Web Appendix

Markets for Ideas:
Prize Structure, Entry Limits, and the Design of Ideation Contests

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A Instructions to Participants and Sample Submissions

In Figure 1, I include several images from the platform's website that illustrate the process participants must go through when making submissions.

[Figure 1 about here.]

In the first picture, the platform provides an example contest organized around the question "What does Lego mean to you?" and sponsored by Lego. Participants are encouraged to submit 140 character ideas to address this question. The ideas may later be used to develop an ad. The platform often partners with popular brands to generate ideas for advertising content for media such as television, video streaming sites, mobile applications, and social networking platforms.

In the second picture, participants fill in a text box for each submission they make. The participant must provide a title for their idea, a 140 character summary of the idea, and check that they have read and agreed to several legal and project requirements before pressing a red "SUBMIT" button. Participants must complete this process for each submission. The submission box is available throughout the duration of the contest.

In the third picture, the platform shows a sample of four winning ideas from the contest, each of which received a $500 prize. The order of submissions is random. From top to bottom, the text of the winning submissions is as follows:

- Creator: Hey Reginer; Title: *The Need to Build*; Idea: "Man's innate desire to build through time. Stonehenge. Pyramids. Bridges. Skyscrapers. Space stations. LEGOs feed our primal urge to build."

- Creator: Jason Balas; Title: *500 Pieces*; Idea: "3 people. Each given 500 legos to see what they create. Real,Docu-style. Each talks life and what Legos mean to them. Conclude w/ creations."

- Creator: Mindfruit Studio; Title: *Lego Documentary*; Idea: "Collect dozens of personal stories from people about how a moment with Lego impacted their childhood - then build each one with Lego bricks."

- Creator: Benjamin B; Title: *The Future of Lego*; Idea: "Growing up imagining, tinkering, & building little brick societies, we are the future inventors, designers, explorers, and civil leaders."

B Discussion of Model Limitations and Assumptions

Selection and Unobserved Participant Heterogeneity

The model allows for rich sources of observed and unobserved participant heterogeneity. Before entering a contest, participants differ in their observed characteristics X_i and cost unobservables ν_{it}, and can choose how many submissions to make based on these variables. Hence, the model allows for selection on observable components of ability and unobservable components of costs. Furthermore, participants can exhibit persistent differences in ability through X_i and persistent differences in costs as the ν_{it} may be correlated across contests for the same participant.

The model does not allow for persistent unobserved heterogeneity in the quality of a participant's submissions. Participants cannot choose how many submissions to make based on an unobserved component of expected submission quality. I include an indicator in X_i for whether or not a participant won a contest prior to 2011 to allow for persistent differences in skill and submission quality across participants. Submission quality may depend on an unobservable ξ_{it} which is iid across participants and contests, and is not known before entry. The quality unobservable may explain correlation in the quality of submissions made by the same participant in the same contest. A similar assumption is made in recent empirical work on contests (Yoganarasimhan 2016, Gross 2017) and two-stage entry models (Ishii 2008, Eizenberg 2014, Wollmann 2018), where the authors assume that an unobserved component of demand (also labeled ξ in all cases) is not known to firms before entry into a market. Incorporating unobserved components of demand known to participants in entry games with multiple equilibria is an active area of research (Ciliberto et al. 2018). See Web Appendix L for a continued discussion and an empirical analysis of the importance of unobservables known to the participant but not to the researcher. Section 'Impact of Assumption 1 on Parameter Estimates' in this appendix presents additional empirical results to gauge the extent of selection on unobserved components of submission quality.

Correlation Between Ideas Within Participants

Participants may submit ideas that differ substantially from each other in an attempt to find the most appealing idea for the sponsor, which may induce a negative correlation among ideas submitted by the same participant. I address this potential concern by including characteristics of the idea text directly into the jury rating model specification in Equation 2 in the main paper. Additionally, I provide evidence below that ideas submitted by the same participant are more similar than ideas submitted by different participants to motivate the presence of the unobservable ξ_{it} which is common to all submissions made by the same participant within a contest.

Figure 2 illustrates the dispersion in idea characteristics such as idea length (as a fraction of total permissible length), submission time (as a fraction of contest duration), positive sentiment, negative sentiment, joy, and surprise within and across participants by contest. For each idea characteristic, dispersion across participants is measured as the standard deviation in the idea characteristic across all submissions within the contest divided by the mean value of the idea characteristic within the contest. Dispersion within participant is measured in the same way for each participant individually within a contest (Yoganarasimhan 2016). Each plot in Figure 2 focuses on participants who made at least four submissions and, for each contest, reports the overall dispersion across participants (solid black line), the mean dispersion within participants (gray line), and the median dispersion within participants (dashed line). In each plot, contests are ordered by increasing value of overall dispersion in the associated idea characteristic.

[Figure 2 about here.]

Figure 2 shows that overall dispersion in idea characteristics is greater than the mean or median dispersion in idea characteristics within participants for all but a very small number of contests. Notably, in the case of submission time, most participants tend to submit all of their ideas on the same day which leads to very low within-participant dispersion for this characteristic. The plots suggest that idea content and characteristics tend to be positively correlated within participant.

Cost Function Shape

Incorporating non-linearities in the cost function requires instruments for participant actions, restrictions on the distribution of cost unobservables, or covariance restrictions between observable participant or contest characteristics and cost unobservables. Note that d_{it} cannot be used as an instrument to construct additional inequalities unless ν_{it} is assumed to be zero as $E[\nu_{it}|d_{it}] \neq 0$. In Section 'Cost Estimates', I present estimates of θ_2 under the assumption that $c_{it}(d_{it}) = (\theta_2 d_{it} + \nu_{it})d_{it}$. I find that the assumption of constant marginal costs is unlikely to hold as small perturbations in a contest's prize would lead all participants to submit either 0 or 5 times given the approximate linearity of participant marginal expected returns. It is possible that the expected returns function is not sufficiently concave as it does not incorporate risk-aversion. However, the descriptive evidence in Web Appendix C does not support risk-aversion.

It is not uncommon to use characteristics of markets as instruments to identify cost parameters in entry models in industrial organization. For example, Ishii (2008) uses the number of firms in a market as an instrument to identify the parameters of a linear cost function for firms making entry decisions. In the context of contests, the equivalent would be to use contest characteristics as instruments for participant actions within a contest. I experiment with several potential instruments in an attempt to identify both θ_1 and θ_2 in the cost function. I find that an "informative" identified set can be obtained only if I use variables that are highly correlated with participant actions, such as indicators for whether or not the participant was victorious in prior contests, or is a producer. However, these participant characteristics are likely to be correlated with costs as producers and prior winners may have more external commitments or, on the contrary, be more efficient than other participants. Unfortunately, I fail to find an informative identified set for both cost function parameters using other candidate instruments. Hence, I choose to impose a restriction on the shape of the cost function instead.

Similarly, the cost function does not allow for the possibility of a fixed cost of making the first submission. I assume that participants have sufficiently familiarized themselves with the contest description and already incurred the fixed cost regardless of whether or not they made a submission. Incorporating a fixed cost parameter or any additional non-linearities into the cost function would require additional assumptions as discussed at the beginning of this section.

Choice of Which Contests to Enter

The model treats each contest independently although it is possible that participants choose which contest to enter from a set of contests, and sponsors compete for the attention of participants on the platform. However, the platform does not offer ideation contests with such a high frequency, and virtually all contests that are active on a given day are visible on the home page of the platform. In this research, I abstract away from the possibility of inter-contest competition and focus on the impact of incentives on participant behavior within contests, which is equivalent to assuming that any constraints on maximum effort are non-binding, and the costs from participating in multiple contests are simply additive. Future work may examine the impact of offering multiple contests simultaneously in settings where the platform offers a large number of contests, or where each contest requires a substantial investment such that participants cannot realistically participate in more than a few.

Assumption that the Contest is a Static Game

Throughout, I assume that each contest is an independent static game and that participants face no dynamic incentives within or across contests. This assumption is primarily a simplification in line with the theoretical literature (Moldovanu and Sela 2001, Stein 2002, Szymanski and Valletti 2005, Terwiesch and Xu 2008) and the current state of the empirical literature on contests (Boudreau et al. 2016, Yoganarasimhan 2016, Gross 2017). Below, I discuss this assumption in more detail and provide some evidence to support it.

First, it is possible that within a contest participants have a dynamic incentive to wait before submitting. I show in Figure 3 that participants mostly make submissions either at the beginning or at the end of a contest. The plot labeled 'Submission Time' in Figure 2 shows that most participants tend to make all of their submissions on the same day (the average and median within-participant dispersion in submission day is almost zero for all but a few contests). In addition, the estimates of the jury rating model in Table 6 in the main paper suggest that submission timing may represent participant type rather than a measure of effort (there is no simple monotonic relationship between timing and rating). As participants do not observe the behavior of their competitors throughout the duration of a contest and show no evidence of strategically timing submissions it is safe to assume that they do not have any competitive reason to wait before submitting as they cannot learn about the behavior or performance of their competitors.

[Figure 3 about here.]

Finally, it may be the case that participants have a dynamic incentive to build reputation through contest participation. Both the jury and the sponsor are blind to a participant's past success when evaluating submissions for all ideation contests on the platform. As a result, there are no gains to reputation within the platform. It is possible that participants benefit from reputation through other channels, but I am unable to measure the extent of this effect absent data on a participant's external activities.

Although I am unable to measure the extent of reputation benefits participants may accrue outside of the platform, I am able to show that immediate incentives matter in the descriptive analysis in Appendix C. As a result, I focus this research on the immediate incentives while acknowledging the lack of data on participant activities outside of the platform as a limitation. I expect that reputational incentives should be limited, at least within the platform for the set of contests I consider, because the jury and sponsors are blind to participant identity when evaluating submissions.

Impact of Assumption 1 on Parameter Estimates

To further explore the impact of Assumption 1 on the parameter estimates and counterfactual outcomes, I conduct a series of descriptive analyses of the choice to enter a contest and outcomes related to ratings and victories. A primary concern is that an unobserved variable (for example, interest in the contest topic) affects participant entry decisions and the quality of their submissions. As discussed in Section 'Selection and Unobserved Participant Heterogeneity', the current specification does not allow for selection into contests based on an unobservable component of idea quality.

Table 1 shows estimates from a logistic regression of participant entry decisions and victory outcomes on participant characteristics. For the column labeled "Entry," the model is estimated on the full set of participants, and the outcome variables indicates if participant i made at least one submission to contest t. For the column labeled "Win," the model is estimated only on the set of entrants, and the outcome variable indicates if participant i won in contest t. I include submissions as an additional variable in the model for participant wins to control for the fact that participants who make more submissions are more likely to win. The estimates show that participants who are most likely to enter are not necessarily more likely to win. An interesting discrepancy emerges in the behavior of participants who previously won a contest (labeled as paid) and producers. Both types of participants have a higher chance of winning, but a lower chance of entering contests. This can be explained by the current model as the case when both producers and paid participants have high costs of ideation but also a high ability and generate high quality ideas. However, it may also be the case that of these participants, those who enter have an inherent interest in the contest topic and expect to perform better than non-entrants. Although it is not possible to distinguish these explanations without data on the winning chances or jury ratings of the submissions not made by non-entrants, an advantage of this setting is that participants may vary in their number of submissions and thereby in their *intensity* of entry. I can compare outcomes for participants who made a different number of submissions rather than compare outcomes for entrants and non-entrants.

[Table 1 about here.]

I explore the possibility of selection on unobserved components of quality further by examining the relationship between a participant's jury ratings and the number of submissions that she makes. In the presence of selection on unobserved components of idea quality, participants who make more submissions in a contest should receive a higher rating for a random submission. This is because in the presence of selection on unobservables, participants who submit more (have a higher intensity of entry) are expected to have higher draws of unobservable components of idea quality. The estimates in Table 2 show a that participants who make 2 or 5 submissions are significantly more likely to receive a higher average vote for a random submission than participants who make 1 submission. Although I do not find a significant effect for participants who make 3 or 4 submissions, the results in Table 2 may suggest that participants who make more submissions tend to have a higher-valued unobserved component of idea quality. More generally, ideas of participants who enter altogether may also exhibit such a selection effect.

[Table 2 about here.]

As a robustness check, I re-estimate the jury rating model using data only from participants who made 5 submissions to assess the potential impact of participant selection on an unobserved component of idea quality. The estimates in Table 2 show evidence that these participants have a higher expected idea quality that cannot be explained by their observable characteristics. I assess the potential biases induced by selection on unobservables by comparing the implications of the full model to the implications of a model estimated only on this selected subset of participants for whom the *intensity* of entry was the greatest. Although it is not possible to fully evaluate the impact of selection without data on the outcomes of non-entrants, it is possible to use data on the outcomes of entrants with different intensities of entry to evaluate the impact of the selection bias induced by ignoring participants who make fewer submissions.

Table 3 shows estimates from the jury rating model for the subset of participants who made 5 submissions. Table 4 shows the resulting average cost estimates for all participants in the data. The parameters of the jury rating model do not differ substantially from when the model is estimated on the full sample (Table 6 in the main paper). Naturally, standard errors are higher because of the smaller sample sizes used in estimation. The cost estimates also do not differ substantially from those obtained using the full sample for the jury rating model (Table 7 in the main paper). These results suggest that even though a selected sample is used to estimate the jury rating model, the parameters of the participant entry model and contest design implications should not differ substantially from the case when the jury model is estimated on the full sample, thus mitigating some concerns about the biases induced by selection on idea quality unobservables.

[Table 3 about here.]

[Table 4 about here.]

Identifying Non-Entrants

The moment inequality estimation procedure used in Section 'Upper Bound' of the main paper requires that the number of non-entrants does not exceed the number of entrants. Otherwise, one would not have enough information on the shape of the distribution of cost unobservables to impute upper bounds on the marginal costs of non-entrants. I restrict the set of potential non-entrants to include participants who viewed the contest page more than once and were active within 3 months of participating. In part, this restriction reflects the reality that many users may simply be browsing the site without an intention to participate. However, this restriction may also lead to an under-estimation of the costs of submitting an idea if an insufficient number of non-entrants is included in the analysis.

One approach to allow for more non-entrants than entrants in the model is to assume an upper bound on marginal costs for all non-entrants as in Eizenberg (2014). A possible choice for the upper bound would be the greatest marginal return observed in the data: $\max\{\Delta R_{it}(d_{it} + 1, d_{it})\}$. Increasing the number of non-entrants in the sample with such an upper bound on their marginal costs would increase the estimated upper bounds on the cost parameters, which may widen estimated confidence bounds on counterfactual outcomes.

Although I do not develop a perfect solution to incorporate non-entrant behavior, this research is one of the first to consider the possibility of non-entrants in an empirical model of contests. As a result, I am able to track changes in the number of entrants as an outcome metric that responds to varying contests designs, which would not be possible in prior models of contests that assume away the possibility of non-entry.

To further explore the impact of different definitions of non-entrants on counterfactual outcomes, I rerun the participant entry model and contest design simulations focusing only on the set of entrants (assuming that there are no non-entrants as in previous research). The following section summarizes the results. Overall, the confidence bounds on the cost estimates shrink considerably as do the confidence bounds on expected counterfactual outcomes. An increase in the number of non-entrants typically results in a widening of the confidence bounds on cost estimates and counterfactual outcomes. In the extreme case where the number of non-entrants exceeds the number of entrants for a given contest, the upper bound on costs approaches infinity.

The Impact of Ignoring Non-Entrants

Table 5 shows the cost estimates for the participant entry model estimated only on the set of entrants. The bounds on the cost estimates are lower than when the model is estimated on the full data, and the distance between the bounds within categories is considerably shorter (see Table 7 in the main paper). The average cost of making the first submission is between \$0.26-0.53 in contrast to \$0.34-1.95 for the main specification.

[Table 5 about here.]

I recover average counterfactual outcomes across all contests as in Section 'Counterfactuals' using only data on entrants and the associated cost estimates. The resulting predictions in Table 6 are considerably more precise, but tend to lie close to or within the predictions presented in Table 9 in the main paper. A greater uncertainty in the cost estimates in the main model translates to wider bounds on counterfactual outcomes, which tend to include the predictions of a model estimated only on the set of entrants. In addition, the model which ignores non-entrants is unable to predict an increase in the number of entrants. In some cases, the model predicts a decrease in the number of entrants as some entrants choose to no longer participate when the number of submissions made by their competitors with lower costs increases in response to the counterfactual policy. These results show that excluding non-entrants from the model, as has been the predominant approach in past research, may yield counterfactual predictions that are too precise or unreliable regarding the number of entrants.

[Table 6 about here.]

C Descriptive Evidence of the Importance of Prizes

Is there evidence in the data that participants respond to prizes? Such evidence would suggest that prize structure is an important design parameter that can alter behavior. In addition, it would provide support for using submissions as a measure of participant effort.

First, consider the impact of prize amount on submissions. Figure 4 shows the raw correlation between total award and three outcomes: the total number of submissions a contest receives, the number of entrants, and the number of submissions made by each entrant. Contests that award a higher prize attract more entrants and receive more submissions in total and more submissions per entrant.

[Figure 4 about here.]

I regress the outcome metrics on the logarithm of total award and include fixed effects to control for differences in contest category and the number of prizes, as well as a control for the logarithm of the total number of potential entrants. Identifying variation comes from differences in the outcome across contests that share the same set of fixed effects but offer different prizes. Table 7 shows the estimated coefficients on the logarithm of total award. All columns show positive coefficients, consistent with the notion that a larger total award increases entry and effort.

[Table 7 about here.]

Contest Duration

In addition to the variables described above, contests may differ in their duration. Figure 5 shows the distribution of contest duration in days. To investigate if contest duration affects participation, I run a series of regressions of the total number of contest submissions on contest length and other controls such as category and total prize amount. The estimates in column I of Table 8 show that longer contests attract fewer submissions. However, this effect is mitigated and vanishes after controlling for contest category and prize amount (columns II-IV), suggesting that longer contests may be more difficult to participate in. I expect that categories with longer contests will have higher associated cost estimates as participants may need to exert more effort to make a submission.

[Figure 5 about here.]

[Table 8 about here.]

Descriptive Analysis of Prize Allocation

In this section, I use data on variation in prize allocations across contests to asses the impact of changing prize allocation on participant behavior. Such an analysis would provide support for model assumptions and, at least locally, some guidance into choosing the number of prizes. However, a descriptive analysis may not adequately take into account differences in participant abilities and costs across contests. In addition, it may not be suitable for exploring the impact of contest designs not attempted in the data.

Consider the impact of the number of prizes on submission behavior. Table 9 shows the coefficient estimates for a series of regressions of submission outcomes on the logarithm of the number of prizes offered in a contest, controlling for total award as well as category fixed effects. I find a negative relationship between the outcome metrics and the number of prizes for all regressions in the first two columns, suggesting that participants are possibly not sufficiently heterogeneous or risk-averse for multiple prizes to be optimal. Alternatively, contests that award more prizes may be more difficult or inconvenient, even after controlling for category.

In terms of contest design, the regression results in the first two columns of Table 9 may suggest that decreasing the number of prizes will increase the number of submissions. However, as the number of submissions per entrant does not increase in contests with fewer prizes, it may simply be the case that contests with fewer prizes have more entrants because of a larger pool of potential participants. Indeed, the effect of the number of prizes becomes insignificant after including the logarithm of the total number of potential participants in the regression, as indicated in the third column of Table 9. A descriptive analysis may conclude that altering the number of prizes has no impact on contest outcomes. The counterfactual analysis in Section 'Counterfactuals' agrees with this conclusion within the range of prizes offered by the company. If the number of prizes is too small relative to the number of submissions, changes in prize allocation should have a negligible impact on participant behavior. Hence, one of the primary arguments brought forth by the structural model is that sponsors should consider increasing the number of prizes to at least 20% of the expected number of submissions.

[Table 9 about here.]

Participant-Level Descriptive Analysis

To further investigate the impact of the number of prizes on submission behavior, I draw on individual participant-level submission patterns. Theory (Moldovanu and Sela 2001, Terwiesch and Xu 2008) predicts that stronger participants prefer a smaller number of prizes, holding fixed total award, whereas the reverse is true for weaker participants. I classify participants into segments based on their participation frequency, defined as the number of contests they viewed. I expect that participants who view a large number of contests either have a low cost of participation or a high expected probability of winning. Each segment contains a similar number of participant decision instances. Contests are grouped based on their observable characteristics. I compare the number of submissions made by the same participant across contests offering a different number of prizes within the same contest group. The regression equation is given by

$$\text{Submissions}_{it} = \alpha \log(\text{Number\_of\_Prizes}_t) + \xi_{iG(t)} + \epsilon_{it}, \tag{1}$$

where Submissions_{it} is the number of submissions made by participant i in contest t. The fixed effects $\xi_{iG(t)}$ control for unobserved participant and observed contest heterogeneity, where $G(t)$ denotes the group of contest t. Finally, α is the parameter of interest and ϵ_{it} is an error term.

Figure 6 illustrates the estimate of the coefficient α when Regression 1 is applied separately to each segment of participants. Participants who view a small number of contests appear to prefer multiple prizes, but participants who view a moderate number of contests show a distaste for multiple prizes. No effect is found for the most frequent participants. Further inspection reveals that participants who consider over 33 contests tend to submit near the maximum number of times to each contest. As a result, there is limited variation in their submission behavior, resulting in a near-zero coefficient for the most frequent participants. Figure 6 shows evidence consistent with the theoretical prediction that stronger participants may prefer fewer prize, holding fixed total award, but is not consistent with explanations that rely solely on risk-aversion or unobserved contest difficulty level.

[Figure 6 about here.]

The descriptive evidence presented in this section suggests that submission decisions respond to changes in prize allocation. Furthermore, the evidence supports models with risk-neutral heterogeneous participants such as Moldovanu and Sela (2001), Stein (2002), and Terwiesch and Xu (2008).

D Sponsor Choice Model Specification

The sponsor choice model relies only on submission ratings. In this section, I re-estimate the model, allowing for it to depend also on participant and idea characteristics as in the jury rating model. If there are any discrepancies between sponsor and jury preferences, then participant and idea characteristics may explain sponsor choice beyond jury ratings.

[Table 10 about here.]

Table 10 shows the resulting estimates from a model specified as $q_{st} = \sum_{m=1}^{5} \gamma_m 1\{W_{st} = m\} + \alpha^* X_i + \beta^* Z_{st} + \epsilon_{st}$ where X_i is a vector of participant characteristics, Z_{st} is a vector of idea characteristics, and α^*, β^* are the associated parameters, similar to the jury rating model. The results show that participant and idea characteristics are largely insignificant, with the exception of age and video production experience, which are significant at the 10%-level. This may be because the number of observations used to estimate the sponsor choice model (905) is considerably smaller than the number of observations per category in the jury rating model (8,319-29,974). In addition, the sponsor is exposed to the jury rating when making a decision which makes it particularly salient. I attempt to implement the simplest possible model with the greatest explanatory power and find that a model which relies only on ratings and pools observations across categories performs well. This is consistent with Gross (2017) who also models a sponsor's choice of logo designs as a simple function of ratings.

E Deriving an Upper Bound on Marginal Costs

In this section, I reproduce the proof presented in Pakes et al. (2015), adapted to my notation and setting, to show that $m^U(\theta) \geq 0$. For clarity, I drop the t subscript and focus on a single contest.

First, let $\Delta r_i = -\Delta r_i^*(d_i + 1, d_i; \theta)$ and use order-statistic notation to rank participants by ν_i and Δr_i, so that $\nu_{(1)} \leq \nu_{(2)} \leq ... \leq \nu_{(I)}$ and $\Delta r_{(1)} \leq \Delta r_{(2)} \leq ... \leq \Delta r_{(I)}$. Then, define the sets $L = \{i : d_i > 0\}$, $L_\nu = \{i : \nu_i \leq \nu_{(n)}\}$, $U = \{i : \Delta r_i \geq \Delta r_{(n+1)}\}$, and $U_\nu = \{i : \nu_i \leq \nu_{(I-n)}\}$, where I is the total number of participants, and n is the number of entrants. Let the change in expected profits from making $d_i - 1$ to d_i submissions for $i \in L$ be

$$\Delta \pi_i(d_i, d_i - 1) = \Delta r_i(d_i, d_i - 1; \theta) - \nu_i + \omega_{id_i,d_i-1} \tag{2}$$

and similarly, let the change in expected profits from making one additional submission be

$$\Delta \pi_i(d_i + 1, d_i) = \Delta r_i^*(d_i + 1, d_i; \theta) - \nu_i + \omega^*_{id_i+1,d_i}, \tag{3}$$

where $\omega^*_{id_i+1,d_i} = \omega_{id_i+1,d_i}$ if $d_i < 5$ and $\omega^*_{id_i+1,d_i} = 0$ otherwise. Then, we have that

$$\begin{aligned}
&\frac{1}{I}\sum_{i\in L}\Delta r_i(d_i, d_i-1;\theta) - \frac{1}{I}\sum_{i\in U}\Delta r^*_i(d_i+1, d_i;\theta) \\
&\qquad \geq \frac{1}{I}\sum_{i\in L}\Delta r_i(d_i, d_i-1;\theta) - \frac{1}{I}\sum_{i\in U_\nu}\Delta r^*_i(d_i+1, d_i;\theta) \\
&\qquad = \frac{1}{I}\sum_{i\in L}\left(\Delta\pi_i(d_i, d_i-1) + \nu_i - \omega_{id_i,d_i-1}\right) \\
&\qquad\quad - \frac{1}{I}\sum_{i\in U_\nu}\left(\Delta\pi_i(d_i+1, d_i) + \nu_i - \omega^*_{id_i+1,d_i}\right) \\
&\qquad \geq \frac{1}{I}\left(\sum_{i\in L}\nu_i - \sum_{i\in U_\nu}\nu_i\right) - \frac{1}{I}\left(\sum_{i\in L}\omega_{id_i,d_i-1} - \sum_{i\in U_\nu}\omega^*_{id_i+1,d_i}\right),
\end{aligned}$$

where the first inequality follows from the definition of the set U. The second inequality follows from the assumption that participants choose the optimal action. Note that

$$\frac{1}{I}\left(\sum_{i\in L}\nu_i - \sum_{i\in U_\nu}\nu_i\right) \geq \frac{1}{I}\left(\sum_{i\in L_\nu}\nu_i - \sum_{i\in U_\nu}\nu_i\right) = \frac{1}{I}\left(\sum_{i=1}^{n}\nu_{(i)} - \sum_{i=1}^{I-n}\nu_{(i)}\right). \tag{4}$$

The distributional assumption on ν_i (Assumption 4 in the main paper) ensures that

$$E\left[\frac{1}{I}\left(\sum_{i=1}^{n}\nu_{(i)} - \sum_{i=1}^{I-n}\nu_{(i)}\right)\right] \geq 0. \tag{5}$$

Furthermore,

$$E\left[\frac{1}{I}\sum_{i\in L}\omega_{id_i,d_i-1}\right] = \frac{1}{I}\sum_{i=1}^{I}E\left[1\{d_i>0\}\omega_{id_i,d_i-1}\right] = \frac{1}{I}\sum_{i=1}^{I}E\left[1\{d_i>0\}E[\omega_{id_i,d_i-1}]\right] = 0. \tag{6}$$

Expectational errors are mean-zero for entrants because they are assumed to be independent of a participant's action d_i. I also require the following assumption:

$$E\left[\frac{1}{I}\sum_{i\in U_\nu}\omega^*_{id_i+1,d_i}\right] \geq 0.$$

In other words, participants in U_ν cannot consistently underestimate their expected marginal returns. In my empirical setting this assumption applies to less than 5% of all participant entry occasions and, as a result, does not have a consequential impact on estimated identified set of cost parameters. Note that this applies only to participants in U_ν with $d_i < 5$, as otherwise, $\omega^*_{id_i+1,d_i} = 0$.

As a result,

$$E\left[\frac{1}{I}\sum_{i\in L}\Delta r_i(d_i, d_i-1;\theta) - \frac{1}{I}\sum_{i\in U}\Delta r_i^*(d_i+1, d_i;\theta)\right] \geq 0. \tag{7}$$

F Confidence Bounds for Cost Estimates

This section details the procedure used to obtain a 95% confidence interval for the estimates of the cost parameters in Table 7 in the main text. It follows Chernozhukov et al. (2007), Andrews and Soares (2010), and the procedures described in Pakes et al. (2011). First, define contest-specific sample moments, indexed by t:

$$m_t^L(\theta) = -\frac{1}{I_t}\sum_{i=1}^{I_t}\Delta r_{it}^*(d_{it}+1, d_{it};\theta), \tag{8}$$

$$m_t^U(\theta) = \frac{1}{I_t}\left(\sum_{i\in L_t}\Delta r_{it}(d_{it}, d_{it}-1;\theta) - \sum_{i\in U_t}\Delta r_{it}^*(d_{it}+1, d_{it};\theta)\right). \tag{9}$$

Then, $m^L(\theta) = \frac{1}{T}\sum\limits_{t=1}^{T} m_t^L(\theta)$ and $m^U(\theta) = \frac{1}{T}\sum\limits_{t=1}^{T} m_t^U(\theta)$ are the sample moments defined in equations 18 and 22 in the main text. Define the objective function: $Q(\theta) = \left[\frac{m^L(\theta)}{\sigma^L}\right]_-^2 + \left[\frac{m^U(\theta)}{\sigma^U}\right]_-^2$, where $[m]_-^2 = m^2$ if $m < 0$ and $[m]_-^2 = 0$ otherwise. The expressions σ^L, σ^U are the standard deviations of the moments $m_t^L(\theta), m_t^U(\theta)$ respectively across all contests $t = 1, ..., T$.

To obtain confidence bounds for θ, I use the following procedure:

1. Define a grid of point, $\theta_1, ..., \theta_G$, and refer to θ_g as a point in this grid.

2. Construct B bootstrapped datasets which involve sampling with replacement a total of $T = 181$ contests from the data. Let $\mathcal{C}_b$ denote the set of contests in bootstrap sample b.

3. Define the shift factors $\rho_g^L = \frac{\sqrt{T}}{\sqrt{2\log\log T}} \times \frac{[m^L(\theta_g)]_+}{\sigma_g^L}$ and $\rho_g^U = \frac{\sqrt{T}}{\sqrt{2\log\log T}} \times \frac{[m^U(\theta_g)]_+}{\sigma_g^U}$ where $m^L(\theta_g)$ and $m^U(\theta_g)$ are evaluated on the observed data and σ_g^L, σ_g^U are the standard deviations of the moments $m_t^L(\theta_g), m_t^U(\theta_g)$ respectively. The expression $[m]_+ = m$ if $m > 0$ and $[m]_+ = 0$ otherwise.

4. At each value of θ_g, perform the following steps:

   (a) For each bootstrapped dataset, construct the moments $m^{L(b)}(\theta_g) = \frac{1}{T}\sum_{t\in\mathcal{C}_b} m_t^L(\theta)$ and $m^{U(b)}(\theta_g) = \frac{1}{T}\sum_{t\in\mathcal{C}_b} m_t^U(\theta)$. In addition construct $\sigma_g^{L(b)}, \sigma_g^{U(b)}$ as the standard deviations of the moments $m_t^{L(b)}(\theta_g), m_t^{U(b)}(\theta_g)$ respectively across all contests $t \in \mathcal{C}_b$. Make sure to use the same set of bootstrapped datasets for all θ_g.

   (b) Evaluate and store $\iota_g^{(b)} = \left[\frac{m^{L(b)}(\theta_g)-m^L(\theta_g)}{\sigma_g^{L(b)}} + \rho_g^L\right]_-^2 + \left[\frac{m^{U(b)}(\theta_g)-m^U(\theta_g)}{\sigma_g^{U(b)}} + \rho_g^H\right]_-^2$ where $m^L(\theta_g)$ and $m^U(\theta_g)$ are evaluated on the observed data. Intuitively, this procedure generates a distribution of the criterion function under the null hypothesis that all of the moments are equal to zero with a shift. The shift factor is applied to account for the possibility that some moments may be overwhelmingly positive and satisfy the inequality restrictions by a large margin. The shift factor is borrowed from Andrews and Soares (2010) and the simulations in Pakes et al. (2011).[1] A similar procedure is used by Wollmann (2018).

   (c) Evaluate the 95th percentile of $\iota_g^{(b)}$ across all B bootstrapped datasets. This is the critical value ι_g.

5. Find the smallest θ_g such that $Q(\theta_g) < \iota_g$, where $Q(\theta_g)$ is evaluated on the observed data. This is the reported lower bound on θ.

6. Find the largest θ_g such that $Q(\theta_g) < \iota_g$. This is the reported upper bound on θ.

The above procedure can be modified to incorporate first-stage estimation error. Consider step 2. For each bootstrapped dataset, I re-estimate the sponsor choice model and the jury rating model before proceeding to steps 3 and 4. The parameter estimates from these re-estimated models are used to construct the moments in steps 3 and 4. Thereby, each bootstrapped dataset will yield an associated set of first-stage parameters which will most likely differ across the datasets, creating additional variation in the sample moments to incorporate first-stage estimation error.[2]

Note that many of the articles that use moment inequalities do not incorporate first-stage estimation error (Ishii 2008, Ho 2009, Ho et al. 2012, Wollmann 2018). This is because there

[1] See Section 4.2 of Andrews and Soares (2010) for a step-by-step description of the procedure.

[2] For internal consistency, the standard errors presented in Table 5 for the sponsor choice model and in Table 6 for the jury rating model in the main text are based on these bootstrapped datasets.

is limited research on how to incorporate first-stage estimation error in moment inequalities. It may be expected that the procedure described above will yield conservative bounds based on the simulations in (Pakes et al. 2011).

I use $B = 200$ bootstrapped datasets in practice. To identify the grid points θ_g, I initially evaluate $Q(\theta)$ on the observed data for each category, and define a grid of 20 points to the left of the lower bound and 20 points to the right of the upper bound on θ. The range of these points is refined through trial and error to identify as precisely as possible the parameters at which the criterion function lies below the critical value. This procedure can be computationally intensive.

G Asymmetric Information Counterfactuals

As discussed in Section 'Participant Entry Model', I make the simplifying assumption that participants know the characteristics and actions of their competitors (Assumption 1 in the main paper) to reduce to simulation burden of estimating the participant entry model and counterfactuals. In this appendix, I relax this assumption and propose a model which allows for participants to be uncertain about the quantity, characteristics, and actions of their competitors. In essence, the model requires that participants know the empirical distribution of competitor information conditional on contest structure. A participant's expected returns can be calculated by averaging the expected returns she would have received had she replaced a random participant in each one of the contests in the data with the same prize structure.

In the asymmetric information scenario, I focus on a subset of contests with the same prize structure and allow for participant uncertainty with regards to sponsor and jury preferences, and the number, characteristics, and actions of competitors. Participant i's information set in contest t is given by $\mathcal{J}_{it}^{II} = \{d_{it}, X_i, C_t\}$, and the participant knows the conditional joint density of the number of participants and sponsor/jury preferences $H(I_t, \delta_t|C_t)$, and the conditional joint density of competitor actions and characteristics $G(d_{-it}, X_{-it}|I_t, C_t, \delta_t)$. I assume that participants use an iterative updating procedure, described further in Section 'The Impact of Asymmetric Information' and Appendix I, to converge to a new equilibrium from their current state. The procedure can be interpreted as a learning algorithm that participants use to find a new equilibrium under a different contest structure (Lee and Pakes 2009). Assumption 1 in the main paper can be replaced with the following assumption.

Assumption 1 *Participants do not know the realizations but do know the distributions of idea characteristics Z_{st}, sponsor/jury preference shocks ϵ_{st} and η_{st}, and the unobserved participant-contest component of idea quality ξ_{it} before making submission decisions. Also, participants do not know the total number of participants I_t, competitor actions d_{-it}, competitor characteristics X_{-it} and costs ν_{-it}, and sponsor/jury preference parameters γ_m for $m = 1, ..., 5$, α, and β for each contest category. Participants do know the conditional joint density of the number of participants and sponsor/jury preferences $H(I_t, \delta_t|C_t)$, and the conditional joint density of competitor actions and characteristics $G(d_{-it}, X_{-it}|I_t, C_t, \delta_t)$, where C_t is contest t's prize structure, and δ_t is the vector of sponsor and jury preference parameters defined in Section 'Counterfactuals'.*

Participant Entry Model With Asymmetric Information

I begin by discussing the estimation procedure for the participant entry model. Note that the same estimation procedure as in Section 'Estimation' yields accurate confidence bounds for the parameters of the cost function even when participants have asymmetric information. To see this, I redefine the expectational error $\omega_{itd_{it}}$ as the difference between a participant's expected and actual returns: $\omega_{itd_{it}} = E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})|\mathcal{J}_{it}\right] - R_t(d_{it}, d_{-it}; X_i, X_{-it})$, where $\mathcal{J}_{it}$ is participant i's information set in contest t (given by $\mathcal{J}_{it}^{II} = \{d_{it}, X_i, C_t\}$ in this case). I assume that participants have correct expectations, or equivalently, that the expectations operator $E\left[.\right]$ used by participants is equivalent to the statistical expectations operator as applied to the data.[3] Note that Assumption 2 in the main paper holds trivially as

$$\begin{aligned} E[\omega_{itd_{it}}] &= E\left[E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})|\mathcal{J}_{it}\right]\right] - E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})\right] \\ &= E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})\right] - E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})\right] = 0. \quad (10) \end{aligned}$$

The same estimation procedure as detailed in Section 'Estimation' can be applied to the participant entry model as expectational errors will reflect participant uncertainty about competitor behavior and simply average out when forming bounds.

[3] Note that the two expectations operators do not have to be equivalent. For example, they differ if a participant's beliefs about the equilibrium distribution of competitor actions is not the same as the distribution of competitor actions in the data.

To see the result in Equation 10 more clearly, I present a toy example contest with a single prize of \$$p$, 2 participants labeled A and B, and 2 possible actions $d_i \in \{0,1\}$. I drop the subscript t for exposition and further simplify by assuming that $\gamma_m = 0$ from the sponsor choice model for any rating received such that participant characteristics become irrelevant. Participant A's expected payoffs can be written as

$$E\left[R_t(d_A, d_B)|d_A\right] - (\theta_2 d_A + \nu_A)d_A = E\left[\frac{d_A p}{d_A + d_B}|d_A\right] - (\theta_2 + \nu_A)d_A \tag{11}$$

Note that the expectation operator represents the participant's expectation with respect to the ditribution of her competitor's action d_B. Furthermore,

$$E\left[\frac{d_A p}{d_A + d_B}|d_A\right] = \Pr\{d_B = 1\}\frac{d_A p}{d_A + 1} + (1 - \Pr\{d_B = 1\}) \tag{12}$$

where $Pr\{d_B = 1\}$ may depend on the distribution of ν_A as is common in entry games with incomplete information (Seim 2006). For example, assuming that ν_A follows a mean-zero logistic distribution implies that $\Pr\{d_A = 1\} = \frac{\Pr\{d_B=1\}d_A p/(d_A+1)+(1-\Pr\{d_B=1\})-\theta_2}{1+\Pr\{d_B=1\}d_A p/(d_A+1)+(1-\Pr\{d_B=1\})-\theta_2}$.

Returning to Equation 10, the expectational error can be written as

$$E\left[\frac{d_A p}{d_A + d_B}|d_A\right] - \frac{d_A p}{d_A + d_B} = \underbrace{\Pr\{d_B = 1\}\frac{d_A p}{d_A + 1} + (1 - \Pr\{d_B = 1\})}_{\text{participant's expectation}} - \underbrace{\frac{d_A p}{d_A + d_B}}_{\text{actual realization}} . \tag{13}$$

Suppose that we observe the equilibrium outcomes of this game over multiple contests. Then, an application the statistical expectations operator over the distribution of competitor actions in the data yields

$$\begin{aligned}
E\left[\Pr\{d_B = 1\}\frac{d_A p}{d_A + 1} + (1 - \Pr\{d_B = 1\}) - \frac{d_A p}{d_A + d_B}\right] = \\
\Pr\{d_B = 1\}\frac{d_A p}{d_A + 1} + (1 - \Pr\{d_B = 1\}) - E\left[\frac{d_A p}{d_A + d_B}\right] = \\
\Pr\{d_B = 1\}\frac{d_A p}{d_A + 1} + (1 - \Pr\{d_B = 1\}) - \Pr\{d_B = 1\}\frac{d_A p}{d_A + 1} - (1 - \Pr\{d_B = 1\}) = 0
\end{aligned} \tag{14}$$

where the second equality follows from the assumption that participant expectations are correct and coincide with the distribution of competitor actions in the data. As this simple example and the more general expression in Equation 10 demonstrate, correct participant expectations imply that expectational errors average out to zero just as in Assumption 2 in the main paper, implying that the estimation procedures in Section ‘Estimation’ are also valid under asymmetric information.

The Impact of Asymmetric Information

To simulate counterfactuals under asymmetric information, it is necessary to recover $H(I_t, \delta_t|C_t)$ and $G(d_{-it}, X_{-it}|I_t, C_t, \delta_t)$, which can theoretically be achieved by flexible density estimation. However, I find this to be infeasible given the large number of contest-specific variables. Instead, I focus on a subset of 49 contests that offered four \$250 prizes and treat each contest as an independent draw from the joint density of sponsor/jury parameters, the number of competitors, and competitor actions and characteristics conditional on contest structure. All asymmetric information analyses are conducted only for this subset of contests, labeled $\mathcal{W}$.

To understand the impact of asymmetric information on behavior, I recover participant expectational errors, which capture the difference between a participant's expected returns under asymmetric information and her expected returns under symmetric information. To do so, I draw a large sample of contests of size B from $\mathcal{W}$ (with replacement) and label these contests $b = 1, ..., B$. Then, letting j_b denote a random participant in contest b, the expected returns $E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})|\mathcal{J}_{it}\right]$ can be approximated by

$$ER_{it}(d_{it}) = \frac{1}{B}\sum_{b=1}^{B} R_b(d_{it}, d_{-j_b b}; X_i, X_{-j_b b}) \tag{15}$$

for $t \in \mathcal{W}$. This is akin to assuming that the participant knows the variables associated with each contest in $\mathcal{W}$ but does not know which one of these contests she is playing. An estimate of participant i's expectational error is given by $\hat{\omega}_{itd_{it}} = ER_{it}(d_{it}) - R_t(d_{it}, d_{-it}; X_i, X_{-it})$.

I find that participants who make higher quality submissions tend to underestimate their expected returns ($\hat{\omega}_{itd_{it}} < 0$) as they do not know with certainty that they are the most skilled participants in their contests. Similarly, participants who make lower quality submissions tend to overestimate their expected returns ($\hat{\omega}_{itd_{it}} > 0$) as they do not know with certainty that they fall in the lower range within the contests they participate in.

I evaluate the impact of reducing the maximum number of submissions to 4 under asymmetric information for the contests in $\mathcal{W}$ using the simulation procedure in Appendix I. Table 11 shows the impact of this design compared to its predicted impact under the assumption of symmetric information as in the main model for the same set of contests. The two do not differ significantly from each other which suggests that counterfactuals performed under a symmetric information assumption may well approximate an asymmetric information environment, at least for the considered contest designs and on average across contests.

[Table 11 about here.]

H Validation of Jury Rating Model Parameter Estimates

I explore the relationship between the parameter estimates of the jury rating model and observed participant submission decisions. For each participant, I use the parameter estimates to recover $\alpha_t X_i$, which I refer to as the participant's observed *ability*. I introduce a subscript t on α to reflect the differences in parameters of the jury rating model across contest categories. Given the model assumptions, higher ability participants are expected to make more submissions unless one of the following conditions is true: participants do not consider or cannot evaluate their chances of winning when making submission decisions, participants do not know their own abilities, or participant-specific cost unobservables exhibit a sufficiently strong correlation with abilities such that the marginal cost of making an additional submission offsets the marginal return from doing so. I estimate the following regression:

$$\text{Submissions}_{it} = \beta \text{Ability}_{it} + \xi_t + \epsilon_{it} \tag{16}$$

where Submissions_{it} is the number of submissions made by participant i in contest t, Ability_{it} is defined as $\alpha_t X_i$ at the estimated parameters α_t which vary by contest category, ξ_t is a contest-specific fixed effect that controls for differences in the mean levels of abilities of participants across contests, β is the parameter of interest, and ϵ_{it} is an error term. The identification of β originates from variation in submissions and abilities within contests. I recover an estimate of 0.456 for β with a standard error of 0.045, which points to significant evidence of a positive relationship between participant ability and number of submissions.

The descriptive analysis presented in this section provides evidence of internal consistency in the model estimates. Participants with higher estimated abilities tend to make more submissions. Furthermore, participants appear to have sufficient knowledge about their chances of winning to guide submission decisions.

I Counterfactual Simulation Procedure

Symmetric Information

To simulate counterfactual contest designs under symmetric information, I draw sample parameters from the identified set and use iterated best response to obtain equilibrium strategies. I make the assumption that first-stage ability estimates are obtained without error. The following steps can be used to obtain counterfactual equilibrium outcomes for a contest t:

1. Uniformly sample θ^s from the identified set of average cost parameters.

2. At the sampled parameter, obtain bounds on the cost draw for each participant. Note that if θ^s were the true parameter, then by revealed preference, $\nu_{it} \geq \Delta r^*_{it}(d_{it}+1, d_{it}; \theta^s)$ at the observed submission decisions, where $\Delta r^*_{it}(d_{it}+1, d_{it}; \theta^s)$ is evaluated at the sampled parameter θ^s. Similarly, $\nu_{it} \leq \Delta r_{it}(d_{it}, d_{it}-1; \theta^s)$ if participant i submitted at least once to contest t. Otherwise, I use $\nu_{it} \leq \max\limits_{j=1,\ldots,I_t} \{-\Delta r^*_{jt}(d_{jt}+1, d_{jt}; \theta^s)\}$ as an upper bound. For each participant, obtain a lower bound ν^{Ls}_{it} and an upper bound ν^{Us}_{it}.

3. Uniformly sample ν^s_{it} from the interval $\left[\nu^{Ls}_{it}, \nu^{Us}_{it}\right]$ for each participant to obtain a cost draw that is consistent with the observed behavior and the estimated parameters.

4. Compute equilibrium actions according to the following procedure:

   (a) For each participant $i = 1, ..., I_t$, choose a random starting action $d^s_{it} \in \{0, 1, ..., D\}$, where D is the submission limit.

   (b) Loop through participants, updating participant i's action according to

$$d^s_{it} = \arg\max_{d_{it}} \left[R_t(d_{it}, d^s_{-it}; X_i, X_{-it}) - (\theta^s_1 + \theta^s_2 d_{it} + \nu^s_{it}) d_{it}\right] \tag{17}$$

for $d_{it} \in \{0, 1, ..., D\}$, where D is the counterfactual submission limit and $R_t(.)$ is the counterfactual contest expected returns function.

(c) Repeat 4b until the updating procedure no longer changes participant actions. This rest-point is a Nash Equilibrium of the contest game.

5. Calculate contest outcome metric V_t^s at the equilibrium actions, the parameter vector θ^s and the cost draws $\{\nu_{it}^s\}_{i=1}^{I_t}$.

Steps 1-5 are repeated S times. I report the lower bound on the counterfactual outcome as $V_t^L = \min(V_t^s)$ and the upper bound as $V_t^U = \max(V_t^s)$. To obtain the average outcome across contests, as shown in Table 9 in the main paper, I use $V^L = \frac{1}{T}\sum_{t=1}^{T} V_t^L$ for the lower bound and $V^U = \frac{1}{T}\sum_{t=1}^{T} V_t^U$ for the upper bound.

Asymmetric Information

The procedure described in Section 'Symmetric Information' can be modified as follows to incorporate asymmetric information. First, in Step 2, all instances of $R_t(d_{it}, d_{-it}; X_i, X_{-it})$ must be replaced with $ER_{it}(d_{it})$, which can be obtained using the procedure described in Appendix G. Then, the resulting cost intervals $\left[\nu_{it}^{Ls}, \nu_{it}^{Us}\right]$ will take into account that participants had asymmetric information when choosing their actions. Second, Step 4 must be modified to capture the change in the density of the number of competitors, participant actions, and characteristics when the structure of the contest changes, as in Yoganarasimhan (2016). Formally, Step 4 can be modified as follows, assuming that $\left[\nu_{it}^{Ls}, \nu_{it}^{Us}\right]$ have been obtained for all participants in the contests in $\mathcal{W}$ in a previous step.

4. Compute equilibrium actions according to the following procedure:

(a) For each participant $i = 1, ..., I_t$, set d_{it}^s to the participant's observed action.

(b) At iteration $k+1$, loop through participants and contests, updating participant i's action in contest t according to

$$d_{it}^{sk+1} = \arg\max_{d_{it}} \left[ER_{it}^k(d_{it}) - (\theta_1^s + \theta_2^s d_{it} + \nu_{it}^s)d_{it}\right], \tag{18}$$

where

$$ER_{it}^{k}(d_{it}) = \frac{1}{B}\sum_{b=1}^{B} R_b(d_{it}, d_{-j_b b}^{sk}; X_i, X_{-j_b b}) \tag{19}$$

for $d_{it} \in \{0, 1, ..., D\}$, where D is the counterfactual submission limit, $R_b(.)$ is the counterfactual contest expected returns function, and j_b denotes a random participant in contest b as in Appendix G.

(c) Repeat 4b until $d_{it}^{sk+1} = d_{it}^{sk}$ for all $t \in \mathcal{W}$ and all i in contest t. This rest point is an equilibrium of the asymmetric information contest game.

In general, the procedure will only recover one of many possible equilibria. However, I find that when multiple equilibria do exist, the outcome metrics do not differ significantly across equilibria. Lee and Pakes (2009) obtain similar results in their analysis of counterfactual equilibria in the model of Ishii (2008).

Note that this counterfactual procedure compares predicted counterfactual outcomes with the observed entry behavior in the data. This approach is common in entry models (Eizenberg 2014, Wollmann 2018) and bypasses the issue of solving for multiple equilibria at the parameter vector that explains the observed behavior. Furthermore, the procedure implies that the observed actions constitute an equilibrium and can be used as a valid baseline.

J Alternative Outcome Metric: Quality of Top 50 Submissions

In contests that offer multiple prizes, the sponsor may care about the expected quality of the winning submissions. However, this outcome metric will be closely related to expected total quality. In addition, for contests that offer a small number of prizes relative to submissions (as do most contests in the data), the impact of counterfactuals on the expected quality of the top few submissions will be very similar to their impact on the expected quality of the top submission.

I use simulation to evaluate the impact of two of the most effective counterfactuals in Table 8 in the main paper - 'Optimal Number of Prizes and (B)' and '4 Submission Limit' - on the expected quality of the top 50 submissions in the sample contest. I find that offering the optimal number of prizes (180) while restricting the number of prizes per participant to 1 increases expected quality of the top 50 submissions by 2-3% (compared to an 8-11% impact on expected total quality).

Restricting the maximum number of submissions to 4 reduces the expected quality of the top 50 submissions by 1-3% (compared to a 4-11% reduction in expected total quality). As expected, the effect of the counterfactual design decision is in the same direction in both cases. Interestingly, even if the sponsor is only interested in the quality of the top 50 submissions, she is better off offering more than 50 prizes.

K Theoretical Model and Simulation of a Small Contest

I present a simple theoretical model with 3 participants, at most 2 submission per participant, and at most 2 prizes to highlight how heterogeneity may influence the optimality of different design decisions. Suppose that the sponsor perceives submission s by participant i to have quality $\log(a_i) + \epsilon_{is}$, where a_i is the ability of participant i and $\epsilon_{is} \sim T1EV$ is an iid shock which captures idiosyncratic differences in quality across submissions. Suppose that participant i receives a payoff

$$R(d_i, d_{-i}; P) - \nu d_i - \theta d_i^2 \tag{20}$$

where d_i is the number of submissions made by participant i, d_{-i} is a vector of submissions made by her competitors, P is the total award, $R(d_i, d_{-i}; P)$ is the return to participant i given actions d_i, d_{-i}, and ν and θ are parameters of a quadratic cost function that reflects the increasing effort required to make more submissions. I assume that participants have complete and symmetric information about abilities but know only the distribution and not the realizations of the unobservables ϵ_{is}.

In a contest with a single prize, the returns function for participant i can be written as

$$R(d_i, d_{-i}; P)^{\text{1-prize}} = \frac{d_i a_i}{\sum_j d_j a_j} P. \tag{21}$$

The chance that participant i will win increases with her submissions and ability but falls as the submissions and abilities of her competitors increase. In a contest with 2 prizes, assuming the same participant may win multiple prizes, the returns function becomes more complicated:

$$R(d_i, d_{-i}; P)^{\text{2-prizes}} = \underbrace{\frac{d_i a_i}{\sum_j d_j a_j} \left(\frac{(d_i - 1)a_i}{(d_i - 1)a_i + \sum_{j \neq i} d_j a_j} \right) P}_{\text{win both prizes}} +$$

$$\underbrace{\sum_{k \neq i} \frac{d_k a_k}{\sum_j d_j a_j} \left(\frac{d_i a_i}{(d_k - 1)a_k + \sum_{j \neq k} d_j a_j} \right) \frac{P}{2}}_{\text{lose first prize but win second}} + \underbrace{\frac{d_i a_i}{\sum_j d_j a_j} \sum_{k \neq i} \left(\frac{d_k a_k}{(d_i - 1)a_i + \sum_{j \neq i} d_j a_j} \right) \frac{P}{2}}_{\text{win first prize but lose second}}. \quad (22)$$

I also experiment with a returns function that allows for each participant to win at most one prize:

$$R(d_i, d_{-i}; P)^{\text{2-prizes*}} = \underbrace{\frac{d_i a_i}{\sum_j d_j a_j} \frac{P}{2}}_{\text{win first prize}} + \underbrace{\sum_{k \neq i} \frac{d_k a_k}{\sum_j d_j a_j} \left(\frac{d_i a_i}{\sum_{j \neq k} d_j a_j} \right) \frac{P}{2}}_{\text{lose first prize but win second}}. \quad (23)$$

Other authors have noted how solving imperfectly discriminating contests with multiple prizes and heterogeneous participants can be intractable even in the simplest settings (Szymanski and Valletti 2005). In addition, this game can have multiple equilibria at a single parameter vector because of the discrete action space. I do not attempt to derive closed form solutions to equilibrium strategies but rather illustrate examples of counterfactual comparisons where the impact of a contest design decision differs with the extent of participant heterogeneity. I fix the prize at $P = 40$, the cost parameters at $\nu = 1$ and $\theta = 1$, and the ability parameters at $a_1 = 1$ and $a_2 = 1$. I allow for the third participant's ability a_3 to vary from 1 to 40 to capture increasing levels of heterogeneity. I obtain all counterfactual outcomes using an iterated best response algorithm (see Appendix I).

Reducing the Number of Prizes From 2 to 1

For each value of a_3, I obtain equilibrium outcomes under $R(d_i, d_{-i}; P)^{\text{1-prize}}$ and $R(d_i, d_{-i}; P)^{\text{2-prizes*}}$. Then, I evaluate the difference in the total number of entrants $\sum 1\{d_i > 0\}$ and the total number of submissions $\sum d_i$ between the 2-prize scenario and the 1-prize scenario. Figure 7 shows how each outcome metric varies as a_3 increases.

[Figure 7 about here.]

Both the number of entrants and submissions increase as participant heterogeneity increases.

When there is limited heterogeneity ($a_3 = 1$), the sponsor maximizes the number of submissions by offering a single prize. With multiple prizes, participants do not exert as much effort as the amount of money per prize is reduced and participants are rewarded for not winning. As heterogeneity increases, the equilibrium number of submissions per entrant increases when multiple prizes are offered. If the difference in participant abilities is sufficiently large, the sponsor prefers to offer multiple prizes, as otherwise the weakest participants would not have any chance of winning against the stronger participant and would not enter the contest altogether.

Reducing the Submission Limit From 2 to 1

For each value of a_3, I obtain equilibrium outcomes under $R(d_i, d_{-i}; P)^{\text{2-prize}}$ for two scenarios. In the first scenario, participants are allowed at most 1 submission. In the second scenario, participants are allowed at most 2 submissions. Then, I evaluate the difference in the total number of entrants and the total number of submissions between the 2 submission limit scenario and the 1 submission limit scenario. Figure 8 shows how each outcome metric varies as a_3 increases.

[Figure 8 about here.]

For low values of a_3, the sponsor benefits from allowing for more submissions per participant. However, as a_3 increases, a submission limit of 1 handicaps the stronger participant and presents an opportunity for the weaker participants to win at least one prize. As a result, for high values of a_3 the sponsor prefers to offer a lower submission limit.

Reducing the Number of Prizes Per Participant From 2 to 1

In the special example provided in this section, reducing the number of prizes per participant from 2 to 1 has the same impact as reducing the submission limit from 2 to 1. To see this, consider the returns function $R(d_i, d_{-i}; P)^{\text{2-prizes}}$ from Equation 22 in a scenario where each participant can make at most 1 submission. The first expression collapses to zero as a participant cannot win both prizes with a single submission. In the second and third expressions, the participant who won the first prize can no longer win the second prize. As a result, the second expression becomes

$$\underbrace{\sum_{k\neq i}\frac{d_k a_k}{\sum_j d_j a_j}\left(\frac{d_i a_i}{(d_k-1)a_k+\sum_{j\neq k} d_j a_j}\right)\frac{P}{2}}_{\text{lose first prize but win second}} = \sum_{k\neq i}\frac{d_k a_k}{\sum_j d_j a_j}\left(\frac{d_i a_i}{\sum_{j\neq k} d_j a_j}\right)\frac{P}{2} \tag{24}$$

whereas the third expression becomes

$$\underbrace{\frac{d_i a_i}{\sum_j d_j a_j}\sum_{k\neq i}\left(\frac{d_k a_k}{(d_i-1)a_i+\sum_{j\neq i} d_j a_j}\right)\frac{P}{2}}_{\text{win first prize but lose second}} = \frac{d_i a_i}{\sum_j d_j a_j}\sum_{k\neq i}\left(\frac{d_k a_k}{\sum_{j\neq i} d_j a_j}\right)\frac{P}{2} = \frac{d_i a_i}{\sum_j d_j a_j}\frac{P}{2}. \tag{25}$$

As a result,

$$R(d_i, d_{-i}; P)^{\text{2-prizes}} = \underbrace{\frac{d_i a_i}{\sum_j d_j a_j}\frac{P}{2}}_{\text{win first prize}} + \underbrace{\sum_{k\neq i}\frac{d_k a_k}{\sum_j d_j a_j}\left(\frac{d_i a_i}{\sum_{j\neq k} d_j a_j}\right)\frac{P}{2}}_{\text{lose first prize but win second}} = R(d_i, d_{-i}; P)^{\text{2-prizes}*}. \tag{26}$$

Hence, in this particular example, reducing the maximum number of prizes per participant is equivalent to reducing the number of submissions per participant. The stronger participant is handicapped as she no longer has a chance of winning both prizes which reduces her effort but creates opportunities for weaker participants to win a lower ranking prize and increases their effort. When participant heterogeneity is high, restricting the number of prizes per participant can improve the contest outcome.

Connection to the Literature

The counterfactual exercises presented in this section highlight the results found in the theory literature as surveyed in Section 'Contest Design with Heterogeneous Participants'. They illustrate that optimal design decisions depend crucially on participant heterogeneity. In addition, these simulations point at the complexity of expected returns functions in contests with a large number of submissions and more than 2 prizes. In Section 'Estimation', I turn to simulation to evaluate the expected returns functions.

L Empirical Support for Assumption 1

Assumption 1 requires that participants do not know the realizations of several unobservables that enter the sponsor choice model and the jury rating model. As a result, participants cannot affect the rating they receive for an individual submission. To further test the validity of this assumption, I examine how the ratings awarded to a participant vary across contests offering different total awards. I use the following regression:

$$Y_{it} = \alpha \log(\text{Total\_Award}_t) + \xi_{iG(t)} + \epsilon_{it} \tag{27}$$

where Y_{it} takes on various aggregations of the ratings received by participant i in contest t for all of her submissions. The fixed effect $\xi_{iG(t)}$ controls for persistent sources of participant and contest heterogeneity. In particular, $G(t)$ denotes the group of contest t, and all contests within the same group have the same number of prizes. Finally, α is the parameter of interest and ϵ_{it} is an error term.

Table 12 shows the parameter estimates α for several regressions. I run each regression holding fixed the number of submissions such that any differences in ratings can be attributed to the participant's effort or selection into the contest.

[Table 12 about here.]

The first row shows significant evidence of the impact of an increase in total award on the average ratings of a participant's submissions for participants who make 1, 4, or 5 submissions to multiple contests that offer the same number of prizes. However, the second row shows that an increasing award has no impact on the participant's chance to achieve a rating of 4 or 5. In the third row, it is evident that participants making 1, 4, or 5 submissions to multiple contests are more likely to achieve a rating higher than 2 when total award is larger.

To summarize, I find evidence that participants can affect their chance to receive a low rating (1 or 2) but cannot affect their chance to receive a high rating (4 or 5) conditional on the number of submissions. However, the impact of increasing award on rating is not economically significant. Consider the case of participants who make only one submission to multiple contests. For these participants, increasing total award from \$1000 to \$2000 increases the chance that the participant achieves a rating greater than 2 by 2.3% but does not substantially alter the participant's chance of achieving a rating greater than 3. For the average participant, this increases her chances of achieving a rating of 3 by 0.6% over a baseline of 27% whereas she has a 5.2% chance of achieving a rating of 4 or 5 by making one new submission. As a result, although I find evidence that participants may attempt to improve the ratings of individual submissions in contests with a higher total award, I do not expect this to have as significant an impact on a participant's chance of winning as the choice of how many submissions to make.

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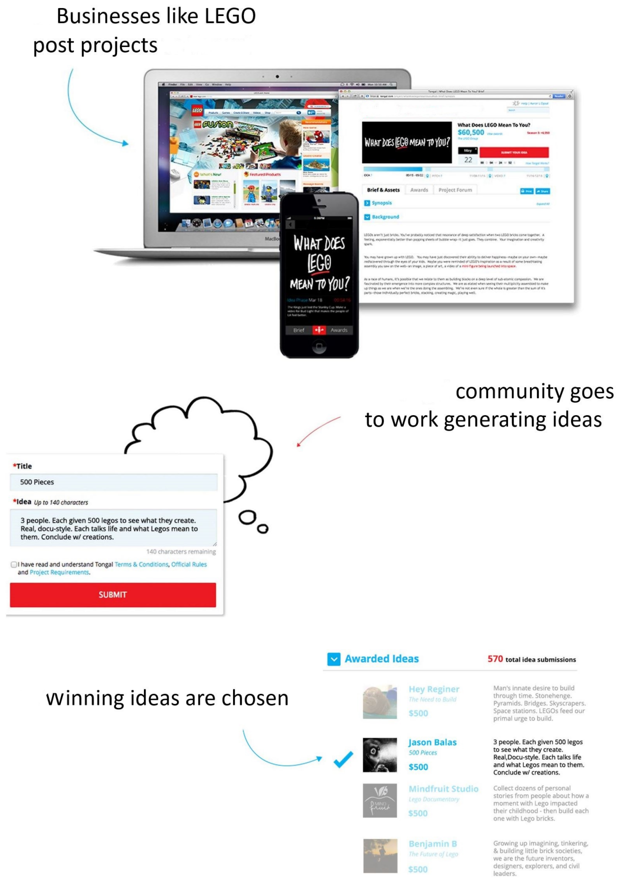
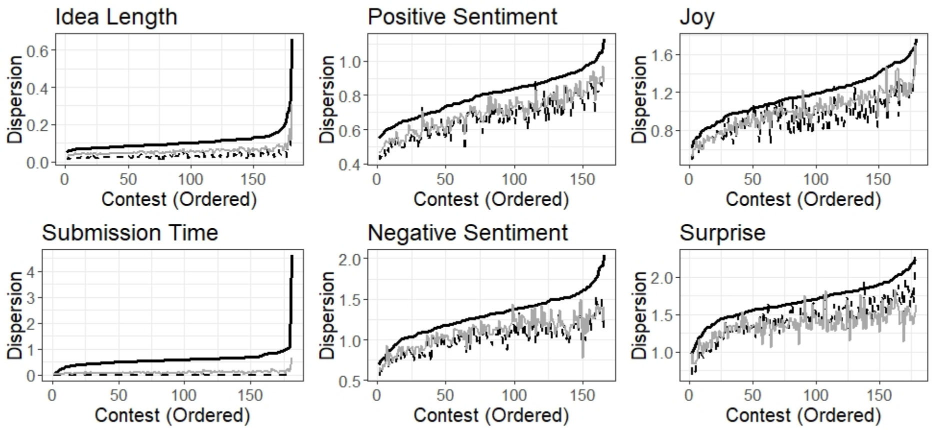
Figure 1: The Idea Submission Process



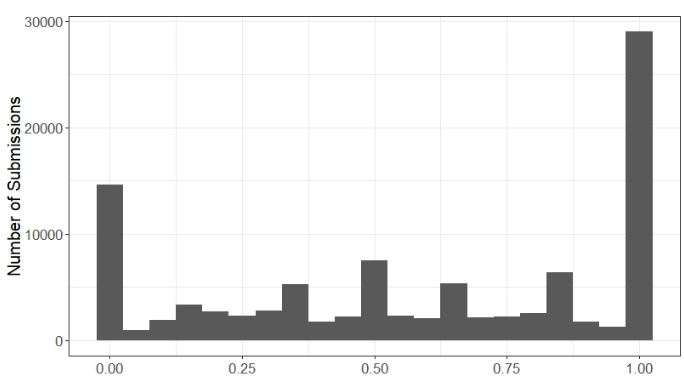
Note: Figure shows images that instruct participants on how a contest works.

Figure 2: Dispersion in Idea Characteristics Within and Across Participants



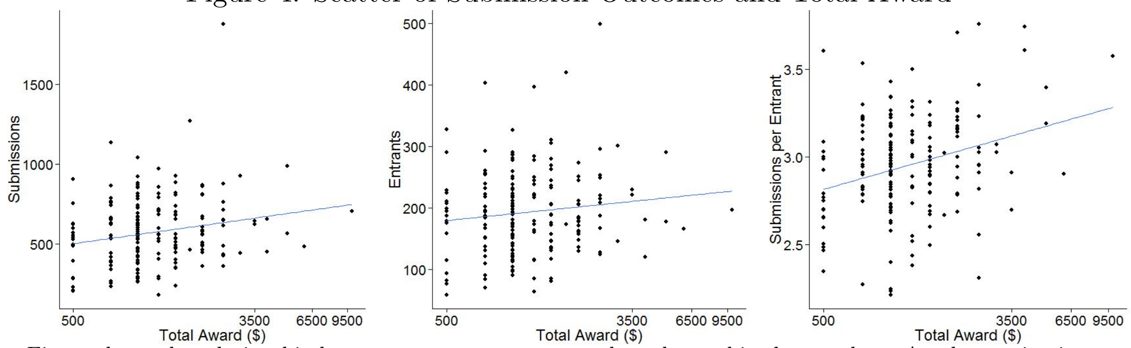
Note: Figure illustrates the dispersion in idea characteristics such as idea length (as a fraction of total permissible length), submission time (as a fraction of contest duration), positive sentiment, negative sentiment, joy, and surprise within and across participants by contest. For each idea characteristic, dispersion across participants is measured as the standard deviation in the idea characteristic across all submissions within the contest divided by the mean value of the idea characterstic within the contest. Dispersion within participant is measured in the same way for each participant individually within a contest. Each plot focuses on participants who made at least four submissions and, for each contest, reports the overall dispersion across participants (solid black line), the mean dispersion within participants (gray line), and the median dispersion within participants (dashed line). In each plot, contest are ordered by increasing value of overall dispersion in the associated idea characteristic.

Figure 3: Distribution of Idea Submission Times



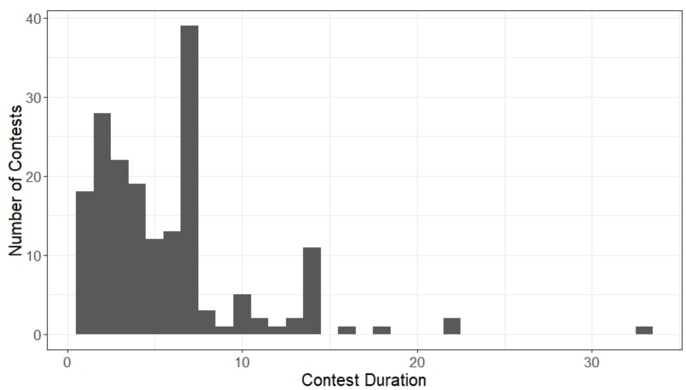
Note: Figure shows the distribution of submission times as a fraction of contest duration for all submissions in the sample. Most ideas are submitted either at the start or at the end of each contest.

Figure 4: Scatter of Submission Outcomes and Total Award



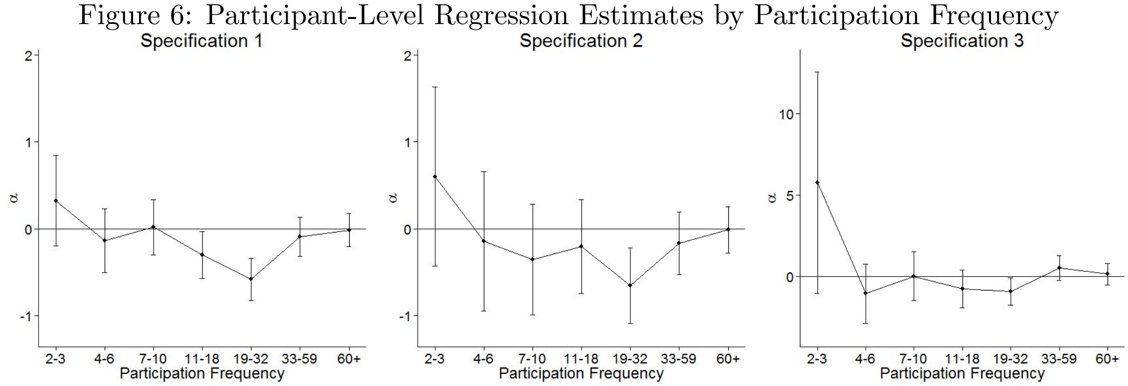
Note: Figure shows the relationship between contest outcomes and total award in the raw data. An observation is a contest. The left plot shows the relationship between total submissions and total award. The center plot shows the relationship between the number of entrants and total award. The right plot shows the relationship between the number of submissions per entrant and total award. Total award is presented on a logarithmic scale. Line shows best-fitting linear model.

Figure 5: Distribution of Contest Duration



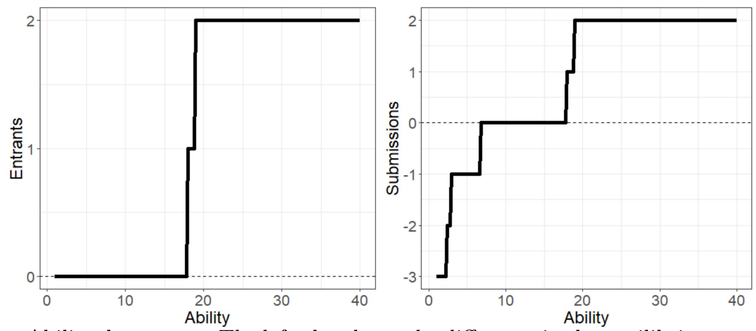
Note: Figure shows the distribution of contest duration in days. Most contests last for one week or less with the longest contest open for slightly over a month.

Figure 6: Participant-Level Regression Estimates by Participation Frequency



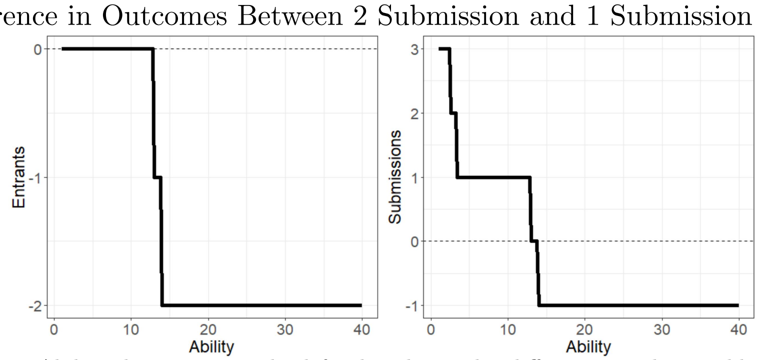
Note: Plots show estimates and robust 95% confidence intervals for α in Regression 1. Participants are segmented based on their participation frequency, defined as the number of contests they viewed. Specification 1 groups contests by total award. Specification 2 groups contests by category and total award. Specification 3 groups contests by sponsor and total award. Estimates show a pattern that is consistent with theory predictions - participants with a low participation frequency may prefer multiple prizes, whereas other participants may prefer fewer prizes. However, most estimates are not statistically significant, which may point to the fact that the number of prizes is usually too small relative to the number of submissions to meaningfully affect participant behavior, consistent with the counterfactual simulation results in Section 'Counterfactuals'.

Figure 7: Difference in Outcomes Between 2-Prize and 1-Prize Scenarios



Note: Ability denotes a_3. The left plot shows the difference in the equilibrium number of entrants between the 2-prize scenario and the 1-prize scenario. The right plot shows the difference in the equilibrium number of submissions between the 2-prize scenario and the 1-prize scenario. Both plots shows equilibrium outcomes for one of possibly many equilibria at each value of a_3 which is selected by iterative best response. The sponsor prefers to offer multiple prizes when ability heterogeneity is sufficiently large. Otherwise, the sponsor prefers to offer a single prize.

Figure 8: Difference in Outcomes Between 2 Submission and 1 Submission Limit Scenarios



Note: Ability denotes a_3. The left plot shows the difference in the equilibrium number of entrants between the 2 submission limit scenario and the 1 submission limit scenario. The right plot shows the difference in the equilibrium number of submissions between the 2 submission limit scenario and the 1 submission limit scenario. Both plots shows equilibrium outcomes for one of possibly many equilibria at each value of a_3 which is selected by iterative best response. The sponsor prefers to impose a 1 submission limit when ability heterogeneity is sufficiently large. Otherwise, the sponsor prefers to impose a 2 submission limit.

Table 1: Participant-Level Logistic Regressions of Entry and Victory on Participant Characteristics

DV:	Entry	Win
Age	0.023***	-0.003**
	(0.004)	(0.002)
Country	0.063***	0.003
	(0.005)	(0.002)
Gender	0.033***	-0.002
	(0.005)	(0.002)
Paid	-0.062***	0.017***
	(0.006)	(0.003)
Producer	-0.051***	0.012***
	(0.004)	(0.002)
Referred	-0.023***	-0.008***
	(0.005)	(0.002)
Submissions		0.009***
		(0.001)
Contest Fixed Effects	Y	Y
Observations	44743	35011

Note: Table shows estimates of α from Equation $Y_{it} = \alpha X_i + \xi_t + \epsilon_{it}$ where ξ_t is a contest-specific fixed effect and ϵ_{it} is a T1EV error. The vector X_i includes participant characteristics. For the column labeled "Entry," the model is estimated on the full set of participants, and Y_{it} indicates if participant i made at least one submission to contest t. For the column labeled "Win," the model is estimated only on the set of entrants, and Y_{it} indicates if participant i won in contest t. I include submissions as an additional variable in the model for participant wins. The estimates show that participants who are most likely to enter are not necessarily more likely to win controlling for the number of submissions they make. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2: Participant-Level Regressions of Average Rating on Submissions and Participant Characteristics

DV:	Average Vote for Random Submission
2 Submissions	0.053***
	(0.014)
3 Submissions	0.022
	(0.015)
4 Submissions	0.009
	(0.017)
5 Submissions	0.052***
	(0.012)
Age	-0.019**
	(0.009)
Country	0.104***
	(0.012)
Gender	0.000
	(0.011)
Paid	0.084***
	(0.014)
Producer	0.059***
	(0.010)
Referred	-0.026***
	(0.011)
Contest Fixed Effects	Y
Observations	35011
R^2	0.114

Note: Table shows estimates of α from Equation $Y_{it} = \alpha X_i + \xi_t + \epsilon_{it}$ where ξ_t is a contest-specific fixed effect and ϵ_{it} is a T1EV error. The vector X_i includes indicators for the number of submissions made by a participant and participant characteristics. Y_{it} is the jury rating for a random submission made by participant i in contest t. The estimates show that participants who made 2 or 5 submissions tend to receive a higher rating for a random submission than participants who made 1 submission. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 3: Jury Rating Model Parameter Estimates for Selected Sample

	Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Age	-0.119	0.021	0.106	-0.041	-0.065	-0.130	0.090	-0.031
	(0.083)	(0.059)	(0.079)	(0.073)	(0.098)	(0.096)	(0.087)	(0.089)
Country	0.239**	0.186**	0.116	0.177	0.287**	0.195	-0.017	0.339**
	(0.120)	(0.089)	(0.111)	(0.109)	(0.143)	(0.134)	(0.124)	(0.135)
Gender	0.114	0.104	-0.056	0.034	-0.043	0.065	0.210**	0.193*
	(0.092)	(0.067)	(0.093)	(0.084)	(0.104)	(0.111)	(0.097)	(0.101)
Paid	0.377***	0.154*	0.371***	0.110	0.327**	0.456***	0.226*	0.136
	(0.116)	(0.085)	(0.131)	(0.105)	(0.134)	(0.130)	(0.116)	(0.125)
Producer	0.170*	0.312***	0.228***	0.186**	0.200*	0.201**	0.186**	0.310***
	(0.088)	(0.061)	(0.087)	(0.077)	(0.103)	(0.100)	(0.090)	(0.092)
Referred	-0.064	0.026	-0.075	-0.007	-0.046	-0.195*	0.052	0.004
	(0.113)	(0.074)	(0.105)	(0.090)	(0.133)	(0.116)	(0.111)	(0.117)
First Day	0.045	0.061	0.041	0.604***	0.164	0.091	-0.593***	-0.067***
	(0.105)	(0.075)	(0.170)	(0.092)	(0.143)	(0.138)	(0.144)	(0.109)
Last Day	-0.342***	-0.197***	-0.229**	0.142*	-0.138	-0.252***	-0.164*	-0.423***
	(0.086)	(0.060)	(0.100)	(0.082)	(0.096)	(0.092)	(0.096)	(0.088)
Length	0.862***	0.969***	-0.128	0.151	1.009***	0.915***	0.937***	0.552*
	(0.302)	(0.204)	(0.160)	(0.317)	(0.285)	(0.340)	(0.278)	(0.313)
Positive	1.017**	0.180	0.303	0.143	0.667	-0.985**	0.122	0.292
	(0.433)	(0.292)	(0.372)	(0.446)	(0.462)	(0.494)	(0.475)	(0.431)
Negative	-1.717***	-0.686**	-1.068***	-1.037**	-0.009	-0.717	-1.349***	0.229
	(0.473)	(0.310)	(0.412)	(0.475)	(0.560)	(0.559)	(0.513)	(0.441)
Joy	-0.642	0.205	-0.433	0.213	0.174	0.892	0.702	-0.543
	(0.628)	(0.415)	(0.631)	(0.608)	(0.640)	(0.765)	(0.714)	(0.616)
Surprise	0.061	-0.063	-0.349	-0.681	-0.606	0.358	-1.932**	-0.802
	(0.720)	(0.439)	(0.678)	(0.642)	(0.816)	(0.854)	(0.796)	(0.690)
ϕ_1	-0.652***	-0.524***	-1.490***	-0.767***	-0.117	-0.433	-0.752***	-0.903***
	(0.307)	(0.213)	(0.181)	(0.317)	(0.301)	(0.343)	(0.281)	(0.324)
ϕ_2	1.851***	2.190***	1.164***	1.416***	2.355***	1.930***	1.403***	2.012***
	(0.308)	(0.214)	(0.179)	(0.318)	(0.303)	(0.345)	(0.282)	(0.325)
ϕ_3	4.437***	5.035***	4.011***	3.845***	4.733***	4.359***	3.351**	4.659***
	(0.314)	(0.219)	(0.196)	(0.323)	(0.311)	(0.352)	(0.287)	(0.331)
ϕ_4	5.055***	5.525***	5.011***	4.266***	5.513***	5.208***	4.112***	5.196***
	(0.318)	(0.221)	(0.216)	(0.325)	(0.318)	(0.358)	(0.291)	(0.335)
Std. Dev. (σ)	1.140	1.321	1.383	1.051	1.187	1.183	0.940	1.295
P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Contests	22	45	12	21	18	19	20	24
Observations	6290	15540	4875	6540	4840	5165	4265	6735

Note: Table shows estimates from the jury rating model as specified in Section 'Jury Rating Model'. The model is estimated separately for each contest category and only using data on participants who made 5 submissions. Bootstrapped standard errors in parentheses. P-Value refers to result of a likelihood ratio test comparing estimated model to model with no unobserved heterogeneity ($\sigma = 0$). A P-Value of zero means that the test uncovers significant evidence and does not fail to reject the hypothesis that $\sigma = 0$. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Ideation Cost Estimates for Selected Sample

Cost Function		Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Quadratic	LB	0.286	0.248	0.234	0.400	0.396	0.347	0.652	0.331
($\theta_1 = 0, \theta_2 \neq 0$)	UB	1.232	0.823	0.756	1.463	2.706	1.446	6.733	1.508

Note: Table shows the bootstrapped 95% lower bound (LB) and upper bound (UB) on the parameter θ_2 estimated from the participant entry model using moment inequalities. The model specification and estimation procedure are described in Section 'Participant Entry Model'. The jury rating model parameters are obtained using data only on participants who made 5 submissions. I restrict the parameter θ_1 to zero for identification purposes as discussed in Section 'Identified Set' and Section 'Cost Function Shape' in Web Appendix B.

Table 5: Ideation Cost Estimates Ignoring Non-Entrants

Cost Function		Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Quadratic	LB	0.224	0.189	0.179	0.294	0.288	0.241	0.479	0.249
$(\theta_1 = 0, \theta_2 \neq 0)$	UB	0.476	0.387	0.357	0.631	0.600	0.502	0.914	0.500

Note: Table shows the bootstrapped 95% lower bound (LB) and upper bound (UB) on the parameter θ_2 estimated from the participant entry model using moment inequalities. The model specification and estimation procedure are described in Section 'Participant Entry Model'. The model is estimated using only data on entrants and ignoring the possibility of non-entrants. I restrict the parameter θ_1 to zero for identification purposes as discussed in Sections 'Identified Set' and 'Cost Function Shape' in Appendix B.

Table 6: Average Counterfactual Design Outcomes Across Contests Ignoring Non-Entrants

	Entrants		Submissions		Total Quality	
	LB	UB	LB	UB	LB	UB
Offer 150 Prizes (A)	-1.2	-0.2	0.5	2.2	0.3	1.6
One Prize Per Participant (B)	0.0	0.0	0.0	0.0	0.0	0.0
Both (A) and (B)	-0.1	0.0	2.7	6.1	2.5	5.5
4 Submission Limit	0.0	0.0	-8.8	-6.2	-8.9	-6.3

Note: Table shows the average lower bound (LB) and upper bound (UB) of percentage change in counterfactual outcomes across all contests, evaluated using the procedure described in Appendix I. Simulations ignore the possibility of non-entrants and use cost estimates from a participant entry model that assumes there are no non-entrants.

Table 7: Contest-Level Regressions of Outcomes on $\log(\text{Total\_Award}_t)$

DV: $\log(\text{Submissions}_t)$	0.154***	0.187***	0.260***	0.238***	0.120***
	(0.053)	(0.025)	(0.061)	(0.069)	(0.041)
R^2	0.045	0.071	0.050	0.055	0.823
DV: $\text{Submissions}_t/\text{Entrants}_t$	0.156***	0.166***	0.147	0.097	0.162**
	(0.039)	(0.051)	(0.095)	(0.065)	(0.064)
R^2	0.082	0.090	0.032	0.015	0.233
Category Fixed Effects	N	Y	N	Y	Y
Number of Prizes Fixed Effects	N	N	Y	Y	Y
Control for Number of Total Potential Entrants	N	N	Y	N	Y
Observations	181	181	178	167	167

Note: Table shows estimates of α for the regression equation $\text{DV} = \alpha \log(\text{Total\_Award}_t) + \xi_{G(t)} + \epsilon_t$, where DV is either $\log(\text{Submissions}_t)$ or $\text{Submissions}_t/\text{Entrants}_t$, $\log(\text{Total\_Award}_t)$ is the logarithm of the total award of contest t, $\xi_{G(t)}$ is a fixed effect, $G(t)$ determines the group of contest t based on its category or number of prizes, and ϵ_t is an error term. Robust standard errors in parentheses. Contests with a larger total award attract more submissions. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 8: Contest-Level Regressions of Submissions on Contest Duration

DV: log(Submissions)	I	II	III	IV
Intercept	6.407***	5.339***	6.288***	5.017***
	(0.061)	(0.378)	(0.094)	(0.357)
log(Duration)	-0.089**	-0.085**	-0.062*	-0.057
	(0.037)	(0.036)	(0.036)	(0.035)
log(Total_Award)		0.150***		0.184***
		(0.052)		(0.050)
Food			0.241**	0.211**
			(0.093)	(0.090)
Hardware			0.348***	0.304**
			(0.129)	(0.125)
Health			0.119	0.037
			(0.110)	(0.108)
Health(F)			0.000	-0.067
			(0.114)	(0.111)
Tech			-0.025	-0.057
			(0.112)	(0.108)
Toy			-0.213*	-0.291***
			(0.111)	(0.109)
Other			0.063	0.032
			(0.106)	(0.102)
Observations	181	181	181	181
R^2	0.031	0.074	0.186	0.246

Note: Table shows coefficient estimates from regressions of the logarithm of the total number of submissions in a contest on the logarithm of contest duration. Additional controls include contest category and the logarithm of prize amount. Longer contests attract fewer submissions. However, this effect is mitigated and vanishes after controlling for contest category and prize amount, suggesting that longer contests may be more difficult to participate in. Category estimates are relative to the "Consumer" category. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 9: Contest-Level Regressions of Outcomes on log(Number_of_Prizes$_t$)

DV: log(Submissions$_t$)	-0.296***	-0.306***	-0.077
	(0.096)	(0.116)	(0.057)
R^2	0.034	0.032	0.829
DV: Submissions$_t$/Entrants$_t$	-0.085	-0.068	-0.067
	(0.089)	(0.099)	(0.090)
R^2	0.006	0.002	0.231
Category Fixed Effects	N	Y	Y
Total Award Fixed Effects	Y	Y	Y
Control for Number of Total Potential Entrants	N	N	Y
Observations	179	158	158

Note: Table shows estimates of α for the regression equation $\text{DV} = \alpha \log(\text{Number\_of\_Prizes}_t) + \xi_{G(t)} + \epsilon_t$, where DV is either log(Submissions$_t$) or Submissions$_t$/Entrants$_t$, log(Number_of_Prizes$_t$) is the logarithm of the number of prizes in contest t, $\xi_{G(t)}$ is a fixed effect, $G(t)$ determines the group of contest t based on its category or total award, and ϵ_t is an error term. Robust standard errors in parentheses. Column 3 indicates that changes in the number of prizes do not significantly affect outcomes, consistent with the counterfactual results in Section 'Counterfactuals'. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10: Sponsor Choice Model Parameter Estimates

Specification:	All Characteristics	Ratings Only
γ_1	-2.633***	-2.932***
	(0.240)	(0.259)
γ_2	-2.035***	-1.938***
	(0.366)	(0.176)
γ_3	-0.609***	-0.004
	(0.239)	(0.298)
γ_4	1.594***	1.941***
	(0.258)	(0.217)
γ_5	2.624***	3.064***
	(0.334)	(0.239)
Age	-0.166*	
	(0.117)	
Country	-0.025	
	(0.393)	
Gender	-0.029	
	(0.232)	
Paid	0.304	
	(0.267)	
Producer	0.276*	
	(0.178)	
Referred	-0.286	
	(0.385)	
First Day	0.048	
	(0.143)	
Last Day	0.002	
	(0.226)	
Length	0.007	
	(0.279)	
Positive	0.389	
	(0.439)	
Negative	-0.573	
	(1.436)	
Joy	0.072	
	(0.672)	
Surprise	-0.155	
	(1.196)	
Contests	181	181
Observations	905	905

Note: Table shows estimates of the sponsor choice model. The column labeled "Ratings Only" shows the same estimates as in Table 5 in the main text. The column labeled "All Characteristics" shows estimates from the model $q_{st} = \sum_{m=1}^{5} \gamma_m 1\{W_{st} = m\} + \alpha^* X_i + \beta^* Z_{st} + \epsilon_{st}$ where X_i is a vector of participant characteristics, Z_{st} is a vector of idea characteristics, and α^*, β^* are the associated parameters, similar to the jury rating model. The estimates show that participant and idea characteristics are largely insignificant and of limited value in the sponsor choice model. Bootstrapped standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: Average Impact of 4 Submissions Limit on a Subset of Contests

	Entrants		Submissions		Total Quality	
	LB	UB	LB	UB	LB	UB
Symmetric Information	0.0	3.4	-10.3	-7.0	-10.3	-6.8
Asymmetric Information	1.1	4.3	-9.5	-6.8	-10.2	-5.9

Note: Table shows the average lower bound (LB) and upper bound (UB) of percentage change in counterfactual outcomes across all contests that offered 4 $250 prizes, evaluated using the procedure described in Appendix I. Symmetric Information refers to the informational assumption made in the main model - participants are aware of the number of potential competitors and competitor actions. Asymmetric Information refers to the assumption made in Appendix G - participants do not know competitor behavior, sponsor, or jury preferences, but do know the equilibrium distributions of these variables conditional on contest prize structure.

Table 12: Participant-Level Regressions of Rating on log(Total_Award$_t$)

Number of Submissions	1	2	3	4	5
DV: $\text{mean}_s(\text{Rating}^i_{st})$	0.124**	0.036	0.070	0.178**	0.089***
	(0.054)	(0.055)	(0.056)	(0.059)	(0.021)
DV: $1\{\max_s(\text{Rating}^i_{st}) > 3\}$	-0.001	0.009	0.012	0.008	0.008
	(0.013)	(0.025)	(0.032)	(0.016)	(0.016)
DV: $1\{\max_s(\text{Rating}^i_{st}) > 2\}$	0.075***	0.013	-0.005	0.101**	0.035**
	(0.027)	(0.040)	(0.045)	(0.047)	(0.017)
Participant Fixed Effects	Y				
Number of Prizes Fixed Effects	Y				

Note: Table shows estimates of α from Equation 27 for different aggregations of a participant's ratings within a contest as the dependent variable. The regression is run separately for each level of submissions. Robust standard errors in parentheses. Regressions show that participants may be able to affect their chance of achieving a rating below 3. However, the economic impact of a larger prize on rating is not economically significant as discussed in Appendix L. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.