ANALYZING KNOWLEDGE-SHARING ACTIVITIES IN OPEN INNOVATION CONTESTS UNDER OPTIMAL REWARD MECHANISM[1]

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ABSTRACT

A contest sponsor or crowdsourcing intermediary hosting an open innovation contest can employ knowledge-sharing activities such as panels, meetings, or even community forums to help maximize each contestant's performance. However, in addition to the paradox of openness resulting from the incentive to protect their knowledge assets, contestants face a predicament related to sharing, as benevolently helping others may reduce their opportunity to win the contest. In this research, we integrate two stylized models to determine how a contest sponsor can most efficiently deploy its resources under budget constraints, and explore how to stimulate co-creation in knowledge-sharing activities. Our findings indicate that employing educational workshops to encourage brainstorming among contestants before submitting their work results may be inefficient if the prize is too high. In addition, if a contest sponsor values the overall contribution made by contestants, encouraging knowledge-sharing behavior can benefit the intermediary in a crowdsourcing-based open innovation contest when the number of contestants and the contest sponsor's budget are set appropriately.

Keywords: Open innovation; Knowledge sharing; Dilemma of sharing; Crowdsourcing; Hackathon

1. Introduction

Open innovation contests in which the knowledge of crowds and organizations is leveraged to source solutions and to complete tasks have become increasingly popular in daily business operations (Bandyopadhyay & Pathak, 2007; Chesbrough & Brunswicker, 2014; Gilpatric, 2009). Although various approaches (such as crowdsourcing, supplier innovation awards, and entrepreneurship competitions) can be adopted, most rely on a similar architecture (Peng et al., 2021) to efficiently fuel the development of new products and services under budget constraints. Numerous crowdsourcing intermediaries, which take advantage of the benefits of a large network, can offer firms a convenient platform via which to rapidly initiate an open innovation contest, and charge a commission fee for their services.[2] In innovation contests in general, participants who outperform others in the activity are granted a monetary reward (Leimeister et al., 2009).

1.1. Problems and Motivation

To enable each participant to work more efficiently, a contest sponsor or intermediary can boost contestants' performance and hasten the innovation process (Leimeister et al., 2009) by enabling knowledge sharing among contestants. For instance, contestants can be invited, prior to the contest, to take part in a meeting in which they exchange valued information to improve their performance. In general, relevant information, such as that concerning themes, important dates, prize amounts, and evaluation criteria, is spread through various media, including official

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[2] For example, the requester in Amazon Mechanical must pay Amazon a 20% service fee on the reward (see https://www.mturk.com/).

websites and social networks. A deadline is set for registering for the contest, and all registered contestants are then invited to participate in knowledge-sharing activities to develop contestants' problem-solving skills.

For example, in some organized challenges (such as hackathons[3]) or open-source contests for creating innovative software solutions, contestants are encouraged to share their knowledge and skills to solve specific problems. Contest sponsors or intermediaries may therefore organize a panel discussion or a development workshop at which the invited speakers answer questions and contestants exchange valuable information and build their social networks. Furthermore, some crowdsourcing-related intermediaries also demonstrate how participants can learn from their competitors during the contest period through the use of a community forum[4] (Luo et al., 2023; Lyu & Kim-Vick, 2022).

Another example is a two-stage program in which scholars brainstorm ideas on game design in a workshop. Professional game developers are then paired with these scholars to implement a prototype based on their ideas[5]. Other similar examples of this "sharing before contest" approach can also be found in startup pitch competitions and science olympiads. In practice, for personal reasons, some contestants may not participate in workshops, panels, or online meetings; however, participation in such activities could be made mandatory[6]. Moreover, although the measurement of brainstorming performance is a challenging task, a news report[7] notes that some senior or highly experienced contestants in hackathons may be reticent to share ideas with junior or less experienced contestants.

Studies have explored the paradox of openness (Arora et al., 2016; Foege et al., 2019; Laursen & Salter, 2014) and have contended that contestants may wish to protect their knowledge in open innovation settings, which is inconsistent with the goal of holding a knowledge-sharing meeting or a community forum. In other words, from an economic and psychological perspective (Foege et al., 2019), a contestant who is more active in a knowledge-sharing meeting or community forum has a higher opportunity cost for knowledge sharing (Allon & Babich, 2020; Glazer & Hassin, 1988; Shao et al., 2012). In addition, knowledge-sharing behavior may be detrimental to benevolent contestants, as such actions can boost their competitors' work efficiency while simultaneously reducing their own chance of winning the prize (Hu et al., 2020; Lenart-Gansiniec, 2017; Lu et al., 2018). Since the payoffs to the intermediaries depend on the winner's prize, contest sponsors aiming to take advantage of crowd intelligence must understand the interplay between each contestant's efforts and knowledge-sharing behavior.

Numerous empirical studies have thus examined contestants' motivation for sharing knowledge and the benefits contestants can derive from this (Dissanayake et al., 2021; Jin et al., 2021; Mo et al., 2018); however, few studies have analyzed the impact of knowledge-sharing behavior on a contest sponsor's reward mechanism. If a contest sponsor hosts an innovation contest on an intermediary's crowdsourcing platform, these two stakeholders may have divergent levels of interest in the development of knowledge-sharing activities, as the benefits they gain from the contest may not be perfectly aligned. As a result, our major research questions are as follows: (1) How does the prize amount affect a contestant's knowledge-sharing decision? How much should the contest sponsors allocate from their budget as the reward? (2) Is the intermediary incentivized to support the development of knowledge-sharing activities during the contest period? If a contest sponsor can gain additional benefits from knowledge-sharing activities, how does this new revenue stream affect the optimal reward program? (3) In a large-scale crowdsourcing contest, how does the growth of the contest scale affect an intermediary's incentive to encourage knowledge-sharing behavior?

1.2. Contributions and Findings

Overall, our research extends the literature regarding innovation contests, and focuses on the integration of knowledge-sharing activities and optimal reward schemas. Moreover, we investigate the knowledge-sharing decisions and effort decisions made by heterogeneous contestants and consider these decisions in a sequential setup, which is a popular approach in hackathons or competitions requiring brainstorming. Finally, we also demonstrate the relationship between the scale of the contest and an intermediary's attitude toward the knowledge-sharing activity. Our findings, and how they answer our research questions, are summarized as follows.

Firstly, we find that a higher prize amount discourages brainstorming among contestants. Contestants exert more effort, but share less of what they know, as they to strive to win. Hence, when determining the value and format of prizes, contest sponsors must evaluate the importance of knowledge-sharing activities and final work results. Secondly, if a winner's prize is not too high and the knowledge-sharing activities do not bring in an

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[3] https://neonewstoday.com/events/neo-to-host-walletconnect-workshop-and-panel-featuring-previous-hackathon-participants/

[4] https://www.hyvecrowd.com/welcome

[5] https://www.gamesforchange.org/professional_service/hiv-prevention-game-design-workshop-and-game-jam/

[6] An alternative approach is to view them as "the participants who share nothing" in our model.

[7] https://www.csoonline.com/article/555117/the-ultimate-hackathon-survival-guide.html

additional revenue stream for contest sponsors, the practice of supporting workshops and panel discussions before a contest may benefit the intermediary. However, a contest sponsor would reduce the value of the prize if they were to gain a considerable revenue stream from the knowledge-sharing activity. Finally, we find that growth in the scale of a contest can be a key motivation for an intermediary to promote knowledge-sharing activities.

2. Literature Review

This research primarily considers the design of an optimal reward mechanism in an innovation contest and the implementation of knowledge sharing in a crowdsourcing contest. We first briefly review the evolution of the reward mechanisms used to boost contestant effort, and then examine the recent literature on how contestants share knowledge in a crowdsourcing contest and show how our study fills a research gap.

2.1. Optimal Reward Mechanism for Innovation Contests

In most studies using game theoretic models to examine the efficiency of an innovation contest, the total effort exerted by contestants has usually served as a key indicator to measure a contest sponsor's payoff in the contest (Harbring & Irlenbusch, 2005; Lazear & Rosen, 1981). The model proposed by Lazear and Rosen (1981) is one of the earliest examinations of such contests, and has therefore been widely extended and applied as a benchmark in subsequent studies of the design of reward mechanisms in crowdsourcing. In particular, Lazear and Rosen's model (1981) and a subsequent variant of it (Gürtler & Kräkel, 2010) have frequently been used in innovation contests to estimate a contestant's probability of winning. In their approaches, the relation between the quality of the submission and the effort exerted by a contestant is affected by uncertain noise that follows a random distribution (Harbring & Irlenbusch, 2005; Hvide, 2002; Kräkel, 2008; Lazear & Rosen, 1981; Terwiesch & Xu, 2008).

Investigations into the design of optimal reward mechanisms typically either assume a single prize (Cornes & Hartley, 2005; Fu et al., 2012; Jost & Kräkel, 2008; Koh, 2017; Terwiesch & Xu, 2008) or prizes granted to multiple winners (Cheng et al., 2019; Hvide, 2002; Kräkel, 2008; Lee, 2014). In addition to announcing a fixed monetary prize to boost each contestant's efforts (Cheng et al., 2019; Cornes & Hartley, 2005; Fu et al., 2012; Hvide, 2002; Jost & Kräkel, 2008; Koh, 2017; Kräkel, 2008; Lee, 2014; Terwiesch & Xu, 2008), a contest sponsor can also choose to share part of the revenue from the subsequent sales of the winner's work (Stein, 2002; Stracke, 2013; Terwiesch & Xu, 2008). For a systematic review of the equilibrium behavior of contestants in crowdsourcing contests, see Segev (2020).

The Tullock success function (Amegashie, 2006; Chowdhury & Sheremeta, 2011) has also been widely adopted in relevant studies (Jost & Kräkel, 2008; Stracke, 2013) to identify a contestant's probability of winning a crowdsourcing contest. For example, Terwiesch and Wu (2008) used this approach to explore optimal research and development contests for expertise-based, ideation, and trial-and-error projects. Their findings explain why granting the total reward to a single winner can be the most efficient approach. The adoption of a single prize is also supported by Cheng et al. (2019), who examined the operation of a crowdsourcing platform and the optimal intermediary fee. Although the Tullock success function can be used to analyze the effort decisions made by contestants with asymmetric capabilities, the tractability of this approach limits its application in two respects.

Firstly, the cost function in this method is generally linear. Cornes and Hartley (2005) determined that a linear production function is required to guarantee the existence of a unique pure-strategy equilibrium. Secondly, when considering multiple asymmetric contestants, the formulation of a contestant's effort decision is too cumbersome for further analysis in a backward induction approach. Consequently, studies tend to adopt a contest model involving two asymmetric contestants when investigating how a contestant's earlier decision affects their subsequent effort decision in a two-stage contest. For instance, contestants can opt to take risks that may increase their probability of winning (Kräkel, 2008), or may invest in education or training to strengthen their working capability (Jost & Kräkel, 2008). Similarly, model design can become a concern when the contest sponsor must make various decisions. For instance, in Fu et al. (2012), the contest sponsor was required to decide not only on an overall reward but also on direct subsidies to two firms.

2.2. Knowledge Sharing in Crowdsourcing

Danilov et al. (2019) considered a model comprising three agents who can exert effort and choose to act in productive (known as "help") or destructive manners (known as "sabotage"); in addition to the winner's prize, each contestant can receive a fixed payment plus a team bonus. The results for a symmetric equilibrium indicate that a contestant will engage in sabotage when the individual bonus is sufficiently high. Similarly, Itoh (1991) employed a two-agent model to investigate a moral hazard problem, in which each agent was allowed to choose their own effort and the effort exerted to help others. In their model, the principal (i.e., the contest sponsor) could consider each agent's performance when deciding on the wage schedule, because comprehensive information was available on each agent's performance in all tasks. In particular, the contest success function introduced by Tullock (Amegashie, 2006; Chowdhury & Sheremeta, 2011) has frequently been adopted to measure a contestant's expected benefit from knowledge-sharing activities.

Crowdsourcing contestants in a community forum need to find a tradeoff between value creation and value appropriation (Foege et al., 2019). For example, if some contestants publish their work in the community forum, this sharing behavior may deter contestants from searching for solutions independently, and could potentially even jeopardize a contestant's creative capability (Jin et al., 2021). In addition, the competitive intensity of a crowdsourcing contest affects a contestant's intention to help others in that contest. Dissanayake et al. (2021) confirmed the benefit of knowledge sharing in a crowdsourcing contest but also emphasized that in a competition environment, this benefit is relatively weak. Moreover, as the number of crowdsourcing platforms grows, contestants may require a recommendation system to help them identify suitable contests in which their winning opportunities will be maximized (Mo et al., 2018).

However, few studies have investigated the ways in which knowledge-sharing behavior affects the effort decision of contestants and subsequently shapes a contest sponsor's reward mechanism. In this study, we therefore follow the suggestions made in previous studies to consider a stochastic relationship between the effort exerted by contestants and the evaluation of the quality of their final submitted work. We then investigate the interplay between each contestant's effort decision and their knowledge-sharing behavior. Moreover, we examine the design of an optimal reward mechanism and the intermediary's willingness to support the development of knowledge-sharing activities.

3. The Model

Consider a contest sponsor who offers a monetary prize ω to secure ideas or effort from n contestants through an open innovation contest. The prize is guaranteed to be awarded, and the contest can be hosted by the contest sponsor itself or an intermediary. Charging a percentage of the prize as the service fee is a prevailing approach among crowdsourcing platforms with high market shares (Wen & Lin, 2016). Accordingly, in our model, the contest sponsor pays the intermediary $\gamma \cdot \omega$ as the service fee if an intermediary hosts the contest; if the sponsor hosts the contest independently, γ is assigned a value of zero.

3.1. Knowledge Sharing

Moreover, these contestants differ in terms of their knowledge level (or capability), and each contestant i chooses the level of effort e_i to apply in pursuit of the contest reward. Following the approach in Lin et al. (2005), the level of a contestant's knowledge can be either high, denoted as κ_H, or low, denoted as κ_L, where $\kappa_H > \kappa_L > 0$. The subscripts H and L are used to indicate the type of contestant. In other words, the knowledge level of a high-type (low-type) contestant is κ_H (κ_L). To analyze the impact of the asymmetric knowledge level on each contest stakeholder (e.g., contestants, contest sponsor, and intermediary), the research limitations of our model are detailed in Section 6.

During the contest period, the contest sponsor (or the intermediary) can support information exchange or knowledge sharing among contestants via complementary activities such as panels, meetings, or even community forums. Both meetings and community forums are media for knowledge-sharing activities, but differ in their respective time frames. Meetings can be as short as one day, or even hours, but community forums can last until the contest is finished. We therefore regard knowledge-sharing activities such as meetings and community forums as "sharing before contest" and "sharing during contest", respectively. In our model, we first consider the concept of "sharing before contest" and assume that two contestants with different knowledge levels are invited to take part in a meeting before vying for a reward. In a later section, we apply the concept of "sharing during contest," and extend the same research question to a larger-scale crowdsourcing approach in which the contest sponsor hosts a community forum to facilitate knowledge-sharing activities during the contest.

Our original model thus includes the following stages. First, the contest sponsor announces the task and the reward ω. Each contestant i then decides on their knowledge-sharing level $\phi_i \in [0,1]$ in the knowledge-sharing meeting. Thereafter, they exert effort e_i to complete the task in the contest. Finally, the contest sponsor inspects each contestant's work to select a winner.

Most related empirical studies have reported that knowledge-sharing behavior is mainly motivated by reciprocity and reputation (Lai & Chen, 2014; Wang & Hou, 2015; Zhang et al., 2017). However, contestants face a level of conflict between knowledge sharing and knowledge protection, which is known as the paradox of openness (Arora et al., 2016; Foege et al., 2019; Laursen & Salter, 2014). Overall, the probability of gaining a favorable reputation increases when the contestants share more knowledge in knowledge-sharing activities. In addition, a contestant with a high knowledge level is much more easily recognized than one with a low knowledge level. Notably, the opportunity cost of sharing knowledge for a contestant with a high knowledge level is also higher, because the cost of sharing personal knowledge or information depends on the value thereof. As a result, we employ the Tullock probability function (Amegashie, 2006; Chowdhury & Sheremeta, 2011) to define the expected benefit gained by a contestant after sharing knowledge, as follows:

$$F \cdot \frac{\phi_i \kappa_i}{\phi_i \kappa_i + \phi_{-i} \kappa_{-i}}, \tag{1}$$

where F is the total benefit of knowledge sharing resulting from reputational strength and additional benefits from the contest sponsor or the intermediary. A contestant's loss resulting from knowledge sharing depends on their knowledge level κ_i and sharing level ϕ_i. A contestant's opportunity cost pertaining to knowledge sharing is denoted as $\tau \cdot \phi_i \cdot \kappa_i$, where τ is an opportunity cost coefficient.

3.2. Link between Knowledge Sharing and Working Effort

We can then construct the relationship between the decisions on knowledge sharing and the optimal effort made by contestants. For convenience, a contestant's effort cost is a quadratic function[8] with respect to effort e_i, which can be expressed as $\frac{c}{\kappa_i + \phi_{-i}\kappa_{-i}} \cdot e_i^2$, where c is an effort cost coefficient. As for the difficulty level of the task, contestants may discover this information during the contest, as they share knowledge and exchange information through an online meeting or a learning community. Sometimes, these contestants may have clear knowledge about the difficulty level of a task due to a close relationship with the contest sponsor (e.g., through serving as the contest sponsor's supplier or retailer for years). We therefore consider the number of contestants to be complete information in our model, and ignore the issue of information asymmetry between the contestants and the sponsor.

In our model, a contestant's effort cost depends not only on their knowledge level but also on the help they receive from their rivals by exchanging information as part of knowledge-sharing activities. In other words, a contestant can exert effort more efficiently to increase the winning probability if their counterpart shares more knowledge; yet taking the initiative to share more knowledge encourages the counterpart to exert more effort, thereby decreasing their own probability of winning. This highlights a contestant's cognitive conflict between the effort decision and sharing decision. Although helping others can improve the reputation of the helper, providing support can also hurt them. In summary, a contestant's payoff can be modeled as follows:

$$\Pi_i = \omega \cdot \mathrm{Prob}(winning) - \frac{c}{\kappa_i + \phi_{-i}\kappa_{-i}} \cdot e_i^2 + F \cdot \frac{\phi_i \kappa_i}{\phi_i \kappa_i + \phi_{-i}\kappa_{-i}} - \tau \cdot \phi_i \cdot \kappa_i \tag{2}$$

Regarding $\mathrm{Prob}(winning)$, i.e., a contestant's winning probability, numerous contest studies have extended the work of Lazear and Rosen (1981) and considered the presence of noise ξ_i (Hvide, 2002; Koh, 2017; Terwiesch & Xu, 2008), which positively or negatively affects each contestant's performance. However, these approaches turn out to be intractable if asymmetric multiple contestants and sequential decisions are taken into account. We therefore adopt a variant model proposed by Gürtler and Kräkel (2010) to calculate a contestant's winning probability at the outset. Each contestant's performance is subject to uncertain factors, such as measurement error and sponsor preferences. A contestant i's winning probability is therefore expressed as

$$\mathrm{Prob}(winning) = \mathrm{Prob}(e_i > e_{-i} + \xi), \tag{3}$$

where ξ is an exogenous uniform random variable with zero mean over $[-q, q]$. The value of q is used to measure the degree of uncertainty regarding measurement error and sponsor preferences.

3.3. Payoff to Contest Sponsor

In our model, a contest sponsor chooses only one of the contestants who submits the best solution as the winner; thus, the benefit derived by the contest sponsor from these submissions may not be valued equally. Moreover, the process of information exchange or knowledge sharing may benefit the contest sponsor insofar as it leads to the sponsor developing a strong reputation, attracting more participants, or even generating new revenue streams (e.g., display ads). The contest sponsor's payoff from the contest is therefore given by

$$\pi_S = e_H + \delta e_L + \lambda \sum \phi_i \kappa_i - (1+\gamma)\omega \;\; s.t. \;\; (1+\gamma)\omega \le \beta, \tag{4}$$

where λ, β, and $\delta \in (0,1)$ represent the benefit from knowledge sharing gained by the contest sponsor, the contest sponsor's available resources (for the contest budget), and the discount for a less favorable result submitted or achieved by a low-type contestant, respectively. Due to budget constraints, the contest sponsor must evaluate whether to allocate all or only part of the budget as the reward. We employ the backward induction technique to determine a contestant's knowledge-sharing and effort decisions, as summarized in Lemma 1.

[8] Economic models often assume that work effort is an increasing convex function; we therefore use a quadratic function for exposition (see Cheng et al., 2019).

Lemma 1. (Optimal knowledge-sharing and effort decisions[9])

$$e_H^* = \begin{cases} \frac{\omega(\kappa_H+\kappa_L)}{4qc}, & \omega < \omega_2 \\ \frac{\omega\left(\kappa_H+\frac{2Fq^2c}{\omega^2+8q^2c\cdot\tau}\right)}{4qc}, & \omega \geq \omega_2 \end{cases},\ e_L^* = \begin{cases} \frac{\omega(\kappa_H+\kappa_L)}{4qc}, & \omega < \omega_1 \\ \frac{\omega}{4qc}\sqrt{\frac{8Fq^2c\kappa_L}{\omega^2+8q^2c\cdot\tau}}, & \omega_1 \leq \omega < \omega_2 \\ \frac{\omega\left(\kappa_L+\frac{2Fq^2c}{\omega^2+8q^2c\cdot\tau}\right)}{4qc}, & \omega \geq \omega_2 \end{cases},$$

$$\phi_H^* = \begin{cases} 1, & \omega < \omega_1 \\ \frac{1}{\kappa_H}\sqrt{\frac{8Fq^2c\kappa_L}{\omega^2+8q^2c\cdot\tau}} - \frac{\kappa_L}{\kappa_H}, & \omega_1 \leq \omega < \omega_2 \\ \frac{2Fq^2c}{(\omega^2+8q^2c\cdot\tau)\kappa_H}, & \omega \geq \omega_2 \end{cases}, \text{ and } \phi_L^* = \begin{cases} 1, & \omega < \omega_2 \\ \frac{2Fq^2c}{(\omega^2+8q^2c\cdot\tau)\kappa_L}, & \omega \geq \omega_2 \end{cases}, \text{ where } \omega_1 \equiv$$

$\sqrt{\frac{8Fq^2c\kappa_L}{(\kappa_H+\kappa_L)^2} - 8q^2c\cdot\tau}$ and $\omega_2 \equiv \sqrt{\frac{2Fq^2c}{\kappa_L} - 8q^2c\cdot\tau}$.

Based on Lemma 1, we find some noteworthy results when investigating how the reward amount, knowledge level, and uncertainty of winning a contest affect a contestant's knowledge-sharing behavior. Note that all proofs in this paper are given in Appendix A.

Proposition 1.

(i) Contestants have less incentive to share knowledge when the reward amount is higher, which can be expressed as $\frac{\partial\phi_i^*}{\partial\omega} \leq 0$.

(ii) More knowledgeable contestants are less active in the knowledge-sharing activity, which can be expressed as $\phi_H^* \leq \phi_L^*$.

(iii) If the uncertainty of winning an open innovation contest is higher, contestants share more knowledge but reduce the effort they devote to the task; this can be expressed as $\frac{\partial\phi_i^*}{\partial q} \geq 0$ but $\frac{\partial e_i^*}{\partial q} \leq 0$.

Each contestant exerts more effort when they receive more help in the knowledge-sharing activity. However, knowledge sharing can intensify the competition between contestants. When the reward amount is higher, both types of contestants will therefore be less active in the knowledge-sharing meeting, due to their intention to win the prize on offer. Moreover, highly knowledgeable contestants will share less information, as their capabilities in comparison with contestants with low knowledge levels will be recognized by the other contestants more easily. Finally, if contestants lack confidence in their ability to win the contest, they have less incentive to exert effort in the task but spend more time on peer discussion in the knowledge-sharing activity.

Proposition 1 is robust when the convexity of the effort cost is sufficiently large[10]. However, some of our analytical results change when the cost function is approximately linear. More specifically, whether a high-type contestant shares less knowledge than a low-type contestant depends on the convexity of the effort cost function. Figure 1 shows that a high-type contestant exerts more effort than a low-type contestant, regardless of the convexity of the effort cost function, which accords with our intuition; however, Figure 2 shows that a high-type contestant shares more knowledge than a low-type contestant when the effort cost function is approximately linear.

As the effort cost function gradually levels off, the difficulty of submitting a solution or finishing a task in the contest decreases. In other words, a high-type contestant gains less benefit by keeping their knowledge to themselves for the sake of increasing their winning probability. When refusing to share knowledge cannot help a high-type contestant gain a significant advantage over a low-type contestant, the high-type contestant stands to gain more (e.g., in terms of a more positive reputation) by sharing more knowledge, and flaunting their ability, rather than keeping their knowledge to themselves.

In this study, for convenience, each contestant's winning probability is neither zero nor one; that is, $|e_i^* - e_{-i}^*| < q$. In other words, no one is guaranteed a victory or loss in the contest. Consequently, we only discuss our analytical results under the condition given in Lemma 2.

Lemma 2. $|e_i^* - e_{-i}^*| < q$ if $\sqrt{\frac{\kappa_H\beta}{4(1+\gamma)c}} < q$.

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[9] To avoid a redundant analysis in other sub-cases, our approach implicitly assumes that $\omega_1 \geq 0$, as our interest lies in the optimal rewards in the three segments $[0, \omega_1]$, $[\omega_1, \omega_2]$, and $[\omega_2, \infty)$.

[10] The experimental results and the related numerical configuration are detailed in Appendix B.

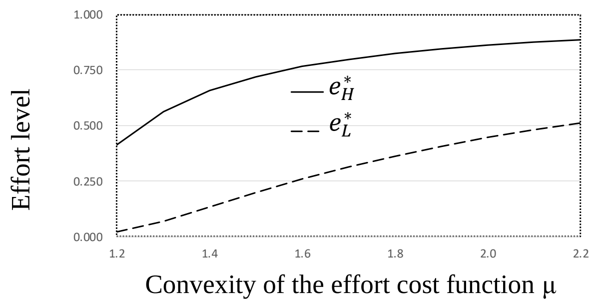

Figure 1: Comparison of effort level between contestants

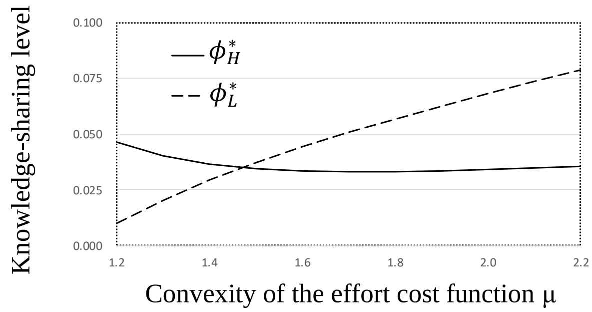

Figure 2: Comparison of knowledge-sharing level between contestants

3.4. Contest before Sharing

Finally, we also consider an alternative game sequence in which each contestant first decides on their effort level and then their knowledge-sharing level. This setup may apply to "contest before sharing" scenarios, such as game shows or quiz shows, in which contestants compete against each other on TV programs and share what they know after each contestant submits their answers. We summarize a contestant's knowledge-sharing and effort decisions in this case as follows.

Lemma 3. (Contest before sharing**)**

$$e_H^* = \begin{cases} \frac{\omega(4\tau\kappa_H+F)}{16qc\tau}, & F < 4\tau\cdot\kappa_L \\ \frac{\omega(\kappa_H+\kappa_L)}{4qc}, & F \geq 4\tau\cdot\kappa_L \end{cases} \text{ and } e_L^* = \begin{cases} \frac{\omega(4\tau\kappa_L+F)}{16qc\tau}, & F < 4\tau\cdot\kappa_H \\ \frac{\omega(\kappa_H+\kappa_L)}{4qc} & F \geq 4\tau\cdot\kappa_H \end{cases}$$

$$\phi_H^* = min\left\{\frac{F}{4\tau\cdot\kappa_H}, 1\right\} \text{ and } \phi_L^* = \left\{\frac{F}{4\tau\cdot\kappa_L}, 1\right\}$$

In our setup, the winning probability of a contestant is linked to the gap between the effort exerted by the contestants. Hence, knowledge-sharing behavior cannot be further stimulated by controlling the size of the reward, as this decision, which follows the competition stage, does not affect the expected reward earned by contestants. In contrast to Lemma 1, Lemma 3 reveals that the contest sponsor's payoff function given in (4) increases or decreases linearly with the size of the reward. We therefore only explore the optimal reward mechanism in the context of "sharing before contest", as the contest sponsor's reward decision in the context of "contest before sharing" is comparatively straightforward.

4. Optimal Reward Mechanism

We divide our analysis into three segments: (i) the low-budget region, where $\beta < (1+\gamma)\omega_1$; (ii) the moderate-budget region, where $(1+\gamma)\omega_1 \leq \beta < (1+\gamma)\omega_2$; and (iii) the abundant-budget region, where $(1+\gamma)\omega_2 \leq \beta$. The profit π_S to the contest sponsor in each region is expressed as:

$$\pi_{S,I} = (1+\delta)\frac{\omega(\kappa_H+\kappa_L)}{4qc} + \lambda(\kappa_H+\kappa_L) - (1+\gamma)\omega \text{ where } \omega < \omega_1, \tag{5}$$

$$\pi_{S,II} = \frac{\omega(\kappa_H+\kappa_L)}{4qc} + \left(\frac{\delta\omega}{4qc} + \lambda\right)\sqrt{\frac{8Fq^2c\kappa_L}{\omega^2+8q^2c\cdot\tau}} - (1+\gamma)\omega \text{ where } \omega_1 \leq \omega < \omega_2, \tag{6}$$

$$\pi_{S,III} = \frac{\omega(\kappa_H+\delta\kappa_L)}{4qc} + \left(\frac{\omega(1+\delta)}{4qc} + 2\lambda\right)\frac{2Fq^2c}{(\omega^2+8q^2c\cdot\tau)} - (1+\gamma)\omega \text{ where } \omega_2 \leq \omega. \tag{7}$$

In the low-budget region, $\pi_{S,I}$ is a linear function with respect to the reward amount ω. The optimal reward[11] is then

$$\omega^* = \begin{cases} 0, & c > \frac{(1+\delta)(\kappa_H+\kappa_L)}{4q(1+\gamma)} \\ \frac{\beta}{1+\gamma}, & c \le \frac{(1+\delta)(\kappa_H+\kappa_L)}{4q(1+\gamma)} \end{cases}. \tag{8}$$

If the contest sponsor has a low budget, the contest should not be hosted when each contestant's effort cost is too high; otherwise, the full budget should be allocated as the prize, to encourage contestants to exert significant effort. If the contest sponsor has a moderate budget, its optimal reward decision is given in Lemma 4. For analytical simplicity, we ignore the contest sponsor's revenue stream from knowledge-sharing activities by setting $\lambda = 0$, as explored in a later subsection.

Lemma 4. If the budget is moderate, a contest sponsor who does not employ a knowledge-sharing activity to gain additional revenue can evaluate 0, ω_1, $\widehat{\omega}$, and $\frac{\beta}{1+\gamma}$ to determine the optimal reward amount. Formally, given $(1+\gamma)\omega_1 \le \beta < (1+\gamma)\omega_2$ and $\lambda = 0$, $\omega^* =$

$$\begin{cases} 0, & c > \dfrac{(1+\delta)(\kappa_H+\kappa_L)}{4q(1+\gamma)} \\ \omega_1, & \dfrac{1}{4q(1+\gamma)}\left((\kappa_H+\kappa_L) + \dfrac{\delta\tau(\kappa_H+\kappa_L)^3}{F\cdot\kappa_L}\right) < c \le \dfrac{(1+\delta)(\kappa_H+\kappa_L)}{4q(1+\gamma)} \\ \min\left(\widehat{\omega}, \dfrac{\beta}{1+\gamma}\right), & \dfrac{1}{4q(1+\gamma)}\left((\kappa_H+\kappa_L) + \dfrac{8\delta\tau\kappa_L^2}{F}\right) < c \le \dfrac{1}{4q(1+\gamma)}\left((\kappa_H+\kappa_L) + \dfrac{\delta\tau(\kappa_H+\kappa_L)^3}{F\cdot\kappa_L}\right) \\ \dfrac{\beta}{1+\gamma}, & c \le \dfrac{1}{4q(1+\gamma)}\left((\kappa_H+\kappa_L) + \dfrac{8\delta\tau\kappa_L^2}{F}\right) \end{cases}$$

, where $\widehat{\omega} \equiv \sqrt{8q^2c\left((F\kappa_L)^{\frac{1}{3}}\left(\frac{\delta\tau}{4qc(1+\gamma)-(\kappa_H+\kappa_L)}\right)^{\frac{2}{3}} - \tau\right)}$.

Lemma 4 indicates that a local extreme value over $\omega \in [\omega_1, \omega_2]$ may exist under certain conditions when the contest sponsor has a moderate budget. In other words, in addition to considering the relation between each contestant's effort and the reward amount, the contest sponsor should understand each contestant's momentum in the knowledge-sharing activity, as this enables the sponsor to maximize the efficiency of the contest. When each contestant's effort cost is still high, the contest sponsor can fully leverage the benefits of knowledge sharing by announcing a small reward ω_1; however, when each contestant's effort cost is relatively low, all budget resources should be deployed as the prize.

Finally, if each contestant's effort cost is moderate, the optimal reward amount depends on the tension between the benefit of knowledge sharing and each contestant's effort cost. Where $\omega^* = \widehat{\omega}$, when the benefit of knowledge sharing in a given contest is higher or contestants are more knowledgeable, the optimal reward amount may increase. The impact of a higher knowledge-sharing opportunity cost on the optimal reward amount is twofold: if the opportunity cost of sharing knowledge remains low, the contest sponsor can raise the reward amount to compensate contestants for their opportunity cost; however, a high opportunity cost can result in contestants reducing their knowledge sharing to lower their total effort. Thus, when the contestants' opportunity cost is excessively high, the contest sponsor may announce a smaller reward instead. This result is formally stated in Corollary 1.

Corollary 1. Suppose that $\omega^* = \widehat{\omega}$ and $\lambda = 0$. If each contestant's opportunity cost related to sharing knowledge increases, the contest sponsor should raise the reward amount when each contestant's opportunity cost is still low, but should reduce it when the opposite holds true. This notion can be expressed as $\partial\widehat{\omega}/\partial\tau > 0$ when $\frac{8F\kappa_L}{27}\left(\frac{\delta}{4qc(1+\gamma)-(\kappa_H+\kappa_L)}\right)^2 > \tau$, but $\partial\widehat{\omega}/\partial\tau \le 0$ when the opposite is true.

We then consider the abundant-budget region, where $(1+\gamma)\omega_2 \le \beta$. We can identify the optimal reward amount in the region in which $\omega \ge \omega_2$ and compare it to the optimal outcome derived in Lemma 4. In addition,

[11] The condition in (8) is given by solving $\frac{\partial \pi_{S,I}}{\partial \omega} = 0$ with respect to *c*.

$\pi_{S,III}(\omega)$ is a concave function when $\omega < \sqrt{24q^2c\tau}$. Thus, we define $\widetilde{\omega} = \underset{\omega\in[0,\omega_2]}{\arg} \max \pi_S$ and $\omega' \in \left[\omega_2, \sqrt{24q^2c\tau}\right]$, to satisfy $\partial\pi_{S,III}/\partial\omega\big|_{\omega'} = 0$. The former $\widetilde{\omega}$ is the optimal reward in Lemma 4, whereas the latter ω' does not have a closed form; both of these are used in Lemma 5.

Lemma 5. If the budget is sufficiently large, a contest sponsor who does not employ a knowledge-sharing activity to gain additional revenue can evaluate 0, ω_1, $\widehat{\omega}$, ω_2, ω', and $\frac{\beta}{1+\gamma}$ to determine the optimal reward amount. Formally, when $(1+\gamma)\omega_2 \leq \beta$ and $\lambda = 0$, the optimal reward amount is given by

(i) $\omega^* = \underset{\omega\in\{\widetilde{\omega},\omega_2\}}{\arg} \max \pi_S$ if $\frac{(\kappa_H+\delta\kappa_L)}{4qc} - (1+\gamma) \leq 0$ and $\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq} < c$,

(ii) $\omega^* = \underset{\omega\in\left\{\widetilde{\omega},\omega_2,\frac{\beta}{1+\gamma}\right\}}{\arg} \max \pi_S$ if $\frac{(\kappa_H+\delta\kappa_L)}{4qc} - (1+\gamma) > 0$ and $\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq} < c$,

(iii) $\omega^* = \underset{\omega\in\{\widetilde{\omega},\omega'\}}{\arg} \max \pi_S$ if $\frac{(\kappa_H+\delta\kappa_L)}{4qc} - (1+\gamma) \leq 0$, $\omega_2 < \sqrt{24q^2c\tau}$, and $\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F}{128(1+\gamma)q\tau} < c \leq \frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$, and

(iv) $\omega^* = \underset{\omega\in\left\{\widetilde{\omega},\omega',\frac{\beta}{1+\gamma}\right\}}{\arg} \max \pi_S$ if $\frac{(\kappa_H+\delta\kappa_L)}{4qc} - (1+\gamma) > 0$, $\omega_2 < \sqrt{24q^2c\tau}$, and $\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F}{128(1+\gamma)q\tau} < c \leq \frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$. Otherwise,

(v) $\omega^* = \underset{\omega\in\left\{\widetilde{\omega},\frac{\beta}{1+\gamma}\right\}}{\arg} \max \pi_S$.

In Lemma 5, we set out how a contest sponsor determines the reward amount when an abundant budget is available. Our results indicate that the choice of reward amount is closely linked to each contestant's effort cost and knowledge-sharing behavior. If the marginal effort cost is high, ω_2 is likely to be the optimal reward, which must then be compared with the outcome derived in Lemma 4. However, the choice of the optimal reward amount is not straightforward if the marginal effort cost is moderate or small; in this case, due to the abundant budget and consequent large reward, contestants have less incentive to share their expertise in the knowledge-sharing activity. In other words, the impact of contestants' knowledge-sharing behavior may be minor. As a result, the contest sponsor should consider whether it is prudent to disregard the benefit of knowledge sharing and instead maximize each contestant's effort by fully employing their budget resources. Otherwise, the result would be similar to that of Lemma 4, in which the optimal reward solution may be a local extreme value of $\pi_{S,III}$. In this case, the contest sponsor determines the optimal reward amount by evaluating how the prize scale affects knowledge-sharing behavior and each contestant's effort.

Notably, the optimal reward amount ω' cannot be explicitly formulated, because its closed form does not exist; we therefore use Figures 3, 4, 5, and 6 to illustrate four typical examples when searching for the optimal reward amount. The dashed line and solid line represent, respectively, the contest sponsor's payoff when $\delta = 1$ and $\delta = 0.75$.

Our results indicate that ω_1 in Figure 3, $\widehat{\omega}$ in Figure 4, and ω_2 in Figure 5 are the optimal reward amounts in the three budget ranges, as these rewards enable the contest sponsor to achieve the highest payoff. On the other hand, $\pi_{S,III}$ in Figure 6 increases with ω when the reward amount is of a sufficient size; hence, both ω' and $\frac{\beta}{1+\gamma}$ should be evaluated to determine the optimal reward amount. In addition, all figures indicate that the contest sponsor's payoff decreases if the value of the contribution made by the low-type contestant declines (that is, a lower value of δ).

Since the boundary solutions (such as ω_1 and ω_2) in our optimal reward mechanism are irrelevant to the value of δ, Figures 3 and 5 indicate that the optimal reward amount remains unchanged even if the value of δ decreases. However, both $\widehat{\omega}$ (the interior optimal reward in $\pi_{S,II}$) and ω' (the interior optimal reward in $\pi_{S,III}$) are linked to the value of δ; hence, the optimal reward amount in Figure 4 (Figure 6) differs between $\delta = 1$ and $\delta = 0.75$. Figures 4 and 6 reveal that the contest sponsor lowers the reward amount if the importance of the contribution made by the low-type contestant declines.

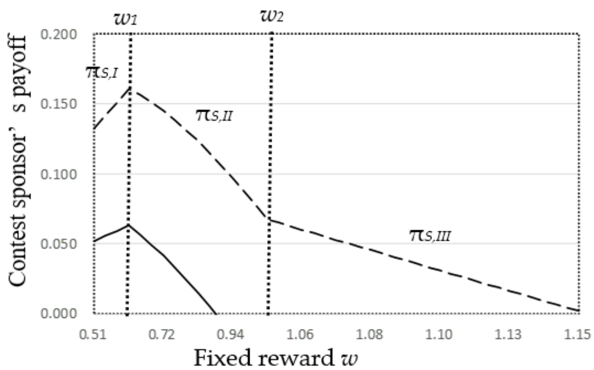

Figure 3: Contest sponsor's payoff when $\omega^* = \omega_1$

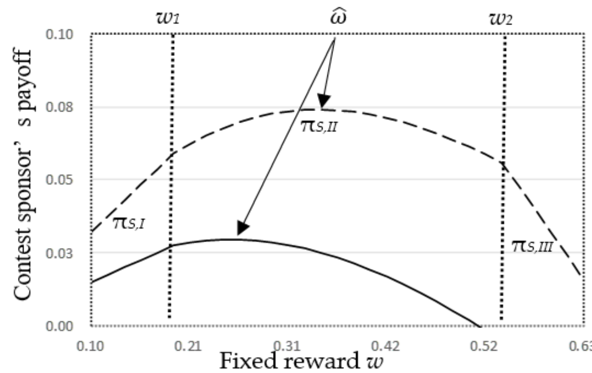

Figure 4: Contest sponsor's payoff when $\omega^* = \widehat{\omega}$

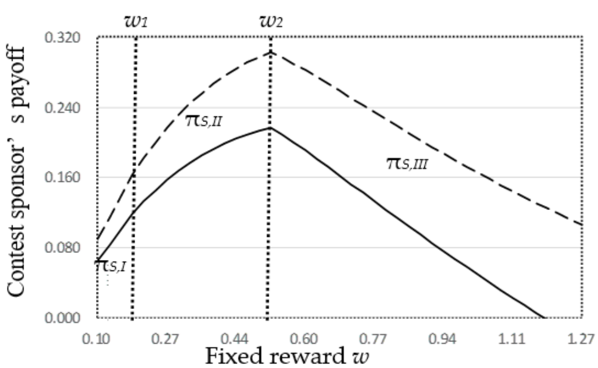

Figure 5: Contest sponsor's payoff when $\omega^* = \omega_2$

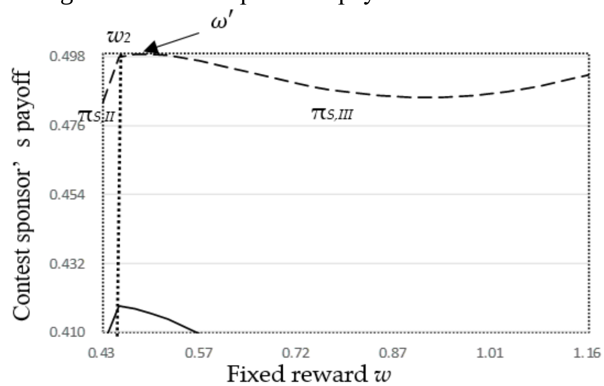

Figure 6: Contest sponsor's payoff when $\omega^* = \omega'$ or $\omega^* = \frac{\beta}{1+\gamma}$, where $\beta > (1+\gamma)\omega'$

δ=1

δ=0.75

4.1. Effect of Additional Revenue Stream from Knowledge Sharing ($\lambda > 0$)

We now investigate the effect of the benefit derived by the contest sponsor from the knowledge-sharing activity on the optimal reward size. Moreover, we consider the perspective of the intermediary regarding the knowledge-sharing activity in the contest.

Proposition 2.

(i) The optimal reward amount does not increase with the contest sponsor's additional revenue stream from the knowledge-sharing activity. Formally, $\frac{\partial\widehat{\omega}}{\partial\lambda} < 0$ and $\frac{\partial\omega'}{\partial\lambda} < 0$. Otherwise, $\frac{\partial\omega^*}{\partial\lambda} = 0$ if $\omega^* \neq \widehat{\omega}$ or $\omega^* \neq \omega'$.

(ii) If the budget is not fully utilized, the boundary optimal reward amount can increase with the benefit to contestants from knowledge sharing. Formally, $\frac{\partial\omega_1}{\partial F} > 0$ and $\frac{\partial\omega_2}{\partial F} > 0$.

(iii) If the budget is not fully utilized, the interior optimal reward amount can increase with the benefit to contestants from knowledge sharing when the reward amount is not too high and the new revenue stream derived by the contest sponsor from the knowledge-sharing activity is minimal. Formally, $\frac{\partial\widehat{\omega}}{\partial F} > 0$ if and only if $\lambda < \frac{2\delta\tau q}{\omega}$, whereas $\frac{\partial\omega'}{\partial F} > 0$ if and only if $\lambda < \frac{(1+\delta)(8q^2c\tau-\omega^2)}{16qcw}$.

Overall, boosting knowledge-sharing behavior in the meeting benefits the contest sponsor, because knowledgeable contestants are more productive. As a result, when the reward amount is small or moderate, the contest sponsor is incentivized to raise the reward amount in pursuit of higher contestant productivity, which can be achieved by efficient knowledge-sharing meetings. In other words, a policy encouraging knowledge-sharing behavior in this case will help to increase the reward amount.

On the other hand, if the reward amount is too high, promoting knowledge-sharing behavior in the meeting may not only increase the work effort but also help the contest sponsor reduce reward expenditures. In the latter case, any policy to encourage knowledge-sharing behavior will help the contest sponsor lower their expenses while reducing the intermediary's payoff in the form of the service fee. Hence, if the contest is operated by an intermediary, the contest sponsor and intermediary will not necessarily exhibit consistent attitudes regarding knowledge sharing activities. The contest sponsor's new revenue stream from the knowledge-sharing activity also fuels this phenomenon; if the process of knowledge sharing benefits the contest sponsor directly, the motivation to cut the size of the reward is stronger, as a high prize reward discourages contestants from actively sharing more knowledge with other competitors.

5. A Large-Scale Crowdsourcing Approach

In this section, we discuss the case where multiple contestants ($n > 2$) are invited to complete a task through a crowdsourcing approach. In this scenario, a community forum is provided to help contestants exchange information and share knowledge during the contest. In reality, a contest may run over multiple days, and each day can be viewed as a single period. In each period, contestants are able to adjust their effort and sharing levels according to what they share and learn via the community forum. Such a model would be somewhat complicated, and would probably be hard to analyze, since both the dynamics and the relationships between effort levels and sharing would be hard to express accurately. We therefore assume that effort and sharing levels are determined simultaneously in the crowdsourcing approach.

The model setup described in an earlier section is then modified as follows. First, the expected benefit to a contestant *i* through sharing knowledge via the community forum is expressed as $F \cdot \frac{\phi_i \kappa_i}{\phi_i \kappa_i + \sum_{j \neq i} \phi_j \kappa_j}$, which is similar to Equation (1). As contestants can rely on their own knowledge and the aggregated knowledge in the community forum to improve their performance, we model the effort cost to contestant *i* as $\frac{c}{\kappa_i + A_i} \cdot e_i^2$, where A_i is used to measure the aggregated knowledge in the community forum.

The Tullock success function (Chowdhury & Sheremeta, 2011) or the scheme of Lazear and Rosen (1981) is often adopted in crowdsourcing contests or innovation contests to formulate the winning probability. The inherent limitations of these approaches are discussed in Section 6. However, the approach developed by Gürtler and Kräkel (2010) in Section 3 is suitable only for two contestants, as uncertain factors (such as the measurement error and sponsor preferences) are expressed as a single random variable; with multiple contestants, one random variable is insufficient to measure the uncertain factors associated with all contestants. We therefore use Lazear and Rosen's model (1981) to define a contestant i's probability of winning a large-scale crowdsourcing contest as follows:

$$P_i \equiv \text{Prob}(winning) = \text{Prob}(e_i + \xi_i > e_{-i} + \xi_{-i}), \tag{9}$$

where ξ_i is an independent and identically distributed uniform random variable over $[-q, q]$.

Next, we follow Gilpatric's approach (2009) to solve the symmetric equilibrium with *n* identical contestants where $\kappa_i = \kappa$. Consequently, we consider $\frac{\partial A_i}{\partial \phi} > 0$, $\frac{\partial A_i}{\partial n} > 0$, and $\frac{\partial^2 A_i}{\partial n \partial \phi} \geq 0$, where $A_i \equiv \hat{A}(\phi_{-i}, \kappa, n)$, for two reasons[12]: firstly, each contestant works more efficiently if their competitors share more knowledge in the community forum or if more contestants share knowledge in the community forum; and secondly, as competitors share more knowledge in the community forum, an increasing number of contestants has benefits in terms of the growth of the aggregated knowledge.

In their approach, there are two prize levels, where all contestants can receive a small prize ω_L and a large prize ω_H is awarded to the winner (i.e., the one with the highest $e_i + \xi_i$). A contestant therefore aims to maximize

$$\underset{e_i, \phi_i}{Max}\ \Pi_i = P_i \cdot S + \omega_L - \frac{c}{\kappa_i + A_i} \cdot e_i^2 + F \cdot \frac{\phi_i \kappa_i}{\phi_i \kappa_i + \sum_{j \neq i} \phi_j \kappa_j} - \tau \cdot \phi_i \cdot \kappa_i, \tag{10}$$

where $S = \omega_H - \omega_L$ is the prize spread. The contest sponsor then pays the intermediary an amount $\gamma \cdot \omega_H$ as the service fee if the intermediary hosts the contest; the contest sponsor's objective is therefore

$$\underset{S, \omega_L}{Max}\ \pi_S = e_i + (n-1)\delta e_i + \lambda \sum \phi_i \kappa_i - (1+\gamma)(S + \omega_L) - (n-1) \cdot \omega_L\ s.t.,$$

$$(1+\gamma)(S + \omega_L) + (n-1)\omega_L \leq \beta\ ,$$

$$\Pi_i \geq 0\ . \tag{11}$$

Since these contestants are assumed to have the same knowledge level in the large-scale crowdsourcing approach, the value of δ can here be used to indicate whether the benefit of the contest sponsor is predominantly derived from

[12] The aggregate knowledge received by a contestant depends on all of the other contestants.

the winner. The effort decision and knowledge sharing decision of each contestant, as well as the optimal reward amount for the contest sponsor, are expressed as follows:

Proposition 3. Suppose that $\kappa_i = \kappa$ for each contestant.
(i) $e_i^* = \frac{S^*(\kappa+\hat{A})}{4qc}$ and $\phi_i^* = \min\left\{F \cdot \frac{(n-1)}{\tau \cdot \kappa \cdot n^2}, 1\right\}$.
(ii) $\omega_L^* = \frac{\kappa+\hat{A}}{c} \cdot \left(\frac{S^*}{4q}\right)^2 + \tau \cdot \phi_i^* \cdot \kappa - \frac{S^*}{n} - \frac{F}{n}$, where $S^* = \frac{2q\left((1-\delta)n(\kappa+\hat{A})+\delta n^2(\kappa+\hat{A})-4(n-1)qcr\right)}{n(\kappa+\hat{A})(\gamma+n)}$ if $(1+\gamma)(S^* + \omega_L^*) + (n-1)\omega_L^* \leq \beta$; otherwise, $S^* = \frac{4q\left(-2(n-1)q\gamma c+\sqrt{(2(n-1)q\gamma c)^2+cn(\gamma+n)\left(rF+nF+\beta n-(\gamma+n)\tau\kappa n\phi_i^*\right)(\kappa+\hat{A})}\right)}{n(\gamma+n)(\kappa+\hat{A})}$.

Under symmetric equilibrium conditions, knowledge-sharing behavior does not affect a contestant's probability of winning. As numerous contestants may participate in a contest, the financial gain a contestant can expect is mainly affected by the number of contestants. Consequently, this association can be regarded as an approximated outcome in a real large-scale crowdsourcing contest when the impact of sharing knowledge on a contestant's expectation of winning the contest is slight. In this case, contestants who share knowledge via the community forum can obtain reputational improvements, and can even receive further benefits from the contest sponsor or the intermediary; in addition, the negative impact on their winning probability of sharing their knowledge is minor. Moreover, akin to Proposition 1, contestants have less incentive to share knowledge if they are more knowledgeable. Their motivation for sharing knowledge in the community forum also gradually declines with the number of people participating in the contest. As for the optimal reward amount, a contest sponsor with a sufficient budget lowers the winner's reward if the commission rate γ increases[13]. Hence, the intermediary must prudently evaluate the relationship between the commission rate and the winner's reward, in order to boost its revenue. In the following, we discuss the attitude of an intermediary toward the development of the community forum in a large-scale crowdsourcing contest.

Proposition 4.

Where the contest sponsor has a sufficient budget and the contestants share only some of their knowledge, the intermediary is incentivized to encourage knowledge-sharing behavior when the number of contestants is large enough and the contribution made by non-winners is still important. Formally, if $\phi_i^* < 1$ and $\beta > (1+\gamma)(S^* + \omega_L^*) + (n-1)\omega_L^*$, $\frac{\partial \omega_H^*}{\partial F} > 0$ when both n and δ are large enough[14].

Contestants share more knowledge via the community forum if the intermediary is able to increase the benefit of doing so, while the effort efficiency of each contestant is linked to the aggregated knowledge in the community forum. If these contestants can exert effort more efficiently, the contest sponsor will encourage these contestants to exert more effort by enlarging the winner's prize. In addition, a higher winner's prize can encourage all contestants to exert more effort. Where the contest sponsor pays attention only to the contribution made by the winner and ignores the work results of the others, the incentive to raise the winner's reward amount is weakened.

Yet the only concern for the intermediary is whether the contest sponsor is incentivized to employ the benefit of sharing knowledge via the community forum to reduce the reward expense of holding the contest. Our result indicates that the contest sponsor will increase the amount of the winner's prize to encourage contestants to exert more effort if securing a better reputation in the community forum is challenging and the contribution made by the other non-winners is also important. In this scenario, the intermediary is willing to stimulate knowledge-sharing activity in the community forum to improve each contestant's performance due to the increase in the winner's reward.

5.1. Numerical Experiments

In this section, several numerical experiments are conducted to investigate how different contextual parameters affect the crowdsourcing contest. For contestant i, we consider $\hat{A} = \left(\sum_{j \neq i} \phi_j \kappa_j\right)^{\frac{1}{\alpha}}$, where $\alpha > 1$ is used to measure

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[13] $\frac{\partial \omega_H^*}{\partial \gamma} = -\frac{\left((1-\delta+\delta n)(\kappa+\hat{A})+4qc(n-1)\right)^2}{2(\kappa+\hat{A})(\gamma+n)^3 c} < 0$ if the budget constraint is not binding. When the budget constraint is binding, our numerical result also indicates that the winner's reward decreases.

[14] Our numerical experiments reveal that Proposition 4 still holds when the convexity of the effort cost function changes; however, the contest scale (that is, n) and the importance of the non-winners' effort (that is, δ) must be higher when the cost function more closely approximates a linear one.

the efficiency of employing aggregated knowledge. The degree of efficiency is linked to the convenience of accessing the knowledge repository. Figures 7–11 are based on the same dataset, where $\alpha = 20, \beta = 120$, $c = 2$, $\delta = 0.5$, $\kappa = 1$, $q = 10$, $\gamma = 0.1$, and $\tau = 5$. In Figure 12, we fix the value of F at 600 and examine how the value of α affects the size of the winner's prize.

The payoff to the intermediary in our model depends on the size of the winner's prize, and this dependence may be such that encouraging knowledge-sharing behavior (that is, an increase in *F*) makes the intermediary worse off (that is, a decrease in ω_H^*). However, the transition from Figures 7 to 9 clearly reveals how the benefit from encouraging knowledge-sharing behavior is linked to the number of contestants, which is consistent with Proposition 4. Moreover, Figure 10 indicates that contestants share more knowledge when the benefit from sharing knowledge increases, which facilitates a rise in each contestant's effort owing to the increased aggregated knowledge in the community forum, as shown in Figure 11.

Figures 10 and 11 also show an interesting phenomenon in which each contestant shares less knowledge and exerts more effort when the contest is more competitive. Although there is an inevitable need to invest more effort when the number of contestants increases in order to secure victory, the presence of a larger contestant pool also poses a challenge when it comes to earning peer recognition through knowledge-sharing via the community forum. Finally, we also demonstrate how the efficiency of knowledge-sharing activities affects the amount of the winner's prize in Figure 12. The increased value of α implies a lower efficiency of accessing the aggregated knowledge. When the number of contestants increases, the contest sponsor must raise the winner's prize to encourage competition among contestants. However, the winner's prize decreases when the efficiency of accessing the aggregated knowledge declines, as shown in Figure 12. This result also serves as a reminder for the intermediary to improve the user interface within the knowledge repository to make access to the aggregated knowledge more efficient.

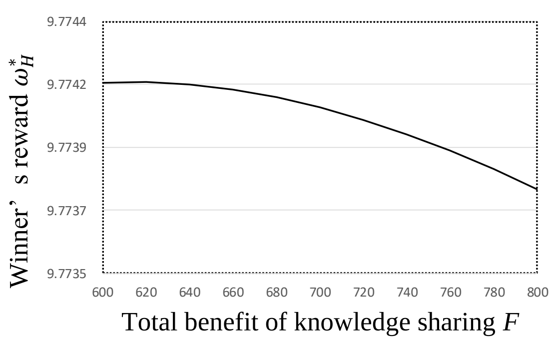

Figure 7: Winner's prize when *n* = 250

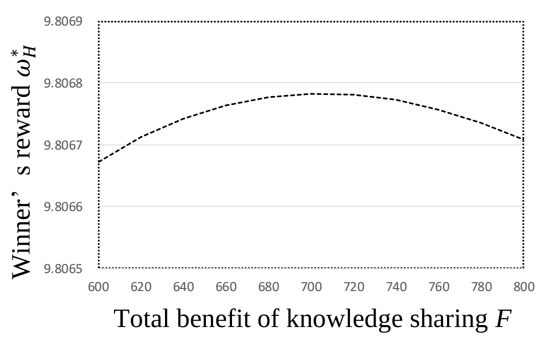

Figure 8: Winner's prize when *n* = 280

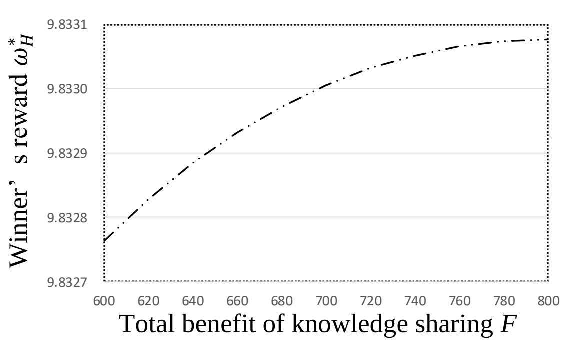

Figure 9: Winner's prize when *n* = 310

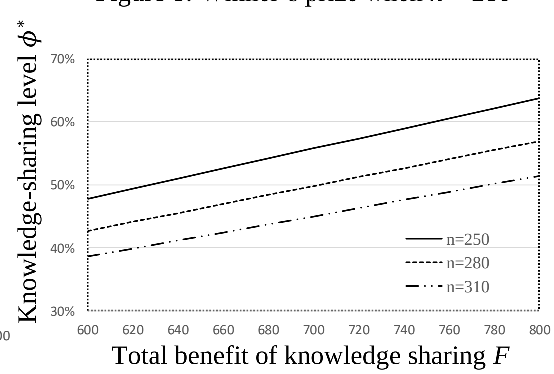

Figure 10: Each contestant's knowledge-sharing level

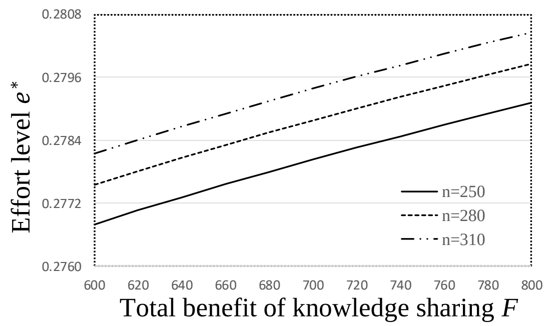

Figure 11: Each contestant's effort level

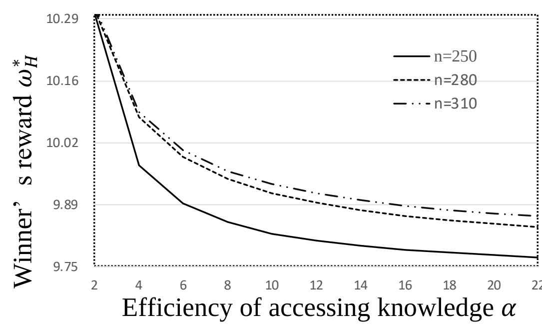

Figure 12: Impact on the winner's prize of the efficiency of accessing knowledge

6. Research Limitations, Theoretical Contributions, and Managerial Implications

Contest models extending the work of Tullock Chowdhury and Sheremeta, (2011) and Lazear and Rosen (1981) have some common limitations. Firstly, prior studies based on the framework proposed by Lazear and Rosen have considered symmetric equilibriums due to the framework's tractability (Green & Stokey, 1983). Indeed, Chen et al. (2011) demonstrated that the closed form of the effort decision does not exist when more than three asymmetric contestants are considered. Secondly, although the Tullock success function can be used to examine multiple contestants with asymmetric capabilities (Terwiesch & Xu, 2008), each contestant must be equipped with a linear production function to ensure the existence of a pure Nash equilibrium (Cornes & Hartley, 2005). Thirdly, when a subgame perfect equilibrium in a two-stage contest is the goal, deriving the asymmetric effort decisions using the Tullock success function is fairly cumbersome, due to the higher-order polynomials involved.

6.1. Theoretical Contributions

Our research extends the literature regarding innovation contests by exploring the integration between knowledge-sharing activities and optimal reward schemas. We first examined the effort decisions of two contestants when both had asymmetric knowledge levels, and then extended our model to accommodate multiple contestants through symmetric equilibria. We investigated how asymmetric contestants decide on their knowledge-sharing level and effort level by considering these decisions in a sequential setup, which is structurally similar to hackathons or competitions that require brainstorming before work results or solutions are submitted.

Moreover, the intermediary's payoff in our setup depends on the winner's reward amount; we therefore observed whether boosting the performance of knowledge-sharing activity could benefit the intermediary. However, we did not consider the intermediary's decision in our model. Whether or not a contest sponsor should employ an intermediary to host a contest depends on their own operational costs. Suppose that we additionally considered a fixed operational cost that a contest sponsor were to bear if it chose not to delegate hosting of the contest to the intermediary; then, the contest sponsor could select the best option by comparing the payoffs in the two approaches.

6.2. Knowledge-Sharing Behavior and Work Effort

Recently, the Web3 ecosystem MultiversX hosted its xDay Hackathon, featuring a million-dollar prize fund, accompanied by invaluable learning workshops[15]. Clearly, a huge prize such as this can encourage programmers or freelancers to put more effort into this competition, but innovation through knowledge sharing and winning the contest through knowledge protection come into conflict. In fact, knowledge sharing is the critical driving force for innovation[16,17], and incentivizing contestants to engage in friendly competition is therefore of paramount importance.

From the perspective of a contest sponsor, knowledge-sharing behavior in an open innovation contest can boost the performance of all contestants. In addition, when the criterion for winning the contest is highly uncertain, contestants with less incentive to exert effort in their final submission can still perform well by exchanging their ideas, opinions, and experiences with other contestants through knowledge-sharing activities. The contest sponsor must measure the benefit of implementing knowledge sharing in the contest, as contestants are less likely to engage in the activity if the reward size is more attractive (Proposition 1). Hence, to foster collaborative knowledge sharing in contests such as hackathons, our result reminds contest sponsors of the conflict between the extrinsic motivation

[15] https://www.cityam.com/multiversx-offers-up-massive-million-dollar-hackathon-prize-fund/
[16] https://www.pentalog.com/blog/company-life/smartoffice-hackaton-fostering-knowledge-sharing-and-innovation/
[17] https://www.linkedin.com/pulse/knowledge-exchange-hackathon-power-user-generated-content-tanner

that the prize provides and the brainstorming effect facilitated by development workshops.

In addition, since the strength of knowledge sharing decreases with the reward size, the contest sponsor must evaluate a contestant's effort cost and the benefit of knowledge sharing to effectively determine the amount of money to allocate as the reward. Contestants should not choose a contest with high-value prizes if their goal is to enhance their capabilities through knowledge-sharing in the contest. Similarly, if knowledge-sharing activities are important to contest sponsors, driving up the prize amount as high as possible may not be particularly helpful for stimulating innovation in the contest. The contest sponsor must consider many other factors, such as the difficulty of the contest, the capability of the contestants, the pros and cons of knowledge-sharing activities for contestants, and even the procedure for evaluating the contestants' creations.

Finally, the impact of knowledge-sharing behavior on large-scale crowdsourcing contests differs from that of small-scale contests, such as supplier innovation awards or entrepreneurship competitions. In a large-scale crowdsourcing contest, the relation between sharing knowledge via the community forum and the likelihood of winning the contest becomes weaker as the number of contestants increases, meaning that the free-rider problem is likely to arise in community forums. The contest sponsor should therefore maintain an appropriate contest scale by verifying each contestant's qualification and expertise before allowing them to compete against others (Proposition 3). Our finding also serves to encourage contest sponsors to consider giving a token of appreciation to all participants. Contest sponsors could provide non-monetary incentives such as badges, free access to the online knowledge base, or feedback from mentors to ignite the passion of participants and to make the contest more beneficial for them.

6.3. Knowledge-Sharing Activity and Intermediary Revenue

Knowledge-sharing activities can help the contest sponsor reduce their contest-related expenditure, as they can reduce the size of the reward by improving work efficiency. Many innovation contests are operated by intermediaries rather than the contest sponsors themselves. We therefore considered the winner's prize as the basis for determining revenue sharing between both sides, to assess whether the intermediaries had an incentive to promote knowledge-sharing activities. In a small-scale contest with a knowledge-sharing meeting, the contest sponsor may be incentivized to reduce the reward amount if an excessively large part of the budget is allocated as the reward (Proposition 2). If the winner's prize is high, or if the knowledge-sharing activities can generate a new revenue stream, our analytical results indicate that contest sponsors should consider hosting contests themselves rather than delegating the hosting to intermediaries. If a contest sponsor still employs an intermediary to host a contest, the service contract should be modified by linking the intermediary's payoff to the extent to which it stimulates knowledge sharing in the contest. However, determining how to measure each contestant's performance in an objective and fair manner remains a challenge for practitioners in the industry. A possible improved alternative would be to link the intermediary's service fee to the number of submissions or contestants.[18]

In a large-scale crowdsourcing contest, our research results indicate that the development of a community forum can help drive the winner's reward upwards when both the contest sponsor's budget and the number of contestants are sufficient. Hence, if the number of participants is low, we suggest that contest sponsors should consider hosting innovation contests themselves, to leverage the benefits of knowledge sharing. However, if the contest scale is large, the contest sponsor can still rely on the platform operated by the intermediary to encourage knowledge-sharing behavior in the community forum (Proposition 4).

7. Conclusion

In an open innovation contest, knowledge sharing benefits all contestants, but it is unclear whether a contestant is incentivized to help their competitors through knowledge-sharing activities. Moreover, the optimal reward mechanism under budget constraints is expected to be affected by each contestant's knowledge-sharing behavior, and the intermediary's attitude toward the development of a community forum should be considered in the reward mechanism, especially when the intermediary's revenue depends on the amount of the reward paid to the contest winner. Few studies have examined the aforementioned issues or have proposed an integrated model that covers both innovation contests and knowledge sharing through a game theory approach, to facilitate further analysis.

In view of the limitations of our research approach, we first considered two contestants with asymmetric knowledge levels in an open innovation contest. With the help of a knowledge-sharing meeting, we ascertained that each contestant's winning probability was affected by their effort decision and knowledge-sharing behavior; hence, as the contest parameters (e.g., a contestant's capability, the influence of knowledge sharing, and the available budget) changed, the optimal reward allocated could differ substantially. Finally, we expanded the research model to accommodate multiple symmetric contestants with the assistance of a knowledge-sharing community forum. Our

[18] For example, Chaordix charges a service fee based on the size of the community (see https://chaordix.com/).

results suggest that although the impact of reward size on each contestant's knowledge sharing behavior may be minor, the provision of the community forum can benefit both the contest sponsor and the intermediary.

7.1. Future Research

Future studies may investigate the following aspects on the basis of our model. Firstly, contestants should receive feedback when they post their own ideas or prototypes in the community forum. The benefit of knowledge sharing at different stages could also be further investigated. Secondly, the contest sponsor may check the results or the solutions submitted by each contestant and then select the winner, and this differs from a scenario where a supervisor monitors whether their employees are working hard. However, our large-scale crowdsourcing approach includes two prize levels, so that an adverse selection challenge may exist if contestants are heterogeneous in a crowdsourcing contest. Thirdly, a contest sponsor who possesses certain information that is unknown to contestants can either hide or reveal such information, depending on whether maintaining this uncertainty would raise the productivity of each contestant. The relationship between the expected value of information and the levels of effort and knowledge sharing in this case should be investigated in future studies.

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Appendix A. **Mathematical Proofs**
Proof of Lemma1.

Let $g(\cdot)$ be a probability density function with respect to the random variable ξ. Then, $\frac{\partial \Pi_i}{\partial e_i} = \omega \cdot g(e_i - e_{-i}) - \frac{2c}{\kappa_i+\phi_{-i}\kappa_{-i}} \cdot e_i = \frac{\omega}{2q} - \frac{2c}{\kappa_i+\phi_{-i}\kappa_{-i}} \cdot e_i$. Solving $\frac{\partial \Pi_i}{\partial e_i} = 0$ yields $e_i^* = \frac{\omega(\kappa_i+\phi_{-i}\kappa_{-i})}{4qc}$. Moreover, $\frac{\partial \Pi_i}{\partial \phi_i} = \omega \cdot g(e_i^* - e_{-i}^*)\left(-\frac{\omega\kappa_i}{4qc}\right) + F \cdot \frac{\partial}{\partial \phi_i}\frac{\phi_i\kappa_i}{\phi_i\kappa_i+\phi_{-i}\kappa_{-i}} - \tau \cdot \kappa_i = F\frac{\kappa_i\phi_{-i}\kappa_{-i}}{(\phi_i\kappa_i+\phi_{-i}\kappa_{-i})^2} - \frac{\omega^2\kappa_i}{8q^2c} - \tau \cdot \kappa_i$.
Next, $\frac{\partial \Pi_i}{\partial \phi_i} = 0$ is equivalent to $F\frac{8q^2c\phi_{-i}\kappa_{-i}}{\omega^2+8q^2c\cdot\tau} = (\phi_i\kappa_i + \phi_{-i}\kappa_{-i})^2$, which implies $\kappa_i\phi_i = \kappa_{-i}\phi_{-i}$. Thus, solving $F\frac{8q^2c\phi_{-i}\kappa_{-i}}{\omega^2+8q^2c\cdot\tau} = (\phi_i\kappa_i + \phi_{-i}\kappa_{-i})^2$ via $\kappa_i\phi_i = \kappa_{-i}\phi_{-i}$ yields $\phi_i^* = \frac{2Fq^2c}{(\omega^2+8q^2c\cdot\tau)\kappa_i}$, where $\phi_H^* \le \phi_L^*$. Note that we need to examine the boundary condition of ϕ_i^* as $\phi_i^* \in [0,1]$. Firstly, $\phi_L^*(\omega) \ge 1$ when $\omega \le \omega_2 \equiv \sqrt{\frac{2Fq^2c}{\kappa_L} - 8q^2c\cdot\tau}$. Where this reward is less than ω_2, solving $\frac{\partial \Pi_H}{\partial \phi_H} = 0$ via $\phi_L = 1$ yields $\phi_H^* = \frac{1}{\kappa_H}\sqrt{\frac{8Fq^2c\kappa_L}{\omega^2+8q^2c\cdot\tau}} - \frac{\kappa_L}{\kappa_H}$. Secondly, $\phi_H^*(\omega) \ge 1$ when $\omega \le \omega_1 \equiv \sqrt{\frac{8Fq^2c\kappa_L}{(\kappa_H+\kappa_L)^2} - 8q^2c\cdot\tau}$. Where this reward is less than ω_1, $\phi_H^* = \phi_L^* = 1$.

Proof of Proposition 1.

$\frac{\partial \phi_i^*}{\partial \omega} \le 0$, $\frac{\partial \phi_i^*}{\partial q} \ge 0$ can simply be observed from FONCs. Subsequently, $\phi_H^* \le \phi_L^*$ holds true because $\phi_H^* < \phi_L^*$ when $\omega \ge \omega_2$ and $\phi_L^* = 1$ when $\omega < \omega_2$. Finally, $\frac{\partial e_i^*}{\partial q} \le 0$ can be proven using the following approach.
Case I. $\omega \ge \omega_2$

We show that $\frac{\partial e_i^*}{\partial q} \le 0$ holds when $e_H^* = \frac{\omega(\kappa_H+\phi_L\kappa_L)}{4qc}$ and $\phi_L^* = \frac{2Fq^2c}{(\omega^2+8q^2c\cdot\tau)\kappa_L}$. Note that $\frac{\partial e_i^*}{\partial q} \le 0$ when $e_L^* = \frac{\omega(\kappa_L+\phi_H\kappa_H)}{4qc}$ and $\phi_H^* = \frac{2Fq^2c}{(\omega^2+8q^2c\cdot\tau)\kappa_H}$ can be verified using the same approach. Firstly, $\frac{\partial e_H^*}{\partial q} = -\frac{\omega\cdot\Delta}{4(\omega^2+8q^2c\tau)^2q^2c}$, where $\Delta \equiv \kappa_H\omega^4 + (16\kappa_H\tau - 2F)\omega^2q^2c + (64\kappa_H\tau + 16F)q^4c^2\tau$. If $\Delta \ge 0$ when $\omega = \omega_2$ and $\frac{\partial \Delta}{\partial \omega} \ge 0$ when $\omega > \omega_2$, then $\frac{\partial e_H^*}{\partial q} \le 0$ when $\omega \ge \omega_2$. This statement is verified as follows.
(i) $\Delta \ge 0$ when $\omega = \omega_2$

This result holds true because $\frac{\partial e_H^*}{\partial q} = -\sqrt{\frac{2q^2c(F-4\tau\kappa_L)}{\kappa_L}} \cdot \frac{F(\kappa_H-\kappa_L)+8\tau\kappa_L^2}{4Fq^2c} \le 0$ when $\omega = \omega_2$.
(ii) $\frac{\partial \Delta}{\partial \omega} \ge 0$ when $\omega > \omega_2$

To begin with, $\frac{\partial \Delta}{\partial \omega} = 4\omega(\kappa_H\omega^2 - Fq^2c + 8\kappa_Hq^2c\tau)$. Thus, (ii) remains true because $\frac{\partial \Delta}{\partial \omega} = 4q^2cF(2\kappa_H - \kappa_L)\sqrt{\frac{2q^2c(F-4\tau\kappa_L)}{\kappa_L^3}} \ge 0$ when $\omega = \omega_2$.
Case II. $\omega_1 \le \omega < \omega_2$

When $e_H^* = \frac{\omega(\kappa_H+\phi_L\kappa_L)}{4qc}$ and $\phi_L^* = 1$, $\frac{\partial e_H^*}{\partial q} \le 0$ is straightforward. As for $e_L^* = \frac{\omega(\kappa_L+\phi_H\kappa_H)}{4qc}$ and $\phi_H^* = \frac{1}{\kappa_H}\sqrt{\frac{8Fq^2c\kappa_L}{\omega^2+8q^2c\cdot\tau}} - \frac{\kappa_L}{\kappa_H}$, $\frac{\partial e_H^*}{\partial q} = -\frac{2\sqrt{8}\tau\kappa_Lcq^2F\omega}{(\omega^2+8q^2c\tau)^2\sqrt{\frac{Fq^2c\kappa_L}{\omega^2+8q^2c\tau}}} \le 0$. The proof of Case III where $\omega < \omega_1$ is omitted, as $\phi_H^* = \phi_L^* = 1$.

Proof of Lemma 2.

W.L.O.G., we assume that contestant *i* has a higher knowledge level. Hence, $|e_i^* - e_{-i}^*| < q \Leftrightarrow \left|\frac{\omega(\kappa_H+\phi_L\kappa_L)}{4qc} - \frac{\omega(\kappa_L+\phi_H\kappa_H)}{4qc}\right| < q \Leftrightarrow |(1-\phi_H)\kappa_H - (1-\phi_L)\kappa_L| < \frac{4q^2c}{\omega}$. Note that $\sqrt{\frac{\kappa_H\omega}{4c}} \le \sqrt{\frac{\kappa_H\beta}{4(1+\gamma)c}}$, as $(1+\gamma)\omega \le \beta$. In addition, $\kappa_H > \kappa_L > 0$ could imply that $-\kappa_L \le (1-\phi_H)\kappa_H - (1-\phi_L)\kappa_L \le \kappa_H$. As a result, if $\sqrt{\frac{\kappa_H\beta}{4(1+\gamma)c}} < q$ holds true, then $|(1-\phi_H)\kappa_H - (1-\phi_L)\kappa_L| < \kappa_H < \frac{4q^2c}{\omega} \Leftrightarrow |e_i^* - e_{-i}^*| < q$.

Proof of Lemma 3.

Through backward induction, the knowledge-sharing level is determined by $\frac{\partial \Pi_i}{\partial \phi_i} = F \cdot \frac{\kappa_i \kappa_{-i} \phi_{-i}}{(\phi_i \kappa_i + \phi_{-i}\kappa_{-i})^2} - \tau \cdot \kappa_i$. Thus, solving $\frac{\partial \Pi_H}{\partial \phi_H} = 0$ and $\frac{\partial \Pi_L}{\partial \phi_L} = 0$ simultaneously yields $\phi_H^* = min\left\{\frac{F}{4\tau \cdot \kappa_H}, 1\right\}$ and $\phi_L^* = \left\{\frac{F}{4\tau \cdot \kappa_L}, 1\right\}$, as $\phi_i^* \in [0,1]$. Note that ϕ_i^* is not linked to e_i . Hence, solving the following equation yields the effort level decision:

$$\frac{\partial \Pi_i}{\partial e_i} = \frac{\partial}{\partial e_i}\left\{\omega \cdot \text{Prob}(winning) - \frac{c}{\kappa_i + \phi_{-i}\kappa_{-i}} \cdot e_i^2\right\} = \frac{\omega}{2q} - 2\frac{c}{\kappa_i + \phi_{-i}\kappa_{-i}} \cdot e_i = 0.$$

Thus, $e_i = \frac{\omega(\kappa_i + \phi_{-i}\kappa_{-i})}{4qc}$. Three cases are given as follows:

(1) $\frac{F}{4\tau \cdot \kappa_H} < \frac{F}{4\tau \cdot \kappa_L} < 1$: $e_H = \frac{\omega(4\tau\kappa_H + F)}{16qc\tau}$, $e_L = \frac{\omega(4\tau\kappa_L + F)}{16qc\tau}$;

(2) $\frac{F}{4\tau \cdot \kappa_H} < 1 < \frac{F}{4\tau \cdot \kappa_L}$: $e_H = \frac{\omega(\kappa_H + \kappa_L)}{4qc}$, $e_L = \frac{\omega(4\tau\kappa_L + F)}{16qc\tau}$;

(3) $1 < \frac{F}{4\tau \cdot \kappa_H} < \frac{F}{4\tau \cdot \kappa_L}$: $e_H = \frac{\omega(\kappa_H + \kappa_L)}{4qc}$, $e_L = \frac{\omega(\kappa_H + \kappa_L)}{4qc}$.

Finally, $\phi_L^* = 1$ implies $F = 4\tau \cdot \kappa_L$, whereas $\phi_H^* = 1$ implies $F = 4\tau \cdot \kappa_H$. The value of F is used to define the segment for each case.

Proof of Lemma 4.

Consider the following facts. Firstly, $\omega_1 > 0$ implies $F > (\kappa_H + \kappa_L)^2 \tau / \kappa_L$. Hence, $\frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{\delta\tau(\kappa_H + \kappa_L)^3}{F \cdot \kappa_L}\right) < \frac{(1+\delta)(\kappa_H + \kappa_L)}{4q(1+\gamma)}$ always holds true. Secondly, if λ is small enough, $\frac{\partial^2 \pi_{S,II}}{\partial \omega^2} = -\frac{\sqrt{2}(4\lambda\tau q^2 c + 3\delta\omega\tau q - \lambda\omega^2)(2Fq^2 c\kappa_L)^2}{(\omega^2 + 8q^2 c\tau)^4 \left(\frac{Fq^2 c\kappa_L}{\omega^2 + 8q^2 c\tau}\right)^{\frac{3}{2}}} < 0$ is a concave function where $\omega_1 \le \omega < \omega_2$. Thirdly,

(i) $\frac{\partial \pi_{S,II}}{\partial \omega} = \frac{\kappa_H + \kappa_L}{4qc} + \frac{2\sqrt{8}cq^3 F\kappa_L \tau\left(\delta - \frac{\lambda\omega}{2q\tau}\right)}{(\omega^2 + 8q^2 c\tau)^2 \sqrt{\frac{Fq^2 c\kappa_L}{\omega^2 + 8q^2 c\tau}}} - (1+\gamma)$;

(ii) $\frac{\partial \pi_{S,II}}{\partial \omega} = \frac{\kappa_H + \kappa_L}{4qc} + \frac{\left(q\delta\tau - \lambda\sqrt{\frac{2q^2 c\left(F\kappa_L - \tau(\kappa_H + \kappa_L)^2\right)}{(\kappa_H + \kappa_L)^2}}\right)(\kappa_H + \kappa_L)^3}{4cq^2 F\kappa_L} - (1+\gamma)$ when $\omega = \omega_1$;

(iii) $\frac{\partial \pi_{S,II}}{\partial \omega} = \frac{\kappa_H + \kappa_L}{4qc} + \frac{\kappa_L^2\left(2q\delta\tau - \lambda\sqrt{\frac{2q^2 c(F - 4\kappa_L \tau)}{k_L}}\right)}{cq^2 F} - (1+\gamma)$ when $\omega = \omega_2$.

We set $\lambda = 0$ to simplify all expressions. Solving $\left.\frac{\partial \pi_{S,II}}{\partial \omega}\right|_{\omega = \widehat{\omega}} = 0$ yields $\widehat{\omega} = \sqrt{8q^2 c\left((F\kappa_L)^{\frac{1}{3}}\left(\frac{\delta\tau}{4 \cdot q \cdot c(1+\gamma) - (\kappa_H + \kappa_L)}\right)^{\frac{2}{3}} - \tau\right)}$. We check the sign of $\frac{\partial \pi_{S,II}}{\partial \omega}$ in $\omega = \omega_1$ and $\omega = \omega_2$ as follows:

(i) when $\omega = \omega_1$, $\frac{\partial \pi_{S,II}}{\partial \omega} > 0 \Leftrightarrow \frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{\delta\tau(\kappa_H + \kappa_L)^3}{F \cdot \kappa_L}\right) > c$;

(ii) when $\omega = \omega_2$, $\frac{\partial \pi_{S,II}}{\partial \omega} > 0 \Leftrightarrow \frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{8\delta\tau\kappa_L^2}{F}\right) > c$.

Consequently, when $c \le \frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{8\delta\tau\kappa_L^2}{F}\right)$, $\omega^* = \frac{\beta}{1+\gamma}$, as $\frac{\partial \pi_{S,II}}{\partial \omega} \ge 0$ over $\omega \in [\omega_1, \omega_2]$. If $\frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{8\delta\tau\kappa_L^2}{F}\right) < c \le \frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{\delta\tau(\kappa_H + \kappa_L)^3}{F \cdot \kappa_L}\right)$, $\omega^* = \min\left(\widehat{\omega}, \frac{\beta}{1+\gamma}\right)$ since $\left.\frac{\partial \pi_{S,II}}{\partial \omega}\right|_{\omega = \omega_1} > 0$ and $\left.\frac{\partial \pi_{S,II}}{\partial \omega}\right|_{\omega = \omega_2} < 0$. Next, if $\frac{1}{4(1+\gamma)q}\left((\kappa_H + \kappa_L) + \frac{\delta\tau(\kappa_H + \kappa_L)^3}{F \cdot \kappa_L}\right) < c \le \frac{(1+\delta)(\kappa_H + \kappa_L)}{4q(1+\gamma)}$, $\omega^* = \omega_1$, since $\frac{\partial \pi_{S,II}}{\partial \omega} \le 0$ over $\omega \in [\omega_1, \omega_2]$ and $\pi_{S,I}$ over $\omega \in [0, \omega_1]$ is a non-decreasing function. Finally, $\omega^* = 0$ if $c > \frac{(1+\delta)(\kappa_H + \kappa_L)}{4q(1+\gamma)}$, as both $\pi_{S,I}$ over $\omega \in [0, \omega_1]$ and $\pi_{S,II}$ over $\omega \in [\omega_1, \omega_2]$ are decreasing functions.

Proof of Corollary 1.

Let $\Gamma \equiv (F\kappa_L)^{\frac{1}{3}}\left(\frac{\delta\tau}{4qc(1+\gamma)-(\kappa_H+\kappa_L)}\right)^{\frac{2}{3}}-\tau$. Thus, $\widehat{\omega}=\sqrt{8q^2c\Gamma}$. The sign of $\frac{\partial\widehat{\omega}}{\partial\tau}$ is the same as that of $\frac{\partial\Gamma}{\partial\tau}$. Since $\frac{\partial\Gamma}{\partial\tau}=\frac{2}{3}(F\kappa_L)^{\frac{1}{3}}\left(\frac{\delta}{4qc(1+\gamma)-(\kappa_H+\kappa_L)}\right)^{\frac{2}{3}}\tau^{-\frac{1}{3}}-1$, $\frac{\partial\widehat{\omega}}{\partial\tau}>0$ if and only if $\frac{8F\kappa_L}{27}\left(\frac{\delta}{4qc(1+\gamma)-(\kappa_H+\kappa_L)}\right)^2>\tau$.

Proof of Lemma 5.

We first seek the optimal reward amount when $\omega\in\left[\omega_2,\frac{\beta}{1+\gamma}\right]$. This result is combined with the outcome derived in Lemma 4 to complete the proof. The following four equations hold true:

(1) $\frac{\partial\pi_{S,III}}{\partial\omega}=\frac{\kappa_H+\delta\kappa_L}{4qc}-\frac{(1+\delta)Fq^2(\omega^2-8q^2c\tau)}{2q(\omega^2+8q^2c\tau)^2}-(1+\gamma)-\frac{32\lambda Fq^3c^2\omega}{4qc(\omega^2+8q^2c\tau)^2}$;

(2) $\frac{\partial^2\pi_{S,III}}{\partial\omega^2}=\frac{Fq\left((1+\delta)\omega^3-24\left(\omega(1+\delta)q^2c\tau-\lambda qc\omega^2\right)-64\lambda q^3c^2\tau\right)}{(\omega^2+8q^2c\tau)^3}$;

(3) $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\omega_2}=\frac{(\kappa_H-\kappa_L)Fq+8(1+\delta)\tau q\kappa_L^2-4(1+\gamma)Fq^2c-8\lambda\kappa_L^2\sqrt{\frac{2q^2c(F-4\kappa_L\tau)}{\kappa_L}}}{4q^2cF}$;

(4) $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\sqrt{24q^2c\tau}}=\frac{(\kappa_H+\delta\kappa_L)32q\tau^2-(1+\delta)Fq\tau-128(1+\gamma)q^2c\tau^2-\lambda F\sqrt{24q^2c\tau}}{128q^2c\tau^2}$.

In the following, we consider $\lambda=0$ to simplify all expressions. Note that $\frac{\partial\pi_{S,III}}{\partial\omega}=\frac{\kappa_H+\delta\kappa_L}{4qc}-\frac{(1+\delta)Fq(\omega^2-8q^2c\tau)}{2(\omega^2+8q^2c\tau)^2}-(1+\gamma)$ and $\frac{\partial^2\pi_{S,III}}{\partial\omega^2}=\frac{(1+\delta)Fq\omega(\omega^2-24q^2c\tau)}{(\omega^2+8q^2c\tau)^3}$. Thus, $\pi_{S,III}(\omega)$ is a convex function when $\omega>\sqrt{24q^2c\tau}$, but a concave function when $\omega<\sqrt{24q^2c\tau}$. Next, $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\omega_2}>0$ if $c<\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$, while $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\omega_2}<0$ if $c>\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$. Moreover, $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\sqrt{24q^2c\tau}}=\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F-128(1+\gamma)qc\tau}{128qc\tau}$. Consequently, $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\sqrt{24q^2c\tau}}<0$ if $\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F}{128(1+\gamma)q\tau}<c$. In other words, the local maximal value $\pi_{S,III}(\omega')$ exists when $\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F}{128(1+\gamma)q\tau}<c\le\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$, where $\omega'\in\left[\omega_2,\sqrt{24q^2c\tau}\right]$, which satisfies $\left.\frac{\partial\pi_{S,III}}{\partial\omega}\right|_{\omega=\omega'}=0$. Finally, $\frac{\partial\pi_{S,III}}{\partial\omega}$ reaches its minimal value when $\omega=\sqrt{24q^2c\tau}$. Hence, if $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)\le 0$, $\partial\pi_{S,III}/\partial\omega<0$ when $\omega\ge\sqrt{24q^2c\tau}$. On the other hand, where $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)>0$, we still need to verify the value of $\left.\pi_{S,III}\right|_{\omega=\frac{\beta}{1+\gamma}}$, because $\partial\pi_{S,III}/\partial\omega$ is positive when ω is sufficiently large. Based on the aforementioned observations, we can summarize all outcomes when $\omega\in\left[\omega_2,\frac{\beta}{1+\gamma}\right]$ as follows:

Case I. $\omega^*=\omega_2$

If $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)\le 0$, $\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}<c$, and $\omega_2<\sqrt{24q^2c\tau}$, $\pi_{S,III}(\omega)$ is a decreasing function over $\left[\omega_2,\sqrt{24q^2c\tau}\right]$, and $\partial\pi_{S,III}/\partial\omega<0$ when $\omega\in\left[\sqrt{24q^2c\tau},\frac{\beta}{1+\gamma}\right]$. Similarly, if $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)\le 0$, $\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}<c$, and $\sqrt{24q^2c\tau}\le\omega_2$, $\pi_{S,III}(\omega)$ is a decreasing function over $\left[\omega_2,\frac{\beta}{1+\gamma}\right]$.

Case II. $\omega^*=\omega_2$ or $\omega^*=\frac{\beta}{1+\gamma}$

If $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)>0$, $\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}<c$, and $\omega_2<\sqrt{24q^2c\tau}$, $\pi_{S,III}(\omega)$ is a decreasing function over $\left[\omega_2,\sqrt{24q^2c\tau}\right]$; however, $\partial\pi_{S,III}/\partial\omega>0$ when ω is sufficiently large. Similarly, if $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)>0$, $\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}<c$, and $\sqrt{24q^2c\tau}\le\omega_2$, $\pi_{S,III}$ is a decreasing function at $\omega=\omega_2$; however, $\partial\pi_{S,III}/\partial\omega>0$ when ω is sufficiently large.

Case III. $\omega^*=\omega'$

If $\frac{(\kappa_H+\delta\kappa_L)}{4qc}-(1+\gamma)\le 0$, $\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F}{128(1+\gamma)q\tau}<c\le\frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$, and $\omega_2<\sqrt{24q^2c\tau}$, $\partial\pi_{S,III}/\partial\omega\ge 0$ when $\omega=\omega_2$ but $\partial\pi_{S,III}/\partial\omega<0$ when $\omega=\sqrt{24q^2c\tau}$. Hence, there exists $\omega'\in\left[\omega_2,\sqrt{24q^2c\tau}\right]$ such that $\pi_{S,III}(\omega')\ge\pi_{S,III}(\omega)$ where $\omega\in\left[\omega_2,\sqrt{24q^2c\tau}\right]$. Moreover, we do not examine $\pi_{S,III}$ when $\omega>\sqrt{24q^2c\tau}$ because

$\pi_{S,III}$ is a decreasing function when $\omega \in \left[\sqrt{24q^2c\tau}, \frac{\beta}{1+\gamma}\right]$.

Case IV. $\omega^* = \omega'$ or $\omega^* = \frac{\beta}{1+\gamma}$

If $\frac{(\kappa_H+\delta\kappa_L)}{4qc} - (1+\gamma) > 0$, $\frac{32(\tau\kappa_H+\delta\tau\kappa_L)-(1+\delta)F}{128(1+\gamma)q\tau} < c \le \frac{(\kappa_H-\kappa_L)F+8(1+\delta)\kappa_L^2\tau}{4(1+\gamma)Fq}$, and $\omega_2 < \sqrt{24q^2c\tau}$, in addition to $\omega^* = \omega'$ (as shown in Case III), we also need to consider $\omega^* = \frac{\beta}{1+\gamma}$, as $\partial\pi_{S,III}/\partial\omega > 0$ when ω is sufficiently large.

Case V. $\omega^* = \frac{\beta}{1+\gamma}$

If none of the aforementioned cases can be satisfied, $\pi_{S,III}(\omega)$ is an increasing function over $\left[\omega_2, \frac{\beta}{1+\gamma}\right]$.

Proof of Proposition 2.

Note that the optimal reward amount could be 0, ω_1, $\widehat{\omega}$, ω_2, ω', and $\frac{\beta}{1+\gamma}$. Firstly, ω_1 and ω_2 are irrelevant to the value of λ. Next, $\frac{\partial\widehat{\omega}}{\partial\lambda} < 0$ because $\frac{\partial^2\pi_{S,II}}{\partial\omega\partial\lambda} = -\frac{\sqrt{8}\omega\left(Fq^2ck_L\right)^{\frac{1}{2}}}{(\omega^2+8q^2c\tau)^{\frac{3}{2}}} < 0$, while $\frac{\partial\omega\prime}{\partial\lambda} < 0$ because $\frac{\partial^2\pi_{S,III}}{\partial\omega\partial\lambda} = -\frac{8Fq^2cw}{(w^2+8q^2c\tau)^2} < 0$. Secondly, $\frac{\partial\omega_1}{\partial F} > 0$ and $\frac{\partial\omega_2}{\partial F} > 0$ are straightforward. Moreover, $\frac{\partial\widehat{\omega}}{\partial F} > 0$ if and only if $\lambda < \frac{2\delta\tau q}{\omega}$ because $\frac{\partial^2\pi_{S,II}}{\partial\omega\partial F} = -\frac{(\lambda\omega-2\delta\tau q)c^2F\kappa_L^2q^4\sqrt{2}}{\left(\frac{Fq^2c\kappa_L}{\omega^2+8q^2c\tau}\right)^{3/2}(\omega^2+8q^2c\tau)^3}$. Likewise, $\frac{\partial\omega\prime}{\partial F} > 0$ if and only if $\lambda < \frac{(1+\delta)(8q^2c\tau-\omega^2)}{16qcw}$, as $\frac{\partial^2\pi_{S,III}}{\partial\omega\partial F} = -\frac{q\left((1+\delta)(\omega^2-8q^2c\tau)+16\lambda qcw\right)}{2(\omega^2+8q^2c\tau)^2}$.

Proof of Proposition 3.

Solving $\left.\frac{\partial\Pi_i}{\partial e_i}\right|_{e_i=e^*} = \frac{S}{2q} - \frac{2c}{\kappa+\hat{A}}\cdot e^* = 0$ and $\left.\frac{\partial\Pi_i(e^*)}{\partial\phi_i}\right|_{\phi_i=\phi^*} = F\cdot\frac{(n-1)\phi^*}{(\phi^*+(n-1)\phi^*)^2} - \tau\cdot\kappa = 0$ yields e^* and ϕ^*, respectively. Moreover, we have $\omega_L^* = \frac{\kappa+\hat{A}}{c}\cdot\left(\frac{S}{4q}\right)^2 + \tau\cdot\phi^*\cdot\kappa - \frac{S}{n} - \frac{F}{n}$ from $\Pi_i(e^*,\phi^*) = 0$. Thus, the contest sponsor's payoff is $\pi_S = \left(1+\delta(n-1)\right)e^* + \lambda\sum\phi_i\kappa_i - (1+\gamma)(S+\omega_L^*) - (n-1)\omega_L^*$. Solving $\frac{\partial\pi_S}{\partial S} = 0$ yields $S^* = \frac{2q\left((1-\delta)n(\kappa+\hat{A})+\delta n^2(\kappa+\hat{A})-4(n-1)qcr\right)}{n(\kappa+\hat{A})(\gamma+n)}$. Where $(1+\gamma)(S^*+\omega_L^*) + (n-1)\omega_L^* > \beta$, we discover a boundary solution S that satisfies $(1+\gamma)(S+\omega_L^*) + (n-1)\omega_L^* = \beta$ instead.

Proof of Proposition 4.

Note that $A_i \equiv \hat{A}(\phi_{-i},\kappa,n)$ and $\phi^* = \min\left\{F\cdot\frac{(n-1)}{\tau\cdot\kappa\cdot n^2}, 1\right\}$. Moreover, $\omega_H^* = \omega_L^* + S = \frac{\kappa+\hat{A}}{c}\cdot\left(\frac{S}{4q}\right)^2 + \tau\cdot\phi^*\cdot\kappa + \frac{(n-1)S}{n} - \frac{F}{n}$. Subsequently, $\frac{\partial\omega_H^*}{\partial F} = \left(\frac{\partial\hat{A}}{\partial\phi}\cdot\frac{\partial\phi^*}{\partial F}\right)\cdot\frac{1}{c}\cdot\left(\frac{S}{4q}\right)^2 + \frac{\kappa+\hat{A}}{c}\cdot\frac{S}{2q}\cdot\frac{\partial S}{\partial F} + \tau\cdot\frac{\partial\phi^*}{\partial F}\cdot\kappa + \frac{n-1}{n}\frac{\partial S}{\partial F} - \frac{1}{n}$. We consider the interior case where $S^*(\hat{A}) = \frac{2q\left((1-\delta)n(\kappa+\hat{A})+\delta n^2(\kappa+\hat{A})-4(n-1)qcr\right)}{n(\kappa+\hat{A})(\gamma+n)}$ and $\phi^* < 1$. The following facts help to show that $\frac{\partial\omega_H^*}{\partial F} > 0$ when n is large enough:

(1) $\frac{\partial\phi^*}{\partial F} > 0$, $\frac{\partial\hat{A}}{\partial\phi} > 0$, and $\frac{\partial\hat{A}}{\partial n} > 0$;

(2) $\frac{\partial\hat{A}}{\partial F} = \frac{\partial\hat{A}}{\partial\phi}\cdot\frac{\partial\phi^*}{\partial F} > 0$;

(3) $\frac{\partial S}{\partial F} = \frac{\partial S}{\partial\hat{A}}\frac{\partial\hat{A}}{\partial F} > 0$ due to $\frac{\partial S}{\partial\hat{A}} = \frac{8q^2(n-1)c\gamma}{n(\kappa+\hat{A})^2(\gamma+n)} > 0$.

As a result,

$$\frac{\partial\omega_H^*}{\partial F} = \left(\frac{\partial\hat{A}}{\partial\phi}\cdot\frac{\partial\phi^*}{\partial F}\right)\cdot\frac{1}{c}\cdot\left(\frac{S}{4q}\right)^2 + \frac{\kappa+\hat{A}}{c}\cdot\frac{S}{2q}\cdot\frac{\partial S}{\partial F} + \tau\cdot\frac{\partial\phi^*}{\partial F}\cdot\kappa + \frac{n-1}{n}\frac{\partial S}{\partial F} - \frac{1}{n}$$

$$= \left(\frac{\partial\hat{A}}{\partial\phi}\cdot\frac{\partial\phi^*}{\partial F}\right)\cdot\frac{1}{c}\cdot\left(\frac{S}{4q}\right)^2 + \left(\frac{\kappa+\hat{A}}{c}\cdot\frac{S}{2q} + \frac{n-1}{n}\right)\frac{\partial S}{\partial F} - \frac{1}{n^2}$$

$$= \left(\frac{\partial\hat{A}}{\partial\phi}\cdot\frac{\partial\phi^*}{\partial F}\right)\cdot\frac{1}{c}\cdot\left(\frac{S}{4q}\right)^2 + \left(\frac{\kappa+\hat{A}}{c}\cdot\frac{S}{2q} + \frac{n-1}{n}\right)\left(\frac{8q^2(n-1)c\gamma}{n\left(\kappa+\hat{A}\right)^2(\gamma+n)}\right)\left(\frac{\partial\hat{A}}{\partial\phi}\cdot\frac{\partial\phi^*}{\partial F}\right) - \frac{1}{n^2}$$

$$= \left(\left(\frac{1}{c} \cdot \left(\frac{S}{4q} \right)^2 + \left(\frac{\kappa + \hat{A}}{c} \cdot \frac{S}{2q} + \frac{n-1}{n} \right) \left(\frac{8q^2(n-1)c\gamma}{n\left(\kappa + \hat{A}\right)^2 (\gamma + n)} \right) \right) \left(\frac{\partial \hat{A}}{\partial \phi} \cdot \frac{n-1}{\tau \cdot \kappa} \right) - 1 \right) \cdot \frac{1}{n^2}$$

Note that $S(\hat{A}) = \frac{2q\left((1-\delta)n(\kappa+\hat{A})+\delta n^2(\kappa+\hat{A})-4(n-1)qcr\right)}{n(\kappa+\hat{A})(\gamma+n)} = \frac{2q((1-\delta)+\delta n)}{(\gamma+n)} - \frac{8(n-1)q^2cr}{n(\kappa+\hat{A})(\gamma+n)}$; thus, $\lim_{n\to\infty} S(\hat{A}) = 2q\delta$, as $\frac{\partial \hat{A}}{\partial n} > 0$. In addition, $\frac{\partial \hat{A}}{\partial \phi} > 0$ and $\frac{\partial^2 \hat{A}}{\partial n \partial \phi} \geq 0$; thus, $\frac{\partial \omega_H^*}{\partial F} > 0$ when both n and δ are sufficiently large.

Appendix B. **Robustness Checks for Convexity of the Effort Cost Function**

To investigate whether our model is robust when the convexity of the effort cost function changes, we represent the contestant's effort using the function $\frac{c}{\kappa_i + \phi_{-i}\kappa_{-i}} \cdot e_i^{\mu}$, where $\mu > 1$, in our numerical experiment. The value of μ can be used to measure the degree of convexity of the effort cost function. In our numerical experiments, we consider $\mu \in \{1.2, 1.8, 2{,}4, 3.0, 3.6\}$ and test whether Proposition 1 still holds. The other parameters used in the experiments are $\beta = 3$, $c = 0.5$, $F = 0.05$, $\delta = 0.75$, $\kappa_H = 2$, $\kappa_L = 1$, $q = 3$ (if required), $\gamma = 0.01$, $\tau = 0.01$, and $\omega = 2.5$ (if required). Figures B.1 and B.2 are used to determine whether $\frac{\partial \phi_i^*}{\partial \omega} \leq 0$ is robust when the convexity of the effort cost function changes. Figures B.3, B.4, B.5, and B.6 are used to examine the cases where $\frac{\partial \phi_i^*}{\partial q} \geq 0$ and $\frac{\partial e_i^*}{\partial q} \leq 0$.

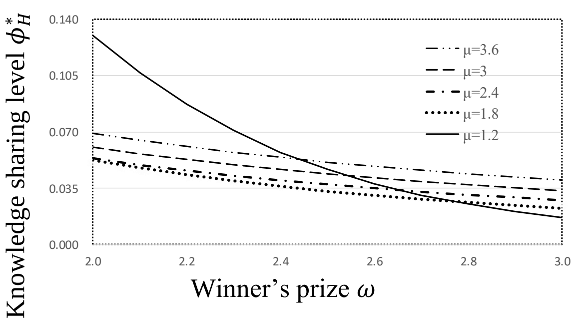

Figure B.1: Relation between a high-type contestant's knowledge-sharing level and the winner's prize

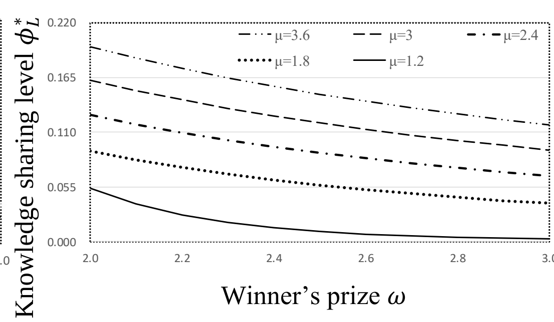

Figure B.2: Relation between a low-type contestant's knowledge-sharing level and the winner's prize

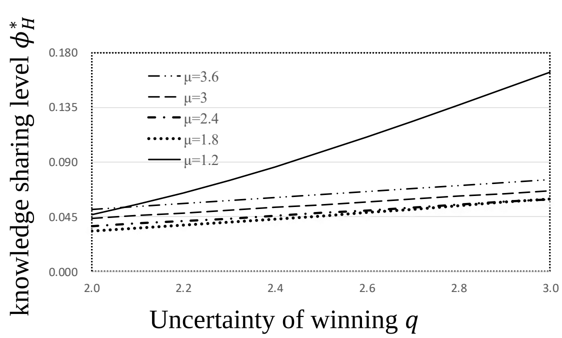

Figure B.3: Relation between a high-type contestant's knowledge-sharing level and the uncertainty of winning the contest

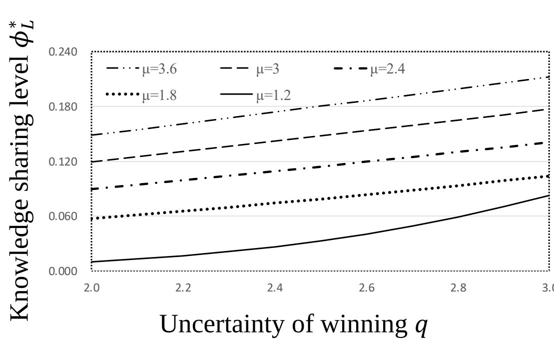

Figure B.4: Relation between a low-type contestant's knowledge-sharing level and the uncertainty of winning the contest

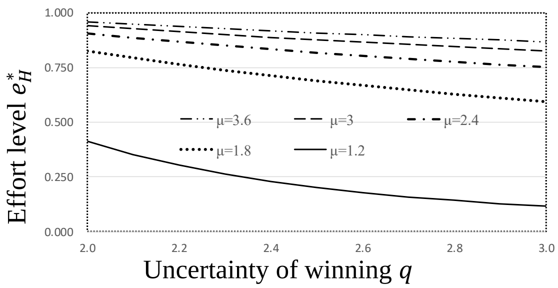

Figure B.5: Relation between a high-type contestant's effort level and the uncertainty of winning the contest

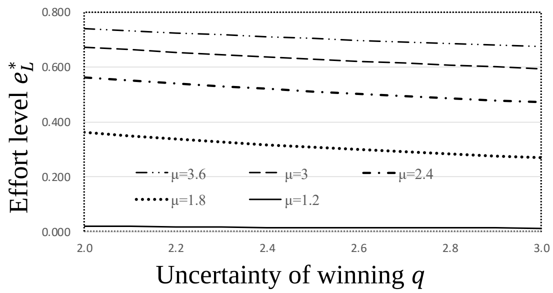

Figure B.6: Relation between a low-type contestant's effort level and the uncertainty of winning the contest