Information Provision in Dynamic Contests: An Experimental Study

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Abstract

Many real-world innovation contests and R&D races have an end goal with uncertain feasibility. This uncertainty may make participants abandon the contest even when the goal is feasible. In exerting effort towards the goal, participants learn about its feasibility from their own progress (or lack thereof) as well as the progress of their competitors. This study uses a novel real-effort experiment to examine the role of information provision in dynamic winner-take-all contests. Specifically, we study three information provision mechanisms: (1) Darkness, where players receive no information about their opponent; (2) Daylight, where players are immediately notified as soon as their opponent makes progress; and (3) Silent Period, where players are told they will receive information about the status of their opponent at a pre-determined time. Our results show that, when the environment is highly uncertain and the goal is feasible, the Silent Period mechanism increases the likelihood that players complete the uncertain part of the contest compared to the other mechanisms. These results suggest that contest designers should adopt the Silent Period mechanism when they face problems that are highly uncertain. By contrast, we find that the same mechanism does not generally improve the earning rates of contest participants.

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1 Introduction

Contests are increasingly used as a mechanism for solving open-ended problems. Participants compete by putting effort to accomplish a goal and the winners, if any, are awarded a prize. These contests range from large, well-publicized competitions, like the Netflix Prize and the Heritage Prize, to everyday competitions on platforms like Top Coder, Kaggle, and InnoCentive. The increasing popularity of problem-solving contests has generated a number of design questions, including the optimal number of prizes, prize amount (Moldovanu and Sela, 2001; Terwiesch and Xu, 2008), number of contestants (Boudreau et al., 2011), and contest structure, e.g. multiple-round knock-out tournament (Moldovanu and Sela, 2006). Most studies in this stream of research model contests as static games where participants make a one-time decision regarding how much effort to exert. However, in reality, many of these contests unfold over time, with players making multiple or even continuous effort decisions based on the information they learn about their competitors and the underlying environment. An emerging theoretical literature has begun to explore these dynamic aspects, with a focus on how contest designers can leverage the provision of information as an incentive device to extract greater participant effort (Halac et al., 2017; Bimpikis et al., 2019).

In this paper, we contribute to the field of dynamic contest design by using a laboratory experiment to study the role of information in these contests. A distinguishing characteristic of these contests is that they entail a high degree of uncertainty regarding the feasibility of the end goal. In particular, the goal may be one that is unattainable or one that requires too many resources so that it makes little economic sense to pursue. The Netflix Prize and Heritage Prize offer good examples of such contests. In the Netflix prize, participants were asked to provide a recommendation algorithm that improves on Netflix's in-house algorithm by a margin of at least 10%, with the winning solution receiving a million-dollar prize. Netflix acknowledged this uncertainty in their contest announcement, saying "We suspect the 10% improvement is pretty tough, but we also think there is a good chance it can be achieved. It may take months; it might take years."[1] Despite this uncertainty, the goal was achieved and the prize was awarded. On the other hand, the Heritage Prize offered $3 million dollars for a solution that could use patient data to predict hospital readmission rates, with a pre-specified target prediction error. The contest ended after two years when none of the approximately 13,000 participants were able to achieve that goal.

Our experiment examines contests with uncertain end goal feasibility where participant progress towards the goal happens over time and is a *stochastic* function of effort. In such contests, a lack of progress towards the goal could indicate that the goal is infeasible or that it is feasible but the agent is unlucky in mapping her effort to goal progress. These two scenarios elicit different responses from players: the former implies that players should abandon the contest, whereas the latter leaves open the possibility that a player can make progress with continued effort. Because of this, information about the progress of *other players* allows players to update their beliefs about the feasibility of the goal not just from their own experience, but also from observing the progress (or lack thereof) of

[1] See https://www.netflixprize.com/rules.html, retrieved on December 12, 2019.

others. This information may have opposite effects. It may have an *encouragement* effect if a player observes that the other player achieves partial progress and thus ascertain the goal is feasible. In this case, they adjust their beliefs about the feasibility of the goal upwards. On the other hand, this information may have a *competition* effect if players become more pessimistic about their chances of winning after observing the progress of other players. In this case, they may be deterred from continuing to put effort into the contest.

The goal of our experiment is to examine how uncertainty interacts with three information provision mechanisms. Specifically, we answer the following questions: 1) how do contest participants behave in the presence of uncertainty and competition? and 2) how is this behavior shaped by the different information provision mechanisms we consider?

In addition to the above questions, we examine the earning rates of participants under the different information mechanisms – an aspect that usually receives less attention in the contests literature. Earning rates are an important consideration in contest design, as greater earning rates imply that players are more inclined to participate in contests, in turn leading to sustained gains for both the platforms and firms that organize these contests. From the discussion in the previous paragraph, it is reasonable to expect that if information has an effect on how players make their decisions, then it should also impact their earning rates, In our study, we examine whether this impact is indeed present in our experimental results.

Contribution and Results: Our study makes several important contributions to the literature. First, we use a novel experimental design that embeds uncertainty in a dynamic environment in order to study how players react to information in the presence of encouragement and competition. Second, we provide evidence for how players in this setting respond to different information mechanisms and, importantly, which mechanisms are suitable for alleviating some of the undesirable outcomes of uncertainty about goal feasibility. Finally, we provide evidence for the impact of the different information mechanisms on the earnings rates of participants. We elaborate on each of these points below.

In our experimental design, we model an innovation task with uncertain feasibility as a knapsack problem. In this problem, a player is given a set of items of different weights and values, along with a knapsack of a certain weight capacity. The problem the player must solve is to find a subset of items that fits into the knapsack and is worth a total of at least $\$y$. We call an instance of the problem **infeasible** if, for a given value of $\$y$, no such subset exists; otherwise, the instance is feasible. Because the knapsack problem is NP-Complete, finding such a subset – if it exists – is not easy. In particular, a player cannot determine if the inability to find a solution reflects a lack of feasibility or insufficient effort.

To model this problem within a dynamic environment, we closely follow the theoretical model developed in Bimpikis et al. (2019). We set each contest to consist of two sequential stages, with each stage containing a knapsack problem with a pre-specified goal (for example, fit items worth $50 or more in the knapsack). The player who finishes both stages first wins a prize while the runner-up receives nothing. In this setup, the second-stage knapsack problem is always feasible, but cannot be started until the first stage is completed; thus, finishing the first stage constitutes *partial progress* towards the final goal.[2] By contrast, the first-stage knapsack problem may not be feasible. In this case, partial progress (and therefore contest completion) is impossible. In our contest, players are given a prior on the feasibility of the first stage, which corresponds to different levels of uncertainty: **No** uncertainty (first stage is 100% feasible), **Mild** uncertainty (20% chance first stage is infeasible), or **High** uncertainty (40% chance first stage is infeasible).[3] As long as the contest is active, i.e. as long as no player has completed both stages, *players can choose to quit* at any time and exercise an outside option.

In addition to varying the level of uncertainty, we vary the information mechanism used. We consider three information provision mechanisms. The **Daylight** mechanism corresponds to a real-time leaderboard design, where the current status of the contest is always visible. In this mechanism, a player is informed as soon as her opponent completes the first stage. This information signals that the first stage is feasible, immediately resolving any uncertainty. Conversely, in the **Darkness** mechanism, no opponent information is made available at any point, unless the opponent has finished the entire contest, indicating that the contest is over. In our final information treatment, the **Silent Period** mechanism, participants receive opponent information, i.e. whether a player is in the second stage or not, only once a pre-specified amount of time has elapsed.

We are interested in understanding the interaction between these information mechanisms and problem uncertainty, and how this interaction affects subject behavior. Similar to Bimpikis et al. (2019), our experiment associates uncertainty with only the first stage of the contest. This allows us to isolate the interaction of uncertainty and information by studying the outcomes of the first stage. Note that the second stage is necessary to capture both encouragement and competition effects, as it allows us to examine whether players who are still in the first stage choose to exit or to continue competing upon receiving news about their opponent advancing to the second stage. We are interested in agent-level and contest-level outcomes. For the former, we are interested in what makes subjects decide to quit the contest. For the latter, we are interested in i) which mechanisms increase the chances of partial progress, i.e. which mechanisms increase the likelihood that at least one player will overcome uncertainty and complete the first stage, and ii) the number of active players in the second stage, i.e. which mechanisms increase the likelihood that both players remain active all the way to the end of the contest.[4]

We provide four main results, corresponding to the main theoretical predictions from Bimpikis et al. (2019). We first study quitting behavior in the Daylight and Darkness mechanisms. Result 1 shows that in the absence of uncertainty, a player quits when she learns she is trailing behind her

[2]The setup with multiple stages resembles some contests like the Netflix prize, where different stages correspond to different milestones. For example, while the final goal of the prize was to break the 10%-improvement barrier, an intermediate milestone provided an award for breaking the 5%-improvement barrier as well; thus, reaching the 5% improvement constitutes partial progress towards the goal.

[3]As we discuss in Section 4, this uncertainty is implemented by picking a game randomly from a pool of games where some games are infeasible, i.e. have an unattainable target value $\$y$.

[4]Assuming independent discoveries, the likelihood that at least one contestant solves the problem weakly increases with the number of contestants.

competitor, but continues playing in the absence of such information. Hence the Daylight mechanism leads to more players quitting. Result 2 shows that there is a significant increase in quitting when uncertainty is present, but that this increase comes mostly from those subjects playing under the Darkness mechanism, i.e. uncertainty increases quitting in subjects playing under the Darkness mechanism much more than it does for subjects playing under the Daylight mechanism (where quitting behavior is still largely due to players trailing their opponent). Thus, we find no evidence for the encouragement effect in our experiment. Instead, we find that the competition effect leads to players quitting under the Daylight treatment and uncertainty leads to players quitting under the Darkness treatment.

These quitting dynamics give rise to interesting contest-level outcomes. Result 3 shows that when uncertainty is high, the Daylight and Darkness mechanisms offer distinct advantages. Partial progress is more likely under the Daylight mechanism, possibly because the majority of quitting under this mechanism comes from players trailing their opponents, which implies that players usually play until one of them completes the first stage, which in turn ensures partial progress if the stage is indeed feasible. By the same token however, since subjects who trail their opponents usually quit under the Daylight mechanism, it is unlikely that both players advance to the second stage, hence the Darkness mechanism offers an advantage when it comes to both players staying in the contest conditional on the first stage being completed.

This leads to the central result of the paper. Result 4 shows that the Silent Period mechanism combines the benefits of the Daylight and Darkness mechanisms. For a carefully-chosen revelation time, the design decreases quitting, increases the chance of partial progress, and ensures both players remain in the contest. These simultaneous effects reflect the incentive for a player to remain in the contest until the designated time when a feasibility signal is revealed. It also avoids the discouragement that occurs when a player learns she is trailing in the contest. This willingness to remain in the contest increases the chances that a player may make a breakthrough in the interim, thereby increasing the chance of partial progress and the chance that both players remain in the contest through the second stage.

While our paper focuses primarily on subjects' behavioral reactions to different information mechanisms, we also examine the impact of these mechanisms on participant earning rates, defined as final earnings divided by the time spent on the contest. We find that the information treatments yield similar earning rates for the winners, but that the Daylight mechanism yields the best earning rate for losers whenever the contest is completed. This is because these players quit the contest immediately once their opponent makes progress and exercise their outside option. This happens significantly more under the Daylight mechanism compared to the other two mechanisms where: a) subjects may not have the opportunity to quit and exercise their outside option if their opponent wins while they are still playing or b) subjects may take longer before deciding to quit, resulting in a decrease in their final earning rate. Interestingly, the situation is reversed when the contest is not completed. In this case, earning rates are significantly negatively impacted under both the Daylight and Silent Period mechanisms.

The rest of the paper is organized as follows. We review the related literature in Section 2, summarize the theoretical framework in Section 3, and present our experimental design in Section 4. Section 5.1 lays out the differences between the Daylight and Darkness mechanisms and tests several hypotheses comparing their performance on our criteria of interest. Section 5.2 introduces the Silent Period design as well as our hypotheses regarding its comparative performance. Section 5.3 discusses the earnings rates of participants under the different information mechanisms. Lastly, Section 6 concludes with a discussion of our results in the context of the theoretical predictions as well as their implications for contest design.

2 Literature Review

Our research is closely related to both the theoretical and experimental literature on contests. We refer the reader to Konrad (2009) for a review of the earlier theoretical literature in this field and to Dechenaux et al. (2015) for a comprehensive survey of the respective experimental literature. In what follows, we summarize results from the most closely related theoretical models and experiments.

Within the experimental literature, the stream of research closest to our work is the area related to dynamic races, where players compete towards a goal and the first player to make it to the goal wins. Within the theoretical literature, our study draws on the seminal theoretical work of Harris and Vickers (1987) in which they set up a sequence of component contests. In their model, contestants receive full feedback regarding the outcome of the stage game at the end of each component contest. This model yields several testable predictions. First, it predicts that the leader in a race will expend greater effort than the other participants. Second, it predicts that effort will increase as the gap between competitors decreases. In an experiment designed to test these predictions, Zizzo (2002) finds that leaders do not invest significantly more than followers unless the gap is extremely wide, whereas followers invest less as the gap increases. In a related experiment, Mago et al. (2013) set up a best-of-three contest where the first player to win two stages obtains the final prize. Their results show that leaders expend more effort than followers. Both the theoretical and experimental studies assume there is technological uncertainty regarding how effort translates to progress. In our study, we include not only technological uncertainty, but environmental uncertainty as well, namely uncertainty regarding the feasibility of the goal. This extra dimension of uncertainty gives rise to different dynamics compared to those found in the dynamic race studies. Importantly, our focus is on how different information provision mechanisms perform in these uncertain environments.

A related literature examines the effects of feedback on contestant behavior. Within this area of research, Ederer (2010) develops a theoretical framework to investigate the effects of (strategic) feedback among heterogeneous agents in a two-period tournament mode and proposes several competing effects with no unequivocal endorsement of interim performance feedback. In a related experiment, Ederer and Fehr (2007) find that principals in a tournament exhibit lying aversion. While this aversion renders their feedback informative, this feedback is still discounted by agents. Our study differs from these in that we specify when participants receive feedback and examine the effects of that feedback when the environment is uncertain.

In addition to the experimental literature based on abstract tasks, our study shares similarities with experiments based on real effort tasks. In one study using piece-rate and rank-order tournaments, Eriksson et al. (2009) study the impact of relative performance feedback on subject performance on an addition task under three conditions: no feedback, halfway feedback, and continuous feedback. While they find no effect under the piece-rate scheme, they find positive peer effects in the rank-order tournament, that is, those who trail remain in the contest and leaders sustain their effort. In another experiment examining the effect of feedback on the racing choices of high school runners, Fershtman and Gneezy (2011) find that continuous feedback on opponent performance increases the likelihood a runner will quit compared to the case when runners receive only post-race running times. Our study differs from these in that we test the effect of information provision under conditions of environment uncertainty.

In addition to the literature on the effect of feedback, our study is related to the literature on the design of innovation contests. In this domain, Taylor (1995) analyzes a multi-period tournament game where there is no pre-specified goal, but an award is given out to the agent who obtains the best outcome. Terwiesch and Xu (2008) provide a theoretical analysis and categorization of different innovation tasks based on the respective relative importance of expertise and uncertainty in the performance function. In a simultaneous innovation contest, they demonstrate that the benefits of increased participation, or diversity, can mitigate its negative effect on average participant effort in ideation or trial-and-error projects.

In another study, Jeppesen and Lakhani (2010) empirically examine the effect of uncertainty on effort on InnoCentive, a platform where many challenges were previously unsuccessfully attempted by internal scientists from different industries, and therefore involve an important uncertainty component in the performance function. They find that both technical and social marginality play an important role in explaining individual success in specific problem-solving. Their observed positive effect of diversity in solving highly uncertain problems is consistent with the predictions of Terwiesch and Xu (2008) for ideation or trial-and-error projects.

Our setup examines a competitive setup in an uncertain environment, but the role of feedback about relative performance was also recently studied as a mechanism to bolster productivity in organizations. Song et al. (2017) show that providing public feedback about top performers in a hospital has a measurable positive effect on worker productivity. In a similar vein, recent work by Cadsby et al. (2019) examines effects of private versus public feedback about relative ranking on worker and student performance, and how these effects are moderated by risk attitudes.

As mentioned, our study focuses on the role of information in dynamic contests. The literature in this field is quite recent. Theoretically, our contest structure follows the framework in Bimpikis et al. (2019). However, our findings about the relative strengths and weaknesses of the different information mechanisms are different from the predictions outlined in their paper, and we discuss in Section 6 possible reasons for why that might be the case. In another theoretical study, Halac et al.

(2017) show that, when players can split the contest prize, providing no information about the status of the contest increases the incentive for contestants to experiment, and therefore increases the chance that someone reaches the goal. Our study differs from theirs in that we allow for partial progress and are thus able to study whether an encouragement effect exists. Finally, our paper shares some elements with the model of Choi (1991), who describes the encouragement effect that an opponent's progress can have. However, Choi does not study how the different information mechanisms affect player behavior. Finally, our paper also presents exploratory findings on how different information mechanisms contribute to participant earnings, which is an aspect that is absent in all of the above models.

3 Theoretical Framework

In this section, we outline a simplified version of the theoretical model in Bimpikis et al. (2019), adapted to our experimental setting.[5] In addition, we summarize some of their main results, which serve as a benchmark for our experimental design and hypotheses.

To begin, Bimpikis et al. (2019) consider an innovation contest with two identical agents, 1 and 2, competing for a final prize, R. The contest consists of two sequential stages, A and B, and the winner, if any, is the agent who finishes both stages first. To capture the uncertainty inherent in the environment, they assume that Stage A may or may not be feasible, while Stage B is always feasible. This means that if Stage A is feasible, then the entire contest can be completed. By contrast, if Stage A is infeasible, then no one can complete the stage and, consequently, no one can advance to Stage B, meaning the contest cannot be completed. In this model, whether Stage A is feasible is uncertain, and agents have a common prior p_A on its feasibility, i.e. $p_A = Pr(\text{Stage A is feasible})$.

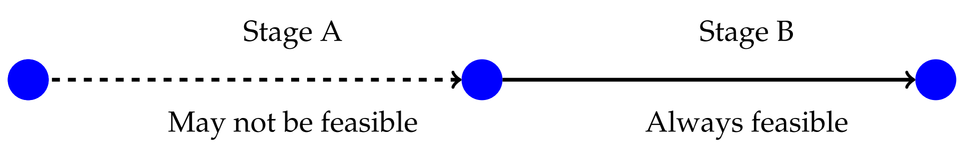

Figure 1: A dynamic contest with two stages, A and B.

Agent i puts effort $x_{it} \in [0, 1]$ towards finishing the contest at time t, and incurs an instantaneous cost of effort at a constant marginal cost. If Stage A is feasible, the breakthrough to complete the stage is described by a Poisson process whose rate is modulated by the agent's effort, so that for example if the process has rate λ and the agent puts effort x_{it} at time t then the effective arrival rate for that agent at t is equal to λx_{it}. If Stage A is infeasible then a breakthrough never arrives regardless of effort. Similarly, the breakthrough to complete Stage B (assuming an agent reaches that stage) is

[5] In Bimpikis et al. (2019), agents have to be incentivized (through payments) to share information (that can later be disseminated by the contest designer). This requirement adds a layer of complexity that is absent in our experiment, since we can observe everything that subjects do on their computers. This ability to continuously observe behavior allows us to focus on the effects of the different information mechanisms without worrying about these incentive issues or designer budget constraints. As such, the results from Bimpikis et al. (2019) are written to reflect this simpler setup.

described by a Poisson process with parameter μ, and the probability of completing the stage is again modulated by the agent's effort. Agents can choose to quit the contest at any time.

As Stage B is always feasible, we study the effect of the interplay between uncertainty and information provision that occurs within Stage A.[6] Specifically, we are interested in what mechanisms make players quit Stage A and what mechanisms make them persevere in the face of uncertainty and achieve *partial progress* towards the goal (i.e. complete Stage A when it is feasible). In particular, we study the effect of two information provision mechanisms: Daylight, whereby an agent is informed as soon as her opponent completes Stage A, and Darkness, where no information is revealed unless one of the agents has completed the entire contest. The following three propositions summarize the equilibrium predictions under these two mechanisms. A third information design, the Silent Period mechanism, is discussed in Proposition 4.

Proposition 1 (Bimpikis et al. (2019) Section 5: Environments with no Uncertainty)**.** *When $p_A = 1$, i.e when there is no uncertainty about the feasibility of the first stage, then:*

(i) Under the Daylight mechanism, both players continue playing in the contest until one player finishes Stage A. At this point, the trailing player quits the contest.

(ii) Under the Darkness mechanism, no player quits and the contest continues until someone achieves the goal and completes the contest.

The above proposition implies that, when there is no uncertainty in the environment, Stage A will be finished regardless of the information mechanism used. In such an environment, learning that an opponent has made progress has no upside since players already know that Stage A is feasible, and the player trailing her opponent quits when she learns that she is behind. This will later serve as the basis for Hypothesis 1.

On the other hand, the next proposition shows that in the presence of uncertainty, partial progress is not always going to happen —even when the stage is actually feasible— and we should expect to see more players quitting compared to environments with no uncertainty. Further, this impact depends on the initial beliefs that players have about the feasibility of Stage A. This serves as the basis of Hypotheses 2.

Proposition 2 (Bimpikis et al. (2019) Propositions 1 and 2)**.** *When $p_A < 1$, players follow a cutoff experimentation policy under both the Daylight and Darkness mechanisms: : players exert full effort until a specific time (different for each mechanism), at which point, they drop out if Stage A has not yet been completed. Further, the likelihood of quitting Stage A is a decreasing function in p_A (i.e. higher priors about feasibility lead to less quitting).*

The next proposition shows that, when Stage A is feasible, we should expect to see more players completing the Stage under the Darkness mechanism. However, conditional on a player completing

[6] As noted in the introduction. Stage B is necessary to capture both encouragement and competition effects, as it allows us to examine whether players in Stage A choose to exit or to continue competing upon receiving news about their opponent advancing to Stage B.

Stage A, we should see a greater likelihood of both players participating in Stage B under the Daylight mechanism. This leads to the next proposition.

Proposition 3 (Bimpikis et al. (2019) Proposition 3: Daylight vs. Darkness)**.** *The probability that the first stage is completed is higher under the Darkness mechanism. On the other hand, conditional on Stage A being completed, the likelihood that two players are active in Stage B is higher under the Daylight mechanism.*

The above proposition suggests that the two mechanisms offer complementary advantages. The Darkness mechanism increases the chances that uncertainty is resolved and partial progress occurs, while the Daylight mechanism increases the chances that, conditional on that event happening, both players remain active in the contest.

Finally, Bimpikis et al. (2019) consider the Silent Period information mechanism, which is an intermediate case that combines elements from the other two mechanisms. Under the Silent Period mechanism, the designer commits to not revealing the status of the contest, i.e. whether a player is in Stage B, until a certain pre-specified amount of time had elapsed. This leads to our final proposition.

Proposition 4 (Bimpikis et al. (2019) Propositions 5 and 6: Silent Period Design)**.** *There is a value $\bar{p}$ such that if $p_A < \bar{p}$, the Silent Period design with an appropriately chosen duration outperforms both the Daylight and Darkness mechanisms: that is, it increases the chances a player breaks through to Stage B and, conditional on someone reaching Stage B, it increases the chances that both players remain in the contest in Stage B.*

Note that the previous proposition states that the desirable effects of the Silent Period mechanism occur when subjects are pessimistic about feasibility, i.e. when the prior about feasibility is low.

In the next section, we outline our experimental design based on the framework presented above. As we will see in Section 5, some of the experimental results contradict some of the propositions. In Section 6, we discuss differences between the theory and our experimental setup that might lead to these discrepancies.

4 Experimental Design

In our experiment, we use a 3×3 factorial design to investigate the effects of uncertainty and information provision on contestant behavior. One factor represents the different levels of uncertainty about the feasibility of the problem being solved, with possible values of **No**, **Mild**, and **High** uncertainty, while the other represents the type of mechanism that provides information about competitor progress, with possible mechanisms of **Darkness**, **Daylight**, and **Silent Period**.

In our design, we use the knapsack problem as a proxy for an innovation task. In this sense, we follow Meloso et al. (2009), who use the knapsack problem to compare whether patents or markets are better information aggregators for tasks solutions requiring creativity. Formally stated, in the knapsack problem, there is a knapsack with weight capacity C and a set of N items. Item i is described by a tuple of non-negative numbers (w_i, v_i), where w_i is the weight of the item and v_i is its value. In this problem, we consider the following question: "For a target value y, can you produce a subset

$S \subseteq N$ of items such that $\sum_{i \in S} w_i \leq C$ and $\sum_{i \in S} v_i \geq y$?" This problem is NP-Complete, meaning that while it is easy to check whether a given set of items satisfy the condition in the question, it is difficult to produce such a set (if it exists). We call an instance of the problem *infeasible* if no such subset exists. Note that whether an instance of the knapsack problem is feasible or not depends on the target value y. There is no direct measure of how difficult an instance of a (feasible) knapsack problem is, but a recent framework for modeling its complexity is provided in Franco et al. (2018).

In addition to being easily tested in a lab setting, the knapsack problem also appropriately characterizes the problem uncertainty in our experiment: since the problem is difficult, a player who exerts effort and is unsuccessful in finding a subset that satisfies the conditions in the instance cannot be certain that no such subset exists (i.e. that the problem is infeasible). We discuss how we embed this problem in our experimental design in the "Contest Phase" section below.

4.1 Experimental Procedure

Each session of our experiment consists of 12 subjects, who are students at a large public university. After completing a training phase to become familiar with the task, each subject participates in three contests. A subject completes the session after completing both the training and contest phases. Subjects are paid a show up fee of $5 in addition to what they earn from the experiment.

Training Phase Before the contest begins, subjects are individually presented with an identical sequence of six training games of increasing difficulty. Each game is a knapsack problem with a given target value x. The games in the training phase are always feasible and subjects are informed of this fact at the beginning. The training games are designed to achieve two goals: to familiarize subjects with the knapsack problems and to measure each subject's skill level. Subjects are paid $1 per successfully completed game and that amount is announced before the training phase starts. In a given game, if a subject is unable to fit the target value into the knapsack, they can skip that game and receive no payment for it. Subjects have a total of 30 minutes to complete the training games. To represent each player's skill level, let s_{ij} be the score of player i in training game j, where $s_{ij} = 1$ if the subject finds the subset of items that achieve the target value and $s_{ij} = 0$ otherwise. Let t_{ij} be the time it takes player i to solve training game j, then the (normalized) skill of player i is measured according to the following formula:

$$skill(i) = \sum_{j=1}^{6} \frac{\frac{s_{ij}}{t_{ij}} - \min\limits_{i'} \dfrac{s_{i'j}}{t_{i'j}}}{\max\limits_{i'} \dfrac{s_{i'j}}{t_{i'j}} - \min\limits_{i'} \dfrac{s_{i'j}}{t_{i'j}}}.$$

After the training phase is completed, subjects are divided into three groups of four subjects of similar skills. Each group consists of subjects with adjacent skills. Thus, the first group contains the four subjects with the lowest skills, the second group the next four subjects and so on. We group subjects of similar skills together as the theoretical model assumes symmetry of abilities. Within each group, subjects participate in contests in a round-robin fashion, so that each subject plays three

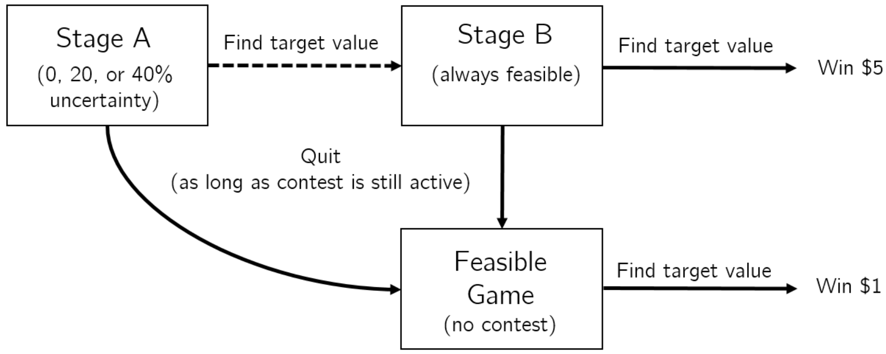

Figure 2: Contest Progress Diagram. The dotted arrow between Stage A and Stage B indicates that progress may not always be possible, due to the chance that Stage A can be infeasible (in the mild and high uncertainty treatments). A player who finishes both stages earns $5, while a player who quits at any time while the contest is active, i.e. while the opponent is still playing, gets to play a non-competitive consolation game that earns them $1.

contests, one against each member of his group. Therefore, we observe a total of 6 contests in a group and 18 contests per session.

Contest Phase Once the training phase is complete, subjects are presented with the instructions for the contest phase and given a short multiple-choice quiz that ensures they understand the instructions.[7] The contest phase then starts. In the contest phase, subjects are paired up within each group and participate in a real-effort two-stage contest. We refer to the first stage as Stage A and to the second stage as Stage B. Each stage consists of a single knapsack problem and is completed if a contestant finds the target value y. Stage B cannot be started unless Stage A is finished, so that finishing the first game constitutes partial progress towards the goal. The contestant who first completes Stage B wins a prize of $5 while her opponent receives nothing. A contestant can choose to quit the contest at any point as long as the contest is active (i.e. as long as her opponent has not completed Stage B), with the outside option of solving a knapsack problem similar to the training games, i.e. a feasible, non-competitive game, for which she receives a prize of $1 if she finds the target value, and zero otherwise. A player who does not quit and continues to play until her opponent has completed both stages receives $0. Thus the three possible outcomes and payoffs for any player are: i) win the contest and receive $5, ii) quit while the contest is active and get $1 for completing the feasible game or $0 otherwise, or iii) neither win nor quit, and receive $0 once the other contestant has completed the entire contest.

The experimental instructions and the list of knapsack games are included in Appendices B and C, respectively. The software is archived on Github.[8] Data are available from the authors upon request.

[7]Subjects receive 20 cents for each correct answer. They can earn up to $1 for answering all quiz questions correctly.

[8]The authors will provide a link to the software hosted on Github prior to publication. The link cannot be provided during the review process as it will violate anonymity.

4.2 Treatments

As mentioned, we implement a 3×3 complete factorial design, with one factor representing the levels of uncertainty and the other representing the information provision mechanism.

Uncertainty (within-subject): A contest where Stage A is infeasible cannot be completed since it is not possible for any player to reach Stage B. To distinguish our uncertainty condition, subjects are given a prior on the probability of that event before the contest begins. For example, they are correctly told that the first game in the contest they are about to play has a 20% chance of being infeasible. We produce an infeasible game by taking a feasible game with optimal target M (where M is the maximum value that can be fit into the knapsack) and slightly increasing the target value to $y > M$. In all treatments, since Stage B is always feasible, a subject who completes Stage A no longer has any residual uncertainty about the feasibility of the end goal.

The three uncertainty levels are as follows. The likelihood that a contest is infeasible can be 0%, 20%, or 40%. The first treatment is a benchmark with no uncertainty, meaning that it is always possible for players to to finish Stage A (and consequently, the contest), whereas the other two cases represent mild (20% chance of being infeasible) and high (40% of chances being infeasible) uncertainty. The progress of the contest is summarized in Figure 2, which is also the diagram that is shown to subjects when they receive the instructions for the experiment.

In the contest phase, each subject plays three contests in a row, each against a different opponent within his group. The problems that players face in each contest are given in Appendix C. In the treatment with no uncertainty, the target value for the first game of a contest is the *optimal* solution to the knapsack problem, i.e. it is not possible to fit items worth more than this value in the knapsack. This means that subjects play the games exactly as written in Appendix C. To set the parameters for the mild uncertainty treatment, a number in $(0, 1)$ is generated uniformly at random prior to the contest, and if the number is less than or equal to 0.2, then we make the first game of the contest infeasible, so that subjects are presented with a slightly-inflated target value that cannot be fit in the knapsack;[9] if the number is above 0.2 then the game is feasible and the target value is again equal to the optimal solution as given in the Appendix. Subjects play the game knowing that they are in the first scenario (game is infeasible) with probability 20% or in the second scenario (game is feasible) with probability 80%. A similar procedure is used for the high uncertainty treatment, but with a threshold of 0.4 instead of 0.2.

Information Provision Mechanisms (between-subject): To distinguish the information provision mechanisms, we change if and when information about participant progress is provided to subjects. In the Daylight treatment, participants receive information on the position of their opponent at all times, so that both contestants know exactly which stage the other one is in throughout the contest's duration. By contrast, in the Darkness treatment, participants receive no information about the op-

[9]How we increment the target depends on the values in the problem. For example, in Contest 1 Game 1 in Appendix C, the values of all items end in either 0 or 5, and hence the modified infeasible target should also end in one of these values since otherwise it is clear that it is not possible to fit that amount into the knapsack.

Table 1: Features of Experimental Conditions

Information Provision	No. of Subjects	Pr(Stage A is infeasible) 0%	20%	40%	Total no. of contests (feasible)
Daylight	120	59 (59)	57 (49)	58 (37)	174 (145)
Darkness	120	57 (57)	57 (48)	60 (34)	174 (139)
Silent Period	120	60 (60)	60 (44)	60 (35)	180 (139)

Notes: Our dataset contains a total of 528 contests. The numbers in parentheses indicate the number of feasible contests in the corresponding treatment. The first stage of each contest is always attempted by two subjects, for a total of 1056 observations of that stage under the different conditions.

ponent unless one of the contestants finishes both stages and wins the contest. Finally, in the Silent Period treatment, the experimenter informs participants at the beginning of the contest that they will learn about their positions only after a certain pre-specified amount of time has elapsed (provided neither subject has finished the entire contest nor both subjects have quit prior to the announcement time).

To examine the effect of different revelation time durations on the choices that players make, we select a few times for each game in the Silent Period and randomize among these selected times whenever contestants play that particular game. To obtain our set of possible revelation times, we first conduct the Darkness treatment. In this treatment, we construct an empirical distribution for each game of the time it takes the first player to complete Stage A in all Darkness sessions. We then choose times at the $50^{th}, 60^{th}, 70^{th}$, and 80^{th} percentiles of that distribution. Thus, for each game i, we have a set of four possible revelation times T_i, corresponding to the values described above. A time is chosen randomly from this set whenever this game is played in the Silent Period treatment.

Note that, while information on participant progress directly informs contestants about the status of contest, it also affects their beliefs about the feasibility of Stage A by providing information about whether their opponent has been able to complete that stage.

Table 1 summarizes the features of experimental conditions. For each of the three information provision mechanisms, we conduct 10 independent sessions at the Behavioral Economics and Cognition Experimental Lab at a large public university in the United States. As mentioned, each session consists of 12 subjects. No subject participates in more than one session. This design gives us a total of 30 independent sessions and 360 distinct subjects.[10] Our subjects are students from a large public university in the United States, recruited using ORSEE (Greiner, 2015) as well as a separate subject pool from the university's business school. The sessions comprise a total of 528 contests, including 174 Daylight, 174 Darkness, and 180 Silent Period contests. Of these contests, 423 are feasible, with 145 (139, 139) under the Daylight (Darkness, Silent Period) condition.

[10]Before starting the sessions, we ran two pilot sessions to test the software and the interface. Data from the pilot sessions are not included in the analysis.

5 Results

This section reports our experimental results. We discuss our results for the Daylight and Darkness mechanisms in Section 5.1 and those for the Silent Period mechanism in Section 5.2.

Our results are divided into i) results about player behavior; specifically, we ask what makes players decide to quit and how does uncertainty contribute to that decision? And ii) results about contest-level outcomes. We focus on contests where Stage A is feasible but subjects are uncertain about this fact, since if Stage A is infeasible then there is only one possible outcome: the stage is never completed and both subjects eventually quit.

To study these questions, we define the *agent-level* binary outcome variable **Quit**, which is equal to 1 if the subject quits Stage A and 0 otherwise. We also define the following *contest-level* binary outcome variables: **Partial Progress** and **Both Advance**. The Partial Progress variable is equal to 1 if uncertainty is resolved and Stage A is completed by at least one player, otherwise it is equal to 0. On the other hand, a contest designer is sometimes interested in having as many active participants as possible in the contest, and the variable Both Advance measures whether, conditional on Stage A being completed, both players reach Stage B or not.[11] In particular, Both Advance is equal to 1 if *both* players complete Stage A and advance to the second stage, and is equal to 0 otherwise. Thus Both Advance = 1 implies that Partial Progress = 1 but not vice versa.

5.1 Daylight versus Darkness

To examine the questions above, we start with the benchmark case when there is no uncertainty about the feasibility of Stage A. In this case, Proposition 1 suggests that there should be no significant difference between the Daylight and Darkness mechanisms when it comes to Partial Progress, i.e. at least one player always completes Stage A. However, there should be a larger effect of the Daylight mechanism on the likelihood a player will quit the contest upon learning that she is trailing behind her opponent. This prediction is summarized in the following hypothesis.

Hypothesis 1 (Daylight vs. Darkness: Contests with no Uncertainty)**.** In the absence of uncertainty, there should be no difference in Partial Progress between the Daylight and Darkness treatments. However, the Daylight treatment increases the likelihood that those who are trailing their opponent will quit the contest.

Under the Darkness mechanism, since players have no access to information about their opponents, they are more inclined to continue playing the contest even when their opponents have reached Stage B compared to those who receive opponent progress information. Under the Daylight mechanism, players immediately see when their opponents advance to Stage B, and because there is no uncertainty to resolve, this information is strictly bad news and makes trailing players learn that their

[11] Assuming independent discoveries, the likelihood that at least one contestant solves the problem weakly increases with the number of contestants.

Table 2: Contests with no uncertainty: Logistic Specifications

	Dependent variable:		
	Quit	Partial Progress	Both Advance
	(1)	(2)	(3)
Daylight	0.173^{**}	0.001	-0.062
	(0.070)	(0.036)	(0.086)
	$[0.057]$	$[1.0]$	$[0.611]$
Silent Period	0.059	-0.014	-0.117
	(0.069)	(0.038)	(0.09)
	$[0.53]$	$[0.8]$	$[0.326]$
No. of contests	176	176	169
Observations	352	176	169

Notes: The omitted category is Darkness. Coefficients represent average marginal effects and robust standard errors in parentheses are clustered at the group level, with *p<0.1; **p<0.05; ***p<0.01. False discovery rate adjusted q-values in square brackets correct for multiple testing (Benjamini and Hochberg, 1995; Benjamini et al., 2001).

chances of winning the contest are slimmer. In this case, they are more likely to quit so that they can play the consolation game. Our first result supports this prediction.

Result 1. In the absence of uncertainty, players are 17 percentage points (p.p.) more likely to quit under the Daylight treatment. Despite this, Partial Progress is still equally likely under the Daylight and Darkness treatments.

Table 2 reports three logistic specifications in contests with no uncertainty. The dependent variables are (1) Quit; (2) Partial Progress; and (3) Both Advance. The independent variables include treatment dummies, Daylight and Silent Period, with Darkness being the omitted category (throughout the paper). In all specifications, robust standard errors are clustered at the group level, as each group of four contestants interacts only within its group during a session. In these and subsequent analyses, we report the false discovery rate adjusted q-values in square brackets to correct for multiple hypothesis testing (Benjamini and Hochberg, 1995; Benjamini et al., 2001). We follow the convention of using 5% (respectively 10%) cutoff for p-values (respectively q-values) to claim statistical significance (Efron, 2010).

Support. From Specification (1) in Table 2, we see that subjects quitting is significantly more likely under the Daylight treatment. Specifically, the probability of quitting increases by more than 17 percentage points (0.173, $p = 0.013$, $q = 0.057$) and 96% of players who quit under the Daylight treatment are those who are trailing their opponent. There are no differences between the two treatments when it comes to the contest-level outcomes, Partial Progress and Both Advance ($p > 0.1$). ■

It is interesting to note that there is a significantly larger number of subjects who quit Stage A under the Daylight mechanism, and yet Partial Progress is comparable across both mechanisms. The reason for this is that the majority of quitting under the Daylight mechanism comes from players who trail their opponents, which means that for every trailing subject there is another subject who completes Stage A and therefore Partial Progress has already happened in that contest.

We next examine the effect of uncertainty on quitting behavior. Recall that Proposition 2 states that uncertainty should have a negative impact on players quitting, and that this effect becomes worse as players' priors about feasibility become more pessimistic. This leads to our second hypothesis:

Hypothesis 2 (Effect of Uncertainty)**.** Uncertainty increases the likelihood that a player quits Stage A. As the level of uncertainty increases, players quit Stage A more often, which leads to a smaller number of contests with partial progress and both players advancing to Stage B.

When there is a chance that Stage A is infeasible, players who are unable to complete the stage start revising their priors about feasibility downwards in the absence of news about their opponent's progress. According to Proposition 2, these players will quit Stage A after a certain point and therefore we should expect to see more players quitting when the feasibility of the goal is uncertain.

Table 3 reports three logistic specifications, with the independent variables being the treatment dummies, Mild Uncertainty and High Uncertainty, with No Uncertainty being the omitted category. Consistent with Proposition 2, our results show that high uncertainty has much stronger effects (in both magnitude and significance) on the outcomes of interest compared to mild uncertainty.

Result 2. Players are 9.8 p.p. (20.3 p.p.) more likely to quit Stage A under Mild (High) Uncertainty. For contest-level outcomes, high uncertainty significantly decreases the chances of Partial Progress and Both Advance by 23 p.p. and 16.5 p.p., respectively.

Support. Specification (1) in Table 3 shows that, as the level of uncertainty changes from No to Mild, the likelihood that subjects quit Stage A increases by 9.8 p.p. ($p = 0.04$, $q = 0.084$). On the other hand, high uncertainty increases the probability that subjects quit by 20.3 p.p. ($p < 0.0001$, $q = 0.001$). The difference between Mild and High uncertainty is significant at the 5% level (one-sided test for proportion, $p = 0.0281$).

Furthermore, High Uncertainty has strong and significant effects on Partial Progress and Both Advance, reducing the first by 23.4 p.p. ($p = 0.0031$, $q = 0.0168$) and the second by 16.5 p.p. ($p = 0.0038$, $q = 0.0163$). The difference between Mild and High Uncertainty is significant at the 1% level (one-sided test for proportion, $p = 0.004$). ■

In terms of magnitude and significance, Result 2 shows the most pronounced negative effects of uncertainty in the high uncertainty condition. Given this, we focus the remainder of our analysis in this section on our results under high uncertainty and relegate the results under mild uncertainty to Appendix A.

The result that uncertainty leads to more players quitting is in line with theory. It is important to note that the majority of this extra quitting comes from subjects playing under the Darkness treatment, whereas quitting is more or less unaffected by uncertainty in the Daylight treatment. Indeed, Table 7 in Appendix A shows that the quitting behavior due to uncertainty is almost localized to subjects playing in the Darkness treatment, with Specification (1) showing strong and significant effects on

Table 3: Effects of Uncertainty: Logistic Specifications

	Dependent variable:		
	Quit	Partial Progress	Both Advance
	(1)	(2)	(3)
Mild Uncertainty	0.098^{**}	-0.104^{*}	-0.092
	(0.047)	(0.060)	(0.058)
	[0.084]	[0.14]	[0.196]
High Uncertainty	0.203^{***}	-0.234^{***}	-0.165^{***}
	(0.053)	(0.080)	(0.056)
	[0.001]	[0.0168]	[0.0163]
No. of contests	284	284	255
Observations	568	284	255

Notes: The omitted category is No Uncertainty. Coefficients represent average marginal effects and robust standard errors in parentheses are clustered at the group level, with *p<0.1; **p<0.05; ***p<0.01. False discovery rate adjusted q-values in square brackets correct for multiple testing (Benjamini and Hochberg, 1995).

quitting in that treatment. On the other hand, Specification (2) in the same table shows that high uncertainty only has a marginal effect on quitting in the Daylight treatment and that mild uncertainty has no effect at all.

Summary of Quitting Behavior İt is worth pausing before the next result to review what we have learned about quitting behavior from Results 1 and 2. When there is no uncertainty, the ability of players to observe each other in the Daylight mechanism increases the chances that players quit when they are trailing their opponents. Uncertainty does not change this behavior and does not increase quitting under the Daylight mechanism. Conversely, while the inability of players to observe each other in the Darkness mechanism leads to less quitting in the absence of uncertainty, it is associated with significantly more players quitting when uncertainty is present.

The conclusion from the previous paragraph is that while subjects quit under the two information mechanisms for seemingly different reasons, the effects of the mechanisms on quitting even out when uncertainty is present. Indeed, we see that in both mildly and highly uncertain contests, there is no significant difference between the effects of the two information mechanisms on the likelihood that a subject quits Stage A: Table 4 reports three logistic specifications for the highly uncertain environments. The Daylight coefficient in Specification (1) shows that the Daylight and Darkness mechanisms are remarkably similar when it comes to subjects quitting Stage A (0.002, $p > 0.10$). Specification (1) in Table 8 in Appendix A reports similar results for the mildly uncertain environments.

While, in the presence of uncertainty, the Daylight and Darkness mechanisms yield similar quantitative effects on Stage A agent-level quitting behavior, we are also interested in the respective effects of the mechanisms at the contest design level. To examine the contest-level results, we recall Proposition 3 that conjectures that the Darkness mechanism leads to a higher chance of Partial Progress, while the Daylight mechanism leads to a higher chance that both players advance to Stage B (given

Table 4: Effects of different information mechanisms in highly uncertain environments: Logistic specifications

	Dependent variable:		
	Quit	Partial Progress	Both Advance
	(1)	(2)	(3)
Daylight	0.002	0.124^{*}	-0.285^{**}
	(0.077)	(0.064)	(0.117)
	[1.0]	[0.093]	[0.059]
Silent Period	-0.181^{**}	0.148^{**}	0.154
	(0.08)	(0.064)	(0.142)
	[0.083]	[0.071]	[0.42]
No. of contests	106	106	87
Observations	212	106	87

Notes: The omitted category is Darkness. Coefficients represent average marginal effects and robust standard errors in parentheses are clustered at the group level, with *p<0.1; **p<0.05; ***p<0.01. False discovery rate adjusted q-values in square brackets correct for multiple testing (Benjamini and Hochberg, 1995; Benjamini et al., 2001).

that a player completes Stage A). We outline these conjectures in the following hypotheses.

Hypothesis 3 (Daylight vs. Darkness in Highly-Uncertain Environments)**.** In the presence of high uncertainty, the Darkness treatment increases the likelihood of partial progress, i.e. it increases the chances that uncertainty is resolved and at least one player completes Stage A. On the other hand, conditional on one player completing Stage A, the Daylight mechanism increases the likelihood that there are two players in the second stage.

The theoretical reasons behind Proposition 3 and Hypothesis 3 are the following: when neither player is able to make progress, beliefs about feasibility decline at a faster rate when players can observe each other compared to when they cannot, since in the latter case a player who is unable to make progress uses only her own experience to update her beliefs. This means that in the absence of progress players become pessimistic faster under Daylight and therefore are more likely to quit. This should be reflected in lower Stage A completion rate and lower Partial Progress under Daylight.

For both players advancing, Proposition 3 states that under Daylight, when players learn that their opponent has advanced to Stage B, all their uncertainty about feasibility is resolved. Thus they become encouraged and are more likely to continue in Stage A until they too successfully reach Stage B.

The next result shows that we observe the *opposite* behavior in our experiment:

Result 3. Compared to Darkness, the Daylight mechanism marginally increases the likelihood of partial progress (i.e., that at least one player completes Stage A) by 12 p.p. On the other hand, the Daylight mechanism significantly decreases the likelihood that both players advance to Stage B by 28 p.p.

Support. Specification (2) in Table 4 yields a positive and marginally significant coefficient for Daylight. It shows that Daylight increases the likelihood that at least one player breaks through to the second stage by 12.4 p.p. ($p = 0.053$, $q = 0.10$).

Specification (3) in Table 4 shows that conditional on one player advancing to Stage B, the Daylight mechanism decreases the likelihood that there are two players in the second stage by 28.5 p.p. ($p = 0.015$, $q = 0.059$). ■

Result 3 show that the behavior of subjects in our experiment contradicts the theoretical predictions in Proposition 3. This difference between the theoretical predictions and our findings may reflect participant beliefs about the skill level of their opponents. While the theory assumes all players have the same ability, and while we designed the experiment to approximate that assumption by including subjects of similar skills in the same group (and letting them know this fact), participants in the lab may still use the information provided about their opponent's progress to infer whether their opponent is more skillful than they are. Knowing that an opponent has advanced to Stage B not only resolves the uncertainty regarding the feasibility of the game, but may also inform the player who is trailing that her opponent is more skillful than she is. We discuss the differences between theory and experiment in more detail in Section 6.

Overall, our results in this section show that, in the presence of uncertainty, the ability of players to observe each other under the Daylight mechanism makes it more likely that they persevere in the contest, as a player is not likely to quit as long as she can see that her opponent has not quit either. However, once an opponent advances to Stage B, the player who trails is likely to quit so that she can play the non-competitive consolation game. By contrast, it is possible that players who cannot observe each other under the Darkness mechanism are more likely to both end up quitting in Stage A because they believe that the stage is infeasible (c.f. Result 2). On the other hand, under the Darkness mechanism, players also do not learn if they are trailing and thus they may not immediately quit when their opponent advances to Stage B, which increases the chance that the trailing player herself finishes Stage A and that we end up with two players in Stage B.

The next section discusses the Silent Period mechanism, which is an information provision design that reveals information about opponent progress at a pre-specified time announced to participants at the beginning of the contest.

5.2 The Silent Period Mechanism

The Silent Period mechanism combines aspects of the Daylight and Darkness mechanisms. It is parameterized by a time τ, and is structured like the Darkness mechanism over $[0, \tau]$, i.e. no information is revealed about the status of the contest during that period (unless a player completes the entire contest before τ). Assuming the contest is still active, then once time τ is reached, information is released and players learn about their respective positions in the contest. This means that, for example, if τ was equal to 1 minute and one of the players completed Stage A after 20 seconds, the other player would not learn this information until one minute has passed. The mechanism reverts back to revealing no information after τ. The revelation time τ is common knowledge and is announced before the contest starts.

The benefits and drawbacks of the Daylight and Darkness mechanisms highlighted at the end of the previous section provide a foundation for how we expect players will behave under the Silent Period mechanism in highly uncertain environments. First, we expect that players will wait until the revelation time before deciding to quit based on their status in the contest. This keeps players in the contest and maintains part of the observability that gives the Daylight mechanism an edge over the Darkness mechanism when it comes to a player finishing Stage A. We further expect that a player who trails her opponent will stay in the contest until the revelation time since the progress of the opponent remains unobservable until τ. This increases the chances that this player will finish Stage A as well.

Based on the above discussion, we expect that, in highly uncertain environments, the Silent Period mechanism will outperform the other mechanisms in discouraging the quitting that arises from either the uncertainty of the environment (which happens in the Darkness mechanism) or the competition effect (which happens in the Daylight mechanism).

Before presenting the main hypothesis and result for this section, we make the following observation.

Observation 1. Uncertainty has no significant effects on the likelihood that a player will quit Stage A under the Silent Period mechanism. Specification (3) in Table 7 (Appendix A) shows that the uncertainty coefficients have no significant effect on quitting ($p > 0.1$).

This observation suggests that players who know they will learn the status of the contest after some time are no longer influenced by uncertainty regarding the feasibility of the goal. Based on this observation (and Proposition 4), we state the following hypothesis.

Hypothesis 4 (Silent Period vs. Daylight and Darkness: Uncertain Contests)**.** In highly uncertain environments, the Silent Period design i) decreases the likelihood that a subjects quits Stage A, and ii) increases the likelihood of Partial Progress and both players advancing to Stage B.

Hypothesis 4 reflects the expectation that the Silent Period mechanism will outperform the Daylight and Darkness mechanisms in alleviating the negative effects of uncertainty observed earlier. The following result confirms this expectation.

Result 4. The Silent Period mechanism decreases the likelihood that subjects quit Stage A by 18 p.p. and increases the likelihood of Partial Progress by 14.8 p.p. It also dominates the Daylight mechanism and is comparable to the Darkness mechanism when it comes to the number of players in Stage B.

Support. Specification (1) in Table 4 shows that, compared to the Darkness mechanism, subjects are 18.1 p.p. less likely to quit Stage A under the Silent Period mechanism ($p = 0.034$, $q = 0.083$). They are also significantly less likely to quit compared to the Daylight mechanism (one-sided test for proportion, $p = 0.0134$). Specification (2) shows that the Silent Period mechanism increases the chances of Partial Progress by 14.8 pp ($p = 0.026$, $q = 0.071$) and is comparable to the Daylight mechanism on that dimension (two-sided test for proportion, $p > 0.1$). Finally, Specification (3) shows that there is no significant difference between Darkness and Silent Period in the likelihood of both players advancing to Stage B ($p > 0.1$), but that the Silent Period mechanism is significantly better than the Daylight mechanism on that dimension (one-sided test for proportion, $p = 0.0007$). ■

Result 4 is the central result of our paper, and shows that when the level of uncertainty is high, the Silent Period mechanism outperforms the Daylight and Darkness mechanisms on all outcomes of interest and is therefore the dominant mechanism across all three treatments. Interestingly, the theoretical results in Bimpikis et al. (2019) show that the Silent Period mechanism is also the dominant mechanism when uncertainty is high. When uncertainty is mild, both theory and experiment show that the Silent Period mechanism has little or no effect, as can be seen in Table 8 in Appendix A.

In addition to testing the dominance of the Silent Period mechanism over the other mechanisms, we are interested in what revelation time(s) best lead to the benefits documented in Result 4. In theory, this time is difficult to compute because it is directly tied to the award structure of the contest, the agent continuation values, and the evolution of their beliefs about goal feasibility and their own relative progress. Intuitively, longer silent periods allow players sufficient time for finding a solution. On the other hand, a silent period that is too long starts resembling the Darkness mechanism and may induce players to quit in the presence of uncertainty as in Result 2. Recall that the set of revelation times for each game were selected from an empirical distribution for the time it took the first player to complete Stage A in all previous Darkness sessions. We then chose the times at the 50^{th}, 60^{th}, 70^{th}, and 80^{th} percentiles of that distribution. This led to a set of four possible revelation times for each game. A time was then chosen randomly from this set whenever this game was played in the Silent Period treatment. Our results for the different revelation times follow.

Result 5 (Effect of Different Silent Period Durations)**.** For highly uncertain environments, the Silent Period design decreases quitting rates when the time τ is chosen from the 50^{th} or 60^{th} percentile of the empirical distribution of completion times under Darkness.

Support. Table 5 reports the logistic specification investigating the effects of different revelation times on quitting in contests with high uncertainty, and shows that setting τ at the 50^{th} percentile marginally decreases quitting by 19.1 p.p. ($p = 0.0753$), while the 60^{th} percentile decreases the chances of quitting by 24.9 p.p. ($p = 0.003$). Waiting too long is usually not beneficial, as the design starts resembling the Darkness mechanism and inherits its associated pitfalls; setting τ to the 70^{th} percentile has no significant effect on quitting ($p > 0.10$) compared to the 80^{th} percentile. ■

Finally, an important question is how to set the time duration τ in practice. A possible starting point is to adjust the time based on previous tasks that resemble the task at hand. For example, a firm that wants to run a contest on a high-volume platform like TopCoder or Kaggle can have the platform recommend revelation times based on task attributes and features similar to those of past tasks that were successfully completed.

Table 5: Effect of different revelation times on completion and quitting in contests with high uncertainty: Logistic specifications

	Dependent variable:
	Quit
50^{th} percentile	-0.191^{*}
	(0.107)
60^{th} percentile	-0.249^{***}
	(0.085)
70^{th} percentile	0.065
	(0.131)
Observations	70

Notes: The omitted category is the 80^{th} percentile. Coefficients represent average marginal effects and robust standard errors in parentheses are clustered at the group level, with *p<0.1; **p<0.05; ***p<0.01.

5.3 Earning Rates

As mentioned in the introduction, a contest is a design where one or a few participant(s) receive prizes and the other participants receive nothing. While the majority of the literature on contest design focuses on effort maximization, few studies analyze the effect of contest design on participant earnings (see Vojnović (2016) for a summary of these results in static contests.)

In this section, we examine how the information provision mechanisms we consider affect the contestants' *earning rates*, defined as how much money a player earns divided by the amount of time it takes to earn that amount. Recall that there are only three possible amounts to earn in each contest ($0, $1, or $5), and so the time spent becomes a major differentiating factor between the different mechanisms.

Examining our results regarding participant earnings rates, we find no effect of information provision mechanisms on the earnings rates of those who win the contest. Players who manage to complete the entire contest win $5 and do so in roughly the same amount of time under the different information mechanisms. By contrast, the effect of information provision mechanisms on the earnings rates of those who do not win depend on how the dynamics of the contest unfold.

Table 6 presents three OLS specifications, with earning rate (dollar per minute) as the dependent variable, and dummies for the Daylight and Silent Period mechanisms as the independent variables. The first two columns show the treatment effects on earning rates among winners (1) and losers (2) in the subset of complete contests, whereas the last column shows treatment effects on earning rates in the subset of incomplete contests.

Complete Contests We first consider the subset of complete contests. From Specification (1) in Table 6, we see no significant impact of the information provision mechanism on winner earning rates ($p > 0.10$ for the coefficients of the Daylight and Silent Period dummies).

Shifting our attention to the earning rates of those players who lost the contest, we consider both

Table 6: Effect of different information mechanisms on earning rates: OLS specifications

	Dependent variable: Earning Rate (dollar per minute)		
	Complete Contests		Incomplete
	Winner	Loser	Contests
	(1)	(2)	(3)
Daylight	-0.126	0.416^{***}	-0.037^{**}
	(0.301)	(0.126)	(0.018)
Silent Period	-0.179	-0.077	-0.033^{*}
	(0.309)	(0.130)	(0.0174)
Constant	2.26^{***}	0.267^{***}	0.227^{***}
	(0.214)	(0.09)	(0.0126)
No. of contests	192	192	336
No. of observations	192	192	672

Notes: The first two columns are for completed contests, whereas the last column is for contests that neither player was able to complete. The omitted category is Darkness. *p<0.1; **p<0.05; ***p<0.01.

the amount earned and the time spent. Regarding the amount earned, a player who quits and plays the non-competitive consolation game earns \$1 for completion, while a player who stays in the game until her opponent finishes the contest forfeits the outside option and makes \$0. This latter scenario is least likely under the Daylight mechanism (42% compared to 68% and 63% for the Darkness and Silent Period mechanisms, respectively). Regarding time spent in the contest, recall that players quit earliest under the Daylight mechanism, often as soon as their opponent has completed Stage A. By contrast, those who are trailing their opponents spend more time earning the same amount of money under the Darkness and Silent Period mechanisms. Therefore when the contest is completed, players who do not win and are playing under the Daylight mechanism earn a higher amount on average (\$1 instead of \$0) and spend less time to earn that amount.

Specification (2) in Table 6 reflects the above discussion and shows that losers' average earning rates more than double under Daylight compared to the Darkness and Silent Period mechanisms (since the Daylight mechanism adds almost \$0.41/minute to the baseline earning rate of \$0.267/minute) and the effect is significant ($p = 0.0012$).

Incomplete Contests Ṙegarding contests that were not completed, our results in this section show that while those who trail are able to quit earlier in the Daylight mechanism, decreasing their time spent, they may also choose to stay if they see their opponent has not made any progress, in which case they increase their time spent. Indeed, learning about a lack of opponent progress may actually decrease earning rates if Stage A is infeasible or players cannot solve it. The reason for this decline is that players spend a longer amount of time in these games (each player waiting for the other to either quit or finish the stage) and end up with the same \$1 prize or with \$0 (in case they do not complete the consolation game).

The results from the previous paragraph are summarized in Specification (3) in Table 6, which shows that in contests with no winner, the earning rates decrease by 16% in the Daylight mechanism ($p = 0.0375$) and 14.5% in the Silent Period mechanism compared to Darkness ($p = 0.0564$).

In sum, from an innovation contest designer's perspective, the Silent Period mechanism generates superior performance than either the Daylight or Darkness mechanism, especially in a highly uncertain environment. From the contestants' perspectives, however, while winners are indifferent among these information provision mechanisms, losers are better off under Daylight (Darkness) for completed (incomplete) contests.

6 Discussion

This paper offers a novel experimental design that studies the role of information in an environment that combines goal uncertainty and dynamic competition. The setting captures the interplay between the effects of uncertainty on players' behavior and how these effects can be adjusted through information provision.

Uncertainty regarding the feasibility of a goal can impact quitting behavior if the uncertainty is sufficiently high. In this case, we find that providing information on a player's relative progress can reduce the likelihood that both players quit before partial progress is made. Specifically, we find that players who can observe each other are more reluctant to quit the game if their opponent has not quit, which ultimately increases the chance that one of the players will complete Stage A. However, as soon as a player completes Stage A, the trailing player immediately quits, leaving only one player in Stage B.

Comparison with Theoretical Predictions The above finding contrasts with the theoretical predictions in Bimpikis et al. (2019), where under the Daylight mechanism, players are more likely to quit in the absence of a breakthrough. The theoretical mechanism is through players updating their beliefs about feasibility in a Bayesian fashion. If players learn that neither player has completed Stage A, their beliefs decline at twice the rate than they would based only on their own experience. Thus one would expect that the Daylight mechanism decreases the chances of partial progress, which is not what we observe in the experiment. Three assumptions in Bimpikis et al. (2019) might explain this discrepancy. First, while the theory assumes players have identical skills, the players in our lab still learn about their environment and also about their relative skills. A player who sees that her opponent has advanced not only learns that the problem is feasible but also that her opponent might be more skilled than she is, which makes her decision problem of whether to continue or quit more involved. This multidimensional learning problem is quite complicated and has not yet been analyzed in the theoretical literature on contests.

Second, Bimpikis et al. (2019) assume that the award for winning the contest is high enough that the trailing participant still chooses to remain even when she learns she is behind. The third assumption is that the second stage of the contest takes much longer to finish compared to the first stage, and thus there is still ample time to catch up with a contestant once uncertainty about the first stage is resolved. Taken together, the theoretical setup assumes that the news of a player advancing to Stage

B is unequivocally good for both players. The only negative effect comes in the Daylight mechanism if neither player advances. By contrast, in our setup, an advance by one player puts the player who is trailing in immediate danger of not being able to exercise the outside option, and thus dominates the encouragement effect that arises from the assumptions in the theoretical framework. This suggests that the encouragement and competition effects, as well as their connection to the information provision mechanism, may be sensitive to the expected duration and prize of the contest. However, the fact that in the Daylight mechanism players are not more discouraged by their lack of progress compared to the Darkness mechanism stands in contrast to the theory predictions regardless of the assumptions imposed

While the results in this paper diverge from the theoretical predictions for the Daylight and Darkness mechanisms, both theory and experiment find that the Silent Period design improves the outcome for the designer when uncertainty is high. The mechanism combines the benefits of the two extreme mechanisms when the environment is highly uncertain. If the duration of the silent period is carefully-chosen to not be too long or too short (given the game being played), then players are more inclined to continue playing until the revelation time. This increases the chances that one or both of them make a breakthrough in the interim. If the time is too short, the players do not spend enough time for the chances of a breakthrough to increase, and if the time is too long players quit before the revelation time as the design becomes too close to the Darkness mechanism.

The challenging aspect of mechanism selection is that the contest designer and contestants do not necessarily have their interests aligned. The downside of the mechanisms that often perform well for the designer is that they do not necessarily have the same positive effects for the players. In contests where no breakthroughs happens, either because the goal was infeasible or the players just could not finish the first stage, players fare worse under the Daylight and Silent Period mechanisms, because they spend too much time before deciding to quit, hence decreasing their earning rates. Conversely, when a breakthrough happen, the laggard usually immediately quits under the Daylight mechanism (but not under the Silent Period mechanism), and hence the earning rate is higher. This presents the typical quandary to a platform: it has to balance maximizing the objective of the contest designer with the welfare of participants in order to keep them both coming back.

In designing our experiment we chose to focus on the factors that we consider the most salient (environment uncertainty and information provision) but other factors can be studied in future experiments. Some of these factors include the sharing not only of progress, but the methodology used to achieve it. Another question is to study the dynamics of team formation in contests with more than two players, which remains a problem that is not well-studied either theoretically or experimentally.[12] All of these are possible areas to further the work in this paper and constitute interesting directions for future research.

[12] For example, after intermediate prizes were announced in the NetFlix Prize competition, the winning teams were required to write reports that describe how their solution was obtained. Teams were also given the chance to merge with other teams for the rest of the contest, and in fact the team that ultimately won the competition was a combination of two previous teams. The recent experimental work of Boudreau et al. (2017) examines scientific collaborations and teams formation in a non-contest setting.

Appendix

A Additional Tables

Table 7 shows that uncertainty has a strong effect on quitting when subjects plays under the darkness mechanism, but that this effect is mild or absent under the Daylight mechanism and is not present at all under the Silent Period mechanism.

Table 7: Effect of different uncertainty levels on Quitting under different information mechanisms

	Dependent variable: Quit		
	Darkness	Daylight	Silent Period
	(1)	(2)	(3)
Mild Uncertainty	0.158^{**}	0.054	0.149
	(0.077)	(0.063)	(0.051)
High Uncertainty	0.318^{***}	0.114^{*}	0.052
	(0.086)	(0.066)	(0.086)
Observations	278	290	278
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: The omitted category is No Uncertainty. Coefficients represent average marginal effects and robust standard errors in parentheses are clustered at the group level, with *p<0.1; **p<0.05; ***p<0.01.

Table 8 is analogous to Table 4 in the main body of the text, and shows that in mildly-uncertain environments (and aside from a weakly-significant effect of Daylight on both players advancing to Stage B ($p = 0.093$)), information plays no significant role in shaping the outcomes we are interested in.

Table 8: Effects of different information mechanisms in mildly uncertain environments: Logistic specifications

	Dependent variable:			
	Complete	Quit	Partial Progress	Both Advance
	(1)	(2)	(3)	(4)
Daylight	-0.064	0.091	0.002	-0.139^{*}
	(0.0577)	(0.0739)	(0.057)	(0.083)
Silent Period	-0.023	0.069	0.013	-0.064
	(0.058)	(0.0683)	(0.059)	(0.083)
No. of contests	141	141	141	127
Observations	282	282	141	127

Notes: The omitted category is Darkness. Coefficients represent average marginal effects and robust standard errors in parentheses are clustered at the group level, with *p<0.1; **p<0.05; ***p<0.01.

B Experiment Instructions

The instructions used in the the sessions are reprinted in the next page.

Experiment Instructions

IMPORTANT: PLEASE TURN OFF OR MUTE YOUR PHONES.

Welcome! This is an experiment in the economics of decision making. In this experiment, you will be asked to solve knapsack games. The amount of money you earn will depend on the decisions you make and on the decisions other people make. Please do not communicate with others during the experiment. If you have questions at any point during the experiment, raise your hand and the experimenter will help you.

This experiment includes two phases, the training phase and the contest phase.

1. In the **training phase**, you will play six different knapsack games individually.
2. In the **contest phase**: you will play six different knapsack games in three contests. In each contest, you will compete against another player in solving two knapsack games. The player who finishes first wins.

You will also fill out a short survey after the experiment is over.

You will get paid after completing both phases and filling out the survey.

Knapsack Game Description

Imagine you are going on a trip and have only one suitcase. You cannot fit all the things you would like to take with you, so you try to fit the most important things. This is the knapsack game. In the game, you have a knapsack with limited weight capacity. There are a number of items available and each item has a weight and a value. You cannot fit all the items in the knapsack because their total weight is more than the maximum weight capacity of the knapsack. You will be given a target value and your goal is to find a subset of items that will fit into the knapsack whose total value is at least equal to the target value.

Payment

Your total payment is the sum of what you earn in the training phase and in the contest phase.

In the **training phase**, you will be paid $1 for each game in which you can successfully fit items adding up to the target value (or above) into the knapsack. If you are unable to reach the target value, you can skip to the next game.

In the **contest phase**, there is a final prize of $5.0 for each contest. The player who is able to finish the games first will earn the prize. The other player will get nothing. Finishing a game in the contest phase means being able to fit items in the knapsack whose total value is at least equal to the target value.

1

Training Phase

The items, along with their dollar values and weights, are displayed in a pool on top of the page. Clicking on an item adds it to the knapsack (if it fits). Clicking on an item in the knapsack removes it and returns it back to the pool of items not in the knapsack. You can add and remove items as many times as you like before you submit your solution.

If you succeed in fitting the target value (or higher) into the knapsack, your answer will be submitted automatically and you will go on to the next game. You can also click the "Submit" button at any time to go on to the next game even if you were unable to fit the target value into the knapsack.

Training games are always **feasible**, that is, the target value can always be reached.

You will have a total of 30 minutes to finish the training phase. After this, this phase will automatically stop and we will move to the contest phase.

When you are finished with the training phase, you will enter the **waiting page** until everyone is finished before moving to the contest phase.

Feel free to refer to the experimental instructions at any time during the experiment.

We encourage you to earn as much cash as you can. Are there any questions?

Now we will start the training phase.

Contest Phase

Based on your performance in the training phase, you will be placed in a **group of four players with similar skill levels**. Before you enter a contest, you will go to the **waiting page** until everyone in your group is in the waiting page, ready to start the next contest.

The contest phase consists of **three contests**. In each contest, you will compete with a different player in your group. Each contest consists of two sequential knapsack games. Each game is finished if you can fit the target value (or higher) into the knapsack. You cannot play Game 2 unless you finish Game 1. The player who finishes Game 2 first wins a prize of $5.0.

Uncertainty:

Recall that a **feasible** game is one where the target value can always be reached. While all training games you have played so far are feasible, Game 1 in each contest can either be feasible or not. An **infeasible** game is one where the target value cannot be reached, no matter how hard you try. More precisely, in an infeasible game, there does not exist a subset of items whose values add up to the target value.

Game 2 is always feasible. This means that if you have finished Game 1, you can go on to try and finish Game 2. Naturally, the contest cannot be completed (and no one can win a prize) if Game 1 is infeasible. You will not be told whether Game 1 is feasible or not. Instead, before you start the contest, you will be told that the chance Game 1 is feasible is 100% (definitely feasible), or 80%, or 60%.

Before each contest, you will see one of the following sentences displayed on the screen:

[For the next contest, the chance that Game 1 is feasible is 100%.]

[For the next contest, the chance that Game 1 is feasible is 80%.]

[For the next contest, the chance that Game 1 is feasible is 60%.]

The Quit Option: At any point in the contest, unless your opponent has already won, you will have an option to quit by pressing the "**Quit**" button. If you press the button, you will be presented with a feasible knapsack game that you can try to solve (with no competition). If you finish it, you will get paid $1.0, similar to the training phase.

Note that if the other player wins, the contest will be over and you will not have the chance to quit and play the feasible game.

At any time during a contest, you will be immediately notified if your opponent finishes Game 1 or quits. This means that, if you do not receive a notification, your opponent is still trying to solve Game 1.

Are there any questions?

Review Questions: To make sure that everyone understands the instructions, you will be asked a number of review questions. When everyone is finished with these questions, we will go through the answers together.

Feel free to refer to the experimental instructions before you answer any question. Each correct answer is worth 20 cents, and will be added to your total earnings.

1. How many people are there in your group?
   a. 3;
   b. 4;
   c. 12.

2. In the contest phase, are you going to play against the same opponent more than once?
   a. Yes;
   b. No.

3. True or false: An infeasible game can be solved if I try hard enough.
   a. True;
   b. False.

4. True or false: In a contest, you are told that "the chance that Game 1 is feasible is 100%." This means that the target value can be reached.
   a. True;
   b. False.

5. In a contest, you are told that "the chance that Game 1 is feasible is 60%." Which of the following statements is correct?
   a. The likelihood that Game 1 is infeasible is 40%.
   b. The likelihood that the target value can be reached is 40%.

4

C Knapsack Games

In this appendix, we present the knapsack games used in our experiment and their solutions.

C.1 Training Games

The training games are designed by the authors and progress with increasing difficulty level. These games are designed and sequenced so that subjects can get used to both the interface and practice solving these games.

Game 1:
Values = [3, 6, 9, 12, 15, 18, 21]
Weights = [1, 4, 7, 10, 13, 16, 19]
Capacity = [43]
Solution = [0, 1, 0, 1, 1, 1, 0]

Game 2:
Values = [15, 100, 90, 60, 40, 15, 10, 1]
Weights = [2, 20, 20, 30, 40, 30, 60, 10]
Capacity = [102]
Solution = [1, 1, 1, 1, 0, 1, 0, 0]

Game 3:
Values = [70, 20, 39, 37, 7, 5, 10]
weights = [31, 10, 20, 19, 4, 3, 6]
Capacity = [50]
Solution = [1, 0, 0, 1, 0, 0, 0]

Game 4:
Values = [350, 400, 450, 20, 70, 8, 5, 5]
weights = [25, 35, 45, 5, 25, 3, 2, 2]
Capacity = [104]
Solution = [1, 0, 1, 1, 1, 0, 1, 1]

Game 5:
Values = [37, 72, 106, 32, 45, 71, 23, 44, 85, 62]
Weights = [50, 820, 700, 46, 220, 530, 107, 180, 435, 360]
Capacity = [1500]
Solution = [1, 0, 0, 1, 1, 0, 1, 1, 1, 1]

Game 6:
Values = [2, 3, 4, 5, 6, 9, 8, 7, 6, 5, 8, 9]
Weights = [3, 4, 6, 3, 5, 13, 6, 9, 2, 4, 7, 7]
Capacity = [14]
Solution = [0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0]

C.2 Contest Games

The contest games are from Meloso et al. (2009) (page 2 of the Supplementary Material).

Contest 1:
Game 1:
Values = [500, 350, 505, 505, 640, 435, 465, 50, 220, 170]
weights = [750, 406, 564, 595, 803, 489, 641, 177, 330, 252]
Capacity = [1900]
Solution = [0, 0, 1, 1, 0, 1, 0, 0, 0, 1]

Game 2:
Values = [31, 141, 46, 30, 74, 105, 119, 160, 59, 71]
weights = [21, 97, 32, 21, 52, 75, 86, 116, 43, 54]
Capacity = [265]
Solution = [0, 1, 0, 0, 1, 0, 0, 1, 0, 0]

Contest 2:
Game 1:
Values = [15, 14, 3, 3, 10, 9, 28, 28, 31, 25, 24, 1]
weights = [129, 144, 77, 77, 66, 60, 184, 184, 229, 184, 219, 72]
Capacity = [850]
Solution = [0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0]
Game 2:
Values = [300, 350, 400, 450, 47, 20, 8, 70, 5, 5]
weights = [205, 252, 352, 447, 114, 50, 28, 251, 19, 20]
Capacity = [1044]
Solution = [1, 0, 1, 1, 0, 0, 0, 0, 1, 1]

Contest 3:
Game 1:
Values = [37, 72, 106, 32, 45, 71, 23, 44, 85, 62]
weights = [50, 820, 700, 46, 220, 530, 107, 180, 435, 360]

Capacity = [1500]
Solution = [1, 0, 0, 1, 1, 0, 1, 1, 1, 1]

Game 2:
Values = [201, 84, 113, 303, 227, 251, 129, 147, 86, 127, 144, 167]
weights = [192, 80, 106, 288, 212, 240, 121, 140, 82, 120, 137, 160]
Solution = [1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1]

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