Coupling Information Disclosure with a Quality Standard in R&D Contests

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Abstract

We study R&D contest design using both an information disclosure policy and a quality standard as instruments. An innovator's ability is only known to himself. The organizer commits ex ante to a minimum quality standard and whether to have innovators' abilities publicly revealed before they conduct R&D activities. We find that with no quality standard, fully concealing innovators' abilities elicits both higher expected aggregate quality and expected highest quality. With optimally set quality standards, while fully concealing the ability information elicits higher expected aggregate quality, fully disclosing the ability information elicits higher expected highest quality. Moreover, the optimal quality standards are compared across different objectives and disclosure policies.

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Keywords: Information disclosure; Quality standard; R&D contests.

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1 Introduction

R&D contests are widely used to promote innovation. In an R&D contest, the procurer/organizer posts an innovation-related problem to suppliers/innovators and awards the supplier/innovator who comes up with the best solution. Typically, the procurer can set a minimum acceptable quality standard to guarantee the quality of the innovations that result from the R&D contest. For example, in the first automobile race held in the United States, sponsored by the *Chicago Times-Herald* in 1895, participating automobiles were required to have enough power to climb all of the course's grades. More recently, the 2018 Honda Motor (China) Energy Saving Competition required the original vehicle body to have three wheels or more, and be in accordance with all safety regulations. As a further example, participants in the 2018 City University (Hong Kong) App Innovation Contest had to create an app or visually interactive scene in a Swift playground that could be experienced within three minutes. Similarly, in many government-sponsored R&D contests, competitors are required to meet ISO 9001, which is the international standard that specifies the requirements for a quality management system.

In addition to the design on quality standards, to better incentivize innovators, the procurer/organizer can strategically choose an information disclosure policy regarding the competing innovators' competencies. Very often, each innovator knows his own competency but not that of his competitors. This competency information, however, can be revealed to be innovators. For example, research proposals or other materials (e.g., qualifications documents, certificates, financial reports, etc.) serve as good signals of the competing innovators' backgrounds; procurers/organizers can learn about participants' abilities from their submitted materials and reveal such information publicly. In the meanwhile, they can also require participants to share information among themselves.[1] We would like to emphasize that the revelation of information does not depend on the obsevability of innovators' types by the organizer. For example, Eső and Szentes (2007) assume in their model that the seller can control the release of information to buyers about their values even when the seller cannot observe the information.

In this paper, we study the optimal design of R&D contests when both the information disclosure policy and quality standard are available to the organizer as design instruments. We adopt an analytical framework of an all-pay auction with incomplete information to model R&D innovation contests. We use a minimum bid to capture the minimum quality standard in contests. Following Moldovanu and Sela (2006) and Konrad and Kovenock (2010), innovators' abilities (private types) are measured by the inverse of their marginal effort costs, which are randomly distributed. The contest organizer has two instruments: the disclosure

[1] This kind of information exchange agreement among participants can be enforced by competition law.

policy and quality standard. She strategically sets up a quality standard and chooses between two policy alternatives: (1) fully revealing innovators' competency profiles publicly versus (2) fully concealing them. Her disclosure policy is ex ante committed prior to the realization of innovators' ability profiles.

The timing of the game is as follows. First, the contest organizer announces a quality standard and commits to her disclosure policy publicly. Second, innovators' cost profiles are realized and everyone's cost is only known by himself. This information is disclosed to all innovators if and only if the organizer has chosen full disclosure policy. Finally, innovators submit their effort entries simultaneously in competition for a single prize.

The design objectives we accommodate include both aggregate quality maximization and highest quality maximization. In an R&D contest, the organizer might care about only the best innovation only or the aggregate level of research output, depending on the specific context. The central question we investigate is how the disclosure policy should be optimally coupled with the quality standard to best incentivize the innovators in each of these design goal contexts, i.e., aggregate and highest quality maximizations. How should quality standards be set for different goals under different disclosure policies? If the quality standard can be optimally set by the contest organizer, should she disclose or conceal the innovators' types? How does this answer depend on the design goal?

When the contest organizer chooses to have innovators' types disclosed, a complete-information all-pay auction with a reserve price occurs. Bertoletti (2016) characterizes the bidding equilibrium with $n(\geq 2)$ bidders for any given reserve price. The concealment policy leads to an incomplete-information all-pay auction with a reserve price. For this setting, Riley and Samuelson (1981) provide the bidding equilibrium. These studies pave the foundation of equilibrium analysis for our study on optimal design.

Our focus is on optimal design when both disclosure policy and quality standard can be chosen optimally. To provide a comparison benchmark, we first study a scenario without a quality standard. For this benchmark environment, we find that fully concealing innovators' types can elicit both higher ex ante expected aggregate quality and expected highest quality. In contrast, if the quality standard can be chosen optimally, while fully concealing the information elicits a higher ex ante expected aggregate quality, fully disclosing the information elicits higher ex ante expected highest quality.

The intuitions behind these comparison results are as follows. Without quality standards, revealing innovators' types publicly tends to discourage both the stronger and weaker innovators' effort supply. Therefore, full disclosure policy is dominated by full concealment policy for both aggregate and highest quality maximizations. Setting a nontrivial quality standard tends to discourage the weaker types while better motivating the stronger types. Therefore, regardless of the disclosure policy, a quality standard as a design instrument would be more effective for highest quality maximization than for aggregate quality maximization, and a higher quality standard would be set for highest quality maximization. For a fixed goal, setting a quality standard should be more effective, and it should be set higher under the full disclosure policy than under the full concealment policy, as when innovators' types are revealed publicly, both stronger and weaker innovators tend to be discouraged in their effort supply. This conjecture is confirmed analytically for aggregate quality maximization. For highest quality maximization, it is confirmed by numerical simulations for a class of ability distributions. As a result, for aggregate quality maximization, setting a quality standard does not overcome the disadvantage conferred by a full disclosure policy. However, for highest quality maximization, setting a quality standard can reverse the outcome when comparing the two disclosure policies.

Strategic disclosure of information about bidders' abilities has been well studied in the contest literature. Kovenock, Morath, and Münster (2013) consider voluntary information sharing between two bidders regarding their values in an all-pay auction setting. Morath and Münster (2008) compare information structures in all-pay auctions. They find that bidders receive the same expected payoff across full concealment and full disclosure, but full concealment induces higher expected total effort. Fu, Jiao, and Lu (2014) generalize the insight of Morath and Münster by allowing for multiple prizes. Serena (2018) and Lu, Ma, and Wang (2018) study settings of two-player contests with discrete types, and provide complete rankings of four anonymous type-contingent information disclosure policies in environments with different contest technologies. In a two-player Tullock contest setting, using a Bayesian persuasion approach, Zhang and Zhou (2016) study the optimal disclosure policy with one-sided private information, and find that there is no loss of generality to consider full disclosure and full concealment when types are binary. Wu and Zheng (2017) investigate contestants' incentives to disclose their valuations of the prize in a Tullock contest setting, and they find that sharing information is strictly dominated if types are sufficiently dispersed. Aoyagi (2010) studies an optimal feedback policy regarding agents' performance in a multi-stage tournament. Another strand of the literature compares disclosure policies in contests according to the number of participants. Lim and Matros (2009), Fu, Jiao, and Lu (2011), and Fu, Lu, and Zhang (2016) mainly focus on Tullock contests with stochastic entry, while Hu, Zhao, and Huang (2016) and Chen, Jiang, and Knyazev (2017) explore this issue in all-pay auction settings.

Nearly all of these studies on information disclosure in contests focus on total effort maximization, with the only exception being Hu, Zhao, and Huang (2016), who consider two objectives in contests (i.e., maximization of both expected aggregate effort and expected highest effort). Some other studies also consider both objectives, but adopt different design instruments. For example, Moldovanu and Sela (2006) compare a one-stage contest and a two-stage contest; Chen, Zheng, and Zhong (2015) compare random grouping with ability-based grouping; and Serena (2017) studies contestant exclusion. To the best of our knowledge, our paper is the first to study the optimal designs of R&D contests while allowing both a disclosure policy and quality standard as instruments.

The rest of the paper proceeds as follows. In Section 2, we set up an R&D contest model with a quality standard, carry out equilibrium analysis, and compare optimal quality standards under different disclosure policies. Section 3 presents the comparison of disclosure policies under expected aggregate quality maximization and expected highest quality maximization. Examples and intuitions behind the main results are presented in Section 4. Section 5 concludes. Proofs of Lemmas and Propositions are relegated to the Appendix.

2 A model of an R&D contest with quality standard

We adopt an analytical framework of a two-player all-pay auction with incomplete information to model R&D innovation contests. Innovator i's marginal cost is c_i and corresponding innovation ability is $a_i = \frac{1}{c_i}$. A higher a_i implies that he is more efficient in R&D. The innovators' abilities a_i are independently and identically distributed over a compact support $[\underline{a}, \overline{a}] \in (0, +\infty)$, with a commonly known cumulative distribution function $F(\cdot)$ and a continuous density function $f(\cdot)\,(> 0)$. The realization of a_i is the private information of innovator i. We first impose a regularity condition on the virtual ability, which is a standard assumption in the literature.

Assumption 1: The (aggregate quality) virtual ability $\psi(a) = a - \frac{1-F(a)}{f(a)}$ is increasing in a, for any $a \in [\underline{a}, \overline{a}]$.

Moreover, we make the following assumption to guarantee an interior solution so that the quality standard for aggregate quality maximization under a concealment policy is nontrivial. This will be further discussed after Corollary 2.

Assumption 2: $\psi(\underline{a}) = \underline{a} - \frac{1-F(\underline{a})}{f(\underline{a})} < 0$.

The two innovators compete in their nonnegative R&D qualities, denoted by x_1 and x_2. An innovator wins award $V(> 0)$ if his quality is above the other's. Ties are broken evenly. Delivering quality x_i costs innovator i by $c_i x_i$. Therefore, innovator i's payoff is $V - c_i x_i$ if he wins, and $-c_i x_i$ if he loses.

The organizer sets a minimum quality standard to guarantee the basic product quality and commits to her disclosure policy—either to fully disclose the abilities of the innovators or fully conceal this information to their competitors—and announces the quality standard and her choice of disclosure policy publicly before innovators' types are realized. We denote the full disclosure policy by D, full concealment policy by C, the quality standard under policy D by x_D, and the quality standard under policy C by x_C.

The timing of the game is as follows. First, the organizer announces and precommits to (P, x_P), where $P \in \{D, C\}$. Then, nature determines innovators' ability profile $\mathbf{a} = (a_1, a_2)$ according to $F(\cdot)$. After that, the organizer implements (P, x_P). Note that $\mathbf{a}$ is disclosed if and only if policy D is implemented. Finally, innovators simultaneously invest $\mathbf{x} = (x_1, x_2)$ to vie for the reward V.

2.1 Contests with full disclosure policy D

We first consider the subgame in which policy D has been chosen. Suppose that quality standard x_D is set. In this case, the contest organizer publicly discloses every innovator's ability before innovators choose their efforts. A complete-information all-pay auction with minimum bid x_D thus arises.

Define $a_D = \frac{x_D}{V}$, which is interpreted as a threshold ability level in the following analysis. Without loss of generality, assume $a_1 > a_2$.

Bertoletti (2016) considers a contest setting in which bidders bear the same marginal effort cost, but value the prize differently. A simple transformation allows us to apply his results to our setting.[2] By his Proposition 1, we characterize the equilibrium under policy D and threshold ability a_D in the following lemma.

Lemma 1 *(Bertoletti, 2016). Consider a two-innovator all-pay auction with complete information with threshold ability a_D. Assume $a_1 > a_2$.*

(a) If $Va_1 > Va_2 \geqslant x_D \geqslant 0$, i.e., $a_1 > a_2 \geqslant a_D \geqslant 0$, innovator 1 has a mixed equilibrium bidding strategy on support $[Va_D, Va_2]$ such that $F_1(x_1) = \frac{x_1}{Va_2}$ for $x_1 \in [Va_D, Va_2]$; innovator 2 has a mixed equilibrium bidding strategy on support $\{0\} \cup [Va_D, Va_2]$ such that $F_2(0) = 1 - \frac{a_2}{a_1} + \frac{a_D}{a_1}$ and $F_2(x_2) = 1 - \frac{a_2}{a_1} + \frac{x_2}{Va_1}$ for $x_2 \in [Va_D, Va_2]$. The expected aggregate quality is given by $R(a_1, a_2, a_D, V) = \left(\frac{a_2^2 + a_D^2}{2a_2} + \frac{a_2^2 - a_D^2}{2a_1}\right) V$.

(b) If $Va_1 > x_D > Va_2$, i.e., $a_1 > a_D > a_2$, the pure-strategy Nash equilibrium is $x(a_1) = Va_D$ and $x(a_2) = 0$. The expected aggregate quality is Va_D.

(c) If $x_D \geqslant Va_1 > Va_2$, i.e., $a_D \geqslant a_1 > a_2$, no one submits a positive bid and the aggregate quality is zero.

Given the equilibrium strategy described in Lemma 1, we can derive the ex ante expected aggregate quality and highest quality induced under policy D and quality standard x_D. We summarize these results in Lemma 2.

[2] Our model is strategically equivalent to that of Bertoletti (2016) when, as in his setting, bidders' uniform marginal effort is normalized to one and bidder i values each prize for $Va_i = \frac{V}{c_i}$.

Lemma 2 *Under policy D, in an all-pay auction contest with quality standard x_D and corresponding threshold ability $a_D = \frac{x_D}{V}$, the ex ante expected aggregate quality induced is*

$$TQ_D(a_D) = 2V \left(\begin{array}{c} \int_{a_D}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} \left(\frac{a_2^2+a_D^2}{2a_2} + \frac{a_2^2-a_D^2}{2a_1} \right) dF(a_1) \right) dF(a_2) \\ +a_D(1-F(a_D))F(a_D) \end{array} \right). \tag{1}$$

The ex ante expected highest quality induced is

$$HQ_D\left(a_D\right) = 2V \left(\begin{array}{c} \int_{a_D}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} \frac{a_1a_2^2+a_D^2(a_1-a_2)+\frac{1}{3}a_2^3+\frac{2}{3}a_D^3}{2a_1a_2} dF(a_1) \right) dF(a_2) \\ +a_D(1-F(a_D))F(a_D) \end{array} \right). \tag{2}$$

Proof. See Appendix. ■

Due to the technical complexity, we are unable to fully characterize the optimal threshold abilities $a_{T,D}^*$ and $a_{H,D}^*$, which maximize expected aggregate quality and highest quality under policy D, respectively. However, we are still able to compare those two optimal threshold ability levels.

Proposition 1 *Under policy D, there exist nontrivial optimal threshold abilities $a_{T,D}^*, a_{H,D}^* \in (\underline{a}, \overline{a})$, which maximize expected aggregate quality and highest quality, respectively. Moreover, the optimal threshold ability under aggregate quality maximization is almost always lower than that under highest quality maximization, i.e., $a_{T,D}^* < a_{H,D}^*$.*[3]

Proof. See Appendix. ■

Note that the corresponding optimal quality standard levels are $x_{T,D}^* = Va_{T,D}^*$, $x_{H,D}^* = Va_{H,D}^*$, which are strictly positive regardless of the distribution function $F\left(\cdot\right)$. By Proposition 1, one can immediately show that when innovators' ability is disclosed, the optimal quality standard levels that maximize aggregate quality and highest quality, respectively, both exist and are almost always unique. Assuming uniqueness, we have the following Corollary.

Corollary 1 *Under policy D, the optimal quality standards, $x_{T,D}^*$ and $x_{H,D}^*$, are nontrivial under both aggregate quality maximization and highest quality maximization. Moreover, under the uniqueness assumption, the optimal quality standard that maximizes aggregate quality is always lower than the one that maximizes highest quality, i.e., $x_{T,D}^* < x_{H,D}^*$.*

2.2 Contests with full concealment policy C

We next consider the subgame in which policy C has been chosen. Suppose quality standard x_C is set. In this case, the contest organizer does not disclose the innovators' abilities before

[3] The optimal threshold ability level is almost always unique, given that $TQ_D(\cdot)$ is continuous and $f\left(\cdot\right) > 0$. In the case in which optimal threshold ability levels are not unique, for any $a_{T,D}^*$, there always exists an $a_{H,D}^*$ such that $a_{T,D}^* < a_{H,D}^*$. However, it is not guaranteed that all $a_{H,D}^*$'s satisfy $a_{H,D}^* > a_{T,D}^*$.

innovators choose their efforts. An incomplete-information all-pay auction with minimum bid x_C thus arises. Define a_C such that $x_C = Va_CF(a_C)$, which is interpreted as a threshold ability level in the following analysis.[4]

Riley and Samuelson (1981) demonstrate a revenue equivalence result among a broad family of auction rules in an independent and private value setting, and they characterize the optimal reserve price. Taking an all-pay auction as a special case of their framework and setting the contest organizer's valuation for the prize to be zero, we can obtain the following symmetric equilibrium and derive the aggregate quality as a function of cutoff ability a_C.

Lemma 3 *(Riley and Samuelson, 1981). Under policy C, in an all-pay auction contest with a quality standard x_C and the corresponding cutoff ability a_C, with $x_C = Va_CF(a_C)$, each innovator has a symmetric equilibrium bidding strategy*

$$x(a_i) = V\left[a_CF(a_C) + \int_{a_C}^{a_i} sf(s)ds\right]. \tag{3}$$

The contest elicits an ex ante expected aggregate quality

$$TQ_C(a_C) = 2V\left[\int_{a_C}^{\overline{a}} a(1-F(a))dF(a) + a_C(1-F(a_C))F(a_C)\right]. \tag{4}$$

Moreover, the aggregate quality maximizing cutoff ability is nontrivial ($a^*_{T,C} \in (\underline{a}, \overline{a})$) and uniquely given by $\psi(a^*_{T,C}) = 0$.

Proof. See Appendix. ■

Before investigating the case of expected highest quality maximization, we first define the highest quality virtual ability as $\phi(a) = a - \frac{1-F(a)}{f(a)}\frac{1+F(a)}{2F(a)}$ and show the following properties.

Lemma 4 *(a)* $\lim_{a\to\underline{a}}\phi(a) = -\infty$.

(b) Under Assumption 1, $\phi(a)$ is increasing in a for any $a \in (\underline{a}, \overline{a}]$.

Proof. See Appendix. ■

If the organizer chooses to conceal the type information, innovators only have private information about their own types. The expected highest quality in an all-pay auction with private values is the expected highest bids of the two innovators $\int_{a_C}^{\overline{a}} x(a)dH(a)$, where $H(a) = F(a)^2$ is the c.d.f of the first order statistics when $n = 2$. Plugging in the corresponding bidding strategy, we obtain the organizer's expected highest quality under full concealment.

[4] Note that a_C is the cutoff ability at which innovators generate quality x_C. Also note that a_C is well-defined; that is, for any $x_C \in [0, V\overline{a}]$, $Va_CF(a_C) = x_C$ has a unique solution for a_C. This is true because $Va_CF(a_C)$ is increasing in a_C, $V\underline{a}F(\underline{a}) = 0$, and $V\overline{a}F(\overline{a}) = V\overline{a}$.

Lemma 5 *Under policy C, an all-pay auction contest with a quality standard x_C and the corresponding cutoff ability a_C, with $x_C = Va_CF(a_C)$, elicits an ex ante expected highest quality*

$$HQ_C(a_C) = V\left[a_CF(a_C)(1 - F(a_C)^2) + \int_{a_C}^{\overline{a}} a[1 - F(a)^2]dF(a)\right]. \tag{5}$$

Moreover, the highest quality maximizing cutoff ability is nontrivial ($a^*_{H,C} \in (\underline{a}, \overline{a})$) and uniquely given by $\phi(a^*_{H,C}) = 0$.

Proof. See Appendix. ■

Under full concealment, the optimal cutoff ability $a^*_{T,C}$ is the root of $\psi(a)$, and $a^*_{H,C}$ is the root of $\phi(a)$. Note that both $\psi(\cdot)$ and $\phi(\cdot)$ are determined by distribution function $F(\cdot)$. Consider two distribution functions $F(a)$ and $G(a)$. We use $a^{*(F)}_{T,C}$ and $a^{*(G)}_{T,C}$ to denote the corresponding optimal cutoff abilities for aggregate quality maximization; and use $a^{*(F)}_{H,C}$ and $a^{*(G)}_{H,C}$ to denote the corresponding optimal cutoff abilities for highest quality maximization. If F dominates G in terms of hazard rate, i.e., $\frac{f(a)}{1-F(a)} \leq \frac{g(a)}{1-G(a)}$, where $g(a) = G'(a)$, we can rank the optimal cutoff abilities across the two distributions.

Proposition 2 *If F dominates G in terms of hazard rate, i.e. $\frac{f(a)}{1-F(a)} \leq \frac{g(a)}{1-G(a)}$, then $a^{*(F)}_{T,C} \geq a^{*(G)}_{T,C}$, and $a^{*(F)}_{H,C} \geq a^{*(G)}_{H,C}$.*

Proof. See Appendix. ■

Proposition 2 immediately means that with better ability distribution in terms of hazard rate dominance, the organizer should set higher quality standard for both aggregate and highest quality maximizations, since $x^*_{T,C} = Va^*_{T,C}F(a^*_{T,C})$, and $x^*_{H,C} = Va^*_{H,C}F(a^*_{H,C})$.

We next present the comparison between optimal cutoff abilities $a^*_{T,C}$ and $a^*_{H,C}$ for a given ability distribution $F(\cdot)$.

Proposition 3 *Suppose that Assumption* 1 *holds, under policy C, the optimal cutoff ability under aggregate quality maximization is lower than that under highest quality maximization, i.e., $a^*_{T,C} < a^*_{H,C}$.*

Proof. See Appendix. ■

Note that the corresponding optimal quality standard levels are $x^*_{T,C} = Va^*_{T,C}F(a^*_{T,C})$, $x^*_{H,C} = Va^*_{H,C}F(a^*_{H,C})$. By Proposition 3, one can immediately show that when an innovator's ability is fully concealed, the optimal quality standard level that maximizes aggregate quality is strictly lower than the one that maximizes highest quality. Moreover, note that $a^*_{T,C}$ and $a^*_{H,C}$ are strictly between $\underline{a}$ and $\overline{a}$ (see the details in the proofs of Lemmas 3 and 5). Therefore $F(a^*_{H,C}) > F(a^*_{T,C}) > 0$, implying the optimal quality standards are strictly positive. We have the following Corollary.

Corollary 2 *Under policy C, the optimal quality standards, $x^*_{T,C}$ and $x^*_{H,C}$, are nontrivial under both aggregate quality maximization and highest quality maximization. Moreover, the optimal quality standard under aggregate quality maximization is lower than that under highest quality maximization, i.e., $x^*_{T,C} < x^*_{H,C}$.*

It is worth noting that $x^*_{T,C}$ can be zero if Assumption 2 fails to hold. If $\psi(\underline{a}) \geq 0$, then $a^*_{T,C} = \underline{a}$ (see the details in the Proof of Lemma 3), which implies that $x^*_{T,C} = V\underline{a}F(\underline{a}) = 0$. However, $x^*_{H,C}$ is always positive, because $\lim_{a \to \underline{a}} \phi(a) < 0$ implies $a^*_{H,C} > \underline{a}$ (see the details in the Proof of Lemma 5).

3 Comparison between disclosure policies

We are now ready to compare the ex ante expected aggregate quality and highest quality between the two disclosure policies.

3.1 Comparison without a quality standard

We first look at a benchmark case in which the contest organizer is only able to choose a disclosure policy, and is unable to set a quality standard. This case reduces to a question about the disclosure policy in all-pay contests without threshold investments. Morath and Münster (2008) compare two information structures (private independent values versus complete information) for standard auctions selling a single item, including all-pay auctions. They find that bidders contribute a higher expected aggregate quality in a private-information setting.

In the case of highest quality maximization, setting both threshold abilities to 0 in equations (2) and (5) and noticing that $\underline{a} > 0$, we have

$$
\begin{aligned}
HQ_D &= 2V \int_{\underline{a}}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(\frac{a_2}{2} + \frac{a_2^2}{6a_1} \right) dF(a_1) \right] dF(a_2) \\
&= V \int_{\underline{a}}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(a_2 + \frac{a_2^2}{3a_1} \right) dF(a_1) \right] dF(a_2),
\end{aligned}
$$

and

$$
\begin{aligned}
HQ_C &= V \int_{\underline{a}}^{\overline{a}} (1 - F^2(a)) a f(a) da \\
&= V \int_{\underline{a}}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} (1 + F(a_2)) a_2 dF(a_1) \right] dF(a_2).
\end{aligned}
$$

The results for the designer's optimal disclosure policy without a quality standard under both aggregate quality maximization and highest quality maximization are summarized in the following proposition.

Proposition 4 *Without a quality standard, fully concealing innovators' abilities elicits both higher ex ante expected aggregate quality and highest quality, i.e., $TQ_C \geq TQ_D$ and $HQ_C \geq HQ_D$, regardless of the distribution of innovators' abilities.*

Proof. See Appendix. ■

Proposition 4 shows that without a quality standard, fully concealing innovators' abilities can kill two birds with one stone: the innovators' aggregate quality and the winner's quality can both achieve higher levels.

3.2 Comparison with the optimal quality standard

We now consider the scenario in which the designer is allowed to optimally set the quality standard. We first present the following comparisons of the optimal cutoff abilities and quality standards across disclosure policies for a given objective.

Proposition 5 *(i) For aggregate quality maximization, we have $a^*_{T,D} > a^*_{T,C}$ and $x^*_{T,D} > x^*_{T,C}$, i.e. the full disclosure policy requires a higher cutoff ability and a higher optimal quality standard than the full concealment policy.*

(ii) For highest quality maximization, we have $a^*_{H,D} \geq a^*_{H,C}$ if and only if

$$\begin{aligned} & a^*_{H,D}\int_{a^*_{H,D}}^{\bar{a}}\left(\int_{a_2}^{\bar{a}}(\frac{1}{a_2}-\frac{1}{a_1})dF(a_1)\right)dF(a_2)+a^*_{H,D}\int_{a^*_{H,D}}^{\bar{a}}\left(\int_{a_2}^{\bar{a}}\frac{1}{a_1a_2}dF(a_1)\right)dF(a_2) \\ \geq\ & \frac{(1-F(a^*_{H,D}))^2}{2}. \end{aligned} \tag{6}$$

Moreover, $x^*_{H,D} \geq x^*_{H,C}$ if and only if $a^*_{H,D} \geq a^*_{H,C}F(a^*_{H,C})$.

Proof. See Appendix. ■

It is not easy to see whether the conditions in Proposition 5(ii) hold analytically. In Section 4, we will present numerical analysis for a class of ability distributions, in which we have $a^*_{H,D} < a^*_{H,C}$ given that condition (6) does not hold, while we still have $x^*_{H,D} \geq x^*_{H,C}$ given that $a^*_{H,D} \geq a^*_{H,C}F(a^*_{H,C})$.

We next move to the comparison of disclosure policies under different objectives. We first compare the aggregate quality between the two disclosure policies, i.e., $TQ^*_D(a^*_{T,D})$ versus $TQ^*_C(a^*_{T,C})$. Recall that $TQ^*_D(a^*_{T,D})$ is the maximum aggregate quality level under full disclosure policy D with optimal quality standard $x^*_{T,D} = Va^*_{T,D}$, and that $TQ^*_C(a^*_{T,C})$ is the maximum aggregate quality level under full concealment policy C with optimal quality standard $x^*_{T,C} = Va^*_{T,C}F(a^*_{T,C})$.

Theorem 1 *When quality standards can be set optimally, fully concealing innovators' abilities elicits higher ex ante expected aggregate quality, i.e.,* $TQ_D^*(a_{T,D}^*) \leqslant TQ_C^*(a_{T,C}^*)$*, regardless of the distribution of innovators' abilities.*

Proof. Recall from equations (1) and (4) that $TQ_D(a_D)$ is the aggregate quality under a full disclosure policy with quality standard x_D and corresponding cutoff ability $a_D = \frac{x_D}{V}$, and that $TQ_C(a_C)$ is the aggregate quality under a full concealment policy with quality standard $x_C = Va_C F(a_C)$ and corresponding cutoff ability a_C.

$$TQ_D(a_D) = 2V\left(\int_{a_D}^{\overline{a}}\left[\int_{a_2}^{\overline{a}}\left(\frac{a_2^2+a_D^2}{2a_2}+\frac{a_2^2-a_D^2}{2a_1}\right)dF(a_1)\right]dF(a_2)+a_D(1-F(a_D))F(a_D)\right). \tag{1}$$

$$TQ_C(a_C) = 2V\left[\int_{a_C}^{\overline{a}} a(1-F(a))dF(a)+a_C(1-F(a_C))F(a_C)\right]. \tag{4}$$

The rest of this proof proceeds in three steps.

Step 1 We claim that for any cutoff ability a, we have $TQ_D(a) \leqslant TQ_C(a)$.

Let

$$\begin{aligned}
G(a) &= \left[TQ_D(a) - TQ_C(a)\right]/V \\
&= 2\int_a^{\overline{a}}\left[\int_{a_2}^{\overline{a}}\left(\frac{a_2^2+a^2}{2a_2}+\frac{a_2^2-a^2}{2a_1}\right)dF(a_1)\right]dF(a_2)+2a(1-F(a))F(a) \\
&- 2\int_a^{\overline{a}} a(1-F(a))dF(a) - 2a(1-F(a))F(a) \\
&= 2\int_a^{\overline{a}}\left[\int_{a_2}^{\overline{a}}\left(\frac{a_2^2+a^2}{2a_2}+\frac{a_2^2-a^2}{2a_1}\right)dF(a_1)\right]dF(a_2) - 2\int_a^{\overline{a}} a(1-F(a))dF(a) \\
&= 2\int_a^{\overline{a}}\left[\int_{a_2}^{\overline{a}}\left(\frac{a_2^2+a^2}{2a_2}+\frac{a_2^2-a^2}{2a_1}\right)dF(a_1) - a_2(1-F(a_2))\right]dF(a_2) \\
&= 2\int_a^{\overline{a}}\left[\frac{a_2^2+a^2}{2a_2}(1-F(a_2)) - a_2(1-F(a_2)) + \int_{a_2}^{\overline{a}}\frac{a_2^2-a^2}{2a_1}dF(a_1)\right]dF(a_2) \\
&= 2\int_a^{\overline{a}}\frac{a^2-a_2^2}{2a_2}(1-F(a_2))dF(a_2) + 2\int_a^{\overline{a}}\int_{a_2}^{\overline{a}}\frac{a_2^2-a^2}{2a_1}dF(a_1)dF(a_2) \\
&= 2\int_a^{\overline{a}}\int_{a_2}^{\overline{a}}\frac{a^2-a_2^2}{2a_2}dF(a_1)dF(a_2) + 2\int_a^{\overline{a}}\int_{a_2}^{\overline{a}}\frac{a_2^2-a^2}{2a_1}dF(a_1)dF(a_2) \\
&= 2\int_a^{\overline{a}}\left[\int_{a_2}^{\overline{a}}(a^2-a_2^2)\left(\frac{1}{2a_2}-\frac{1}{2a_1}\right)dF(a_1)\right]dF(a_2).
\end{aligned}$$

Note that $a_1 > a_2 \geqslant a \geqslant 0$, and thus $G(a) \leqslant 0$ for all a.

Step 2 Suppose $x_{T,D}^*$ is the optimal quality standard level that maximizes aggregate quality under a full disclosure policy, with corresponding cutoff ability $a_{T,D}^* = \frac{x_{T,D}^*}{V}$. Step 1 shows that for $a = a^*_{T,D}$, we have $TQ_D(a^*_{T,D}) \leq TQ_C(a_C = a^*_{T,D})$. By Lemma 3, there is a one-to-one mapping between quality standard x_C and corresponding cutoff ability a_C, i.e., $x_C = Va_C F(a_C)$. Then under quality standard $x_C = Va^*_{T,D}F(a^*_{T,D})$, full concealment yields greater ex ante expected aggregate quality than that under full disclosure.

Step 3 The maximum aggregate quality under a full disclosure policy with optimal cutoff level $a^*_{T,D}$ is lower than the maximum aggregate quality under full concealment with optimal cutoff level $a^*_{T,C}$, given that $TQ^*_D(a^*_{T,D}) \leqslant TQ_C(a_C = a^*_{T,D}) \leq TQ^*_C(a^*_{T,C})$. ■

We then compare the highest quality between the two disclosure policies, i.e., $HQ^*_D(a^*_{H,D})$ versus $HQ^*_C(a^*_{H,C})$. Recall that $HQ^*_D(a^*_{H,D})$ is the maximum highest quality level under a full disclosure policy with optimal quality standard $x^*_{H,D} = Va^*_{H,D}$, and that $HQ^*_C(a^*_{H,C})$ is the maximum highest quality level under a full concealment policy with optimal quality standard $x^*_{H,C} = Va^*_{H,C}F(a^*_{H,C})$.

Theorem 2 *When quality standards can be set optimally, fully disclosing innovators' abilities elicits higher ex ante expected highest quality, i.e., $HQ^*_D(a^*_{H,D}) \geqslant HQ^*_C(a^*_{H,C})$, regardless of the distribution of innovators' abilities.*

Proof. Recall from equations (2) and (5) that $HQ_D(a_D)$ is the highest quality under a full disclosure policy with quality standard x_D and corresponding cutoff ability $a_D = \frac{x_D}{V}$, and that $HQ_C(a_C)$ is the highest quality under a full concealment policy with quality standard $x_C = Va_C F(a_C)$ and corresponding cutoff ability a_C.

$$HQ_D(a_D) = 2V \begin{pmatrix} \int_{a_D}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \frac{a_1 a_2^2 + a_D^2(a_1 - a_2) + \frac{1}{3}a_2^3 + \frac{2}{3}a_D^3}{2a_1 a_2} dF(a_1) \right] dF(a_2) \\ + a_D(1 - F(a_D))F(a_D) \end{pmatrix}. \tag{2}$$

$$HQ_C(a_C) = V \left[a_C F(a_C)(1 - F(a_C)^2) + \int_{a_C}^{\overline{a}} a[1 - F(a)^2] dF(a) \right]. \tag{5}$$

The proof proceeds in two steps.

Step 1 We claim that at the optimal ability level under full concealment $a^*_{H,C}$, we have $HQ_D(a^*_{H,C}) \geqslant HQ_C(a^*_{H,C})$.

According to equation (2), we have

$$\begin{aligned} HQ_D(a^*_{H,C}) &= HQ_D\left(a_D = a^*_{H,C}\right) \\ &= 2V \begin{pmatrix} \int_{a^*_{H,C}}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \frac{a_1 a_2^2 + \left(a^*_{H,C}\right)^2 (a_1 - a_2) + \frac{1}{3}a_2^3 + \frac{2}{3}\left(a^*_{H,C}\right)^3}{2a_1 a_2} dF(a_1) \right] dF(a_2) \\ + a^*_{H,C}(1 - F(a^*_{H,C}))F(a^*_{H,C}) \end{pmatrix}. \end{aligned}$$

Note that $\frac{-\left(a_{H,C}^*\right)^2 a_2+\frac{1}{3}a_2^3+\frac{2}{3}\left(a_{H,C}^*\right)^3}{2a_1a_2}$ of the integral function in the $HQ_D\left(a_{H,C}^*\right)$ is increasing in a_2. Setting $a_2 = a_{H,C}^*$ in this part gives $\frac{-\left(a_{H,C}^*\right)^2 a_2+\frac{1}{3}a_2^3+\frac{2}{3}\left(a_{H,C}^*\right)^3}{2a_1a_2} = 0$. Therefore, we have

$$\begin{aligned}
HQ_D(a_{H,C}^*) &> 2V\int_{a_{H,C}^*}^{\overline{a}}\left[\int_{a_2}^{\overline{a}}\frac{a_1a_2^2+(a_{H,C}^*)^2a_1}{2a_1a_2}dF(a_1)\right]dF(a_2)+2Va_{H,C}^*(1-F(a_{H,C}^*))F(a_{H,C}^*)\\
&= V\int_{a_{H,C}^*}^{\overline{a}}\left[\left(a+\frac{(a_{H,C}^*)^2}{a}\right)(1-F(a))\right]dF(a)+2Va_{H,C}^*(1-F(a_{H,C}^*))F(a_{H,C}^*).
\end{aligned}$$

Define $G(a_{H,C}^*) = \left[HQ_D(a_{H,C}^*) - HQ_C(a_{H,C}^*)\right]/V$, then

$$\begin{aligned}
G(a_{H,C}^*) &> \int_{a_{H,C}^*}^{\overline{a}}\left[\left(a+\frac{(a_{H,C}^*)^2}{a}\right)(1-F(a))\right]dF(a)+2a_{H,C}^*(1-F(a_{H,C}^*))F(a_{H,C}^*)\\
&\quad - a_{H,C}^*F(a_{H,C}^*)(1-F(a_{H,C}^*)^2) - \int_{a_{H,C}^*}^{\overline{a}} a[1-F(a)^2]dF(a)\\
&= a_{H,C}^*F(a_{H,C}^*)(1-F(a_{H,C}^*))^2+\int_{a_{H,C}^*}^{\overline{a}}\left[aF(a)-\frac{(a_{H,C}^*)^2}{a}\right]d\frac{(1-F(a))^2}{2}\\
&= a_{H,C}^*(1-F(a_{H,C}^*))^2\frac{1+F(a_{H,C}^*)}{2}-\frac{1}{2}\int_{a_{H,C}^*}^{\overline{a}}(1-F(a))^2\left[F(a)+af(a)+\frac{(a_{H,C}^*)^2}{a^2}\right]da.
\end{aligned}$$

Given $a > a_{H,C}^*$, we have

$$\begin{aligned}
G(a_{H,C}^*) &> a_{H,C}^*(1-F(a_{H,C}^*))^2\frac{1+F(a_{H,C}^*)}{2}-\frac{1}{2}\int_{a_{H,C}^*}^{\overline{a}}(1-F(a))^2(F(a)+af(a)+1)da\\
&= a_{H,C}^*(1-F(a_{H,C}^*))^2\frac{1+F(a_{H,C}^*)}{2}-\frac{1}{2}\int_{a_{H,C}^*}^{\overline{a}}(1-F(a))^2d(aF(a)+a)\\
&= a_{H,C}^*(1-F(a_{H,C}^*))^2(1+F(a_{H,C}^*))-\int_{a_{H,C}^*}^{\overline{a}}a(1-F(a)^2)dF(a)\\
&= \int_{a_{H,C}^*}^{\overline{a}}[a_{H,C}^*(1-F(a_{H,C}^*)^2)-a(1-F(a)^2)]dF(a).
\end{aligned}$$

Let $D(a) = a(1-F(a)^2)$; thus $D'(a) = 1-F(a)^2-2af(a)F(a)$. Notice that the highest quality virtual value $\phi(a) = a - \frac{1-F(a)^2}{2f(a)F(a)} = a - \frac{1-F(a)}{f(a)}\frac{1+F(a)}{2F(a)}$ is increasing in a by Lemma 4. Given that $a_{H,C}^* - \frac{1-F(a_{H,C}^*)^2}{2f(a_{H,C}^*)F(a_{H,C}^*)} = 0$, then we have $a - \frac{1-F(a)^2}{2f(a)F(a)} > 0$ when $a > a_{H,C}^*$, which implies $D'(a) < 0$ when $a > a_{H,C}^*$. Therefore $a_{H,C}^*(1-F(a_{H,C}^*)^2) > a(1-F(a)^2)$ when $a > a_{H,C}^*$, which implies $G(a_{H,C}^*) > 0$.

Step 2 Note that $HQ_D^*(a_{H,D}^*)$ is the maximum highest quality level under a full disclosure policy with optimal cutoff ability $a_{H,D}^*$; thus we have $HQ_D^*(a_{H,D}^*) \geqslant HQ_D(a_D = a_{H,C}^*) \geqslant$

$HQ_C^*(a_{H,C}^*)$. ■

The logics for proving Theorems 1 and 2 is similar. Step 1 of Theorem 1 shows that if the contest organizer sets quality standard level $x_D = a_D V = aV$ under full disclosure and sets quality standard level $x_C = Va_C F(a_C) = VaF(a)$ under full concealment, then both policies induce the same cutoff ability a, and full concealment always elicits higher aggregate quality. While such a relationship holds for any cutoff ability level a under aggregate quality maximization, step 1 of Theorem 2 shows that the reverse result holds for cutoff ability level $a = a_{H,C}^*$ under highest quality maximization. That is, if the contest organizer sets quality standard level $x_D = a_{H,C}^* V$ under full disclosure and sets quality standard level $x_C = Va_{H,C}^* F(a_{H,C}^*)$ under full concealment, both policies induce the same cutoff ability $a_{H,C}^*$, and full disclosure can elicit a higher winner's quality.

Therefore, for the optimal quality standard level that maximizes aggregate (resp. highest) quality under full disclosure (resp. concealment), there always exists a quality standard level under full concealment (resp. disclosure) that elicits higher aggregate (resp. highest) quality. Although we are not able to pin down the optimal quality standard level under full disclosure explicitly, we show that setting $a_D = a_{H,C}^*$ always elicits a higher level of highest quality under full disclosure, compared with the maximum highest quality under full concealment.

Theorem 1 strengthens Proposition 4 in terms of aggregate quality maximization: fully concealing innovators' abilities is always an optimal choice, regardless of whether the contest organizer is allowed to set a quality standard or not. In contrast, Theorem 2 states that in order to maximize highest quality, if the contest organizer can optimally set a quality standard, fully concealing innovators' abilities is no longer an optimal disclosure policy. Publicly announcing innovators' abilities and setting a quality standard strategically can always elicits higher quality from the winner.

4 Examples and intuitions

In this section, we will first present numerical examples to illustrate the comparisons between optimal quality standards under different disclosure policies, and demonstrate the optimal disclosure policies under different quality maximization goals. We will further provide intuitions behind the comparison results.

We normalize prize V to unity, and let ability a_i be uniformly distributed in $[\underline{a}, \overline{a}]$ where $\underline{a} = 0.1$ and $\overline{a}$ spans the entire interval $[5, 10]$. In Figure 1, Panels (a) and (b) show the optimal quality standards across different objectives for the same disclosure policy, and Panels (c) and (d) show the optimal quality standards across different disclosure policies for a given objective. One can see from Panels (a) and (b) that the optimal quality standard for aggregate quality maximization is always lower than that for highest quality maximization, regardless of the information disclosure policy; this demonstrates the properties in Corollaries 1 and 2. Panel (b) also shows that under concealment policy C, the optimal quality standards increase when the ability distribution F gets better, which is consistent with the implication of Proposition 2. Panel (a) shows that under full disclosure policy D, the optimal quality standards also increase when the ability distribution F gets better, although such a prediction is difficult to establish theoretically. Moreover, Panel (c) demonstrates the property in Proposition 5(i), that is, full disclosure requires a higher optimal quality standard than full concealment for aggregate quality maximization. Panel (d) shows that for this class of distributions, full disclosure still requires a higher optimal quality standard for highest quality maximization.[5]

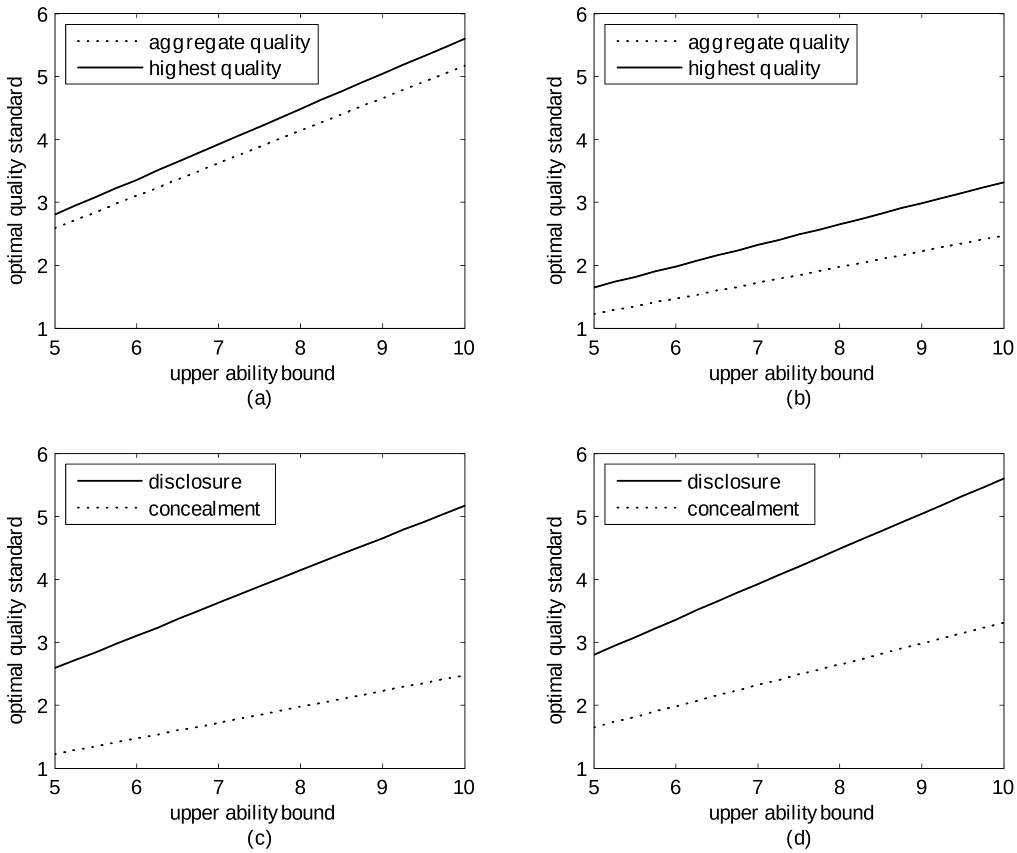

Figure 1: Comparison of Optimal Quality Standards
(a) Full Disclosure Policy (b) Full Concealment Policy
(c) Aggregate Quality Maximization (d) Highest Quality Maximization

Figure 2 demonstrates the properties in Proposition 4 and Theorems 1 and 2. Panels (a) and (b) show that with no quality standard, fully concealing innovators' abilities elicits both higher expected aggregate quality and expected highest quality, demonstrating the properties

[5] Regarding Panel (d), in our numerical examples, we always have $a^*_{H,D} < a^*_{H,C}$ given that condition (6) in Proposition 5(ii) does not hold, while we still have $x^*_{H,D} \geq x^*_{H,C}$ given that $a^*_{H,D} \geq a^*_{H,C} F(a^*_{H,C})$. Simulation data are available from the authors upon request.

depicted by Proposition 4. With optimally set quality standards, Panel (c) shows that fully concealing the ability information elicits higher expected aggregate quality, demonstrating the property in Theorem 1; Panel (d) shows that fully disclosing the ability information elicits higher expected highest quality, demonstrating the property in Theorem 2.

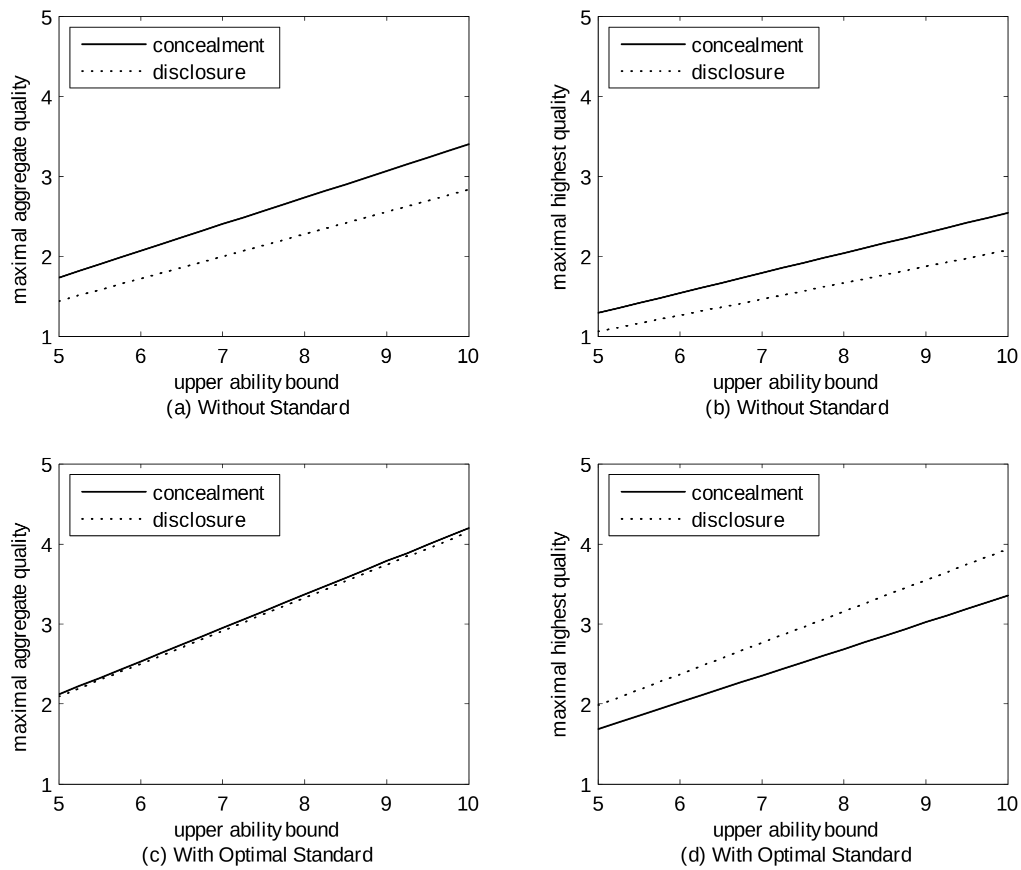

Figure 2: (a) and (c) Comparison of Maximal Aggregate Quality
(b) and (d) Comparison of Maximal Highest Quality

Intuitions behind the comparisons

Corollaries 1 and 2 show that the optimal quality standard for aggregate quality maximization is always lower than that for highest quality maximization, regardless of the information disclosure policy, which is confirmed by Panels (a) and (b) in Figure 1. The intuition is as follows. Imposing a higher quality standard tends to better incentivize the high ability types but at the cost of disincentivizing the low ability types, regardless of the goal of the design and the prevailing disclosure policy. However, when the goal is to maximize the highest quality, the designer benefits more from the higher contribution of high types and suffers less from the lower contribution of low types. It is thus natural for a designer seeking to maximize the winner's quality to set a higher quality standard regardless of the disclosure policy.

Proposition 4 shows that without a quality standard, the full concealment policy always dominates the full disclosure policy regardless of the designer's goal, as suggested by Panels (a) and (b) in Figure 2. This result can be understood as a consequence of the well received disincentivizing effect in asymmetric contests. Revealing the type profiles creates asymmetric contests between the two innovators, which tends to discourage the effort supply of both.

Allowing a quality standard would improve the innovators' performance for both goals under both disclosure policies, and for a given goal, the designer tends to set a higher standard under full disclosure policy than under full concealment, as shown in Panels (c) and (d) in Figure 1. A quality standard is an effective instrument to mitigate the disincentivizing effect in asymmetric contests by forcing the high ability types to work harder, although this might discourage the low ability types. When the goal is aggregate quality maximization, the designer cares about the performance of low ability types; in this case, setting a higher quality standard under full disclosure policy does not generate much advantage compared to setting a lower quality standard under full concealment policy. Given that the full concealment policy induces higher aggregate quality when there is no quality standard, it is logical that setting a higher standard under full disclosure policy cannot fully overcome the initial disadvantage conferred by the full disclosure policy. As a result, the full concealment policy still induces higher aggregate quality even when quality standards are set optimally under both policies, as shown in Panel (c) in Figure 2. For the goal of highest quality maximization, however, the designer does not care much about the performance of low ability types; thus, setting a higher quality standard under full disclosure policy can generate a considerable advantage compared to setting a lower quality standard under full concealment policy, as shown in Panel (d) in Figure 2. As a result, a full disclosure policy with an optimally set quality standard can fully overcome the initial disadvantage in the scenario of no quality standards.

5 Concluding remarks

In this paper, we study optimal R&D contest design. Both an information disclosure policy and a minimum standard are revealed in the literature to be effective instruments for boosting innovators' performance. The innovation of our paper is to study how they interact in an optimal design when both instruments are available to the contest organizer. To our best knowledge, this is the first work in the contest design literature to jointly integrate an information disclosure policy and a minimum standard into an analytical framework of R&D contests.

As a comparison benchmark, we show that without a quality standard, fully concealing innovators' abilities induces better performance for both ex ante expected aggregate quality maximization and expected highest quality maximization. In contrast, when quality standards can be set optimally for both objectives, we find that while un-surprisingly concealing information still elicits higher expected aggregate quality, fully disclosing information elicits higher expected highest quality. These comparison results can be intuitively understood as follows. First, without quality standard, fully disclosing the innovators' types entails a public information contest between two asymmetric innovators, which tends to discourage effort supply. Second, setting a quality standard is more effective in boosting effort supply under a full disclosure policy, especially for the goal of highest quality maximization given that the stronger innovator's effort supply counts more in this case.

Our findings have many economic applications. On the one hand, in an R&D competition inviting participation from a broad spectrum of the public, it is preferable for the organizer to conceal innovators' abilities in order to incentivize all participants to work productively. This is consistent with the real-world observation that participants are normally anonymous in many web-based open innovation platforms. On the other hand, in a public procurement, such as landmark construction bidding, the government only cares about the best performance, and therefore has reason to announce all the bidders' capabilities publicly. Our results also imply that, all other things being equal, contest organizers should set a high bar for quality to inspire the best performers, while they should set the bar lower if their goal is to promote overall performance.

We have focused on the disclosure policies of full disclosure and full concealment. Although we expect that the main insights can be extended to a more general information disclosure policiy setting, new issues related to information disclosure and quality standards would arise and create additional challenges for analysis. We leave these interesting issues to future work.

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Appendix

Proof of Lemma 2

Proof. Combining the three cases studied in Lemma 1, where $a_1 > a_2$, and the other three symmetric cases, where $a_2 > a_1$ (namely, $a_2 > a_1 \geqslant a_D \geqslant 0$, $a_2 > a_D > a_1$, and

$a_D \geqslant a_2 > a_1$), we can obtain the ex ante expected aggregate quality

$$\begin{aligned}
& TQ_D(a_D) \\
&= 2\int_{a_D}^{\overline{a}}\left(\int_{a_2}^{\overline{a}} R(a_1,a_2,a_D,V)dF(a_1)\right)dF(a_2) + 2Va_D\int_{a_D}^{\overline{a}}\left(\int_{\underline{a}}^{a_D} dF(a_2)\right)dF(a_1) \\
&= 2V\int_{a_D}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}\left(\frac{a_2^2+a_D^2}{2a_2}+\frac{a_2^2-a_D^2}{2a_1}\right)dF(a_1)\right)dF(a_2) + 2Va_D(1-F(a_D))F(a_D).
\end{aligned}$$

According to Lemma 1, if $a_1 > a_2 \geq a_D \geqslant 0$, the expected highest quality is

$$\begin{aligned}
& E(max[x_1,x_2]) \\
&= P(x_2=0)E(x_1|x_2=0) + P(x_1=x_D,x_2>x_D)E(x_2|x_1=x_D,x_2>x_D) \\
&\quad + P(x_1>x_2>x_D)E(x_1|x_1>x_2>x_D) + P(x_2>x_1>x_D)E(x_2|x_2>x_1>x_D) \\
&= \left(1-\frac{Va_2-x_D}{Va_1}\right)\left(\frac{x_D}{Va_2}x_D+\left(1-\frac{x_D}{Va_2}\right)\left(\frac{Va_2+x_D}{2}\right)\right)+\frac{x_D}{Va_2}\frac{Va_2-x_D}{Va_1}\frac{Va_2+x_D}{2} \\
&\quad + 2\int_{x_D}^{Va_2}\left(\int_{x_2}^{Va_2}\frac{1}{Va_1Va_2}dx_1\right)dx_2 \times \frac{\int_{x_D}^{Va_2}\left(\int_{x_2}^{Va_2}\frac{x_1}{Va_1Va_2}dx_1\right)dx_2}{\int_{x_D}^{Va_2}\left(\int_{x_2}^{Va_2}\frac{1}{Va_1Va_2}dx_1\right)dx_2} \\
&= \frac{Va_1V^2a_2^2+x_D^2(Va_1-Va_2)+\frac{1}{3}(Va_2)^3+\frac{2}{3}x_D^3}{2Va_1Va_2} \\
&= V\left(\frac{a_1a_2^2+a_D^2(a_1-a_2)+\frac{1}{3}a_2^3+\frac{2}{3}a_D^3}{2a_1a_2}\right).
\end{aligned}$$

If $a_1 > a_D > a_2 \geqslant 0$, the highest quality is just x_D, given that agent 1 will certainly win if he bids $x_D = Va_D$.

Therefore, the ex ante expected highest quality under disclosure is

$$\begin{aligned}
HQ_D(a_D) &= 2V\int_{a_D}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}\frac{a_1a_2^2+a_D^2(a_1-a_2)+\frac{1}{3}a_2^3+\frac{2}{3}a_D^3}{2a_1a_2}dFa_1\right)dF(a_2) \\
&\quad +2x_D\int_{a_D}^{\overline{a}}\left(\int_{\underline{v}}^{a_D}dF(a_2)\right)dF(a_1) \\
&= 2V\int_{a_D}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}\frac{a_1a_2^2+a_D^2(a_1-a_2)+\frac{1}{3}a_2^3+\frac{2}{3}a_D^3}{2a_1a_2}dF(a_1)\right)dF(a_2) \\
&\quad +2Va_D(1-F(a_D))F(a_D).
\end{aligned}$$

■

Proof of Proposition 1

Proof. The existence of an optimal threshold ability level is guaranteed, since the support of a_D, $[\underline{a}, \overline{a}] \in (0, +\infty)$ is compact. Note that $TQ_D(\cdot)$ is continuous and $f(\cdot) > 0$, so the optimal threshold ability level is almost always unique. Without loss of generality, we assume uniqueness hereafter.

Denote the optimal threshold ability that maximizes the expected aggregate quality $TQ_D(a_D)$ by $a^*_{T,D}$, and the optimal threshold ability that maximizes highest quality $HQ_D(a_D)$ by $a^*_{H,D}$.

The first order derivative of the ex ante expected aggregate quality under full disclosure is

$$\frac{dTQ_D(a_D)}{da_D} = 2V \left(\begin{array}{c} a_D \int_{a_D}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2) \\ +[1 - F(a_D)]F(a_D) - a_D f(a_D) F(a_D) \end{array} \right).$$

The first order derivative of the ex ante expected highest quality under full disclosure is

$$\begin{aligned} & \frac{dHQ_D(a_D)}{da_D} \\ = \; & 2V \left(\begin{array}{c} a_D \int_{a_D}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2) \\ +a_D^2 \int_{a_D}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} \frac{1}{a_1 a_2} dF(a_1) \right) dF(a_2) + [1 - F(a_D)]F(a_D) - a_D f(a_D) F(a_D) \end{array} \right). \end{aligned}$$

First, we show that $a^*_{T,D}$ and $a^*_{H,D}$ must be strictly between $\underline{a}$ and $\overline{a}$. This is true by the fact that $\frac{dTQ_D(a_D)}{da_D}|_{a_D=\underline{a}} > 0$, $\frac{dHQ_D(a_D)}{da_D}|_{a_D=\underline{a}} > 0$ and $\frac{dTQ_D(a_D)}{da_D}|_{a_D=\overline{a}} < 0$, $\frac{dHQ_D(a_D)}{da_D}|_{a_D=\overline{a}} < 0$.

Then, we show that $\frac{dHQ_D(a_D)}{da_D} > \frac{dTQ_D(a_D)}{da_D}$ on $[\underline{a}, \overline{a})$. This can be obtained immediately, given that $\frac{dHQ_D(a_D)}{da_D} - \frac{dTQ_D(a_D)}{da_D} = 2V a_D^2 \int_{a_D}^{\overline{a}} [\int_{a_2}^{\overline{a}} (\frac{1}{a_1 a_2} dF(a_1)] dF(a_2) > 0$ for any $a_D \in [\underline{a}, \overline{a})$. We call this **Property A**.

Now we are ready to compare optimal threshold abilities $a^*_{T,D}$ and $a^*_{H,D}$ based on Property A. Given that $a^*_{T,D} \in (\underline{a}, \overline{a})$, we have $TQ_D(a^*_{T,D}) - TQ_D(a_l) = \int_{a_l}^{a^*_{T,D}} \frac{dTQ_D(a_D)}{da_D} da_D \geqslant 0$, where a_l can be any point in $[\underline{a}, a^*_{T,D})$. Thus we have $HQ_D(a^*_{T,D}) - HQ_D(a_l) = \int_{a_l}^{a^*_{T,D}} \frac{dHQ_D(a_D)}{da_D} da_D > \int_{a_l}^{a^*_{T,D}} \frac{dTQ_D(a_D)}{da_D} da_D \geqslant 0$, where the first inequality holds by Property A. This means that for any $a^*_{T,D} \in (\underline{a}, \overline{a})$ and any $a_l \in [\underline{a}, a^*_{T,D})$, we have $HQ_D(a^*_{T,D}) - HQ_D(a_l) > 0$. Note that $a^*_{H,D}$ is the optimal threshold ability of $HQ_D(a_D)$, so $HQ_D(a^*_{H,D}) \geq HQ_D(a^*_{T,D})$ implies that $a^*_{H,D}$ must not locate on the left side of $a^*_{T,D}$, i.e., $a^*_{H,D} \geqslant a^*_{T,D}$.

Furthermore, because $\frac{dTQ_D(a_D)}{da_D}$ is continuous and $TQ_D(a_D)$ is maximized at $a_D = a^*_{T,D}$, we have $\frac{dTQ_D(a_D)}{da_D}|_{a_D=a^*_{T,D}} = 0$. By Property A, we have $\frac{dHQ_D(a_D)}{da_D}|_{a_D=a^*_{T,D}} > 0$. Therefore, we can conclude that $a^*_{H,D} > a^*_{T,D}$. ■

Proof of Lemma 3

Proof. In a private-value all-pay auction contest, the expected utility of bidder i is $U_i(a_i, z_i) = [VF(z_i)a_i - x_i(z_i)]c_i$, where $U_i(a_i, z_i)$ is the utility of i who has ability level a_i, and acts as if his ability level is z_i.

Taking the first order condition with respect to z_i, we have $Vf(z_i)a_i - \frac{dx_i}{dz_i} = 0$. We can derive $x_i(a_i) = V\int_{\underline{a}}^{a_i} f(s)sds$. We can allso verify $\frac{dU_i}{da_i} > 0$, $\frac{dx_i}{da_i} > 0$.

Taking threshold investment x_C into account, given that a_C is the cutoff ability below which it is unprofitable to provide a positive quality, then we have $x(a_C) = x_C$. Also noting that $U(a_C) = 0$, we get $Va_CF(a_C) = x_C$. Therefore, the equilibrium bidding strategy in an R&D contest with cutoff ability is $x(a_i) = V[a_CF(a_C) + \int_{a_C}^{a_i} sf(s)ds]$.

The expected aggregate quality of the two bidder is

$$\begin{aligned}
& TQ_C(a_C) \\
= \;& 2\int_{a_C}^{\overline{a}} x(s)dF(s) \\
= \;& 2V\int_{a_C}^{\overline{a}} \left[\int_{a_C}^{a_i} sf(s)ds\right] dF(a) + 2V\int_{a_C}^{\overline{a}} [a_CF(a_C)]\, dF(a) \\
= \;& 2V\left[\int_{a_C}^{\overline{a}} adF(a) - \int_{a_C}^{\overline{a}} aF(a)dF(a)\right] + 2Va_C(1-F(a_C))F(a_C) \\
= \;& 2V\left[\int_{a_C}^{\overline{a}} a(1-F(a))dF(a) + a_C(1-F(a_C))F(a_C)\right].
\end{aligned}$$

The first part of the third equation is obtained by integrating by parts.

Taking the first order condition with respect to a_C, we have

$$\frac{d(TQ_C(a_C))}{d(a_C)} = -F(a_C)f(a_C)\left[a_C - \frac{1-F(a_C)}{f(a_C)}\right] = 0.$$

By Assumptions 1 and 2, we know that $a_C = \underline{a}$ is not the aggregate quality maximizing cutoff value, given that $\frac{d(TQ_C(a_C))}{d(a_C)}$ becomes positive as a_C departs from $\underline{a}$. Therefore, the optimal value for a_C must be such that $a_C - \frac{1-F(a_C)}{f(a_C)} = 0$, or $\psi(a_C) = 0$. Because (1) by Assumption 1 $\psi(a_C)$ is increasing (and continuous) in a_C, (2) by Assumption 2 $\psi(\underline{a}) < 0$, and (3) $\psi(\overline{a}) = \overline{a} - \frac{1-F(\overline{a})}{f(\overline{a})} = \overline{a} > 0$, we know the equation $\psi(a_C) = 0$ has a unique nontrivial solution $a^*_{T,C}$. Thus, the corresponding threshold investment is $x^*_{T,C} = Va^*_{T,C}F(a^*_{T,C})$. ■

Proof of Lemma 4

Proof. (a) is straightforward, as $\lim_{a\to\underline{a}} F(a) = 0$. For (b), by Assumption 1, $\psi(a) = a - \frac{1-F(a)}{f(a)}$ is increasing in a, thus we have $\psi'(a) = 2 + \frac{(1-F(a))f'(a)}{f^2(a)} > 0$, which implies $f'(a) > \frac{-2f^2(a)}{1-F(a)}$, then we have $F(a)f'(a) + f^2(a) > \frac{-2f^2(a)}{1-F(a)}F(a) + f^2(a) = \frac{(1-3F(a))f^2(a)}{1-F(a)}$. Note that $\phi'(a) = 2+\frac{(1-F^2(a))}{2f^2(a)F^2(a)}[F(a)f'(a)+f^2(a)]$; thus $\phi'(a) > 2+\frac{(1-F^2(a))(1-3F(a))f^2(a)}{2f^2(a)F^2(a)(1-F(a))} = 2+\frac{(1+F(a))(1-3F(a))}{2F^2(a)} = \frac{(1-F(a))^2}{2F^2(a)} \geqslant 0$. Therefore, $\phi(a)$ is increasing in a. ■

Proof of Lemma 5

Proof. Recall $x(a_i) = V[a_C F(a_C) + \int_{a_C}^{a_i} sf(s)ds]$, then

$$\begin{aligned}
& HQ_C(a_C) \\
= & \int_{a_C}^{\overline{v}} x(a_i)dH(a_i) \\
= & 2\int_{a_C}^{\overline{v}} x(a_i)F(a_i)dF(a_i) \\
= & 2V\int_{a_C}^{\overline{v}} \left[a_C F(a_C) + \int_{a_C}^{v} sf(s)d(s)\right] F(a_i)dF(a_i) \\
= & V\left\{a_C F(a_C)(1-F(a_C)^2) + \int_{a_C}^{\overline{v}} a[1-F(a)^2]dF(a)\right\}.
\end{aligned}$$

Take the first order condition with respect to a_C,

$$\begin{aligned}
& \frac{dHQ_C(a_C)}{da_C} \\
= & F(a_C)(1-F(a_C)^2) + a_C f(a_C)(1-F(a_C)^2) - 2a_C f(a_C)F(a_C)^2 - a_C f(a_C)(1-F(a_C)^2) \\
= & F(a_C)(1-F(a_C)^2) - 2a_C f(a_C)F(a_C)^2.
\end{aligned}$$

Letting $\frac{dHQ_C(a_C)}{da_C} = 0$, we obtain $F(a_C)[(1-F(a_C)^2) - 2a_C f(a_C)F(a_C)] = 0$. We know that $a_C = \underline{a}$ is not the highest quality maximizing cutoff value, given that $\frac{dHQ_C(a_C)}{da_C}$ becomes positive as a_C departs from $\underline{a}$. Therefore, the optimal value for a_C must be such that $(1-F(a_C)^2) - 2a_C f(a_C)F(a_C) = 0$, or

$$\phi(a_C) = a_C - \frac{1-F(a_C)}{f(a_C)}\frac{1+F(a_C)}{2F(a_C)} = 0.$$

Because (1) by Lemma 4 $\phi(a_C)$ is increasing (and continuous) in a_C, (2) $\lim_{a\to\underline{a}}\phi(a) < 0$, and (3) $\phi(\overline{a}) = \overline{a} - \frac{1-F(\overline{a})}{f(\overline{a})}\frac{1+F(\overline{a})}{2F(\overline{a})} = \overline{a} > 0$, we know that the equation $\phi(a_C) = 0$ has a unique nontrivial solution $a^*_{H,C}$. Thus, the corresponding threshold investment is $x^*_{H,C} =$

$Va^*_{H,C}F(a^*_{H,C})$. ■

Proof of Proposition 2

Proof. By definition of hazard rate dominance, for any $a \in (\underline{a}, \overline{a})$, we have $\frac{f(a)}{1-F(a)} \leq \frac{g(a)}{1-G(a)}$, which implies $a - \frac{1-F(a)}{f(a)} \leq a - \frac{1-G(a)}{g(a)}$, i.e., $\psi_F(a) \leq \psi_G(a)$. Note $a^*_{T,C}$ is the root of $\psi(a)$, then $\psi_F(a^{*(F)}_{T,C}) = 0 = \psi_G(a^{*(G)}_{T,C}) \geq \psi_F(a^{*(G)}_{T,C})$. Given that $\psi(a)$ is increasing in a by Assumption 1, we have $a^{*(F)}_{T,C} \geq a^{*(G)}_{T,C}$.

Krishna (2010) (Appendix B) shows that hazard rate dominance implies first-order stochastic dominance, i.e., $F(a) \leq G(a)$, which implies $\frac{2F(a)}{1+F(a)} \leq \frac{2G(a)}{1+G(a)}$, and further implies $\frac{f(a)}{1-F(a)}\frac{2F(a)}{1+F(a)} \leq \frac{g(a)}{1-G(a)}\frac{2G(a)}{1+G(a)}$. Therefore $a - \frac{1-F(a)}{f(a)}\frac{1+F(a)}{2F(a)} \leq a - \frac{1-G(a)}{g(a)}\frac{1+G(a)}{2G(a)}$, i.e., $\phi_F(a) \leq \phi_G(a)$. By the same argument above, since $a^*_{H,C}$ is the root of $\phi(a)$, we have $\phi_F(a^{*(F)}_{H,C}) = 0 = \phi_G(a^{*(G)}_{H,C}) \geq \phi_F(a^{*(G)}_{H,C})$. Given that $\phi(a)$ is increasing in a by Lemma 4, we have $a^{*(F)}_{H,C} \geq a^{*(G)}_{H,C}$. ■

Proof of Proposition 3

Proof. Because $a^*_{T,C} \in (\underline{a}, \overline{a})$, we have $F(a^*_{T,C}) \in (0,1)$. By the fact $\frac{1+F(a^*_{T,C})}{2F(a^*_{T,C})} > 1$, we know $\phi(a^*_{T,C}) = a^*_{T,C} - \frac{1-F(a^*_{T,C})}{f(a^*_{T,C})}\frac{1+F(a^*_{T,C})}{2F(a^*_{T,C})} < a^*_{T,C} - \frac{1-F(a^*_{T,C})}{f(a^*_{T,C})} = \psi(a^*_{T,C})$. Given that $\psi(a^*_{T,C}) = 0$, we have $\phi(a^*_{T,C}) < 0$. Note that $\phi(a)$ is increasing in a by Lemma 4, then $\phi(a^*_{H,C}) = 0 > \phi(a^*_{T,C})$ implies $a^*_{H,C} > a^*_{T,C}$. ■

Proof of Proposition 4

Proof. Proposition 2 of Morath and Münster (2008) shows that a private-information setting elicits higher expected aggregate quality, which means that innovators receive a higher expected aggregate quality under the concealment policy in our setting.

For highest quality comparison, note that

$$
\begin{aligned}
& \left(HQ_C - HQ_D\right)/V \\
&= \int_{\underline{a}}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(F(a_2)a_2 - \frac{a_2^2}{3a_1} \right) dF(a_1) \right] dF(a_2) \\
&\geqslant \int_{\underline{a}}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(F(a_2)a_2 - \frac{a_2}{3} \right) dF(a_1) \right] dF(a_2) \\
&= \int_{\underline{a}}^{\overline{a}} a_2 \left(F(a_2) - \frac{1}{3} \right) (1 - F(a_2)) dF(a_2) \\
&= \int_{\underline{a}}^{\overline{a}} a_2 d \left[-\frac{1}{3} F(a_2)(1 - F(a_2))^2 \right] \\
&= m(\overline{a}) - m(\underline{a}) + \int_{\underline{a}}^{\overline{a}} \frac{1}{3} F(a_2)(1 - F(a_2))^2 da_2
\end{aligned}
$$

where $m(a_2) = -\frac{1}{3}a_2 F(a_2)(1 - F(a_2))^2$.

Because $[\underline{a}, \overline{a}] \in (0, +\infty)$, we have $m(\overline{a}) = m(\underline{a}) = 0$; therefore $\left(HQ_C - HQ_D\right)/V \geqslant \int_{\underline{a}}^{\overline{a}} \frac{1}{3} F(a_2)(1 - F(a_2))^2 da_2 \geqslant 0$. ■

Proof of Proposition 5

Proof. Part (i): Recall from the proof of Proposition 1 that we have $a^*_{T,D}$, which must be an interior solution. It is given by

$$
a^*_{T,D} \int_{a^*_{T,D}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2) + [1 - F(a^*_{T,D})] F(a^*_{T,D}) - a^*_{T,D} f(a^*_{T,D}) F(a^*_{T,D}) = 0.
$$

We thus have

$$
a^*_{T,D} - \frac{1 - F(a^*_{T,D})}{f(a^*_{T,D})} = \frac{a^*_{T,D} \int_{a^*_{T,D}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2)}{F(a^*_{T,D}) f(a^*_{T,D})} > 0.
$$

Note that $\psi(a^*_{T,C}) = a^*_{T,C} - \frac{1 - F(a^*_{T,C})}{f(a^*_{T,C})} = 0$, by Assumption 1; we thus have $a^*_{T,D} > a^*_{T,C}$, which further leads to $x^*_{T,D} > x^*_{T,C}$ given that $x^*_{T,D} = V a^*_{T,D}$ and $x^*_{T,C} = V a^*_{T,C} F(a^*_{T,C})$.

Part (ii): Recall from the proof of Proposition 1 that we have $a^*_{H,D}$, which must be an interior solution. It is given by

$$\begin{aligned}
& a_{H,D}^{*} \int_{a_{H,D}^{*}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2) \\
& + a_{H,D}^{*2} \int_{a_{H,D}^{*}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} \frac{1}{a_1 a_2} dF(a_1) \right) dF(a_2) \\
& + [1 - F(a_{H,D}^{*})] F(a_{H,D}^{*}) - a_{H,D}^{*} f(a_{H,D}^{*}) F(a_{H,D}^{*}) \\
= \; & 0.
\end{aligned}$$

We thus have

$$\begin{aligned}
& a_{H,D}^{*} - \frac{1 - F(a_{H,D}^{*})}{f(a_{H,D}^{*})} \frac{1 + F(a_{H,D}^{*})}{2F(a_{H,D}^{*})} \\
= \; & \frac{1}{F(a_{H,D}^{*}) f(a_{H,D}^{*})} \begin{pmatrix} a_{H,D}^{*} \int_{a_{H,D}^{*}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2) \\ + a_{H,D}^{*2} \int_{a_{H,D}^{*}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} \frac{1}{a_1 a_2} dF(a_1) \right) dF(a_2) - \frac{(1 - F(a_{H,D}^{*}))^2}{2} \end{pmatrix}.
\end{aligned}$$

Note that $\phi(a_{H,C}^{*}) = a_{H,C}^{*} - \frac{1 - F(a_{H,C}^{*})}{f(a_{H,C}^{*})} \frac{1 + F(a_{H,C}^{*})}{2F(a_{H,C}^{*})} = 0$, by Lemma 4(b), we thus have $a_{H,D}^{*} > a_{H,C}^{*}$ if and only if

$$\begin{aligned}
& a_{H,D}^{*} \int_{a_{H,D}^{*}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} (\frac{1}{a_2} - \frac{1}{a_1}) dF(a_1) \right) dF(a_2) + a_{H,D}^{*2} \int_{a_{H,D}^{*}}^{\overline{a}} \left(\int_{a_2}^{\overline{a}} \frac{1}{a_1 a_2} dF(a_1) \right) dF(a_2) \\
\geq \; & \frac{(1 - F(a_{H,D}^{*}))^2}{2}.
\end{aligned}$$

Given that $x_{H,D}^{*} = V a_{H,D}^{*}$ and $x_{H,C}^{*} = V a_{H,C}^{*} F(a_{H,C}^{*})$, we have $x_{H,D}^{*} \geq x_{H,C}^{*}$ if and only if $a_{H,D}^{*} \geq a_{H,C}^{*} F(a_{H,C}^{*})$. ■

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