Exclusive or Not? An Experimental Analysis of Parallel Innovation Contests


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We study parallel innovation contests where contest organizers elicit innovative solutions to a set of problems from a group of solvers with limited (financial, time, cognitive) resources. The quality of a solver’s solution improves with their effort, yet it is also subject to an output uncertainty, which affects a solver’s control over the link between their effort and winning the contest. Prior theoretical work shows that organizers should discourage solvers from participating in parallel contests in environments with low output uncertainty, where contest outcomes are primarily driven by solver efforts. In this case, organizers should benefit from solvers focusing all of their efforts on a single “exclusive” contest rather than splitting them across multiple “non-exclusive” contests. We test this prediction with controlled laboratory experiments. Our main result (and key managerial insight) is that non-exclusive contests are attractive to organizers even in environments with low output uncertainty where contest theory favors exclusive contests. We link this result to behavioral drivers that induce solvers to exert less effort than predicted on average, while exhibiting a larger-than-predicted variability.

Key words: Behavioral operations, crowdsourcing, innovation management, quantal response equilibrium

1. Introduction

Advancements in information technology and the Internet allow organizations to reach talented individuals outside of their boundaries to solve their innovation-related problems (Chesbrough 2003). An effective tool to outsource innovation is crowdsourcing via innovation contests, where a contest organizer delegates an innovation-related problem to a group of independent solvers and awards the best solution(s). Companies with leading R&D departments such as P&G and HP, government agencies such as NASA, DARPA and NHS, and non-profit organizations such as the
Gates Foundation and UNICEF are among the many organizations that use innovation contests. Crowdsourcing contest platforms such as Wazoku (formerly InnoCentive) and 99designs facilitate such contests by providing a medium for its member solvers to tackle the problems of their clients.

Innovation contests have outstanding features that make them effective in solving innovation-related problems. They provide an opportunity to reach a large pool of solvers, and the resulting diversity of solutions improves the organizer’s chance of receiving an “extremely good” solution. For example, XPRIZE organized an innovation contest recently with an award of 6 million USD to develop faster, cheaper, and easier to use methods to test for COVID-19, and elicited solutions that are “radically [more] affordable compared to what is currently available on the market” while achieving comparable performance (XPRIZE 2021). Furthermore, innovation contests enable organizers to achieve cost-effective innovations by incentivizing intense competition among solvers (Fullerton and McAfee 1999). In many instances, organizations run multiple contests at once. Crowdsourcing contest platforms such as Wazoku and 99designs simultaneously run many contests under the same category. The abundance of contests and solvers effectively creates an environment where each solver can potentially participate in multiple contests in parallel, posing an important contest design question: when should organizers encourage solvers to do so?

The answer to this question rests on a trade-off between solvers’ efforts to improve their solutions and the diversity of solutions. On the one hand, an innovation-contest organizer aims to maximize the quality of the best solution(s), and hence benefits from increasing solution diversity. To this end, organizers can encourage solvers to participate in multiple contests in parallel (hereafter, “non-exclusive” contests), thereby attracting more solvers to each contest, as many platforms (e.g., Wazoku) and organizations (e.g., Eli Lilly) do. On the other hand, solvers who participate in non-exclusive contests may have to divide their limited (financial, time, cognitive) resources, which may lower solver efforts in each contest. To avoid such an effort loss, organizers may run “exclusive” contests, by discouraging solvers from participating in more than one, and hence focusing solvers’ resources on a single contest. For instance, the Gates Foundation organized a series of contests called Grand Challenges in Global Health and allowed each solver to participate in only one (Challenges 2017). Similarly, Topcoder aims to focus the attention of each solver on a single contest for development challenges that require less novel solutions (Körpeoğlu et al. 2022).

Although many organizations and crowdsourcing platforms run multiple innovation contests in parallel, there is little research on whether (and when) organizers should discourage solvers from participating in more than one contest. The theoretical analysis of Körpeoğlu et al. (2022) provides some guidance on the relative performance of different contest formats (exclusive or not), and emphasizes the important role of solvers’ output uncertainty. The authors show that organizers should discourage solvers from participating in multiple contests in environments with low output uncertainty.
uncertainty, where contest outcomes are primarily driven by solver efforts and less driven by output uncertainty. This way, organizers benefit from solvers focusing their efforts on a single exclusive contest rather than splitting their efforts among multiple non-exclusive contests. Thus, contest theory provides some guidance for organizers. Accordingly, the existence of both formats in practice can be rationalized on theoretical grounds. Whether the theoretical benefits of exclusive (under low uncertainty) and non-exclusive (under high uncertainty) formats translate to practice is an empirical question that we aim to answer in this paper.

We first develop our hypotheses from an analysis of a game-theoretic model of parallel innovation contests that builds on Körpeoğlu et al. (2022). We then test these hypotheses in a controlled laboratory environment that allows us to make precise predictions about the relative performance of different contest formats.

In our theoretical model, organizers first announce the winner awards in their own contests. Solvers then make their costly effort decisions, subject to a capacity limit. The solution quality increases in a solver’s effort, yet it is also subject to an output uncertainty, which affects a solver’s control over the link between their effort and winning the contest. Solvers aim to maximize their total expected award from all contests considering the total cost of their effort. We derive the uncertainty levels where the exclusive or the non-exclusive format is expected to yield a larger (average) organizer profit, and test these predictions under controlled laboratory conditions.

In our experimental study, we run two exclusive and two non-exclusive contests. Our data show that average solver efforts fall short of theoretical equilibrium predictions in both exclusive and non-exclusive formats. This contributes to lower-than-predicted performance in all settings of our study. We also observe that solver efforts vary substantially - solvers differ in their average efforts, and each solver may also vary their efforts across different contests. As a result, we observe that efforts vary within each contest and across different contests. Although variability in the data is not surprising per se, it has a systematic effect on the relative profitability of the two contest formats that we study. While across-contest effort variability decreases the average profit in both contest formats, within-contest effort variability can improve performance in contest formats that are predicated on finding the best solution. Essentially, just like organizers benefit from the diversity of solutions due to random shocks, they also benefit from the diversity due to variability in efforts. This positive effect of within-contest effort variability on profits is relatively larger for non-exclusive contests because they feature more solvers as each solver participates in more contests. As a net result of these effects, we observe that a non-exclusive format outperforms an exclusive format under conditions where theory predicts performance equivalence (Study 1) or a performance advantage of the exclusive format (Study 2). We can reproduce the main departures from equilibrium predictions (i.e., lower average efforts and substantial variability) with a quantal-response equilibrium model.
that accommodates the idea that solvers may make mistakes when calculating their expected payoffs corresponding to different efforts.

2. Related Literature

Our paper contributes to the innovation-contest literature, experimental contest literature, and the behavioral operations management literature.

In line with its popularity in practice, a growing community of scholars contribute to different aspects of the innovation-contest literature. Most of those studies optimize the design of a single contest using theoretical analyses (e.g., Taylor 1995, Terwiesch and Xu 2008, Mihm and Schlapp 2019, Hu and Wang 2021, Korpeoğlu et al. 2021) or empirical analyses (e.g., Boudreau et al. 2011, Jiang et al. 2021, Jiang et al. 2022, Boudreau et al. 2016). Korpeoğlu et al. (2022) is the closest study to ours in the innovation-contest literature. This theoretical study analyzes multiple parallel contests and finds that organizers can improve the contest outcomes by encouraging each solver to participate in multiple contests in a non-exclusive format only when solvers face sufficiently large output uncertainty. We contribute to this literature by running controlled lab experiments with human subjects and showing how actual solver behavior differs from theoretical benchmarks using the standard innovation-contest model. Specifically, a non-exclusive format yields relatively larger profits for organizers even when theory suggests restricting each solver to a single contest using an exclusive format. Furthermore, we provide evidence that solvers’ efforts exhibit a-lower-than-predicted average and a higher-than-predicted variance.

Our study is also related to the experimental literature focusing on contests of other types (e.g., Tullock, sales) where the organizer aims to maximize solvers’ total output (or effort). For instance, in a sales contest, the organizing firm is interested in the total sales of all salespeople rather than the maximum sales by a single salesperson. In such a contest, any variability in solvers’ solutions cancels out, so the organizer cannot benefit from the diversity of solutions. Thus, although the prior literature on such contests reports variability in solvers’ efforts (e.g. Millner and Pratt 1991, Davis and Reilly 1998, Gneezy and Smorodinsky 2006, Chen et al. 2011), the implication of such variability is different in our study. Specifically, effort variability plays a significant role in the profit of an organizer who is interested in the maximum output of solvers. Besides the variability in solvers’ efforts, the most common behavioral regularity in the literature on other types of contests is “overbidding” - solvers exerting more effort than the theory predicts (e.g. Millner and Pratt 1991, DiPalantino and Vojnović 2009 study multiple all-pay contests and show how the participation rate changes depending on exogenously given awards. Azmat and Möller (2009) consider two identical Tullock contests, and analyze the optimal award allocation to obtain the highest participation. Büyükboyacı (2016) compares the organizer profit of designing a single contest and dividing it into two contests with small and large awards, respectively. Not only is our research question different from these works, but also we consider a unique environment in innovation contests in an experimental setting.

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Davis and Reilly 1998, Gneezy and Smorodinsky 2006, Chen et al. 2011). In contrast, our data exhibit underbidding in innovation contests, with important managerial implications. Specifically, for our setting, overbidding would lead the exclusive format to perform better even when theory predicts otherwise. Yet, we observe the opposite effect, underbidding, and show that the non-exclusive format performs better. Underbidding may arise because solvers in an innovation contest face much larger uncertainty about how their effort translates into their outputs.

Our work is also broadly related to the behavioral operations management literature which has documented various decision biases and judgment biases in diverse settings such as newsvendor problem (e.g., Schweitzer and Cachon 2000, Bearden et al. 2008, Ozer et al. 2014), queuing systems (e.g., Song et al. 2021, Hathaway et al. 2022), procurement (e.g., Davis and Hyndman 2020, Beer and Rios 2022), contract design (e.g., Kalkanci et al. 2011, Li et al. 2020), and auctions (e.g., Chaturvedi et al. 2018). In particular, our study relates to a stream of behavioral mechanism design literature that shows how the consideration of decision makers’ (e.g., customers, managers) behavioral tendencies may change the optimal design of incentive and information structures. For example, Becker-Peth et al. (2013) show that a buyback contract that considers behavioral biases in newsvendor decisions can outperform contracts that ignore the biases. Chaturvedi et al. (2018) report that while their theoretical predictions fail to capture the cost equivalence between sealed-bid and open-bid auctions, a regret-based behavioral model explains the lack of expected cost equivalence between two auctions. Song et al. (2021) find that, contrary to traditional theoretical predictions, dedicated queues may have a better operational efficiency than pooling queues when servers can build human connection with their customers. In a similar spirit, our study shows that behavioral tendencies (of solvers, in our case) can change the relative attractiveness of exclusive and non-exclusive contest formats relative to theoretical benchmarks.

3. Theory

We build our theoretical model on Körpeoğlu et al. (2022) and other theoretical papers in the innovation-contest literature (e.g., Terwiesch and Xu 2008, Mihm and Schlapp 2019), while keeping our model as parsimonious as possible for our experimental study.

Our setting features four solvers and two innovation contests posted by two organizers. We compare two contest formats: a non-exclusive format where each solver can participate in both contests and an exclusive format where each solver can participate in only one of these contests. Below, we present our model in a general form where \( N \) solvers can potentially participate in \( M \) contests. This general form helps us capture both formats within the same model setup. Specifically, \( N = 4 \) and \( M = 2 \) corresponds to the non-exclusive format, and each of the two contests in the exclusive format can be modeled by setting \( N = 2 \) and \( M = 1 \). Whenever we need to distinguish between the two contest formats, we use an additional superscript \( x \) for the exclusive format.
3.1. Model of Solvers and Organizers

Each solver \( i \in \{1, 2, \ldots, N\} \) chooses an improvement effort \( e_{im} \) at each contest \( m \in \{1, 2, \ldots, M\} \) she participates in. Each solver \( i \) incurs a total cost of \( \sum_{m=1}^{M} e_{im} \) for her effort in all contests she participates in, and has a capacity \( \overline{E} \) over her total effort due to limited resources such as time and money. The quality of a solution (hereafter “output”) is a function of her effort and it is also subject to some output uncertainty. Specifically, exerting effort \( e_{im} \) deterministically improves the output of solver \( i \) in contest \( m \) by \( \theta \log(e_{im}) \). We incorporate a solver’s output uncertainty into our model through an output shock \( \xi_{im} \). We assume that the output shock \( \xi_{im} \) is independent for each solver \( i \) and for each contest \( m \), and follows a uniform distribution over the support \( \Xi = [-\beta, \beta] \), where \( \beta > 0 \). Thus, the output that solver \( i \) generates in contest \( m \), \( y_{im} \), takes the following form:

\[
y_{im} = \theta \log(e_{im}) + \xi_{im}.
\]

As is common in the innovation-contest literature (e.g., Mihm and Schlapp 2019, Ales et al. 2021), each contest \( m \) features an award \( A_m \) to the solver with the best solution and no award for other solvers. That is, the compensation \( x_{im} \) each solver \( i \) receives from contest \( m \) equals \( A_m \) if solver \( i \) wins the contest by producing the largest output, and zero otherwise. Each solver \( i \)’s utility \( u_i \) consists of the compensation she receives from the contests she participates in, less of the total cost of effort; i.e., \( u_i = \sum_{m=1}^{M} (x_{im} - e_{im}) \). Each organizer \( m \)’s profit \( \pi_m \) consists of the best output in contest \( m \), net of the award \( A_m \), i.e., \( \pi_m = \max_i y_{im} - A_m \).

The sequence of events is as follows. First, the award \( A_m \) in each contest \( m \) is announced. Observing the awards, each solver \( i \) determines her effort \( e_{im} \) in each contest \( m \) she participates in, and then her output shock \( \xi_{im} \) in contest \( m \) is realized after organizer \( m \) evaluates solutions. Each organizer \( m \) gives the award \( A_m \) to the winner of the contest.

3.2. Equilibrium among Solvers

As is standard in the innovation-contest literature (e.g., Terwiesch and Xu 2008, Ales et al. 2017, Mihm and Schlapp 2019), we focus on the symmetric pure-strategy Nash equilibrium among solvers, and we denote the equilibrium effort in contest \( m \) by \( e^*_m \). Let \( P(e_{im}, e^*_m) \) be solver \( i \)’s probability of winning contest \( m \) when she exerts effort \( e_{im} \) and all other solvers exert the equilibrium effort \( e^*_m \). Solver \( i \) chooses her effort \( e_{im} \) to maximize her expected utility \( E[u_i] = \sum_{m=1}^{M} (A_m P(e_{im}, e^*_m) - e_{im}) \) over all contests that she participates in, subject to her capacity constraint:

\[
\max_{(e_{i1}, e_{i2}, \ldots, e_{iM})} \sum_{m=1}^{M} (A_m P(e_{im}, e^*_m) - e_{im}) \quad \text{s.t.} \quad \sum_{m=1}^{M} e_{im} \leq \overline{E}.
\]

Based on Körpeoğlu et al. (2022), we can characterize the equilibrium effort \( e^*_m \) as follows.

**Proposition 1.** Let \( \tilde{e}_m \) be the solution to the following set of equations:

\[
\tilde{e}_m = \frac{A_m \theta}{2\beta} \quad \text{for all} \quad m \in \{1, 2, \ldots, M\}.
\]
When $\sum_{m=1}^{M} \hat{e}_m < \hat{E}$, the unique symmetric equilibrium effort in contest $m$ is $e^*_m = \hat{e}_m$, and when $\sum_{m=1}^{M} \hat{e}_m \geq \hat{E}$, the unique symmetric equilibrium effort $e^*_m$ at contest $m$ satisfies:

$$e^*_m = \frac{\hat{E}A_m}{\sum_{m=1}^{M} A_m}$$ \text{for all } m \in \{1, 2, \ldots, M\}. \quad (4)$$

Proposition 1 shows that when a solver’s capacity constraint does not bind, she chooses her effort in each contest by balancing the marginal benefit and the marginal cost of her effort. However, when a solver’s capacity constraint binds, she optimally splits her capacity among all contests she participates in, where her effort in each contest is proportional to the award given in that contest.

We can use Proposition 1 to generate predictions for the non-exclusive format by setting $N = 4$ and $M = 2$. Specifically, instead of focusing on a single contest, each solver prefers to split her total effort among both contests proportional to the award given in each contest due to diminishing marginal benefit of effort. Moreover, we can use Proposition 1 to calculate the equilibrium effort in the exclusive format as $e^{*x}_m = \min\left\{\frac{A_m \theta}{2 \beta}, \hat{E}\right\}$ by setting $N = 2$ and $M = 1$. Thus, either the capacity constraint is binding, and each solver utilizes her full capacity $\hat{E}$ in a single contest; or the capacity constraint is not binding, and each solver chooses her effort according to (3).

### 3.3. Exclusive versus Non-exclusive

We next compare the exclusive format (two contests where each contest is characterized above using $N (= N_m) = 2$ and $M = 1$) and the non-exclusive format (two contests characterized above using $N = 4$ and $M = 2$), based on the average profit of organizers, which is given by $\Pi \equiv \frac{1}{2} \left( E \left[ \sum_{m=1}^{2} \max_i y_{im} \right] - \sum_{m=1}^{2} A_m \right)$. Furthermore, for a fair comparison with no distortion due to asymmetric awards, we assume $A_1 = A_2 = A$. Given (1), the gap between the average profit in exclusive format and that in non-exclusive format can be written as:

$$\Pi - \Pi^x = \frac{1}{2} \left( \sum_{m=1}^{2} \left( \theta \log(e^*_m) - \theta \log(e^{*x}_m) \right) + \sum_{m=1}^{2} \left( E \left[ \max_{i \in \{1,2,4\}} \xi_{im} \right] - E \left[ \max_{i \in \{1,2\}} \xi_{im} \right] \right) \right). \quad (5)$$

**Proposition 2.** The average profit in the exclusive format $\Pi^x$ equals that in the non-exclusive format $\Pi$ when the uncertainty parameter $\beta = \beta_0 \equiv \max \left\{ \min \left\{ \frac{A_0}{2 \hat{E}}, 2.66 \right\}, -\frac{4 \log \left( \frac{\beta \hat{E}}{A_0} \right)}{\pi^2} \right\}$. Furthermore, $\Pi^x > \Pi$ (resp., $\Pi^x < \Pi$) when $\beta < \beta_0$ (resp., $\beta > \beta_0$).

Proposition 2 shows that the relative performance of exclusive and non-exclusive formats depends on how output uncertainty moderates two opposing effects. First, solvers can focus their capacity on a single contest in the exclusive format, which results in larger per-contest effort than in the non-exclusive format (i.e., $\sum_{m=1}^{2} \left( \theta \log(e^*_m) - \theta \log(e^{*x}_m) \right) \leq 0$). We refer to this as the “effort” effect. Second, the non-exclusive format attracts more solvers to each contest, and this leads to a larger expected value for the maximum of output shocks (i.e., $\sum_{m=1}^{2} \left( E \left[ \max_{i \in \{1,2,4\}} \xi_{im} \right] - E \left[ \max_{i \in \{1,2\}} \xi_{im} \right] \right)$ >
0). We refer to this as the “diversity” effect. Whether effort or diversity effect dominates depends on the level of solvers’ output uncertainty captured by $\beta$; see Figure 1.

The effort effect favors the exclusive format, but it weakens with output uncertainty because more uncertainty reduces the impact of solvers’ effort on their expected awards, and hence induces solvers to exert less effort. In contrast, the diversity effect favors the non-exclusive format, and it grows stronger with output uncertainty because the maximum of output shocks has a larger expectation. At the “breakeven uncertainty” where $\beta = \beta_0$, these two effects offset each other, and exclusive and non-exclusive formats yield the same average profit. When $\beta < \beta_0$, the exclusive format generates a larger average profit, and when $\beta > \beta_0$, the opposite is true.

![Graph](https://ssrn.com/abstract=4256134)

**Figure 1** The comparison of equilibrium efforts, expected values of the largest output shocks, and average expected profits in Exclusive and Non-exclusive formats. Setting: $E = 10$, $A = 30$, $\theta = 20$. 
4. Research Hypotheses and Experimental Design

We design laboratory experiments using human subjects to test key theoretical predictions. We aim to provide guidance for organizers of innovation contests by answering our main research question: When should organizers adopt the non-exclusive format?

4.1. Research Hypotheses

Our analysis in Section 3 starts with the characterization of equilibrium efforts. Proposition 1 predicts that all solvers exert the same equilibrium effort at each contest, leading to no variability in efforts within or across contests; that is, \( \bar{e}_m = e_{im} = e^* \) (where \( \bar{e}_m = \frac{\sum_{i=1}^{N} e_{im}}{N} \)). Thus, we first generate the following hypotheses.

**Hypothesis 1.** (Effort) Solvers’ average effort \( \bar{e} = \frac{1}{MN} \sum_{i=1}^{N} \sum_{m=1}^{M} e_{im} \) equals the equilibrium effort \( e^* \) for both exclusive and non-exclusive formats.

**Hypothesis 2A.** (Effort Variability - Within Contest) For each contest \( m \), \( e_{im} = e_{jm} \), \( \forall i, j \).

**Hypothesis 2B.** (Effort Variability - Across Contests) For contests \( m \) and \( l \) (\( m \neq l \)), \( \bar{e}_m = \bar{e}_l \).

Our analysis from Section 3 suggests that solvers’ efforts along with the diversity of their solutions determine the relative profitability of different contest formats. While the exclusive format yields larger efforts, the non-exclusive format attracts more diverse solutions. Proposition 2 predicts that the level of output uncertainty determines which of these drivers prevails, yielding the following hypothesis.

**Hypothesis 3.** (Average Profit) Compared to the non-exclusive format, the exclusive format yields the same average profit under the breakeven uncertainty (\( \beta = \beta_0 \)), a larger average profit under low uncertainty (\( \beta < \beta_0 \)), and a smaller average profit under high uncertainty (\( \beta > \beta_0 \)).

4.2. Experimental Design and Procedures: All Studies

Subjects in our lab experiments act as solvers and make effort decisions.

**4.2.1. Task and design.** In our study, cohorts of \( N = 4 \) subjects participate in \( M = 2 \) contests. Each contest \( m \) gives an award \( A_m = A = $30 \) to the solver with the largest output. The winner award is chosen as the minimum amount that (theoretically) ensures that solvers find it ex-ante beneficial to participate in all contests they are allowed to, i.e., \( \frac{A}{N} - e^*_m \geq 0 \) and \( \frac{A}{N_m} - e^*_{mx} \geq 0 \). As stated in (1), a solver’s output depends on her effort and a random shock, \( y_{im} = \theta \log(e_{im}) + \xi_{im} \), where we set \( \theta = 20 \). Each solver can invest her total effort up to a capacity \( E = 10 \), and incurs $1 for each unit of effort invested.

To test our hypotheses, our study considers two contest formats (*Exclusive* versus *Non-Exclusive*) and two levels of uncertainty (*Low* versus *Breakeven*), resulting in four treatments that we implement in a between-subject design. First, in *Exclusive*, \( N_1 = N_2 = 2 \) solvers exclusively participate...
in either contest 1 or contest 2, whereas in Non-Exclusive, \( N = 4 \) solvers compete in both contests. Second, we study contests under Breakeven uncertainty (Study 1: \( \beta = \beta_0 = 36.8 \)), where theory predicts profit equivalence of the two formats, and contests under Low uncertainty (Study 2: \( \beta = 30 \)) where theory predicts a profit advantage for Exclusive.

4.2.2. Software, recruitment, and payment. The experiment is compiled with oTree (Chen et al. 2016). We have conducted all sessions at an experimental laboratory of a large public university in Europe, and recruited subjects from their subject pool.

In each session, subjects were randomly assigned to isolated cubicles upon their arrival at the laboratory. On their screens, subjects read the instructions about the task environment. On-screen instructions were accessible throughout the session with a click of a button, and helped subjects understand how they could choose and submit their efforts via sliders and buttons (see §EC.1 in Online Appendix and Figure 2). To help subjects familiarize themselves with the task environment, we included 4 practice rounds in each session, which had 24 rounds in total.

At the beginning of each round, subjects were randomly matched in groups of two solvers in Exclusive and groups of four solvers in Non-Exclusive. At least 12 subjects participated in each session, and they did not know about the number of subjects. During each round, once all subjects had entered their efforts, the computer randomly drawn output shocks to determine the winner for each contest. Figure 2 shows an example of the decision page of Non-Exclusive. At the end of each round, subjects learned whether they won an award or not, but they never learned about
their outputs. This lack of learning opportunity is consistent with the contest practice and our theoretical analyses (e.g., Korpeoglu et al. 2021, Wazoku 2022). After completing all rounds (part 1), we elicited subjects’ risk tendencies using the method developed by Holt and Laury (2002) (part 2, see §EC.1 in Online Appendix for details).

At the end of the session, we computed each subject’s cash earnings as follows. The computer randomly chose one of the 20 rounds in a session for actual payment, independently for each subject. The earnings were converted from laboratory Dollar to Euro by using a treatment specific conversion rate which ensures the same expected average payment in all treatments (see §EC.1 in Online Appendix for conversion rates). Subjects also received a payment from the second part of the experiment. Including €5 fixed participation fee, the final subject payments (in all treatments) ranged from €5 to €42.54 with an average of €16.12.

4.2.3. Data. To describe the structure of our data, in each round $t$, each cohort $c$ of solvers participate in two innovation contests ($m \in \{1, 2\}$). Contests of cohort $c$ are either organized as Exclusive contests with $N_{cm} = 2$ solvers, or organized as Non-Exclusive contests with $N_{cm} = 4$ solvers.$^2$ At the most granular level, our data contains the effort $e_{icmt}$ that solver $i$ exerts in round $t$ ($t \in \{1, 2, \ldots, 20\}$) in contest $m$ of cohort $c$. We calculate the average effort in contest $m$ of cohort $c$ in round $t$ as $\overline{e}_{cmt} = \frac{1}{N_{cm}} \sum_{i=1}^{N_{cm}} e_{icmt}$, and similarly solver $i$’s average effort as $\overline{e}_i = \frac{1}{T \cdot M} \sum_{t=1}^{T} \sum_{m=1}^{M} e_{icmt}$. Finally, we calculate the treatment-level average as $\overline{e} = \frac{1}{T} \sum_{t=1}^{T} \overline{e}_t$, where $I$ denotes the number of subjects in a treatment.

We calculate organizer profits as follows. The realized profit in round $t$ depends on the observed efforts and realized random shocks ($\xi_{icmt}$) associated with all $N_{cm}$ solvers participating in contest $m$ of cohort $c$. To ensure a fair comparison with equilibrium predictions, we replace realized random shocks $\xi_{icmt}$ with ex-ante random shocks $\overline{\xi}_{icmt}$ and take expectation for our analyses. Specifically, we calculate the ex-ante expected organizer profit associated with the observed efforts in contest $m$ of cohort $c$ in round $t$ as $\pi_{cmt} = E[\max_{i \in \{1, \ldots, N_m\}} \{\theta \log(e_{icmt}) + \overline{\xi}_{icmt}\}] - A$. This allows us to eliminate any variability due to the realization of random shocks from our data and focus on the intrinsic variation due to idiosyncrasies in subject behavior. We calculate the treatment-level average profit as $\Pi_{cicmt} = \frac{1}{C \cdot M \cdot T} \sum_{c=1}^{C} \sum_{m=1}^{M} \sum_{t=1}^{T} \pi_{cmt}$, where $C$ denotes the number of cohorts in a treatment.

5. Study 1: Contest Design under Breakeven Uncertainty

5.1. Results

Table 1 presents the aggregate results. We next expand on the specific results related to organizer profits and solver efforts.

$^2$ Note that the definition of a cohort $c$, and the contests ($m \in \{1, 2\}$) associated with it are arbitrary in the Exclusive format, where the two contests are entirely independent.
Exclusive (Π) and Non-Exclusive all contests. Figure 3 shows that counterfactual profits are lower than equilibrium predictions in
Specifically, we calculate the average experiment profit as Π
2 (variability in efforts), or both. We next take a closer look at effort decisions.

5.1.1. Average profits (Hypothesis 3). While calculating average profits, we use each cohort (instead of each contest) as the unit of analysis. This is because in Non-Exclusive, organizer profits in contest 1 and contest 2 are dependent due to the solver capacity constraint. Our results show that observed profits are lower than theoretically predicted profits, in both Exclusive (18.64 vs. 24.30, \(p < 0.001\), two-sided \(t\)-test) and Non-Exclusive (22.05 vs. 24.30, \(p < 0.001\)). Equally importantly, the average profit is significantly lower under Exclusive than under Non-Exclusive (18.64 vs. 22.05, \(p < 0.001\), two-sided \(t\)-test). Thus, our data fails to support Hypothesis 3. In other words, although theory predicts profit equivalence between Exclusive and Non-Exclusive, data we collected in laboratory experiments do not support this hypothesis. Observations depart from theoretical predictions because solver effort decisions violate Hypothesis 1 (average efforts), Hypothesis 2 (variability in efforts), or both. We next take a closer look at effort decisions.

5.1.2. Average efforts (Hypothesis 1). For the analysis of effort decisions, we use solvers’ average effort (i.e., \(\bar{e}_i\)) as the unit of analysis. Table 1 presents the average effort of each treatment (i.e., \(\bar{e}\)). Observed efforts are lower than predicted, both in Exclusive (6.60 vs. 8.15, \(p < 0.001\), two-sided \(t\)-test) and in Non-Exclusive (8.76 vs. 10, \(p < 0.001\)). Thus, our data fails to support Hypothesis 1. To understand the impact of these lower-than-predicted average efforts, we calculate \(\Pi_{\bar{e}}\) as the counterfactual expected average profit that organizers would have made if all solvers had exerted the same treatment-average per-contest efforts from Table 1 (\(\bar{e}^x = 6.60, \bar{e} = 4.38\)) in all contests. Figure 3 shows that counterfactual profits are lower than equilibrium predictions in both Exclusive (\(\Pi_{\bar{e}} = 20.01\) vs. \(\Pi_{x,e} = 24.30\)) and Non-Exclusive (\(\Pi_{\bar{e}} = 21.62\) vs. \(\Pi_{x,e} = 24.30\)).

We also find that counterfactual profits from average efforts are lower in Exclusive than in Non-Exclusive (\(\Pi_{\bar{e}} = 20.01\) vs. \(\Pi_{\bar{e}} = 21.62\)), because the effort underinvestment is relatively stronger in Exclusive (\(\frac{\bar{e}^x-\bar{e}}{\bar{e}} = \frac{8.15-6.60}{8.15} = 19\%\)) than in Non-Exclusive (\(\frac{\bar{e}^x-\bar{e}}{\bar{e}} = \frac{5.438}{5} = 12\%\)). Hence, average efforts may provide some explanation for why our data violate profit equivalence prediction of Hypothesis 3 under \(\beta = \beta_0\). Yet, average efforts only account for a relative performance gap of 8%.\(^4\) The relative performance gap in our data, however, is 16%.\(^5\)

\(^3\) Specifically, we calculate the average experiment profit as \(\Pi_{\bar{e}} = (2 \cdot 20 \log(6.6) + E[\max_{i \in \{1,2\}} \tilde{\xi}_1] + E[\max_{i \in \{1,2\}} \tilde{\xi}_2] - 2A)/2 = 20.01\) and \(\Pi_{\bar{e}} = (2 \cdot 20 \log(4.4) + E[\max_{i \in \{1,\ldots,4\}} \tilde{\xi}_1] + E[\max_{i \in \{1,\ldots,4\}} \tilde{\xi}_2] - 2A)/2 = 21.62\).

\(^4\) \(\frac{\Pi_{\bar{e}} - \Pi_{\bar{e}}}{\Pi_{\bar{e}}} = \frac{21.62 - 20.01}{21.62} = \frac{21.62 - 20.01}{21.62}\).

\(^5\) \(\frac{\Pi_{\bar{e}} - \Pi_{\bar{e}}}{\Pi_{\bar{e}}} = \frac{22.05 - 18.64}{22.05} = \frac{22.05 - 18.64}{22.05}\).

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Sessions</th>
<th>Total solver effort</th>
<th>Per-contest effort</th>
<th>Per-contest profit</th>
<th>Max. shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exclusive</td>
<td>54</td>
<td>3</td>
<td>Pred. 8.15 &gt; 6.60 (0.33)</td>
<td>Pred. 8.15 &gt; 6.60 (0.33)</td>
<td>Pred. 24.30 &gt; 18.64 (0.36)</td>
</tr>
<tr>
<td>Non-Exclusive</td>
<td>48</td>
<td>2</td>
<td>Obs. 10 &gt; 8.76 (0.27)</td>
<td>5 &gt; 4.38 (0.17)</td>
<td>Pred. 24.30 &gt; 22.05 (0.21)</td>
</tr>
</tbody>
</table>
We posit that variability in efforts contributes to the observed between-treatment performance differences. We next take a closer look at variability in efforts, and measure how it affects performance in Exclusive and Non-Exclusive.

5.1.3. Variability in efforts (Hypothesis 2A and 2B). As expected, our data exhibit significant variability in solver efforts $e_{icmt}$ ($\sigma_{e_{icmt}} = 3.04$ and $\sigma_{e_{icmt}} = 2.99$).6 The more interesting pursuit here is how this variability affects organizer profits. To this end, we compare the counterfactual profit $\Pi_{\bar{e}}$ (which eliminates all effort variability) with the experiment profit $\Pi_{e_{icmt}}$ (which includes all effort variability). Figure 3 shows that while Exclusive (20.01 vs. 18.64, $p < .001$, two-sided $t$-test) suffers from effort variability, Non-Exclusive (21.62 vs. 22.05, $p = .038$) benefits from it.

Before we move to more detailed analysis, we need to introduce two concepts: within-contest and across-contest effort variability. Within-contest effort variability stems from variance in efforts of solvers who participate in the same contest. Across-contest effort variability stems from the difference in average efforts in different contests.

Within-contest effort variability (Hypothesis 2A). To measure the variability of efforts among subjects who participate in the same contest, we calculate the standard deviation $\sigma(e_{icmt})$ of efforts for all cohorts $c$, contests $m$, and rounds $t$ as the unit of analysis.7 We observe significant

$$\sigma_{e_{icmt}} = \sqrt{\frac{\sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T} (e_{icmt} - \bar{e}_{icmt})^2}{N \cdot M \cdot T}}$$

where $\bar{e}_{icmt} = \frac{\sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T} e_{icmt}}{N \cdot M \cdot T}$.

$$\sigma(e_{icmt}) = \sqrt{\frac{\sum_{i=1}^{N} (e_{icmt} - \bar{e}_{icmt})^2}{N_m}}$$

where $\bar{e}_{icmt} = \frac{\sum_{i=1}^{N_m} e_{icmt}}{N_m}$.

---

6 $\sigma_{e_{icmt}} = \sqrt{\frac{\sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T} (e_{icmt} - \bar{e}_{icmt})^2}{N \cdot M \cdot T}}$ where $\bar{e}_{icmt} = \frac{\sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T} e_{icmt}}{N \cdot M \cdot T}$.

7 $\sigma(e_{icmt}) = \sqrt{\frac{\sum_{i=1}^{N} (e_{icmt} - \bar{e}_{icmt})^2}{N_m}}$ where $\bar{e}_{icmt} = \frac{\sum_{i=1}^{N_m} e_{icmt}}{N_m}$.
contest-level effort variability in both Exclusive ($\sigma(e_{icmt}) = 2.43$, $p < 0.001$, two-sided $t$-test) and Non-Exclusive ($\sigma(e_{icmt}) = 2.83$, $p < 0.001$). Thus, our data do not support Hypothesis 2A.

We next calculate the counterfactual expected profit $\pi_{e_{icmt}}$ that organizers would have made in a contest if all participating solvers had exerted the same contest-level average effort $\bar{e}_{icmt}$. To quantify the impact of within-contest effort variability on profits, we compare $\Pi_{e_{icmt}} = \frac{1}{C \cdot T \cdot M} \sum_{c=1}^C \sum_{m=1}^M \sum_{t=1}^T \pi_{e_{icmt}}$, which (by construction) excludes within-contest effort variability, with $\Pi_{\bar{e}_{icmt}}$, which includes it. Figure 3 shows that within-contest effort variability improves the average profit in Exclusive (18.64 vs. 18.56, $p < 0.001$, two-sided paired $t$-test), and even more so in Non-Exclusive (22.05 vs. 20.27, $p < 0.001$). Essentially, just like organizers benefit from output shocks, they also benefit from effort variability.\(^8\) This positive effect of within-contest effort variability on profits is larger for non-exclusive contests because they attract more solvers.

So far, we have focused on the contest-level effort variability. Yet, the contest-level effort variability stems from solver-level effort variability. Solver-level effort variability can manifest itself in three ways. First, different solvers may exert different average efforts, which we call heterogeneity. Second, even if solvers exert the same average effort, they may exhibit variability due to randomness in decision making, which we call stochastic choice. Third, variability may occur when solvers change their strategies over time as they gain experience in the task and receive feedback, which we call learning. We do not find strong evidence of learning in our data (see Figure 4). Formally, we fit a simple trend line ($Effort = \beta_0 + \beta_1 \cdot Round + \epsilon$, with standard errors pooled at the solver level) to the data and find no significant effect of rounds on effort choices in Exclusive ($\beta_1 = 0.021$, $p = 0.3$).

\(^8\) For illustration, consider a contest $m$ where solvers exert efforts $e_{1cmt}$ and $e_{2cmt}$. The expected organizer profit calculated based on these efforts is then $\pi_{e_{icmt}} = E[\max\{20 \log(e_{1cmt}) + \xi_{1cmt}, 20 \log(e_{2cmt}) + \xi_{2cmt}\} - A]$, which is larger than the expected organizer profit calculated based on the format where both solvers exert $\bar{e}_{icmt} = (e_{1cmt} + e_{2cmt})/2$, $\pi_{\bar{e}_{icmt}} = 20 \log(\bar{e}_{icmt}) + E[\max\{\xi_{1cmt}, \xi_{2cmt}\} - A]$. You can find the full text at: https://ssrn.com/abstract=4256134
or Non-Exclusive ($\beta_1 = -0.011$, $p = 0.19$). Hence, in the remainder of our analysis, we focus on heterogeneity and stochastic choice. Specifically, we next analyze how heterogeneity and stochastic choice affect within-contest effort variability.

First, to quantify the impact of heterogeneity, we calculate and compare two counterfactual profits. For the first counterfactual profit, we replace each solver’s effort with their average effort in profit calculation (i.e., $\Pi_{e_{icmt}}$).\(^{9}\) This modification removes the variability of a solver’s effort across different rounds, yet different solvers may still have different average efforts. For the second counterfactual profit, we remove within-contest effort variability in each contest $m$ by replacing each participating solver $i$’s effort (i.e., $e_{icmt}$) with the average of all participating solvers’ average efforts (i.e., $\bar{e}_{icmt} = (\bar{e}_{1icmt} + ... + \bar{e}_{N_{m}icmt})/N_{m}$) in profit calculation (i.e., $\Pi_{\bar{e}_{icmt}}$).\(^{10}\) By comparing these counterfactual profits, we find that the within-contest effort variability arising from heterogeneity leads to higher profits in both Exclusive (19.32 vs. 19.29, $p < 0.001$, two-sided paired $t$-test) and Non-Exclusive (21.66 vs. 20.46, $p < 0.001$).

Second, we quantify the impact of stochastic choice. Since the impact of within-contest effort variability (18.64 – 18.56 = 0.08 in Exclusive and 22.05 – 20.27 = 1.78 in Non-Exclusive) originates from heterogeneity or stochastic choice, if we filter out the impact of heterogeneity (19.32 – 19.29 = 0.03 in Exclusive and 21.66 – 20.46 = 1.2 in Non-Exclusive), we can capture the impact of stochastic choice. We find that the within-contest effort variability arising from stochastic choice also improves profits in both Exclusive (0.08 – 0.03 = 0.05, $p < 0.001$, two-sided paired $t$-test) and in Non-Exclusive (1.78 – 1.2 = 0.58, $p = 0.013$).

**Across-contest effort variability (Hypothesis 2B).** Using the average contest effort $\bar{e}_{cmt}$ as the unit of analysis, we observe effort variability across contests in Exclusive ($\sigma(\bar{e}_{cmt}) = 2.16$, $p < 0.001$, one-sided $\chi^2$ test) and Non-Exclusive ($\sigma(\bar{e}_{cmt}) = 1.48$, $p < 0.001$). Thus, our data do not support Hypothesis 2B. We next study how effort variability across contests affects profits by comparing $\Pi_{\bar{e}_{cmt}}$, which eliminates only within-contest effort variability, with $\Pi_{e}$, which eliminates all effort variability. Figure 3 shows that across-contest effort variability reduces average profit in Exclusive (20.01 vs. 18.56, $p < 0.001$, two-sided $t$-test) and Non-Exclusive (21.62 vs. 20.27, $p < 0.001$).

We next study how heterogeneity and stochastic choice affect across-contest effort variability. First, to quantify the impact of heterogeneity, we again compare the two counterfactual profits $\Pi_{\bar{e}_{icmt}}$ and $\Pi_{\bar{e}}$. Recall that $\bar{e}_{icmt}$ is the average of all participating solvers’ average efforts, so $\Pi_{\bar{e}_{icmt}}$ excludes within-solver and within-contest effort variability, but it includes across-contest

---

\(^{9}\) Replace $e_{icmt}$ with $\bar{e}_{icmt}$ as follows $\pi_{icmt} = E[\max_{l \in \{1, ..., N_{m}\}} \{\theta \log(\bar{e}_{icmt}) + \xi_{icmt}\}] - A$.

\(^{10}\) Replace $e_{icmt}$ with $\bar{e}_{icmt} = (\bar{e}_{1icmt} + ... + \bar{e}_{N_{m}icmt})/N_{m}$ as follows $\pi_{icmt} = \theta \log(\bar{e}_{icmt}) + E[\max_{l \in \{1, ..., N_{m}\}} \xi_{icmt}] - A$. 

Electronic copy available at: https://ssrn.com/abstract=4256134
effort variability. We compare $\Pi_{\text{cont}}$ with $\Pi_{\varepsilon}$, which excludes all effort variability. We find that the across-contest effort variability arising from heterogeneity reduces profits in both Exclusive (20.01 vs. 19.29, $p = 0.003$, two-sided $t$-test) and Non-Exclusive (20.46 vs. 21.62, $p < 0.001$). Second, the unexplained part of the impact of across-contest effort variability is due to stochastic choice. We find that across-contest effort variability arising from stochastic choice reduces profits in Exclusive (-0.73, $p = 0.002$, two-sided $t$-test), but has no significant effect in Non-Exclusive (-0.19, $p > 0.41$).

5.1.4. Risk preferences. We also examine whether risk preferences of our subjects feature any explaining power on the observed efforts. We calculate the correlation between the average solver effort and the number of safe choices made by all subjects. The Spearman’s rank correlation coefficient, $\rho$, is insignificant in all treatments.\footnote{Breakeven uncertainty-Exclusive: $\rho = 0.06$, $p = 0.68$. Breakeven uncertainty-Non-Exclusive: $\rho = -0.03$, $p = 0.84$. Low uncertainty-Exclusive: $\rho = 0.11$, $p = 0.46$. Low uncertainty-Non-Exclusive: $\rho = -0.23$, $p = 0.12$.}

5.2. QRE: Quantifying Departures from Equilibrium

Combining our results so far, we observe that average efforts are lower than predicted, which in turn cause lower-than-predicted average profits in both contest formats. Furthermore, we observe that solvers exhibit substantial variability in their efforts. The overall effect of this effort variability is detrimental to Exclusive, but beneficial to Non-Exclusive, leading the latter contest format to generate a higher average profit than the former one in cases where the standard theory predicts profit equivalence between them. We next try to quantitatively reproduce the main departures from equilibrium predictions with a structural model. To this end, we look at our data through the lens of a quantal-response equilibrium (QRE) model (McKelvey and Palfrey 1995).

The key feature of a QRE is that subjects make mistakes when choosing their optimal strategies. Formally, each effort in $[0, E]$ has a random error, $\mu \varepsilon$, on the expected utility the effort generates, where $\varepsilon$ follows a Gumbel distribution with mean zero and a standard deviation one (e.g., McKelvey and Palfrey 1995), and $\mu$ is a parameter that captures decision noise. A QRE model for Exclusive can be defined as follows. Let $u(e_{im}, e_{-im})$ denote the expected utility of solver $i$ from choosing effort $e_{im}$ when her opponent chooses $e_{-im}$. In this QRE setting, solver $i$’s effort choice $E_i$ is a random variable defined over the decision domain $[0, E]$ and her opponent’s effort choice $E_{-i}$ is also a random variable over the same domain with the same probability distribution. Then, we can write the (logit) choice probability of solver $i$ choosing effort $e_{im}$ in Exclusive contest $m$ as:

$$p(e_{im}, \mu) = \frac{e^{\frac{u(e_{im}, E_{-i})}{\mu}}}{\int_{e_{jm} \in [0, E]} e^{\frac{u(e_{jm}, E_{-j})}{\mu}} de_{jm}},$$

(6)
where \( \mu \) captures decision noise. The model nests the standard theory for \( \mu = 0 \), where solvers choose the Nash equilibrium effort with probability one. As \( \mu \) increases, solvers noisily depart from the Nash equilibrium effort more often, and randomize their efforts uniformly over \([0, \bar{E}]\) as \( \mu \to \infty \).

In Non-Exclusive, we use a joint probability distribution to capture the dependence between efforts in two contests. Let \( u(e_{i1}, e_{i2}, E_{-i1}, E_{-i2}) \) be the expected utility of solver \( i \) from choosing effort \( e_{i1} \) in contest 1 and \( e_{i2} \) in contest 2, while effort choices of her three opponents are determined by random variables \( E_{-i1} \) in contest 1 and \( E_{-i2} \) in contest 2. Accordingly, we calculate the probability that solver \( i \) chooses efforts \((e_{i1}, e_{i2})\) as:

\[
p(e_{i1}, e_{i2}, \mu) = \frac{e^{u(e_{i1}, e_{i2}, E_{-i1}, E_{-i2})}}{\int_{e_{j1} \in [0, \bar{E}]} \int_{e_{j2} \in [0, \bar{E}-e_{j1}]} e^{u(e_{j1}, e_{j2}, E_{-j1}, E_{-j2})} de_{j1} \ de_{j2}}. \tag{7}
\]

While QRE accommodates decision noise in our setting (i.e., effort variability) by construction, our main interest is to understand what predictions this model makes for average efforts and average profits under Exclusive and Non-Exclusive. For experimental parameters of Study 1, Figure 5 shows profits under Exclusive and Non-Exclusive for different values of the decision-noise parameter \( \mu \). When \( \mu = 0 \), QRE aligns with the profit-equivalence prediction that Hypothesis 3 makes for \( \beta = \beta_0 \). As \( \mu \) increases, average efforts and average profits decrease under both Exclusive and Non-Exclusive. Importantly, for \( \mu > 0 \), the average profit decreases more in Exclusive than in Non-Exclusive, which aligns with the key observation from our data.

![Figure 5](https://ssrn.com/abstract=4256134)  

**Figure 5**  Average profits predicted by the QRE model given different \( \mu \) values.

We use the standard maximum likelihood estimation to fit the QRE model to our data. By using effort choices \( X = \{e_{i1t} : i = 1, 2, \ldots, 54; \ t = 1, 2, \ldots, 20\} \) in Exclusive and \( Y = \{e_{i1t}, e_{i2t} : i = 1, 2, \ldots, 48; \ t = 1, 2, \ldots, 20\} \) in Non-Exclusive, the joint log-likelihood function is defined as:

\[
L(\mu|X,Y) = \sum_{i=1}^{54} \sum_{t=1}^{20} \log(p(e_{i1t}, \mu)) + \sum_{i=1}^{48} \sum_{t=1}^{20} \log(p(e_{ic1t}, e_{ic2t}, \mu)). \tag{8}
\]
Maximizing (8) over the pooled data from Exclusive and Non-Exclusive yields $\hat{\mu} = 3.49$. The QRE predicts that the average profit is larger in Non-Exclusive than in Exclusive, and that average profits are smaller than theoretical benchmarks in both treatments.

6. Study 2: Contest Design under Low Uncertainty

Study 1 reveals that Non-Exclusive yields a larger average profit than Exclusive when theory predicts profit equivalence. We design Study 2 with smaller uncertainty as a robustness test for behavioral tendencies observed in Study 1 and as a test of out-of-sample predictions of the QRE model. Because theory predicts that smaller (than $\beta_0$) uncertainty favors Exclusive, such an environment provides a strong test for behavioral benefits of Non-Exclusive observed in Study 1.

6.1. Design and Implementation

To test these ideas, Study 2 sets the output uncertainty at $\beta = 30$, keeping all other parameters and implementation aspects (subject pool, instructions, user interface) identical to Study 1. This smaller uncertainty provides an incentive for solvers to increase their efforts (see Figure 1). Different than Study 1, the effort capacity constraint is binding in Exclusive. Theory predicts that organizers of Exclusive contests benefit from larger equilibrium efforts at low uncertainty. In contrast, organizers of Non-Exclusive contests earn strictly lower profits because larger efforts (effort capacity constraint was already binding at Study 1) do not compensate for smaller output uncertainty.

Study 2 also provides an opportunity for an out-of-sample test of the QRE model from §5.2. While theory predicts substantially larger average profit under Exclusive at $\mu = 0$ (Hypothesis 3), this profit advantage decreases as the decision noise parameter $\mu$ increases (Figure 5). In fact, using the fitted value from Study 1 ($\hat{\mu} = 3.49$), QRE predicts that Exclusive does not yield a larger average profit than Non-Exclusive at the uncertainty level of Study 2 (Figure 6). In other words, if QRE indeed captures the key moments in our data, we would likely reject Hypothesis 3.

6.2. Results

Table 2 presents the aggregate results for Study 2. We next test our main hypothesis about average profits, and then analyze average efforts and variability in efforts.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>$I$</th>
<th>Sess.</th>
<th>Total solver effort</th>
<th>Per-contest effort</th>
<th>Per-contest profit</th>
<th>Max. shock</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td></td>
<td>$Pred.\ QRE$</td>
<td>$Obs.$</td>
<td>$Pred.\ QRE$</td>
<td>$Obs.$</td>
</tr>
<tr>
<td>Exclusive</td>
<td>50</td>
<td>4</td>
<td>10</td>
<td>6.51</td>
<td>6.66 (0.36)</td>
<td>10</td>
</tr>
<tr>
<td>Non-Exc.</td>
<td>44</td>
<td>3</td>
<td>10</td>
<td>7.95</td>
<td>8.79 (0.25)</td>
<td>5</td>
</tr>
</tbody>
</table>
6.2.1. Average profits (Hypothesis 3). Our data do not support the prediction of larger profits in Exclusive than in Non-Exclusive under low uncertainty (17.32 vs. 18.79, \( p = 0.999 \), one-sided t-test). Instead, the gap between the average profits in Exclusive and Non-Exclusive is lower in our data than theoretically predicted (−1.47 vs. 5.9, \( p < 0.001 \), one-sided t-test). These results lend support to the QRE predictions that Exclusive does not lead to a larger average profit than Non-Exclusive even under low uncertainty.

6.2.2. Average efforts (Hypothesis 1). Results in Table 2 show that observed efforts are smaller than predicted in Exclusive (6.66 vs. 10, \( p < 0.001 \), two-sided t-test) and Non-Exclusive (8.79 vs. 10, \( p < 0.001 \)). Thus, our data fail to support Hypothesis 1. Interestingly, in Study 2, the counterfactual profit \( \Pi_e \) (which eliminates all effort variability) is larger in Exclusive than in Non-Exclusive (17.95 vs. 17.63). This finding reinforces our conclusion that effort variability, rather than average effort, is the main driver that eliminates the dominance of Exclusive against Non-Exclusive.

6.2.3. Variability in efforts (Hypothesis 2A and 2B). Figure 7 illustrates the impact of effort variability under low uncertainty. It shows that effort variability reduces the average profit in Exclusive (17.32 vs 17.95, \( p = 0.053 \), two-sided t-test), but it improves the average profit in Non-Exclusive (18.79 vs. 17.63, \( p < 0.001 \)). Thus, effort variability can help explain why Non-Exclusive yields a larger average profit than Exclusive, contrary to theoretical predictions.

The decomposition of effort variability into within- and across-contest effort variability reveals a pattern similar to Study 1. We again find that within-contest effort variability improves the average profit in Exclusive (17.32 vs 16.76, \( p < 0.001 \), two-sided paired t-test) and even more so in Non-Exclusive (18.79 vs. 16.32, \( p < 0.001 \)). Similar to Study 1, the impact of across-contest effort variability is negative and very close to each other in both contest formats (16.76 vs. 17.95 in Exclusive, \( p < 0.001 \), two-sided t-test and 16.32 vs. 17.63 in Non-Exclusive, \( p < 0.001 \)).
7. Conclusion

In the last two decades, innovation contests have grown as a popular tool to crowdsource innovative solutions to a vast set of problems from a group of independent solvers. Today, organizations such as the Gates Foundation and crowdsourcing platforms such as Wazoku or Topcoder run multiple innovation contests in parallel. In a multi-contest environment, when solvers focus their efforts on a single contest, these potentially larger efforts may improve the outcome of these contests. Yet, when solvers participate in multiple contests, the number of solutions submitted to each contest increases, and more diverse set of solutions may improve the outcome of these contests. Depending on which of these opposing factors prevails, organizations may benefit from encouraging solvers to participate in multiple contests in parallel.

Theory suggests that the relative profitability of different contest formats depends on the level of uncertainty that solvers face. Surprisingly, we show that non-exclusive contests can generate larger profits than exclusive contests at uncertainty levels for which the standard theory predicts profit equivalence or an advantage of exclusive contests. The main driver for this result is variability in effort, which favors the non-exclusive format over the exclusive format. A Quantal Response Equilibrium (QRE) model accounts for such variability, and helps reconcile our experimental findings with theoretical predictions.

Our paper contributes to the experimental-contest literature on several dimensions. In contrast to the overbidding behavior observed in other types of contests (e.g., Dechenaux et al. 2015, Millner...
and Pratt 1991), solvers in innovation contests tend to underbid (i.e., underinvest effort). This contrasting result may be because solvers in an innovation contest face much larger uncertainty about the impact of their efforts on their payoffs than other types of contests. This contrasting result leads to the opposite policy insight. While overbidding would favor the exclusive format, behavioral tendencies of solvers in an innovation contest favors the non-exclusive format. Importantly, our study shows that the variability in efforts has a significant effect in innovation contests. It is worth noting that the effort variability is observed in several other studies, yet the impact of the effort variability on the organizer profit is different in an innovation contest from other types of contests (e.g., Tullock or sales). This is because the organizer in an innovation contest is interested in the best solution, hence the effort variability in an innovation contest may improve the organizer profit. In contrast, in other types of contests (e.g., Tullock or sales), effort variability cannot improve the organizer profit because the organizer maximizes the sum (not maximum) of outputs so any variability simply cancels out. Hence, effort variability plays a unique role in innovation contests.

Our study has limitations that provide opportunities for future research. First, to focus on our main research question around the interplay between uncertainty and contest format, our study design uses the same award in all treatments. An interesting future study can investigate whether solvers focus on a single contest when awards are asymmetric, and if so, how this affects the relative attractiveness of the non-exclusive format. Second, to identify cases where the exclusive format can potentially outweigh the non-exclusive format, we study low or breakeven levels of uncertainty where efforts predicted by the contest theory are close to solvers’ capacity. This might be the reason why we do not observe overbidding. Therefore, a future research avenue is to study overbidding in an innovation contest setting under sufficiently large uncertainty so that efforts predicted by the contest theory are further away from solvers’ capacity.

References


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Appendix A. Proofs

We first derive the marginal contribution of effort on the probability of winning while solver $i$ exerts effort $e_{im}$, and other solvers exert effort $e^*_m$ at contest $m$. Let $h(s)$ be the pdf and $H(s)$ be the cdf of the uniform distribution ($s \in [-\beta, \beta]$) that the output shocks are drawn from then $\frac{\partial P_m(e_{im}, e^*_m)}{\partial e_{im}}$ is calculated as follows:

$$\frac{\partial P_m(e_{im}, e^*_m)}{\partial e_{im}} = \int_{s \in \Xi} \frac{\theta}{e_{im}} (N-1)H(s + \theta \log(e_{im}) - \theta \log(e^*_m))^N h(s)^2 ds.$$  

Substituting $e^*_m = e_{im}$ into the equation:

$$\frac{\partial P_m(e_{im}, e^*_m)}{\partial e_{im}} = \int_{s \in \Xi} \frac{\theta(N-1)(s + \beta)^{N-2}}{e^*_m(2\beta)^N} ds = \frac{\theta(s + \beta)^{N-1}}{e^*_m(2\beta)^N} \bigg|_{-\beta}^{\beta} = \frac{\theta}{2e^*_m \beta}.$$  

Second, we characterize $E[\max_i \tilde{\xi}_i]$ under uniform distribution with support $\Xi \in [-\beta, \beta]$. $\tilde{\xi}_i$’s are i.i.d., uniformly distributed over support $\Xi$, then the distribution of $Y = \max \{\tilde{\xi}_1, \tilde{\xi}_2, ..., \tilde{\xi}_N\}$ is

$$P_Y(Y \leq s) = P_{\tilde{\xi}}(\max \{\tilde{\xi}_1, \tilde{\xi}_2, ..., \tilde{\xi}_N\} \leq s) = P_{\tilde{\xi}}(\tilde{\xi}_1 \leq s, \tilde{\xi}_2 \leq s, ..., \tilde{\xi}_N \leq s) = P_{\tilde{\xi}}(\tilde{\xi}_1 \leq s)P_{\tilde{\xi}}(\tilde{\xi}_2 \leq s)...P_{\tilde{\xi}}(\tilde{\xi}_N \leq s) = F_{\tilde{\xi}}(s)^N.$$  

Thus, the pdf of $Y$ is as follows:

$$f_Y(s) = N f_{\tilde{\xi}}(s) F_{\tilde{\xi}}(s)^{N-1} = \frac{N(s + \beta)^{N-1}}{(2\beta)^N}.$$  

By using this derivation, the expected value of $\max_i \tilde{\xi}_i$ is calculated as follows:

$$E[\max_i \tilde{\xi}_i] = \int_{s \in \Xi} \frac{N(s + \beta)^{N-1}}{(2\beta)^N} s ds = \int_{s \in \Xi} \frac{N(s + \beta)^N}{(2\beta)^N} ds - \int_{s \in \Xi} \frac{\beta N(s + \beta)^{N-1}}{(2\beta)^N} ds$$  

$$= \left[ \frac{N(s + \beta)^{N+1}}{(N+1)(2\beta)^N} - \frac{\beta(s + \beta)^N}{(2\beta)^N} \right]_{-\beta}^{\beta} = \frac{\beta(N - 1)}{N + 1}.$$  

**Proof Proposition 1.** There exists a unique $\{\hat{e}_1, \hat{e}_2, ..., \hat{e}_M\}$ that solves the following FOC equation of solvers’ objective function (Körpeoğlu et al. 2022):

$$\frac{A_m \theta}{2 \hat{e}_m \beta} = 1 \text{ for all } m \in \{1, 2\}.$$  

Let $\lambda$ be the Lagrange multiplier for the solver’s capacity constraint. A symmetric equilibrium satisfies the following Kuhn-Tucker conditions:

$$\frac{A_m \theta}{2 \hat{e}_m \beta} - 1 - \lambda^* = 0, \ m \in \{1, 2\},$$  

$$\lambda^* \left( \overline{E} - \sum_{m=1}^M e^*_m \right) = 0, \ \sum_{m=1}^M e^*_m \leq \overline{E}, \text{ and } e^*_m, \lambda^* \geq 0, \ m \in \{1, 2\}.$$  

Case 1: In Case 1, we assume that $\sum_{m=1}^{M} \hat{e}_m < \bar{E}$. Then, $(\hat{e}_1, \hat{e}_2, \hat{\lambda})$, where $\lambda^* = 0$ is a solution to (9-10), and $e^*_m = \frac{A_m \theta}{2 \beta}$ becomes the optimal effort in contest $m$.

Case 2: In Case 2, we assume that $\sum_{m=1}^{M} \hat{e}_m \geq \bar{E}$. In this format, there is a unique candidate for the symmetric equilibrium effort $e^*_m$ at contest $m \in \{1, 2\}$ that satisfies (9-10):

$$\frac{A_m \theta}{2 \beta e^*_m} - 1 = \frac{A_1 \theta}{2 \beta e^*_1} - 1 \text{ and } \sum_{m=1}^{M} e^*_m = \bar{E}.$$  

These conditions boil down to

$$e^*_m = \frac{\bar{E} A_m}{\sum_{m=1}^{M} A_m}.$$  

Proof of Proposition 2. Consider the exclusive format where $N_1$ and $N_2$ solvers participate in contest 1 and 2, respectively. Let the award for each contest be same and equal to $A$. Let the equilibrium effort be $e^*$ in the non-exclusive format and $e^{*,x}$ in the exclusive format. In the non-exclusive format, all $N(=N_1+N_2)$ solvers participate in both contests. Then, the total profit in the non-exclusive format is

$$\Pi = 2 \theta \log (e^*) + \frac{2 \beta (N-1)}{N+1} - 2A.$$  

The total profit in the exclusive format with two contests is

$$\Pi^x = 2 \theta \log (e^{*,x}) + \frac{\beta (N_1-1)}{N_1+1} + \frac{\beta (N_2-1)}{N_2+1} - 2A.$$  

Part A: When the capacity constraint is not binding, we have $e^* = \frac{A \theta}{2 \beta}$. Thus, by setting $\beta$ high enough, we can always obtain such a low equilibrium effort that the capacity constraint does not bind. Since solvers divide their capacity between two contests in the non-exclusive format, ensuring that the capacity constraint does not bind in this case, guarantees that it does not bind in the exclusive format. Thus, it is enough to check $e^* = \frac{A \theta}{2 \beta} < \frac{\bar{E}}{2}$, which boils down to $\beta > \frac{A \theta}{2 \bar{E}}$, to ensure that the capacity constraint does not bind. Then, the equilibrium effort in the non-exclusive format will be equal to the equilibrium effort in the exclusive format, i.e., $e^* = e^{*,x} = \frac{A \theta}{2 \beta}$. Accordingly, the difference between the total profit in the exclusive and non-exclusive formats is

$$\Pi - \Pi^x = \beta \left( \frac{2(N-1)}{N+1} - \frac{(N_1-1)}{N_1+1} - \frac{(N_2-1)}{N_2+1} \right).$$  

Since $N$ is greater than $N_1$ and $N_2$, the result is always greater than 0.

Part B: Now, we assume that $\beta$ is not large enough to ensure a loose capacity constraint in the non-exclusive format, yet it is still large enough to ensure that the capacity constraint is loose in the exclusive format. In Part A, we showed that $\beta \leq \frac{A \theta}{2 \bar{E}}$ means that the capacity constraint binds in the non-exclusive format (i.e., $e^* = \frac{\bar{E}}{2}$). The threshold uncertainty level for a binding capacity constraint in the exclusive format can be obtained by equating the equilibrium effort in the exclusive format to the whole capacity of a solver, i.e., $e^{*,x} = \frac{A \theta}{2 \beta} = \bar{E}$. From this, we have $\beta > \frac{A \theta}{2 \bar{E}}$ as lower end of the range where capacity constraint binds in the non-exclusive format yet it
is loose in the exclusive format. Therefore, when $\beta \in (\frac{A\theta}{2E}, \frac{A\theta}{E})$, the total profit of the non-exclusive format changes as follows:

$$\Pi = 2\theta \log (e^*) + \frac{2\beta(N-1)}{N+1} - 2A = 2\theta \log \left( \frac{E}{2} \right) + \frac{2\beta(N-1)}{N+1} - 2A.$$

The difference between the total profit of the non-exclusive and exclusive formats is

$$\Pi - \Pi^x = \theta \log \left( \frac{2\beta E^2}{2\theta^2 A^2} \right) + \frac{2\beta(N-1)}{N+1} - \beta \frac{N_1 - 1}{N_1 + 1} - \beta \frac{N_2 - 1}{N_2 + 1}.$$

We have $\Pi - \Pi^x \geq 0$ if and only if $\beta \geq \beta_1$ where

$$\beta_1 = \frac{-2\theta \left( \log \left( \frac{\beta E}{A\theta} \right) \right)}{\frac{2(N-1)}{N+1} - \frac{N_1 - 1}{N_1 + 1} - \frac{N_2 - 1}{N_2 + 1}}. \quad (12)$$

**Part C:** As we show in Part B, when $\beta \leq \frac{A\theta}{2E}$, the capacity constraint is binding in both the exclusive and non-exclusive formats. Thus, the total profit for the non-exclusive format changes as the following:

$$\Pi = 2\theta \log (e^*) + \frac{2\beta(N-1)}{N+1} - 2A^* = 2\theta \log \left( \frac{E}{2} \right) + \frac{2\beta(N-1)}{N+1} - 2A.$$

The total profit in the exclusive format with two contests changes as follows:

$$\Pi^x = 2\theta \log (e^{x,\pi}) + \frac{\beta(N_1 - 1)}{N_1 + 1} + \frac{\beta(N_2 - 1)}{N_2 + 1} - 2A = 2\theta \log (E) + \frac{\beta(N_1 - 1)}{N_1 + 1} + \frac{\beta(N_2 - 1)}{N_2 + 1} - 2A.$$

The difference between the total profits of the exclusive and non-exclusive formats is

$$\Pi - \Pi^x = 2\theta \log \left( \frac{1}{2} \right) + \frac{2\beta(N-1)}{N+1} - \frac{\beta(N_1 - 1)}{N_1 + 1} - \frac{\beta(N_2 - 1)}{N_2 + 1}.$$

Thus, we have $\Pi - \Pi^x < 0$ if and only if $\beta \leq \beta_2$ where

$$\beta_2 = \frac{2\theta \log (2)}{\frac{2(N-1)}{N+1} - \frac{N_1 - 1}{N_1 + 1} - \frac{N_2 - 1}{N_2 + 1}}. \quad (13)$$

It is clear that in Part A, the profit of the non-exclusive format is larger so both $\beta_1$ and $\beta_2$ can not lay within this region. If we can find $\beta_1$ which is within the range of $\left(\frac{A\theta}{2E}, \frac{A\theta}{E}\right)$ then the breakeven uncertainty point $\beta_0$ is equal to $\beta_1$. Otherwise, it means that the breakeven point lies within the range of $[0, \frac{A\theta}{2E}]$ since we know that $\beta_2$ is also positive. If $\beta_2$ is larger than $\frac{A\theta}{2E}$ then $\beta_0 = \frac{A\theta}{2E}$; otherwise, $\beta_0 = \beta_2$. We boil these logical relations down to the following characterization:

$$\beta_0 = \max \left\{ \min \left\{ \frac{A\theta}{2E}, \frac{2\theta \log (2)}{\frac{N_1 - 1}{N_1 + 1} - \frac{N_2 - 1}{N_2 + 1}} \right\}, \frac{-2\theta \left( \log \left( \frac{E}{A\theta} \right) \right)}{\frac{2(N-1)}{N+1} - \frac{N_1 - 1}{N_1 + 1} - \frac{N_2 - 1}{N_2 + 1}} \right\}.$$
Online Appendix

EC.1. Instructions

We provide instructions for the non-exclusive treatment under low uncertainty and mark some sections colourfully to present the instructions for the remaining treatments. Sections in black are the same in all treatments. Sections marked in red are only for the non-exclusive treatments. Sections marked in green are only for the exclusive treatments. Sections marked in blue are only for the breakeven uncertainty treatments. In the instructions, we refer to output shocks as the “luck component,” all 24 rounds of innovation contests as the “part 1,” and the part in which we elicit participants’ risk tendencies as the “part 2.”

Instructions for Part 1

Part 1- General instructions. 1/12(11)
This is an experiment in strategic decision making. The experiment is designed to observe your behavior in decision making, not to test your knowledge.

Part 1- Task. 2/12(11)
In part 1 of the experiment, you will make decisions in multiple rounds. In each round, you will compete against 3 (1) other opponents in (a contest) two contests (contest 1 and contest 2). At the beginning of each round, your 3 opponents will be selected randomly by the computer.

Part 1- Your decision. 3/12(11)
You and your 3 opponents will compete against each other in both contest 1 and contest 2 (in the contest) by deciding on your investments at each contest. You can choose an investment between 0 and 10. You can choose your investment by dragging the slider and fine tune your investment by clicking minus and plus buttons. You can test the slider and buttons for the contest given below to see how they work.

Part 1- Your investment cost. 4/12(11)
Your investment results in a cost that equals the invested amount. You can move the slider and click the buttons to see how the cost is updated.

Part 1- Your total investment cost. 5/12
The sum of your investments in both contests cannot exceed 10. Every participant is free to invest this total investment capacity of 10 between contest 1 and contest 2. For instance, one participant may focus on contest 1 (i.e., invest 10 in contest 1) whereas another participant may split the total investment capacity of 10 between contest 1 and contest 2.
Thus, once your total investment reaches 10, in order to further increase your investment in one contest, you have to decrease your investment in the other contest. You will be able to see the sum of your investments in both contests at the top of your decision page.

You can move the slider and click the buttons to see how the total cost is updated.

Your performance in each contest is the sum of two components: The first component depends on your investment and second component depends on your luck.

The first component constitutes the mean of your performance and equals to $20 \times \log(\text{Your investment})$. Your mean performance will be shown as a red dot on the graph once you choose your investment.

You can move the slider and click the buttons to see how these features work.

(e) Exclusive Treatment

(f) Non-exclusive Treatment


The second component of your performance will be a luck component. The luck component is a random number drawn from the range $[-30,30]$ ($[-36.8,36.8]$) where each number within this range is equally likely. Note that although luck components are drawn from the same range, their realized values can be different for different contests and participants.


Your performance will be calculated as the sum of the mean performance and the luck component. Specifically:
Your performance = $20 \times \log(\text{Your investment in contest}) + \text{Your luck component}$

The decision page will display a graph with a shaded region which shows the range of values that your performance can take depending on your investment and luck component.

Once you choose your investment, automatically the range of possible values that your performance can take will be displayed by a red vertical line. The upper end of the line corresponds to the maximum and the lower end of it corresponds to the minimum possible performance value. The chart is responsive, so you can also see possible values by moving the cursor over the graph. You can move the slider and click the buttons to see how these features work.

(g) Exclusive-Breakeven Uncertainty Treatment

(h) Non-exclusive-Low Uncertainty Treatment
Part 1- Profit calculation.  

Your profit in each round will depend on the following factors.

In each round, participants will be given an initial endowment of $10 to be spent on investment. In each of two contests, the participant with the best performance wins the contest and an award of $30.

Therefore, your profit in each round consists of 3 factors:

- Your initial endowment ($10)
- The award(s) you win
- Your investment cost

Part 1- Profit calculation.  

If you win in both contests.

If you win both contest 1 and contest 2, your profit will be the initial endowment ($10) plus the awards (2 × ($30)) you received minus your total investment cost.

Profit = $10 + 2 × ($30) - Investment cost 1 - Investment cost 2

If you win in one contest.

If you win only one of the contests, your profit will be the initial endowment ($10) plus the award ($30) you received minus your total investment cost.

Profit = $10 + $30 - Investment cost 1 - Investment cost 2

If you do not win any of the contests.

If you do not win any of the contests, your profit will be your initial endowment ($10) minus your total investment cost.

Profit = $10 - Investment cost 1 - Investment cost 2


You will be playing 4 practice rounds, followed by 20 rounds that affect your final payment.

After you have played the 20 rounds, the computer will randomly select one of the 20 rounds. Your actual payment will be your profit in the randomly selected round and it will be converted to cash by using $1 = €0.6 ($1 = €0.55 in breakeven uncertainty-exclusive treatment) conversion rate.


At the end of each round, you will see your cost of investment for each contest, whether you win one or both of these contests, and your profit at that round. You can access these values for previous rounds by clicking the Show history button.

You will also have a Show instructions button to access the part 1 instructions as a pdf file.

At the end of the experiment, you will be able to see all of your decisions and the round randomly selected for your payment in a table.

You can try the functionalities of these buttons by clicking them below.
Instructions for Part 2

Part 2- General instructions. 1/5
In this part of the experiment, you will be asked to make a series of decisions. This part is designed to observe your choices between two alternative options, not to test your knowledge. The only right answer is what you would really choose.

Part 2- Your decision. 2/5
You will be given two options (option A and option B) and asked whether you choose option A or option B as in the below example.

<table>
<thead>
<tr>
<th>Option A</th>
<th>Option B</th>
<th>Please select A or B.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Part 2- Your profit. 3/5

If you choose A.
If you choose option A then you will get €1 as your profit for this decision.

<table>
<thead>
<tr>
<th>Option A</th>
<th>Option B</th>
<th>Please select A or B.</th>
</tr>
</thead>
<tbody>
<tr>
<td>€1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

If you choose B.
Option B can lead to either €3 or €0 profit depending on your luck. In this format, the computer will randomly select a number between 1 and 20 (including 1 and 20). For the below example, the separation line (i.e., 4—5) means that you will get €3 for this decision if the randomly selected number falls between 1 and 4 (including 1 and 4), or you will get €0 for this decision if the randomly selected number falls between 5 and 20 (including 5 and 20).

<table>
<thead>
<tr>
<th>Option A</th>
<th>Option B</th>
<th>Please select A or B.</th>
</tr>
</thead>
<tbody>
<tr>
<td>€1</td>
<td>1 4 5</td>
<td></td>
</tr>
</tbody>
</table>

Part 2- Total number of decisions. 4/5
When you select one of the options, a new row will appear to prompt you to choose between option A and B again given a different separation line for option B. You will make this decision for 15 times, each time with a different separation line for option B. You can click option A or B in the
below given example to see how a new row will appear once you made your decision and how the separation line for option B shifts on the new row.

**Part 2- Your payment.**

At the end of part 2, the computer will choose one of the 15 rows randomly and your decision in that row will determine your actual payment from part 2. Your payment will be equal to your payoff within the chosen row. Your earning for this part will be in €, thus you will get your payoff in the chosen round directly without applying a conversion rate.

At the end of the experiment, you will be able to see all of your decisions and the row randomly selected for your payment on a table.