strategic R&D cooperation as long as coordination costs are decreased. Comparing the results in Tables D9 and D10, high level R&D subsidies ($\theta_i$) and low R&D coordination costs ($\sigma_i$) can also promote strategic R&D cooperation in firms with low absorptive capacity. As shown in Tables D11 and D12, only reducing the coordination costs ($\sigma_i$) from 0.009 to 0.001 has a significant impact.

**Table D7**
Decision making of R&D subsidies for firms of HIG

| Values | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.009 | 0.009 | 0.001 | 0.001 | 3.28 |
| Control groups | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 3.28 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |

Note: Evolutionary time represents the time that the fraction of non-cooperation converges to zero (that is 100 % cooperators). "-" indicates that the fraction of cooperation converges to zero. In this case, no firm is willing to engage in strategic R&D cooperation. The green box indicates that the variables' values has changed compared to the benchmark.

Baseline group shows the optimal value of R&D subsidies ($\theta_i$) and the worst values of other variables ($\mu_i$,$\sigma_i$,$\sigma$,$\gamma_i$).

**Table D8**
Decision making of R&D subsidies for firms of LIG

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.009 | 0.009 | 0.001 | 0.001 | 2.36 |
| Control groups | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 2.38 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |

**Table D9**
Decision making of absorptive capacity for firms of HIG

| Values | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 0.001 | 0.009 | 0.009 | 0.001 | 0.001 | 3.28 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 3.28 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |

Note: Baseline group shows the optimal value of absorptive capacity ($\mu_i$) and the worst values of other variables ($\theta_i$,$\sigma_i$,$\sigma$,$\gamma_i$).

**Table D10**
Decision making of absorptive capacity for firms of LIG

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 0.001 | 0.009 | 0.009 | 0.001 | 0.001 | 2.36 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 2.38 |
| | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |

**Table D11**
Decision making of coordination costs for firms of HIG

| Values | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 3.28 |
| | 0.009 | 0.001 | 0.001 | 0.001 | 0.001 | 3.28 |
| | 0.001 | 0.009 | 0.001 | 0.001 | 0.001 | 0.1 |
| | 0.001 | 0.001 | 0.001 | 0.009 | 0.001 | 1.24 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.009 | 3.28 |

Note: Baseline group shows the worst value of coordination costs ($\sigma_i$) and the worst values of other variables ($\mu_i$,$\theta_i$,$\sigma$,$\gamma_i$).

**Table D12**
Decision making of coordination costs for firms of LIG

| Groups | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | Evolutionary time for reaching zero non-cooperator in LIG |
|---|---|---|---|---|---|---|
| Baseline group | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| Control groups | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 2.38 |
| | 0.009 | 0.001 | 0.001 | 0.001 | 0.001 | 2.38 |
| | 0.001 | 0.009 | 0.001 | 0.001 | 0.001 | 0.02 |
| | 0.001 | 0.001 | 0.001 | 0.009 | 0.001 | 0.42 |
| | 0.001 | 0.001 | 0.001 | 0.001 | 0.009 | 2.38 |

Control process for the endogeneity issues

We conduct the simulations by following the logic of quasi-experiment. By setting the baseline groups and control groups, we control the potential influence and recognize the net effects of single factor on the results.

The potential correlation between variables do not influence the results of decision making. We set the baseline group and control group for comparing, which mainly remove the disturbance of variables' correlation. We take absorptive capacity ($\mu_i$) and knowledge spillovers ($\gamma_i$) as an example. In Table D7*(see group 1,2,4,5), for comparing influences of the different values of R&D subsidies ($\theta_i$) on the results, we have already controlled the values of absorptive capacity ($\mu_i = 0.001$) and knowledge spillovers ($\gamma_i = 0.001$). In other words, even if the absorptive capacity has potential influences on the knowledge spillovers, the correlations can exist in group 1,2,4,5 at the same time, which have no disturbance on the results. Between the group 1 and group 2, the only difference is the values of R&D subsidies. The controlling measurements is effective for the analysis of other variables.

Following the same logic, we can also eliminate the interference of other factors (excluding five factors) on our results. As shown in Table D7*, if disturbance from other factors exists in the baseline group, the control groups present the net effect on the results. Other factors may influence firms' strategic R&D cooperation, but they will not affect the results.

**Table D7***
Decision making of R&D subsidies for firms of HIG

| Values | Number of groups | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | Evolutionary time for reaching zero non-cooperator in HIG |
|---|---|---|---|---|---|---|---|
| Baseline group | 1 | 0.001 | 0.009 | 0.009 | 0.001 | 0.001 | 3.28 |
| Control groups | 2 | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 3 | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | - |
| | 4 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 3.28 |
| | 5 | 0.001 | 0.001 | 0.009 | 0.009 | 0.001 | - |
| | 6 | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | - |

## Appendix E

**Table E1**
Results of multifactor combinations for strategic decisions in R&D cooperation of HIG

| Optimal combinations | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | $a$ | Evolutionary time ($x$ first reaches zero) |
|---|---|---|---|---|---|---|---|
| 1 | 0.009 | 0.009 | 0.001 | 0.009 | 0.009 | −13.47543 | 0.3 |
| 2 | 0.005 | 0.009 | 0.001 | 0.009 | 0.009 | −13.47505 | |
| 3 | 0.009 | 0.009 | 0.001 | 0.009 | 0.005 | −13.47505 | |
| 4 | 0.005 | 0.009 | 0.001 | 0.009 | 0.005 | −13.47484 | |
| 5 | 0.001 | 0.009 | 0.001 | 0.009 | 0.009 | −13.47467 | |
| 6 | 0.009 | 0.009 | 0.001 | 0.009 | 0.001 | −13.47467 | |
| 7 | 0.001 | 0.009 | 0.001 | 0.009 | 0.005 | −13.47462 | |
| 8 | 0.005 | 0.009 | 0.001 | 0.009 | 0.001 | −13.47462 | |
| 9 | 0.001 | 0.009 | 0.001 | 0.009 | 0.001 | −13.47458 | |
| 10 | 0.009 | 0.009 | 0.001 | 0.005 | 0.009 | −12.59628 | 0.32 |
| Worst combinations | $\mu_1$ | $\theta_1$ | $\sigma_1$ | $\sigma$ | $\gamma_2$ | $a$ | Evolutionary time ($x$ first reaches one) |
| 1 | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | 10.82895 | 0.06 |
| 2 | 0.001 | 0.001 | 0.009 | 0.001 | 0.005 | 10.82894 | |
| 3 | 0.005 | 0.001 | 0.009 | 0.001 | 0.001 | 10.82894 | |
| 4 | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | 10.82894 | |
| 5 | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | 10.82894 | |
| 6 | 0.005 | 0.001 | 0.009 | 0.001 | 0.005 | 10.82892 | |
| 7 | 0.005 | 0.001 | 0.009 | 0.001 | 0.009 | 10.82890 | |
| 8 | 0.009 | 0.001 | 0.009 | 0.001 | 0.005 | 10.82890 | |
| 9 | 0.009 | 0.001 | 0.009 | 0.001 | 0.009 | 10.82886 | |
| 10 | 0.001 | 0.001 | 0.009 | 0.005 | 0.001 | 10.00585 | |

Note: The stochastic differential equation of HIG is $dX_t = f(X_t)dt + \xi dW_t = aX_t dt + \xi dW_t$. The intensity of stochastic disturbance $\xi = 1$, step size $h = 0.02$, and time-interval $[T_0, T] = [0, 5]$.

**Table E2**
Results of multifactor combinations for strategic decisions in R&D cooperation of LIG

| Optimal combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | $b$ | Evolutionary time (y first reaches zero) |
|---|---|---|---|---|---|---|---|
| 1 | 0.009 | 0.009 | 0.001 | 0.009 | 0.009 | −15.03498 | 0.26 |
| 2 | 0.009 | 0.009 | 0.001 | 0.009 | 0.005 | −15.03454 | |
| 3 | 0.005 | 0.009 | 0.001 | 0.009 | 0.009 | −15.03454 | |
| 4 | 0.005 | 0.009 | 0.001 | 0.009 | 0.005 | −15.03429 | |
| 5 | 0.009 | 0.009 | 0.001 | 0.009 | 0.001 | −15.03409 | |
| 6 | 0.001 | 0.009 | 0.001 | 0.009 | 0.009 | −15.03409 | |
| 7 | 0.005 | 0.009 | 0.001 | 0.009 | 0.001 | −15.03405 | |
| 8 | 0.001 | 0.009 | 0.001 | 0.009 | 0.005 | −15.03405 | |
| 9 | 0.001 | 0.009 | 0.001 | 0.009 | 0.001 | −15.03400 | |
| 10 | 0.009 | 0.009 | 0.001 | 0.005 | 0.009 | −13.86469 | 0.3 |
| Worst combinations | $\mu_2$ | $\theta_2$ | $\sigma_2$ | $\sigma$ | $\gamma_1$ | $b$ | Evolutionary time (y first reaches one) |
| 1 | 0.001 | 0.001 | 0.009 | 0.001 | 0.001 | 11.69954 | 0.02 |
| 2 | 0.005 | 0.001 | 0.009 | 0.001 | 0.001 | 11.69953 | |
| 3 | 0.001 | 0.001 | 0.009 | 0.001 | 0.005 | 11.69953 | |
| 4 | 0.009 | 0.001 | 0.009 | 0.001 | 0.001 | 11.69953 | |
| 5 | 0.001 | 0.001 | 0.009 | 0.001 | 0.009 | 11.69953 | |
| 6 | 0.005 | 0.001 | 0.009 | 0.001 | 0.005 | 11.69950 | |
| 7 | 0.009 | 0.001 | 0.009 | 0.001 | 0.005 | 11.69948 | |
| 8 | 0.005 | 0.001 | 0.009 | 0.001 | 0.009 | 11.69948 | |
| 9 | 0.009 | 0.001 | 0.009 | 0.001 | 0.009 | 11.69943 | |
| 10 | 0.001 | 0.001 | 0.009 | 0.005 | 0.001 | 10.59398 | 0.06 |

Note: The stochastic differential equation of LIG is $dY_t = f(Y_t)dt + \xi dW_t = bY_t dt + \xi dW_t$. The intensity of stochastic disturbance $\xi = 1$, step size $h = 0.02$, and time-interval $[T_0, T] = [0, 5]$.

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