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

Gaoyang Cai† Qian Jiao‡ Jingfeng Lu§ Jie Zheng¶

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**Abstract**

We study two-player R&D contest design using both an information disclosure policy and a quality standard as instruments. The ability of an innovator is known only 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 without quality standard, fully concealing innovators' abilities elicits both higher expected aggregate quality and expected highest quality. With optimally set quality standards, although fully concealing ability information still elicits higher expected aggregate quality, fully disclosing this information leads to a higher level of expected highest quality. Moreover, the optimal quality standards are compared across different objectives and disclosure policies.

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†Gaoyang Cai: Kellogg School of Management, Northwestern University, Evanston, Illinois, 60208, USA. E-mail: gaoyang.cai@kellogg.northwestern.edu.

‡Qian Jiao (Corresponding author): Department of Economics, Lingnan College, Sun Yat-sen University, Guangzhou, China, 510275. E-mail: jiaoq3@mail.sysu.edu.cn.

§Jingfeng Lu: Department of Economics, National University of Singapore, Singapore 117570. E-mail: ecsljf@nus.edu.sg.

¶Jie Zheng: Center for Economic Research, Shandong University, Jinan, China, 250100. E-mail: jie.academic@gmail.com.

# 1 Introduction

R&D contests have long been utilized to foster innovation. In such contests, the procurer/organizer posts an innovation-related problem to suppliers/innovators and rewards the individual or team who submit the most outstanding solutions. The use of R&D contests can be traced back to 1714, when the British Parliament offered a prize of £20,000 to anyone who could devise a simple and practical method for accurately determining a ship's longitude. As societal demand for innovation continues to surge, R&D contests have witnessed an exponential rise in both their frequency and magnitude.

A crucial consideration for procurers in R&D contests is the design of an effective competition mechanism that not only stimulates innovation but also enhances the quality of innovative products. Among various design schemes, two commonly employed instruments are the quality standard and information disclosure policy. Typically, procurers set a minimum acceptable quality standard to ensure that innovations developed during the R&D contest meet certain criteria. In the meanwhile, to better incentivize innovators, she can strategically choose an information disclosure policy about the abilities of competing innovators.

This type of joint design phenomenon is prevalent in R&D procurement. For example, in the venue project tender for the National Stadium in Beijing, the local municipal planning commission established specific design standards. These standards included a requirement for a service life of 100 years, Grade 1 fire resistance rating, an intensity level of 8 on the seismic fortification scale, and Grade 1 underground waterproofing.[1] Similarly, many government-sponsored R&D contests impose basic quality requirements on competitors for their developed products. In these public procurements, each tenderer typically possesses knowledge about their own competency but lacks information about their competitors' abilities. However, this competency information can be disclosed to participating innovators. Since research proposals or other materials (e.g., qualification documents, certificates, financial reports, etc.) are good indicators of the competing innovators' background, procurers/organizers have the opportunity to assess participants' capabilities through these submitted materials and disclose relevant information publicly.

The joint design of minimum quality standards and information disclosure policies is also commonly observed in popular R&D contests. For example, the 2018 City University (Hong Kong) App Innovation Contest demanded participants to develop an app or visually interactive scene in a Swift playground that could be experienced within a 3-minute timeframe. Similarly, the 2019 Honda Motor (China) Energy Saving Competition stipulated that the original vehicle body must possess three or more wheels and comply with all safety regulations. In such R&D contests, participants are required to truthfully disclose their identity

[1] Detailed tender notice can be obtained from https://ggzyfw.beijing.gov.cn/index.html.

when registering online, and the contest organizer reserves the right to disclose this identity information to all participants.[2]

In this paper, we study the optimal design of two-player R&D contests when both the information disclosure policy and the quality standard are available to the organizer as design instruments. The design objectives we use include both aggregate quality maximization and highest quality maximization. In an R&D contest, the organizer may care about the aggregate level of research output or the best innovation only, depending on the specific context. For example, in many popular open innovations, such as the motor energy saving competition or the App innovation contest, the organizer aims to improve the quality of the product for the entire industry, whereas in public procurement, the procurer only cares about the optimal design scheme. The central question we investigate is how the disclosure policy should be optimally coupled with the quality standard to best incentivize innovators in each of these design goal contexts, i.e., aggregate quality maximization and highest quality maximization. How should quality standards be set for different objectives 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 objective?

We adopt an analytical framework of a two-player all-pay auction with incomplete information to model R&D innovation 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. We study an environment in which agents' productive effort translates linearly into a deterministic quality of innovation.[3] The contest organizer has two instruments: the disclosure policy and the quality standard. She strategically sets up a quality standard and chooses between two policy alternatives: (1) fully revealing innovators' competency profiles or (2) fully concealing them. Her disclosure policy is ex ante committed to the realization of innovators' ability profiles.[4]

The timing of the game is as follows. First, the contest organizer announces a quality standard and commits to her disclosure policy publicly. Second, the cost profile of two innovators is realized and each innovator knows only his own cost. This information is disclosed to both innovators if and only if the organizer has chosen the full disclosure policy. Finally, both innovators submit their effort entries simultaneously in competition for a single

[2] Eső and Szentes (2007) assume in their model that the seller can control the disclosure of information to buyers about their value even when the seller cannot observe this information.

[3] The one-to-one correspondence between effort and quality of the R&D outcome has been used in many papers in the contest literature; for example, Kamien, Muller, and Zang (1992) assume a firm's effective R&D investment $x$ can reduce its unit cost in the production stage by $f(x)$, where $f(x)$ is the R&D production function. Fang, Noe and Strack (2020) consider a setup where effort ranking is equivalent to effort-cost ranking.

[4] We focus on full disclosure and full concealment policies. In a web-based open innovation contest, full disclosure means that participants are required to register online with full personal information, and full concealment means that innovators can participate anonymously.

prize.

When the contest organizer chooses to disclose the types of innovators, 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.[5] 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.

We contribute to the literature on R&D contest design by integrating disclosure policy and a quality standard as design instruments. To establish a basis for comparison, 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. Publicly revealing the types of innovators tends to discourage both the stronger and weaker innovators' effort supply (see, e.g., Morath and Münster, 2008; Fu, Jiao, and Lu, 2014). Indeed, the stronger one tends to slack off when he realizes that he is more capable than his competitor, and the weaker one will be frustrated against a strong opponent. In contrast, a nonzero quality standard tends to discourage the weaker types while better motivating the stronger types. Therefore, regardless of the disclosure policy, a higher quality standard should be set for highest quality maximization. For aggregate quality maximization, setting a quality standard does not overcome the disadvantage conferred by a full disclosure policy. However, for highest quality maximization, introducing a quality standard can reverse the outcome, i.e., fully disclosing the competency information leads to a higher level of expected highest quality ex ante.

Our theoretical findings yield important insights about how to boost innovators' performance in a joint design environment, and generate practical implications for information design in R&D contests. For a contest organizer who would like to improve the R&D level of the whole industry, she should fully conceal the innovators' abilities and set a comparatively low-quality standard; while if she cares about the best R&D achievement, she should fully disclose the innovators' abilities and set a high-quality standard. This result provides a rationale for the common practice of revealing innovators' identities in government procurements.

**Related literature.** Contests have been extensively utilized in modelling R&D competitions (e.g., Taylor, 1995; Fullerton and McAfee, 1999; Moldovanu and Sela, 2001; Che and Gale, 2003; Snir and Hitt, 2003; Clark and Konrad, 2008; Terwiesch and Xu, 2008; and Mihm and Schlapp, 2017). A central question in this literature is how to better motivate innovation and foster creativity. Letina and Schmutzler (2019) analyze the design of innovation contests when the quality of an innovation depends on the research approach.

[5] Siegel (2014) characterizes the set of equilibria in a complete-information two-player all-pay auction with interdependent valuations with a reserve price.

Among different aspects of contest design, the strategic disclosure of information about bidders' abilities has been well studied in the literature. In an all-pay auction setting, Morath and Münster (2008) compare the information structures. They find that bidders receive the same expected payoff in the full concealment and full disclosure conditions, but full concealment results in a higher expected total effort. Fu, Jiao, and Lu (2014) generalize the insight of Morath and Münster (2008) by allowing multiple prizes. In a two-player contests setting, Kovenock, Morath, and Münster (2015) consider voluntary information sharing between two bidders about their values. Lu, Ma, and Wang (2018) and Serena (2022) focus on contestants with discrete types, and provide the full ranking of four anonymous type-contingent information disclosure policies in environments with different contest technologies. Lu and Wang (2019) study the auction organizer's optimal information disclosure policy about players' value distribution. Melo-Ponce (2021) analyzes how a designer uses a stochastic communication mechanism to manipulate the beliefs in a class of binary action contests. Chen (2021) analyzes public disclosure with two-sided private information and independent valuations.

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 and players make positive effort.[6] Wu and Zheng (2017) investigate contestants' incentives to disclose their prize valuations, and find that sharing information is strictly dominated if the types are sufficiently dispersed. Aoyagi (2010) studies an optimal feedback policy on the performance of agents in a multi-stage tournament. Zhu (2021) sets up a model of "creative contests" and considers an information disclosure problem wherein the contest organizer commits to either fully revealing or concealing their ideal design (preference).

Another strand of the literature compares disclosure policies in contests based on 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. Hu, Zhao, and Huang (2016) and Chen, Jiang, and Knyazev (2017) explore this issue in all-pay auction settings. In contrast, Feng (2020) studies how to disclose the precision of the winner selection mechanism (discriminatory power $r$ of the Tullock contest) when the information about $r$ is asymmetric between the contest organizer and contestants.

Most studies on information disclosure in contests focus on total effort maximization, with Hu, Zhao, and Huang (2017) being the only exception. They consider two objectives in contests: expected aggregate effort maximization and expected highest effort maximization. Other studies consider these two objectives but adopt different design instruments. Moldovanu and Sela (2006) compare a one-stage contest and a two-stage contest. Chen,

[6] Clark and Kundu (2021) extend the results of Zhang and Zhou (2016). They show that even for binary distributions, if some informed types are allowed to exert zero effort, partial disclosure can be optimal.

Zheng, and Zhong (2015) compare random grouping with ability-based grouping. Mihm and Schlapp (2017) discuss how contest organizers can improve results by designing an optimal information structure for their performance feedback policies. Finally, Serena (2017) studies contestant exclusion.

To the best of our knowledge, our paper represents the first study to delve into the optimal design of R&D contests by employing both a disclosure policy and quality standard as key instruments.[7] Taking aggregate quality as well as highest quality as maximizing goals, we conduct a comparative analysis of the optimal quality standards across various objectives and disclosure policies. This exploration provides valuable insights into the interplay between these design instruments, elucidating their roles in achieving distinct design objectives.

The rest of this paper proceeds as follows. In Section 2, we develop a two-player R&D contest model with a quality standard, carry out equilibrium analysis, and compare the optimal quality standards under different disclosure policies. Section 3 presents the comparison of disclosure policies under aggregate quality maximization and highest quality maximization. Some extensions are provided in Section 4. Section 5 concludes with a brief discussion of directions for future research. The appendix collects some technical proofs.

# 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. The marginal cost of innovator $i$ is $c_i$ and his corresponding innovation ability is $a_i = \frac{1}{c_i}$. A higher $a_i$ indicates 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 abilities of innovators, 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 $a \in [\underline{a}, \overline{a}]$.

In addition, we make the following assumption to guarantee an interior solution, so that the quality standard for aggregate quality maximization under a concealment policy is nonzero. 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.

[7] Drugov, Ryvkin and Zhang (2022) study a joint design by using reserve price and the prize structure as design instruments, under a multi-player tournament setup.

Delivering quality $x_i$ costs innovator $i$ by $c_i x_i$. Therefore, the payoff to innovator $i$ 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 a 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 publicly announces the quality standard and her choice of disclosure policy before the types of innovators are realized. We denote the full disclosure policy by $D$, the 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 the ability profile of innovators $\mathbf{a} = (a_1, a_2)$ 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, both innovators simultaneously invest $\mathbf{x} = (x_1, x_2)$ to compete for reward $V$.

In what follows of this section, we perform an equilibrium analysis and compare the optimal quality standard for different disclosure policies.

### 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 the abilities of all of the innovators before they 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. Specifically, $a_D$ is the ability of the marginal type who will be indifferent between exerting no effort and winning at the quality standard. Thus all types below $a_D$ will submit only zero effort. 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.[8] Based on his Proposition 1, we characterize the equilibrium under policy $D$ and the 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 that $a_1 > a_2$. Then, in the unique bidding Nash equilibrium:*

*(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*

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

*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.*

Lemma 1($a$) shows that, when two innovators are still active, their expected payoffs are exactly as in the case without a positive standard. Introducing a nonzero quality standard increases a strong innovator's winning probability, thereby increasing his expected aggregate quality. At the same time, the expected aggregate quality of a weak innovator decreases, compared with the case of a null quality standard. However, as shown in Lemma 1($b$), when the quality standard is high enough that only the strong innovator is active, the expected payoff of the strong innovator decreases, and the payoff of the weak innovator keeps as 0. In the meanwhile, the aggregate quality of the strong innovator increases, and the aggregate quality of the weak innovator decreases.[9]

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.

**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*

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

*The ex ante expected highest quality induced is*

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

**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 the expected aggregate quality and the highest

[9] Note that, without a standard, as long as $a_1 > a_2 > 0$, the expected payoff of the *strong innovator* is $(a_1 - a_2)V$, the expected payoff of the *weak innovator* is 0. The expected aggregate quality of the *strong innovator* is $\frac{a_2}{2}V$, and the expected aggregate quality of the *weak innovator* is $\frac{a_2^2}{2a_1}V$.

quality under policy $D$, respectively. However, we are able to compare these two optimal threshold ability levels.

**Proposition 1** *Under policy $D$, there exist nonzero optimal threshold abilities $a^*_{T,D}$, $a^*_{H,D} \in (\underline{a}, \overline{a})$, which maximize the expected aggregate quality and the highest quality, respectively. Moreover, if these optimal optimal thresholds are unique, then the one for aggregate quality maximization is always lower than that for highest quality maximization, i.e., $a^*_{T,D} < a^*_{H,D}$.*

**Proof.** The existence of an optimal threshold ability level is guaranteed, as the support for $a_D$, $[\underline{a}, \overline{a}] \in (0, +\infty)$ is compact. Note that $TQ_D(\cdot)$ is continuous and $f(\cdot) > 0$, so the optimal threshold ability level is *almost always* unique, except for a set of points of measure zero. In case the optimal threshold ability level is 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 $a^*_{H,D} > a^*_{T,D}$. Without loss of generality, we assume uniqueness hereafter. Details of the proof are relegated to the 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 $F(\cdot)$. Based on Proposition 1, one can immediately show that when the abilities of innovators is disclosed, the optimal quality standard levels that maximize the aggregate quality and the highest quality exist. Assuming uniqueness, we have the following Corollary.

**Corollary 1** *Under policy $D$, the optimal quality standards, $x^*_{T,D}$ and $x^*_{H,D}$, are nonzero for aggregate quality maximization and highest quality maximization. Moreover, under the uniqueness assumption, the optimal quality standard that maximizes the aggregate quality is lower than the one maximizing the 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 that quality standard $x_C$ is set. In this case, the contest organizer does not disclose the abilities of innovators before they choose their efforts. An incomplete-information all-pay auction with minimum bid $x_C$ thus arises. Define $a_C$ such that $x_C = Va_C F(a_C)$, which is interpreted as a threshold ability level in the following analysis. Similarly to the full disclosure case, $a_C$ is the ability of the marginal type who will be indifferent between exerting no effort and winning at the quality standard. Consequently, all types below $a_C$ will submit zero effort.[10] Assume

[10]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 $x_C \in [0, V\overline{a}]$, $Va_C F(a_C) = x_C$ has a *unique* solution for $a_C$. This is true because $Va_C F(a_C)$ is increasing in $a_C$, $V\underline{a}F(\underline{a}) = 0$, and $V\overline{a}F(\overline{a}) = V\overline{a}$.

the entry cutoff abilities are symmetric and thus unique between two innovators.[11]

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

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

$$x(a_i) = \begin{cases} V\left[a_C F(a_C) + \int_{a_C}^{a_i} sf(s)ds\right] & \text{if } a_i \geq a_C; \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

*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 nonzero ($a^*_{T,C} \in (\underline{a}, \overline{a})$) 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) $\phi(a)$ is increasing in $a$ for any $a \in (\underline{a}, \overline{a}]$.*

**Proof.** See Appendix. ■

If the organizer chooses to conceal the ability information, innovators only have private information about their own ability. 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 largest order statistics when $n = 2$. Plugging in the corresponding bidding strategy, we obtain the organizer's expected highest quality under full concealment.

[11] Without the symmetric assumption, the sufficient condition for the symmetric entry cutoffs is $\frac{F(a_1)}{F(a_2)} \neq \frac{a_1}{a_2}$. This is because the equilibrium entry cutoffs of different innovators satisfy $\frac{x_C}{a_1} = VF(a_2)$ and $\frac{x_C}{a_2} = VF(a_1)$, these two equations admit a symmetric solution $a_1 = a_2 = a_C$ as long as $\frac{F(a_1)}{F(a_2)} \neq \frac{a_1}{a_2}$.

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

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

*Moreover, the highest quality maximizing cutoff ability is nonzero* ($a^*_{H,C} \in (\underline{a}, \overline{a})$) *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 the 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 $a^{*(F)}_{H,C}$ 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., $\frac{f(a)}{1-F(a)} \leq \frac{g(a)}{1-G(a)}$ for all $a \in (\underline{a}, \overline{a})$, 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.,* $\frac{f(a)}{1-F(a)} \leq \frac{g(a)}{1-G(a)}$ *for all* $a \in (\underline{a}, \overline{a})$*, 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 indicates that with a better ability distribution in terms of hazard rate dominance, the organizer should set a higher quality standard for both aggregate quality maximization and highest quality maximization, as $x^*_{T,C} = Va^*_{T,C}F(a^*_{T,C})$, and $x^*_{H,C} = Va^*_{H,C}F(a^*_{H,C})$.

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

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

**Proof.** See Appendix. ■

Note that the corresponding optimal quality standard levels are $x^*_{T,C} = Va^*_{T,C}F(a^*_{T,C})$, $x^*_{H,C} = Va^*_{H,C}F(a^*_{H,C})$. Based on Proposition 3, one can immediately show that when the ability of an innovator is fully concealed, the optimal quality standard level that maximizes the aggregate quality is strictly lower than the one that maximizes the 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 nonzero for both aggregate quality maximization and highest quality maximization. Moreover, the optimal quality standard for aggregate quality maximization is lower than that for 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 does not hold. If $\psi(\underline{a}) \geq 0$, then $a^*_{T,C} = \underline{a}$ (see details in 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 details in Proof of Lemma 5).

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. That is because imposing a higher quality standard tends to better incentivize high ability innovators but at the cost of disincentivizing their low ability counterparts, 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 ability innovators and suffers less from the lower contribution of low ability innovators. It is thus natural for a designer seeking to maximize the quality of the best innovation to set a higher quality standard, regardless of the disclosure policy.

# 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 examine 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 is reduced to a question on 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 generate 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 of the designer's optimal disclosure policy without a quality standard for 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 aggregate quality of the innovation and the quality of the best innovation can both reach a higher level.[12] This result can be understood as a consequence of the well received disincentivizing effect in asymmetric contests. Revealing their type profile creates an asymmetric contest between the two innovators, which tends to discourage their effort supply.

## 3.2 Comparison with the optimal quality standard

We now consider the scenario in which the designer is allowed to optimally set a 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.*

[12] Note that our result for aggregate effort follows directly from Morath and Münster (2008).

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

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

*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. ■

Allowing a choice of quality standard can improve the performance of innovators for both goals under both disclosure policies, and for a given goal, the designer tends to set a higher standard under full disclosure than under full concealment.

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

We next compare the 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 the quality standard can be optimally set, 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 $x_C = Va_CF(a_C)$ and corresponding cutoff ability $a_C$.

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

**Step 2** Suppose that $x^*_{T,D}$ is the optimal quality standard level that maximizes the aggregate quality under a full disclosure policy, with a 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 correspondence between quality standard $x_C$ and its corresponding cutoff ability $a_C$, i.e., $x_C = Va_CF(a_C)$. Then, under quality standard $x_C = Va^*_{T,D}F(a^*_{T,D})$, full concealment generates a higher ex ante expected aggregate quality than 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 the quality standard 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 $HQ_D\left(a_D\right)$ 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 $x_C=Va_CF(a_C)$ and corresponding cutoff ability $a_C$.

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

$$\begin{aligned}HQ_D(a^*_{H,C}) &= HQ_D\left(a_D=a^*_{H,C}\right)\\ &= 2V\begin{pmatrix}\int_{a^*_{H,C}}^{\overline{a}}\left[\int_{a_2}^{\overline{a}}\frac{a_1a_2^2+\left(a^*_{H,C}\right)^2(a_1-a_2)+\frac{1}{3}a_2^3+\frac{2}{3}\left(a^*_{H,C}\right)^3}{2a_1a_2}dF(a_1)\right]dF(a_2)\\ +a^*_{H,C}(1-F(a^*_{H,C}))F(a^*_{H,C})\end{pmatrix}.\end{aligned}$$

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

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

As $a > a^*_{H,C}$, we have

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

Let $D(a) = a(1 - F(a)^2)$, thus $D'(a) = 1 - F(a)^2 - 2af(a)F(a)$. Note 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. As $a^*_{H,C} - \frac{1-F(a^*_{H,C})^2}{2f(a^*_{H,C})F(a^*_{H,C})} = 0$, we have $a - \frac{1-F(a)^2}{2f(a)F(a)} > 0$ when $a > a^*_{H,C}$, which implies that $D'(a) < 0$ 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 that $G(a^*_{H,C}) > 0$.

**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 logic to prove 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 lead to the same cutoff ability $a$, and full concealment always elicits higher aggregate quality. While such a relationship holds for any cutoff ability level $a$ for aggregate quality maximization, Step 1 of Theorem 2 shows that the opposite result holds for cutoff ability level $a = a^*_{H,C}$ for highest quality maximization. That is, if the contest organizer sets quality standard level $x_D = a^*_{H,C}V$ under full disclosure and quality standard level $x_C = Va^*_{H,C}F(a^*_{H,C})$ under full concealment, both policies lead to the same cutoff ability $a^*_{H,C}$, and full disclosure can lead to a better quality on the part of the winner.

Therefore, for the optimal quality standard level that maximizes the aggregate (resp. highest) quality under full disclosure (resp. concealment), there is always 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 reinforces Proposition 4 for aggregate quality maximization: fully concealing innovators' abilities is always an optimal choice, whether or not the contest organizer is allowed to set a quality standard. In contrast, Theorem 2 states that for highest quality maximization, 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 strategically setting a quality standard always elicits better quality from the winning innovation.[13]

Revealing the type profile creates an asymmetric contest between the two innovators, which tends to discourage their effort supply. Because once both sides recognize the difference in their abilities, they may cease putting forth their utmost effort and opt for a more relaxed approach. This is known as the initial disadvantage resulting from the full disclosure policy. A quality standard is an effective instrument to mitigate the disincentivizing effect by forcing high ability innovators to work harder, although this might discourage low type innovators. When the goal is aggregate quality maximization, the designer cares about the performance of low ability innovators. Thereby, she will just set a moderate quality standard to push both innovators to work harder. And the impetus is not strong enough to overcome the initial disadvantage caused by innovators' slacking. As a result, the full concealment policy still induces a higher aggregate quality level.

However, for highest quality maximization, the designer does not care much about the performance of low ability innovators. In contrast to aggregate quality maximization, she can set a higher quality standard under both policies to spur on the high ability innovators. Furthermore, compared to the optimally set quality standard under full concealment, setting a higher quality standard under full disclosure can effectively deter innovators from slacking off, thereby completely overcoming the initial disadvantage of a scenario with no quality standards.

Our results appear to be consistent with the joint design characteristics of many actual contests: In an App innovation contest or motor energy saving competition, organizers aim to increase public awareness of the importance of new energy and technologies by encouraging more people to participate. Therefore, participants are usually anonymous on web-based open innovation platforms, and quality standards are kept at a more accessible level for all; while in the field of high and new technology of the public procurement, such as 5G network bidding, tenderees have strict requirements on product quality, and the identities of the tenderers are often disclosed to the public.

[13] In our working paper version by Cai, Jiao, Lu, and Zheng (2022), we present numerical examples to illustrate the comparisons between the optimal quality standards of different disclosure policies, and demonstrate the optimal disclosure policies for different quality maximization goals.

# 4 Extensions

## 4.1 $N$ innovators

In this subsection, we extend the above analysis to more than two innovators. Assume $N$ innovators with innovation abilities $a_1 > a_2 > \ldots > a_n$.

Under full disclosure policy $D$, according to Bertoletti (2016), only two innovators with the highest and second highest ability remain active. Using the joint first and second highest order statistics among $N$ innovators, we can calculate the ex ante expected aggregate quality and highest quality respectively,

$$TQ_D(a_D) = NV \left\{ \begin{array}{c} \int_{a_D}^{\overline{a}} \int_{a_2}^{\overline{a}} \left( \frac{a_2^2 + a_D^2}{2a_2} + \frac{a_2^2 - a_D^2}{2a_1} \right) dF(a_1) \, dF^{N-1}(a_2) \\ +a_D [1 - F(a_D)] F^{N-1}(a_D) \end{array} \right\}, \tag{7}$$

$$HQ_D(a_D) = NV \left\{ \begin{array}{c} \int_{a_D}^{\overline{a}} \int_{a_2}^{\overline{a}} \frac{a_1 a_2^2 + a_D^2 (a_1 - a_2) + \frac{1}{3} a_2^3 + \frac{2}{3} a_D^3}{2a_1 a_2} dF(a_1) \, dF^{N-1}(a_2) \\ +a_D [1 - F(a_D)] F^{N-1}(a_D) \end{array} \right\}. \tag{8}$$

Note that the second term of the above two expressions are the same, since when the innovator with the second highest ability falls below the cutoff, i.e., $a_2 < a_D$, the designer can only collect the revenue from the innovator with the highest ability $a_1$. Moreover, if $a_2 < a_1 \leq a_D$, both innovators would bid 0; if $a_2 < a_D < a_1$ the innovator with the highest ability will only bid the minimum threshold

$$x_D = V a_D. \tag{9}$$

Under full concealment policy $C$, each innovator is competing against $N-1$ remaining innovators, the symmetric equilibrium bidding strategy in an all-pay auction with private information is

$$x(a_i) = V \left[ a_C F^{N-1}(a_C) + \int_{a_C}^{a_i} s dF^{N-1}(s) \right], \tag{10}$$

the threshold ability level is determined by

$$V a_C F^{N-1}(a_C) = x_C. \tag{11}$$

Based on the equilibrium results, we can obtain the ex ante expected aggregate quality and highest quality,

$$TQ_C(a_C) = NV \left\{ \int_{a_C}^{\overline{a}} a[1 - F(a)] dF^{N-1}(a) + a_C [1 - F(a_C)] F^{N-1}(a_C) \right\}, \tag{12}$$

$$HQ_C\left(a_C\right)=V\left\{a_C F^{N-1}\left(a_C\right)\left[1-F^N\left(a_C\right)\right]+\int_{a_C}^{\overline{a}} a\left[1-F^N(a)\right]dF^{N-1}(a)\right\}. \qquad (13)$$

In general, the cutoff under disclosure is different from the cutoff under concealment, i.e., $x_D \neq x_C$, and so does the corresponding cutoff abilities derived from (9) and (11), namely $a_D \neq a_C$.

Let $a_{T,D}^* \in argmax TQ_D\left(a_D\right)$ in (7), $a_{T,C}^* \in argmax TQ_C\left(a_C\right)$ in (12), $a_{H,D}^* \in argmax HQ_D\left(a_D\right)$ in (8) and $a_{H,C}^* \in argmax HQ_C\left(a_C\right)$ in (13) respectively. Following the steps of proof in Theorem 1, the comparison between disclosure policies for aggregate quality maximization can be obtained immediately.

**Proposition 6** *In an $N$-player innovation contest, when the quality standard can be optimally set, fully concealing innovators' abilities elicits higher ex ante expected aggregate quality, i.e., $TQ_D^*(a_{T,D}^*) \leqslant TQ_C^*(a_{T,C}^*)$.*

**Proof.** See Appendix. ■

However, the comparison for highest quality maximization is not obvious, since we need to evaluate the expected highest quality under disclosure at the optimal ability level under concealment $a_{H,C}^*$, and compare it with the maximum highest quality under concealment. The proof method in step 1 of Theorem 2 is no longer applicable. We rather rely on numerical simulations to carry out the comparisons.

**Simulation 1:** Let $V=1,\ \overline{a}=1,\ N\geq 2,\ F(a)=a^{\beta}$ where $\beta>0,\ a\in[0,1]$. Consider $a_D, a_C \in [0,1]$, note that $x_D = Va_D,\ x_C = Va_C F^{N-1}\left(a_C\right)$. Let $N=2,3,\ldots,20; \beta = 0.5, 1.0, 2.0$. Fix given $N$ and $\beta$, compare $HQ_D^*(a_{H,D}^*)$ and $HQ_C^*(a_{H,C}^*)$.

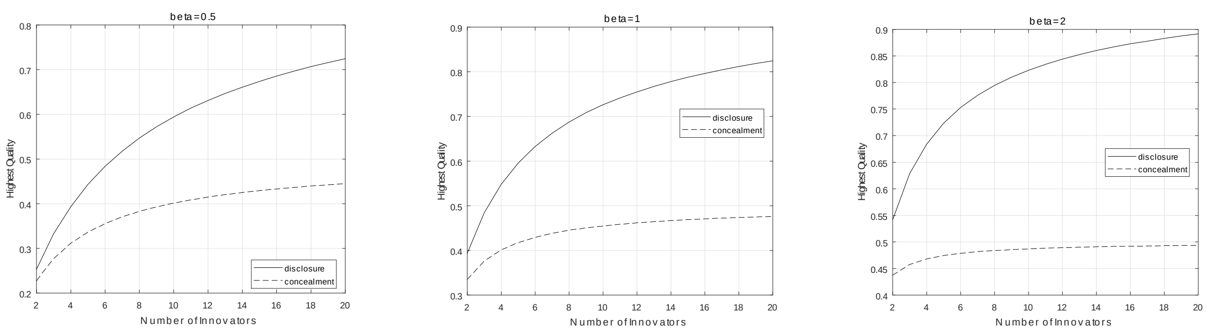



Figure 1: Comparison of Maximum Highest Quality

In all these cases, our simulation results are consistent with the baseline case of two innovators. We conjecture that this observation holds in general. That is, in an $N$-player innovation contest, when the quality standard can be optimally set, fully disclosing innovators' abilities elicits higher ex ante expected highest quality.

## 4.2 Voluntary Information Disclosure

In this subsection, we follow Kovenock, Morath and Münster (2015) and investigate industry-wide voluntary information disclosure equilibrium when the organizer conceals information. That is, we study the subgame in which the contest organizer commits to conceal the innovators abilities in stage 1. Between stage 1 and stage 2, the innovators can independently choose whether or not to disclose their abilities. However, one innovator shares his information if and only if the other also chooses to do so. These decisions are binding commitments.

In this case, we only need to study the cases where the two innovators eventually adopt the same information sharing policy. Denote the fixed minimum standard in this case as $x_S$.

#### Both innovators share information

If both innovators share their information, the resulting subgames have complete information, and the all-pay auction has a unique equilibrium summarized in Lemma 1: If $Va_1 \leq x_D$, all innovators would bid 0, innovators are indifferent between disclosing information or not; If $Va_2 \leq x_D < Va_1$ and innovators disclose information, it is optimal for innovator 1 to bid at the reserve price $x_1^* = x_D$, resulting in the payoff $V(1 - \frac{a_D}{a_i})$, and innovator 2 bid 0; If $Va_2 > x_D$, the unique bidding Nash equilibrium is in mixed strategies, with the cutoff bid replaced by $x_D$. And by standard calculation, the ex ante expected profit of any innovator $i, j \in \{1, 2\}$ equals $V \max\{1 - \frac{a_j}{a_i}, 0\}$.

Therefore, the ex ante expected payoff of innovator $i$ is

$$\int_{a_D}^{\bar{a}} \left[ \int_{\underline{a}}^{a_D} V(1 - \frac{a_D}{a_i}) dF(a_j) + \int_{a_D}^{\bar{a}} V \max\{1 - \frac{a_j}{a_i}, 0\} dF(a_j) \right] dF(a_i),$$

which can be further simplified to

$$\pi_D(a_D(x_S)) = \int_{a_D}^{\bar{a}} \left[ V(1 - \frac{a_D}{a_i}) F(a_D) + \int_{a_D}^{a_i} V(1 - \frac{a_j}{a_i}) dF(a_j) \right] dF(a_i), \tag{14}$$

where $Va_D = x_S$.

#### No innovator shares information

If no innovator shares information, innovators are faced with a standard all-pay auction with private information and minimum standard. The equilibrium bidding strategy is summarized in equation (3).

A innovator's interim expected profit, given a realized $a_i \geq a_C$, equals

$$VF(a_i) - \frac{X(a_i)}{a_i} = \frac{V}{a_i} \int_{a_C}^{a_i} F(s) ds$$

and ex ante expected payoff is

$$\pi_C(a_C(x_S)) = V \int_{a_C}^{\overline{a}} \left[ \frac{1}{a_i} \int_{a_C}^{a_i} F(s) ds \right] dF(a_i), \tag{15}$$

where $V a_C F(a_C) = x_S$.

Without minimum bid, Kovenock, Morath and Münster (2015) find both information sharing and no information sharing give the innovator the same expected payoff. Given the quality standard $x_S$, which is set up by contest organizer under concealment policy, the comparison of expected payoff of innovator $i$ under information sharing (14) and no information sharing (15) is technically challenging. Again, we reply on numerical simulations.

**Simulation 2:** $V = 1,\ \overline{a} = 1,\ N = 2.\ F(a) = a^{\beta}$ where $\beta > 0,\ a \in [0, 1]$. Let $x_S \in [0, 1]$. Define $a_D = x_S$ and $a_C = x_S^{\frac{1}{\beta+1}}$. Compare the resulting ex ante expected payoff of innovator $i$ under information sharing (14) and no information sharing (15), with $\beta = 0.5, 1.0, 2.0$.

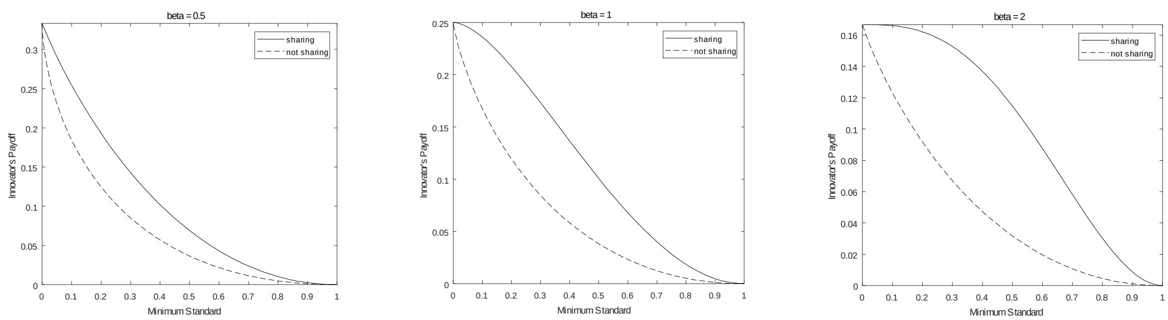



Figure 2: Comparison of Innovator's Payoff

Our simulation results show that in contrast to Kovenock, Morath and Münster (2015), the industry-wide disclosure policy equilibrium crucially depends on whether there is a minimum standard for industry-wide agreement, both of the innovators would agree to disclose their abilities in all cases of Figure 2, i.e., share their informations, if there is an interior minimum standard requirement. We conjecture that this observation holds in general.

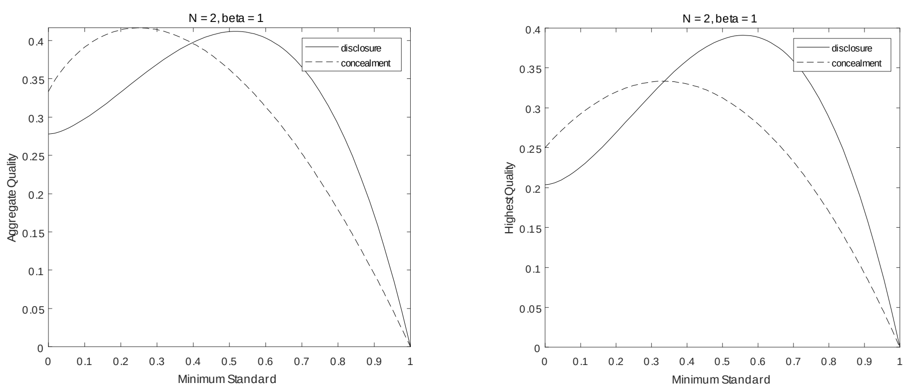
Kovenock, Morath and Münster (2015) also consider another type of voluntary information disclosure, where innovators simultaneously and independently decide whether or not to share information and their choices are binding. They allow one innovator commits to disclose and the other one commits to conceal. Without minimum standard requirement, they characterize the innovators' equilibrium bidding strategies and payoffs with asymmetric disclosure. However, we find that the type of equilibrium for asymmetric policies in Kovenock, Morath and Münster (2015) no longer exists when there exists a minimum standard as in our setting. Detailed proof for this nonexistence result is relegated to Appendix B. Without the needed equilibrium characterization, we are unable to proceed to carry out the concerned disclosure equilibrium analysis.

## 4.3 Fixed quality standard

In Section 3.1, we proceed with the assumption that the contest organizer announces a fixed quality standard, which is independent of information disclosure policies. We aim to investigate whether the preference for full concealment persists when this quality standard is fixed but nonzero.

Based on our numerical simulations, we find the results in the benchmark case could not extend to the case with an exogenous quality standard. A numerical example that can serve this purpose.

**Simulation 3**: Let $V = 1,\ \overline{a} = 1,\ N = 2,\ F(a) = a^{\beta},\ a \in [0, 1]$. Let minimum quality standard $x_R \in [0, 1]$. Since $x_R = Va_D$ and $x_R = Va_C F(a_C)$. Define $a_D = x_R$ and $a_C = x_R^{\frac{1}{\beta+1}}$. When $\beta = 1$, the comparison between two policies for both aggregate quality maximization and highest quality maximization depend on the value of exogenous quality standard.




(a) (b)

Figure 3: (a) Comparison of Maximum Aggregate Quality
(b) Comparison of Maximum Highest Quality

# 5 Concluding remarks

In this paper, we study the optimal design of two-player R&D contests. The literature has shown that either an information disclosure policy or a minimum standard can be an effective instrument to boost 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 the best of our knowledge, this is the first 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 benchmark for comparison, 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 a quality standard can be set optimally for both objectives, we find that although concealing information leads to a higher expected aggregate quality, fully disclosing information leads to a higher level of expected highest quality. These comparisons can be intuitively explained. First, without a quality standard, fully disclosing the innovators' types entails a public information contest between two asymmetric innovators, which tends to discourage their effort supply. Second, setting a quality standard is more effective in boosting effort supply under a full disclosure policy, especially for highest quality maximization, as the efforts of the stronger innovator count more in this case.

Our study considers a model with two symmetric players and two polar cases of information disclosure. To further understand the logic behind our theoretical results and inspect the robustness of our main findings, we extend our basic model to more than two players. Our analytical and simulation results show that, the main findings on optimal disclosure policy could be extended to the general setting with $N$ players.

Our findings carry significant economic implications. First, if an R&D competition invites a wide variety of participants, the organizer should conceal the innovators' abilities to incentivize all of the participants to work productively. However, in public procurement, such as bids for landmark construction, where the government focuses solely on optimal performance, there's a rationale for publicly disclosing all bidders' capabilities. Furthermore, our results imply that, given all other considerations, contest organizers should set a high-quality standard to motivate top performers, whereas a lower standard might be more appropriate if the goal is to boost overall performance.

Another natural extension would be to allow the organizer to partially disclose information. Amman and Leininger (1996) study this case and they show that no closed-form solution is available in general. This creates a technical challenge for analysis. Among the existing studies that consider partial disclosure with two-sided information asymmetry, Lu, Ma, and Wang (2018) and Chen (2021) investigate type-dependent policies, and Kuang, Zhao, and Zheng (2023) allow stochastic disclosure using a Bayesian persuasion approach, all of which assume a binary distribution. Note that although Jiao, Lien, and Zheng (2020) study the optimality of the designer's partial disclosure policies under continuous distribution, they only consider one-sided information asymmetry, and there is a tractability issue to apply their result to our setup where the quality standard is also considered as an instrument by the designer. Thus, identifying the optimal partial disclosure policy under a general all-pay auction contest setting remains an open question, and we want to leave it to future research.

# Appendix A

Appendix A covers the proofs of Lemmas 2-5, Propositions 1-6.

## Proof of Lemma 2

**Proof.** Combining the three cases studied in Lemma 1, where $a_1 > a_2$ (namely, $a_1 > a_2 \geqslant a_D \geqslant 0$, $a_1 > a_D > a_2$, and $a_D \geqslant a_1 > a_2$) 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 simply $x_D$, as agent 1 will certainly win if he bids $x_D = Va_D$.

Therefore, the ex ante expected highest quality under full disclosure is

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

■

## Proof of Proposition 1

**Proof.** Under the assumption of uniqueness, 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 the 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, as $\frac{dHQ_D(a_D)}{da_D} - \frac{dTQ_D(a_D)}{da_D} = 2V a_D^2 \int_{a_D}^{\overline{a}} [\int_{a_2}^{\overline{a}} (\frac{1}{a_1 a_2} dF(a_1)] dF(a_2) > 0$ for any $a_D \in [\underline{a}, \overline{a})$. We call this **Property A**.

Now we can compare the 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 due to 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, as $\frac{dTQ_D(a_D)}{da_D}$ 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 bidder $i$ who has the ability level $a_i$, and acts as if his ability level is $z_i$, assuming $z_i \geq a_C$.

Given $a_i \geq a_C$, 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 also verify that $\frac{dU_i}{da_i} > 0$, and $\frac{dx_i}{da_i} > 0$.

Taking into account threshold investment $x_C$, as $a_C$ is the cutoff ability below which it is not profitable to provide a positive quality, we have $x(a_C) = x_C$. Also note that $U(a_C) = 0$, we get $Va_CF(a_C) = x_C$. Therefore, the equilibrium bidding strategy in an R&D contest with a 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 bidders is

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

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

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

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

Based on Assumptions 1 and 2, we know that $a_C = \underline{a}$ is not the aggregate quality maximizing cutoff value, as $\frac{d(TQ_C(a_C))}{d(a_C)}$ becomes positive when $a_C$ 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 nonzero 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), based on 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 that $f'(a) > \frac{-2f^2(a)}{1-F(a)}$. 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 that $x(a_i) = V[a_C F(a_C) + \int_{a_C}^{a_i} sf(s)ds]$, then

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

Taking the first order derivative with respect to $a_C$,

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

Let $\frac{dHQ_C(a_C)}{da_C} = 0$, 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, as $\frac{dHQ_C(a_C)}{da_C}$ becomes positive when $a_C$ 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 nonzero solution $a^*_{H,C}$. Therefore, the corresponding threshold investment is $x^*_{H,C} = V a^*_{H,C} F(a^*_{H,C})$. ■

## Proof of Proposition 2

**Proof.** Based on the 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 that $a - \frac{1-F(a)}{f(a)} \leq a - \frac{1-G(a)}{g(a)}$, i.e., $\psi_F(a) \leq \psi_G(a)$. Note that $a^*_{T,C}$ is the root of $\psi(a)$, then $\psi_F(a^{*(F)}_{T,C}) = 0 = \psi_G(a^{*(G)}_{T,C}) \geq \psi_F(a^{*(G)}_{T,C})$. As $\psi(a)$ is increasing in $a$ based on 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, as $a^*_{H,C}$ is the root of $\phi(a)$, we have $\phi_F(a^{*(F)}_{H,C}) = 0 = \phi_G(a^{*(G)}_{H,C}) \geq \phi_F(a^{*(G)}_{H,C})$. As $\phi(a)$ 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 that $\phi(a^*_{T,C}) = a^*_{T,C} - \frac{1-F(a^*_{T,C})}{f(a^*_{T,C})} \frac{1+F(a^*_{T,C})}{2F(a^*_{T,C})} < a^*_{T,C} - \frac{1-F(a^*_{T,C})}{f(a^*_{T,C})} = \psi(a^*_{T,C})$. As $\psi(a^*_{T,C}) = 0$, 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 that $a^*_{H,C} > a^*_{T,C}$. ■

## Proof of Proposition 4

**Proof.** Proposition 2 in 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.

To compare the highest quality, 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 $m(a_2) = -\frac{1}{3}a_2 F(a_2)(1 - F(a_2))^2$.

As $[\underline{a}, \overline{a}] \in (0, +\infty)$, 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

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

Thus, we 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 $\psi(a^*_{T,C}) = a^*_{T,C} - \frac{1 - F(a^*_{T,C})}{f(a^*_{T,C})} = 0$, based on Assumption 1, we thus have $a^*_{T,D} > a^*_{T,C}$, which further leads to $x^*_{T,D} > x^*_{T,C}$ as $x^*_{T,D} = V a^*_{T,D}$ 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

$$
\begin{aligned}
& a^*_{H,D}\int_{a^*_{H,D}}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}(\frac{1}{a_2}-\frac{1}{a_1})dF(a_1)\right)dF(a_2) \\
& + a^{*2}_{H,D}\int_{a^*_{H,D}}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}\frac{1}{a_1a_2}dF(a_1)\right)dF(a_2) \\
& + [1-F(a^*_{H,D})]F(a^*_{H,D}) - a^*_{H,D}f(a^*_{H,D})F(a^*_{H,D}) \\
& = 0.
\end{aligned}
$$

Thus, we have

$$
\begin{aligned}
& a^*_{H,D} - \frac{1-F(a^*_{H,D})}{f(a^*_{H,D})}\frac{1+F(a^*_{H,D})}{2F(a^*_{H,D})} \\
& = \frac{1}{F(a^*_{H,D})f(a^*_{H,D})}\left(\begin{array}{c} a^*_{H,D}\int_{a^*_{H,D}}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}(\frac{1}{a_2}-\frac{1}{a_1})dF(a_1)\right)dF(a_2) \\ +a^{*2}_{H,D}\int_{a^*_{H,D}}^{\overline{a}}\left(\int_{a_2}^{\overline{a}}\frac{1}{a_1a_2}dF(a_1)\right)dF(a_2) - \frac{(1-F(a^*_{H,D}))^2}{2} \end{array}\right).
\end{aligned}
$$

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

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

As $x^*_{H,D} = Va^*_{H,D}$ and $x^*_{H,C} = Va^*_{H,C}F(a^*_{H,C})$, we have $x^*_{H,D} \geq x^*_{H,C}$ if and only if $a^*_{H,D} \geq a^*_{H,C}F(a^*_{H,C})$. ■

## Proof of Proposition 6

**Proof.** The proof completely parallels the proof of Theorem 1. We first compare the aggregate quality between the two disclosure policies, i.e., $TQ^*_D\left(a^*_{T,D}\right)$ versus $TQ^*_C\left(a^*_{T,C}\right)$. The proof proceeds in three steps.

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

Let

$$
\begin{aligned}
G(a) &= \left[TQ_D(a) - TQ_C(a)\right]/NV \\
&= \int_{a}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(\frac{a_2^2 + a^2}{2a_2} + \frac{a_2^2 - a^2}{2a_1}\right) dF\left(a_1\right)\right] dF^{N-1}\left(a_2\right) + a(1-F(a))F^{N-1}(a) \\
&\quad - \int_{a}^{\overline{a}} a(1-F(a))dF^{N-1}(a) - a(1-F(a))F^{N-1}(a) \\
&= \int_{a}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(\frac{a_2^2 + a^2}{2a_2} + \frac{a_2^2 - a^2}{2a_1}\right) dF\left(a_1\right)\right] dF^{N-1}\left(a_2\right) - \int_{a}^{\overline{a}} a(1-F(a))dF^{N-1}(a) \\
&= \int_{a}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(\frac{a_2^2 + a^2}{2a_2} + \frac{a_2^2 - a^2}{2a_1}\right) dF\left(a_1\right) - a_2\left(1-F\left(a_2\right)\right)\right] dF^{N-1}\left(a_2\right) \qquad 6 \\
&= \int_{a}^{\overline{a}} \left[\frac{a_2^2 + a^2}{2a_2}\left(1-F\left(a_2\right)\right) - a_2\left(1-F\left(a_2\right)\right) + \int_{a_2}^{\overline{a}} \frac{a_2^2 - a^2}{2a_1} dF\left(a_1\right)\right] dF^{N-1}\left(a_2\right) \\
&= \int_{a}^{\overline{a}} \frac{a^2 - a_2^2}{2a_2}\left(1-F\left(a_2\right)\right) dF^{N-1}\left(a_2\right) + \int_{a}^{\overline{a}} \int_{a_2}^{\overline{a}} \frac{a_2^2 - a^2}{2a_1} dF\left(a_1\right) dF^{N-1}\left(a_2\right) \\
&= \int_{a}^{\overline{a}} \int_{a_2}^{\overline{a}} \frac{a^2 - a_2^2}{2a_2} dF\left(a_1\right) dF^{N-1}\left(a_2\right) + \int_{a}^{\overline{a}} \int_{a_2}^{\overline{a}} \frac{a_2^2 - a^2}{2a_1} dF\left(a_1\right) dF^{N-1}\left(a_2\right) \\
&= \int_{a}^{\overline{a}} \left[\int_{a_2}^{\overline{a}} \left(a^2 - a_2^2\right)\left(\frac{1}{2a_2} - \frac{1}{2a_1}\right) dF\left(a_1\right)\right] dF^{N-1}\left(a_2\right).
\end{aligned}
$$

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

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

We then compare the highest quality between the two disclosure policies, i.e., $HQ_D^*\left(a_{H,D}^*\right)$ versus $HQ_C^*\left(a_{H,C}^*\right)$. Recall that $HQ_D^*\left(a_{H,D}^*\right)$ is the maximum highest quality level under a full disclosure policy with optimal quality standard $x_{H,D}^* = Va_{H,D}^*$, and that $HQ_C^*\left(a_{H,C}^*\right)$ is the maximum highest quality level under a full concealment policy with optimal quality standard $x_{H,C}^* = Va_{H,C}^* F^{N-1}\left(a_{H,C}^*\right)$. ■

# Appendix B

In Appendix B, we explore a scenario where two innovators simultaneously and independently determine whether to share information, as in Kovenock, Morath and Münster (2015). The innovators independently decide ex ante whether or not to share information ex post. We will show that for the cases with asymmetric policies, the type of equilibrium in Kovenock, Morath and Münster (2015) does not exist when there is a minimum standard requirement.

In order to examine the (unilateral) disclosure incentive of one generic innovator, suppose that innovator $i$ conceals while innovator $j$ reveals his ability. Denote the minimum standard in this case as $x_A$. Kovenock, Morath and Münster (2015) study the case without minimum standard, i.e., $x_A = 0$. Note that if $x_A = V\overline{a}$, only the innovator whose true type is $\overline{a}$ would be indifferent between bidding $V\overline{a}$ and 0. And the designer gets zero profit since the innovator with type $\overline{a}$ has 0 measure. Similarly, the event that $a_j = \overline{a}$ has 0 measure ex ante.

Henceforth, we focus on the non-trivial case $x_A \in (0, V\overline{a})$ and $a_j < \overline{a}$. In this case, bidding any value $x \in (0, x_A)$ is dominated for any innovator. Furthermore, there exists no equilibrium strategy that all types of bidder $i$ bid 0. Since the type highest type of agent $i$, $a_i = \overline{a}$ can at least guarantee a strictly positive payoff by bidding $Va_j + \epsilon$, for some small $\epsilon > 0$.

If $Va_j \leq x_A$, innovator $j$ will bid 0 with probability 1 and innovator $i$ effectively faces a single minimum standard.[14] He would exert effort $x_A$ if $Va_i \geq x_A$, and exert effort 0 otherwise. In this case the payoff of innovator $j$ is 0; the payoff of innovator $i$ is 0 if $a_i < \frac{x_A}{V}$, and is $V - \frac{x_A}{a_i}$ if $a_i \geq \frac{x_A}{V}$.

Now, we focus on the case $Va_j > x_A$. Innovator $i$ is competing with innovator $j$, who discloses his ability, subjecting to the minimum standard $x_A$. Denote $a_A = \frac{x_A}{V}$. We summarize innovators' equilibrium bidding strategies and payoffs in the following lemma.

**Lemma B.1** *Given minimum standard $x_A > 0$ and suppose that innovator $j$ discloses his type $a_j$, there exists a cutoff type of innovator $i$: $a'(a_A, a_j) \in [\underline{a}, \overline{a}]$ such that, innovator $i$ plays pure bidding strategy that is continuous and increasing in his own ability,*

$$\xi_i(a_i) = \begin{cases} 0 & \text{for} \quad a_i \in [\underline{a}, a') \\ (F(a_i) - F(a'))Va_j + x_A & \text{for} \quad a_i \in [a', \overline{a}] \end{cases} \tag{16}$$

*where $a'(a_A, a_j)$ denotes the cutoff ability above which innovator $i$ bids strictly above the minimum standard $x_A$.*

[14] It is without loss of generality to break tie in favor of innovator $i$ to calculate the expected revenue.

*Innovator $j$ randomizes according to the cumulative distribution function*

$$B_j\left(x_j\right)=\int_{x_A}^{x_j}\frac{1}{V\xi_i^{-1}(z)}dz+B_j(x_A)\quad \textit{for } x_j\in\{0\}\cup[x_A,\left(1-F\left(a'\right)\right)Va_j+x_A]. \tag{17}$$

*$B_j(0)$ and $a'$ of the interior solution are uniquely defined by the boundary conditions*

$$B_j\left(\xi_i\left(\overline{a}\right)\right)=1 \textit{ and } VB_j(x_A)-\frac{x_A}{a'}=0; \tag{18}$$

*together with one of the following conditions*

$$\begin{aligned} VF(a')-\frac{x_A}{a_j}&>0,\ \ B_j(0)=0; \\ \textit{or } VF(a')-\frac{x_A}{a_j}&=0,\ \ B_j(0)=B_j(x_A). \end{aligned} \tag{19}$$

**Proof.** The payoff of the innovator $j$'s payoff of bidding $x_j\geq x_A>0$ is

$$VP(\xi_i(a_i)\leq x_j)-c_jx_j=VF\left[F^{-1}\left(F(a')+\frac{x_j-x_A}{Va_j}\right)\right]-\frac{x_j}{a_j}=VF(a')-\frac{x_A}{a_j},$$

which does not depend on his own bid. Therefore, innovator $j$ is indifferent among bids in his support. Given the fact that $\xi$ is increasing in $a_i$, it is dominated for innovator $j$ to bid strictly more than $B_j\left(\xi_i\left(\overline{a}\right)\right)=\left(1-F\left(a'\right)\right)Va_j+x_A$. Furthermore, the upper bound of the support of innovator $j$'s strategy must be $\overline{x}_j=\xi_i\left(\overline{a}\right)$, since otherwise it is strictly dominated for the innovator $i$ to bid $x_i\in(\overline{x}_j,\xi_i\left(\overline{a}\right)]$.

Next, we show that the lower bound of the support of innovator $j$ who discloses information within the range $[x_A,v\overline{a}]$ must be equal to the minimum standard $x_A$.

Suppose towards a contradiction that innovator $j$ only randomizes over $[x'_A,v\overline{a}]$, with $x'_A>x_A$. Then we know that bidding $x_A<x<x'_A$ is strictly dominated for innovator $i$. Similarly, since there is no mass of types of innovator $i$ submitting bids within the interval $(x_A,x'_A)$, and there is no mass point for innovator $i$ bidding $x'_A$, it is dominated for innovator $j$ to bid $x'_A$. Instead, innovator $j$ can decrease the bid from $x'_A$ to $x_A+\epsilon$ for some small $\epsilon>0$, which has the same winning probability but strictly decreases the cost.

Now we check for innovator $i$'s incentives. For any interior $a'\in[\underline{a},\overline{a}]$ and $a_j>a_A$, innovator $i$ solves the problem

$$\begin{aligned} \pi_i(a_i)=\max_{x_i}\ &P(x_j\leq x_i)V-\frac{x_i}{a_i} \\ s.t.\ &x_i\geq x_A \end{aligned}$$

Plugging in $P(x_j \leq x_i) = B_j(x_i)$, we obtain the first order condition and the minimum standard condition

$$\frac{1}{F^{-1}\left(F(a') + \frac{x_i - x_A}{Va_j}\right)} \leq \frac{1}{a_i},\ x_i \geq x_A$$

together with the complementary slackness condition

$$\left(\frac{1}{F^{-1}\left(F(a') + \frac{x_i - x_A}{Va_j}\right)} - \frac{1}{a_i}\right)(x_i - x_A) = 0$$

Therefore, we obtain the optimal solution $\xi_i(a_i)$ for $a_i \geq a'$.

Now, we check for boundary conditions. By the argument above, we know that $\xi_i(\overline{a})$ is the least upper bound of the support of innovator $j$'s bidding strategy. Then we have $B_j(\xi_i(\overline{a})) = 1$.

By definition, the expected payoff of type $a'$ innovator $i$ equals to 0. And hence we have $VB_j(x_A) - \frac{x_A}{a'} = 0$. Since at the equilibrium innovator $j$ cannot obtain strictly negative payoff, we rule out the case $VF(a') - \frac{x_A}{a_j} < 0$. Then we obtain the condition (19).

If $VF(a') - \frac{x_A}{a_j} > 0$, we must have $B_j(0) = 0$, and we can pin down $a'$ and $B_j(x_A)$ from (18).

While at the knife edge case $VF(a') - \frac{x_A}{a_j} = 0$, it is without loss of generality to focus on the case where the equilibrium mixing strategy of the innovator $j$ have no mass point at $x_A$, i.e., $B_j(0) = B_j(x_A)$. Similarly, we can pin down $a'$ and $B_j(0)$ from (18). ■

Based on the equilibrium results, we can further obtain the following Lemma.

**Lemma B.2** *When $a_j \geq a_A$ and hence $VF(a') - \frac{x_A}{a_j} \geq 0$, we have $a' \leq a_j$ at equilibrium.*

**Proof.** Suppose towards a contradiction that $a' > a_j$, consider $a_i \in (a_j, a')$. According to the definition of $a'$ in Lemma B.1, we know that innovator $i$ with such type $a_i$ obtains 0 payoff at equilibrium by bidding 0. However, since ties are broken in favor of innovator $i$, he can at least secure a strictly positive payoff $V(1 - \frac{a_j}{a_i})$ by bidding $Va_j$ and win with probability 1, which contradicts with his incentive. ■

Furthermore, we can solve for the cutoff ability of innovator $i$ by combining (17) and (18),[15] $a'(a_A, a_j)$ is determined by

$$\int_{a'}^{\overline{a}} \frac{a_j}{a_i} dF(a_i) = 1 - \frac{a_A}{a'}. \tag{20}$$

[15] By (17) and (18) we have $\int_{x_A}^{\xi(\overline{a})} \frac{1}{V\xi_i^{-1}(z)} dz + B_j(x_A) = 1$. Denote $a_i = \xi_i^{-1}(z)$ and change the variable in the integral we have $\int_{a'}^{\overline{a}} \frac{a_j}{a_i} dF(a_i) + B_j(x_A) = 1$. Plug in $VB_j(x_A) - \frac{x_A}{a'} = 0$ and make a simplification, we get the desired expression in (20).

Note that the left hand side of (20) is strictly decreasing in $a'$ and the right hand side of (20) is strictly increasing in $a'$, then there must exist a unique $a_A < a'(a_A, a_j) < \overline{a}$ satisfies the above equality. Moreover, $a'(a_A, a_j)$ is strictly increasing in $a_A$ and $a_j$ within the range $[\underline{a}, \overline{a}]$, therefore it is almost everywhere continuous.

Consider a type of innovator $j$ that is sufficiently close to but strictly above the cutoff ability $a_A = \frac{x_A}{V}$, i.e., $a_j = a_A + \epsilon$, for some small $\epsilon > 0$. By the boundary condition (19), we know that the innovator $j$ with type $a_j$ obtains non-negative payoff $V\left(F(a') - \frac{a_A}{a_j}\right) \geq 0$. Since this condition holds for all $\epsilon > 0$ and fixed $a_A$, and $a'(a_A, a_j)$ is a continuous function in $a_j$, we can take the limit to obtain that $\lim_{\epsilon \downarrow 0} F(a') = 1$.

However, this contradicts with the fact we have proved in Lemma B.2. Since $a' \leq a_j$ and $a_j = a_A + \epsilon \geq a_A$, and hence $\lim_{\epsilon \downarrow 0} F(a') \leq F(a_A) < 1$ as $a_A < \overline{a}$.

Therefore, innovator $i$ conceals while innovator $j$ reveals his ability could not be an equilibrium, the equilibrium in Kovenock, Morath and Münster (2015) does not exist when the minimum standard $x_A > 0$.

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