The Business School for the World®

Working Paper
2019/40/MKT

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

Pavel Kireyev
INSEAD, pavel.kireyev@insead.edu

August 13, 2019

I develop an empirical model of idea generation contests with heterogeneous participants and endogenous entry, fit the model to data from a platform used by major advertisers, and simulate counterfactual contest designs. The empirical model resolves ambiguous predictions yielded by contest theory about the effects of different prize structures on contest outcomes. Simulations reveal the impact of strategies that hold fixed total award and balance competition by handicapping advantaged participants. Increasing the number of prizes while restricting the number of prizes per participant can improve outcomes for the platform. The results provide guidance for the design of large contests.

Keywords: Contest Design; Incentives; Innovation; Advertising; Idea Generation; Heterogeneity; Entry; Structural Estimation; Partial Identification

JEL Classification: C51, C57, D82, L86, M31, M37, M55, O31

I thank my committee, Elie Ofek, Sunil Gupta, and Ariel Pakes for their support. I thank Karim Lakhani, Robin Lee, Donald Ngwe, Daniel Pollmann, Al Silk, Thomas Wollmann, and participants at numerous seminars for helpful discussions. I thank the editor and two anonymous referees for their helpful comments. I thank the data provider for providing insight into the data and sharing useful information about innovation platforms. All errors are my own.

1 Introduction

Contests have a rich history as a mechanism for the procurement of innovation. Firms involved in research and development use contests to procure ideas for new technologies, products, and even solutions to scientific problems. Firms in creative industries, such as advertising, design, and architecture, extensively rely on contests and pitch competitions to identify the most promising ideas. Recently, firms have turned to online innovation platforms to attract a large number of submissions and improve the efficiency of their procurement efforts. For example, Colgate-Palmolive, a large consumer products firm, turned to a digital creative agency to generate ideas for one of its most visible advertising campaigns. Colgate-Palmolive organized an online *ideation contest* - members of the agency's innovation platform submitted ad ideas for a chance to win a cash prize. The winning ideas were used to develop an ad that aired during a $4 million spot shown to over 109 million viewers of North America's most popular yearly television event - the Super Bowl.

Advertisers are not alone in adopting a scalable model of ideation. Government agencies and firms across a variety of industries have implemented ideation contests. For example, Challenge.gov, a government-operated innovation platform, solicits ideas for projects organized by federal agencies such as DARPA and NASA. Innocentive, a platform for scientific innovation, hosts ideation contests for companies such as Ford, GlaxoSmithKline, and MasterCard. Universities, large corporations, and startup incubators organize ideation contests using proprietary platforms to collect, score, and reward the best ideas.

Contests may attract a large number of participants who differ considerably in their potential. Although theories abound on how to best design contests with heterogeneous participants (Moldovanu and Sela, 2001; Szymanski and Valletti, 2005; Terwiesch and Xu, 2008), the directional impact of a design decision often depends on the extent of participant heterogeneity. As a result, theory often yields ambiguous predictions about the impact of a design decision. Few articles have attempted to quantify heterogeneity or the impact of different design parameters in a field setting. In this research, I develop an empirical framework for answering the following question: how can a sponsor design a contest with heterogeneous participants to achieve the desired participation or quality outcomes? This empirical framework can be applied to data on contest participation and victories in large contests to identify the extent of participant heterogeneity and connect it to optimal design decisions. Thereby, I am able to resolve the ambiguous predictions of theoretical models by relating their inputs directly to data. I examine the impact of several important design decisions that hold fixed total award - how many prizes to award per contest, how many prizes to allow per participant within a contest, and how many submissions to accept per participant - on entry, submissions, and idea quality outcomes such as expected total quality.

I develop and estimate a structural model of ideation contests using data from a popular innovation platform. The model captures participant, jury, and sponsor decision processes. Participants choose how many ideas to submit to a contest based on their expected returns and costs of effort. A jury assigns a quality rating to all submissions. The sponsor then ranks submissions and rewards the winners. Contests are characterized by a large number of possible design decisions. A structural model allows the researcher to vary different levers, identify those that are most important, and guide the platform's choice of which designs to implement in future contests and which experiments to run to explore the effects of previously unaltered design levers. The rich contest theory literature can inform model assumptions and make transparent the connection between observed participant behavior, the predicted impact of a design decision, and the underlying theoretical mechanism. In addition, the space of possible design decisions for contests with many participants is very large - it involves all possible combinations of prizes for any number of winners, potentially coupled with restrictions on entry. A descriptive analysis of the data may only identify designs which performed well among the set of attempted designs, which is usually very small compared to the set of possibilities. A structural model provides a theoretical underpinning for how certain classes of designs affect participant behavior and is able to identify strategies which may be effective but have not been previously attempted. Indeed, through counterfactual simulations, I find that sponsors would have been better off had they offered a larger number of prizes and restricted the maximum number of prizes per participant.

I estimate the structural model in three stages. First, data on sponsor rankings of winning submissions and the ratings assigned to all submissions by a jury identify the chance that a submission will win given a particular rating. Second, jury ratings, participant characteristics, and the availability of multiple submission per participant identify the distribution of ratings conditional on observable and unobservable participant characteristics. Also, I allow for jury ratings to depend on idea characteristics such as timing, length, and sentiment which I recover using natural language processing techniques. Third, participant submission decisions identify the costs of ideation. I estimate the final stage as an empirical discrete game where participants choose how many ideas to submit to a given contest to maximize their expected payoffs and may choose not to submit any ideas at all. I use moment inequalities to partially identify parameters of the cost function. This methodology allows for multiple equilibria, a non-parametric cost unobservable, and yields estimates that are robust to simulation error, optimization mistakes, and different specifications of participant information sets.

Counterfactual simulations reveal the impact of alternative prize structure and submission limit decisions on contest outcomes. I find that offering multiple prizes, restricting the number of prizes per participant, and limiting the number of submissions per participant can all be viewed as strategies that handicap stronger participants and motivate weaker participants. Increasing the number of prizes while simultaneously restricting the number of prizes per participant can increase entry, submissions, and idea quality. However, if too many prizes are offered, participants may no longer have an incentive to exert effort. I examine several additional policies such as varying submission limits, offering a single prize, or offering multiple prizes of decreasing magnitude. The theoretical literature has only considered contests with a small number of participants and a small number of potential prizes (usually 2) for tractability reasons. In contrast, I am able to explore the impact of more complex designs in a large empirical setting using simulation. I conclude with an analysis of the relationship between within-contest participant heterogeneity and contest design outcomes.

2 Contest Design with Heterogeneous Participants

A contest is a game in which players invest costly effort in an attempt to win a prize. Throughout, I refer to players who consider entering a contest as *participants*. Of all participants, those who enter the contest are referred to as *entrants*, and the rest, as *non-entrants*. The *sponsor* organizes the contest and ultimately selects winners and awards prizes.

Traditionally, contests have been modeled as either imperfectly discriminating (Tullock, 1980), all-pay auctions (Baye, Kovenock, and De Vries, 1994), or rank-order tournaments (Lazear and Rosen, 1981). Imperfectly discriminating contests and rank-order tournaments typically allow for uncertain outcomes - the participant exerting the highest effort is not guaranteed to win.

However, a higher effort increases the participant's chances of winning. Ideation contests are similar - participants who submit the most ideas are not guaranteed to win, but may have a higher chance of winning at least one prize. A key aspect of ideation contests is participant heterogeneity. Participants with different levels of skill and experience can enter contests. Although a greater number of entrants improves the sponsor's chances of obtaining a high quality idea (Boudreau, Lacetera, and Lakhani, 2011), increased participant imbalances typically result in reduced effort (Baye, Kovenock, and De Vries, 1993; Stein, 2002). Intuitively, participants with a low chance of winning are discouraged and "give up," which in turn reduces the level of competition for participants with a high chance of winning, resulting in a lower level of effort overall. However, prize structure or submission limits can mitigate this concern.

Multiple Prizes and Submission Limits

Theory literature has examined the impact of prize allocation on the effort of heterogeneous participants. Moldovanu and Sela (2001), Szymanski and Valletti (2005), and Terwiesch and Xu (2008) have shown that, holding fixed total award, a greater number of prizes encourages weaker participants, as they have a chance of winning one of the lower ranking prizes. Stronger participants may exert less effort as, with multiple prizes, the payoff from "losing" increases. The research concludes that multiple prizes may be optimal in contests with heterogeneous participants, but a single prize works best for contests with ex-ante identical participants. However, the effect of multiple prizes on effort is ambiguous and depends on participant heterogeneity and cost function shape.[1]

Although the question of how many submissions to accept per participant is unique to contests where participants can make multiple submissions, researchers have investigated the related aspect of restricted bidding in all-pay auctions. Che and Gale (1998) consider the impact of caps on investments in political lobbying in an all-pay auction with one high-valuation (strong) player and one low-valuation (weak) player. The authors find that bid caps can increase total spending by limiting the strong participant and encouraging the weak participant. Che and Gale (2003) similarly show that handicapping a stronger participant in research contests can improve the contest outcome. My results show that submission limits constrain stronger participants and increase overall entry.

[1] Participant risk-aversion may also motivate sponsors to adopt multiple prizes (Kalra and Shi, 2001). However, experimental research suggests that risk-averse participants are less likely to enter contests altogether (Eriksson, Teyssier, and Villeval, 2009; Dohmen and Falk, 2011).

However, I find that stringent submission limits may reduce total submissions and idea quality.

Empirical Research on Contest Design and Advertising Procurement

Although substantial progress in the empirical literature on contests has been achieved with the increasing availability of online data, research that looks at the role of prize structure or submission limits remains sparse. Research has explored the impact of feedback and submission visibility on outcomes (Wooten and Ulrich, 2015; Wooten and Ulrich, 2017; Gross, 2017) as well as the effects of competition on effort (Boudreau, Lakhani, and Menietti, 2016; Yoganarasimhan, 2016) and experimentation (Gross, forthcoming). These authors do not focus on how to manage participant heterogeneity by handicapping some participants. In addition, the existing model-based empirical work (Boudreau, Lakhani, and Menietti, 2016; Yoganarasimhan, 2016) does not allow for non-entrants. I contribute by suggesting an estimable model for simulating the impact of different design decisions in contests with the possibility of non-entry. Furthermore, prior structural contest models have not used text to explain participant success, despite the fact that most submissions involve text (e.g. programmer code, freelancer bios, or submission descriptions). This study is one of the first to incorporate text characteristics.

Despite its important role in the over $500 billion advertising industry,[2] the production of advertising remains largely understudied because of a lack of data on pitch competitions, the effort exerted by firms, and outcomes. Exceptions include a descriptive study by King, Silk, and Ketelhöhn (2003). I provide one of the first investigations of creative content procurement in the advertising industry.

3 Setting

I use data from a popular innovation platform that produces content for brands. Major brands such as AT&T, General Electric, Google, and the world's largest advertisers, P&G and Unilever, use the platform to organize ideation contests. Brands use the obtained ideas to develop advertising content. The resulting ads have appeared on highly competitive television ad spots and on digital media channels such as video streaming sites and social networking platforms.

[2] www.emarketer.com/Report/Worldwide-Ad-Spending-eMarketer-Forecast-2017/2002019

Ideation contests operate as follows. The platform and the contest sponsor jointly decide on how many prizes to offer and how much money to offer per prize. The sponsor presents participants with the contest prize structure, rules and regulations, and a description of the ideation topic. Participants can then enter the contest by submitting at least one 140 character idea for an ad based on the topic suggested by the sponsor. Each entrant can submit at most 5 ideas to a single contest. Most contests remain open for one week or less. After the contest ends, a jury reviews and rates each submission without knowledge of the identity of its creator. Winning submissions are selected and ranked by the sponsor and their creators receive prize money. The platform does not display the identities or actions of participants during the contest period. Only after the sponsor selects winners does the platform make public the list of winning submissions.

Figure 1 illustrates the sequence of choices made within an example contest that attracted three participants and offered two prizes. First, two participants make one submission each (A and D), and one participant makes two submissions (B and C). Second, the jury assigns a low rating to submission A (depicted with a cross) and a high rating to the remaining submissions (depicted with a check). Finally the sponsor reviews the submissions and offers first prize to submission B and second prize to submission D. The creators of submissions B and D receive prize money.[3]

[Figure 1 about here.]

4 Data

I focus on a sample of 181 ideation contests that ran from 2011 to 2015 and a set of 8,875 participants who entered at least one of these contests. A total of 127 sponsors organized at least 1 and at most 11 contests, with 24 sponsors hosting more than one contest. For each contest, I observe the number of submissions made by each entrant, the rating assigned to each submission, the ranking of the winning submissions, the number of prizes awarded, and prize amount. All contests divide prizes evenly among winners. For example, each winning submission receives $250 if a contest offers 4 prizes with a total award of $1,000. I classify each contest into a category based on the industry of the sponsor. Table 1 shows the distribution of contests by category.

[3]See Web Appendix A for additional information on the instructions provided to participants throughout the submission process as well as sample ideas.

[Table 1 about here.]

An important aspect of many contests is that not all participants who consider entering choose to do so. In contrast to prior empirical research on contests which assumes away non-entrants, I use browsing data to define the set of likely non-entrants. Specifically, participants who did not enter the contest but viewed the contest page more than once and were active in the past 3 months are considered likely non-entrants. I restrict non-entrants to this subset to avoid including participants who were simply "surfing" the site without seriously considering entry into the contest. This procedure yields a total of 9,732 instances of non-entry by likely non-entrants. On 35,011 occasions, participants make at least one submission. Absent data on participant consideration sets, I am unable to more accurately identify the set of non-entrants.[4] Figure 2 presents a plot of the distribution of submissions per participant within a contest for all 181 contests in the data. The plot shows considerable heterogeneity in the number of submissions per participant both across and within contests.

[Figure 2 about here.]

Table 2 presents summary statistics for the contests considered. The contests tend to attract a high number of entrants and submissions relative to the number of prizes, with the average contest securing 193 entrants and 572 submissions for a total of 5 prizes. There is also variation in prize structure across contests, with the number of prizes ranging from 1 to 50 and prize amount per winning spot ranging from \$100 to \$1,250. In a descriptive analysis, I find that participants enter contests with larger prizes more frequently and submit a larger number of ideas conditional on entry in contests with larger prizes. Additionally, less experienced participants react more positively to increases in the number of prizes as predicted by theory.[5] Although the variation in the data provides support for the model assumptions and counterfactual predictions, it yields limited insight regarding optimal contest design. The set of prize structures in the data is limited compared to the space of possibilities and, as shown through counterfactual simulations in Section 'Counterfactuals', may not intersect much with the optimal range of prize structures. Indeed, I

[4]I consider alternative definitions of non-entrants in Web Appendix B. Typically, allowing for more non-entrants widens the confidence bounds on cost parameters and counterfactual outcomes.

[5]See Web Appendix C for these analyses.

find that sponsors may benefit from offering more prizes and restricting the number of prizes per participant.

[Table 2 about here.]

I observe the rating assigned to each submission by a jury. Ratings are assigned on a 5-point scale and based on the jury's perceived quality of the submission. Occasionally, the same submission may be rated by multiple jurors, in which case I use the rounded median rating of all jurors. Figure 3 shows the distribution of ratings across all submissions. Less than 2% of all winning submissions have a rating of 1, and 41% of all winning submissions have a rating of 5. Clearly, jury ratings explain a significant portion of the variance in the sponsor's final choice.

[Figure 3 about here.]

Participant Heterogeneity

I use a set of characteristics collected by the platform to account for possible sources of heterogeneity in the quality of a participant's submissions. Table 3 presents the definitions for all variables used. The set of observable characteristics is deliberately discretized to ensure that there exist only a finite number of participant types for tractability reasons. I use several demographics as well as variables that distinguish participants based on expertise. The characteristic Paid_i captures whether or not a participant i was paid prior to 2011 - the year when my sample for analysis begins. I use this variable to identify participants who previously won on the platform as they may be expected to outperform their competitors. In addition, the characteristic Producer_i identifies participants who have experience producing videos. Typically, producers are small independent film studios, whereas non-producers (or "ideators") are freelance creatives. Participants with a victory during the early stages of the platform received 28% of all prize money awarded despite comprising 5% of the population, and producers received 69% of all available prize money despite comprising 23% of the population, providing preliminary evidence of competitive imbalances on the platform.

[Table 3 about here.]

Submission Timing and Idea Characteristics

I observe the submission time and text for each idea. Given that most ideas are submitted either on the first or final day of the contest, I use only indicators for first and last day to capture variation in timing. I recover sentiment from text with natural language processing. The resulting idea characteristics and their definitions are provided in Table 4. Idea length is measured as the total character length of the idea divided by the maximum permitted length (140 characters). Although the median idea takes up 94.3% of the permitted character length, participants occasionally submit ideas that are very short (as low as 0.7% of the permitted length). These ideas are usually incomplete or irrelevant. For sentiment, I focus on positive and negative sentiment, as well as joy and surprise. Prior research based on survey methods (Derbaix, 1995) and eye-tracking technology (Teixeira, Wedel, and Pieters, 2012) identified joy and surprise as key emotions that are targeted by advertisers. Sentiment scores are calculated using the NRC Word-Emotion Association Lexicon (Mohammad and Turney, 2013).

[Table 4 about here.]

5 Model

I model each ideation contest as an independent game consisting of three stages. First, participants decide on how many submissions to make given their costs and expected payoffs. Second, a jury assigns a quality rating to all submissions. Finally, the sponsor reviews all submissions and ranks the top few. Participants differ ex-ante in their abilities and costs, and each submission will correspond to a random draw from a participant-specific quality distribution. Participants increase their chances of success by making more draws. This approach is common in models of innovation in new product design (Dahan and Mendelson, 2001; Loch, Terwiesch, and Thomke, 2001) and research contests with uncertain outcomes (Taylor, 1995; Fullerton and McAfee, 1999; Terwiesch and Xu, 2008). Gross (2017) applied a similar empirical setup to model logo design contests. Throughout, I use sponsor and contest interchangeably and denote both by t.

Sponsor Choice Model

Consider the sponsor's decision process after it receives a set of submissions. From the perspective of the sponsor, submission s by participant i in contest t has latent quality

$$q_{st} = \sum_{m=1}^{5} \gamma_m 1\{W_{st} = m\} + \epsilon_{st}, \tag{1}$$

where W_{st} is the rating assigned to submission s, γ_m are parameters assigned to each rating, and $\epsilon_{st} \sim T1EV$ is an iid submission-specific quality shock. Given that jury ratings explain a significant portion of the variance in sponsor choices, I follow Gross (2017) and model sponsor choice as a function of submission ratings and a quality shock that explains why rating is not a perfect predictor of victory. Web Appendix D considers a model that includes participant and idea characteristics in addition to jury ratings, but finds that the additional parameters are largely insignificant. The sponsor observes q_{st} for each s and ranks submissions by quality. Only the best N_t submissions receive a ranking, where N_t is at least as large as the number of prizes. In other words, the sponsor chooses a ranking $s_{(1)}, ..., s_{(N_t)}$ such that $q_{s_{(1)}t} \geq q_{s_{(2)}t} \geq ... \geq q_{s_{(N_t)}t} \geq q_{kt}$, where q_{kt} is the quality of any other submission k not in $s_{(1)}, ..., s_{(N_t)}$.

Jury Rating Model

Before the sponsor reviews the submissions and selects winners, a jury gives a rating to each submission in contest t. From the perspective of the jury, submission s has latent quality

$$u_{st} = \alpha X_i + \beta Z_{st} + \xi_{it} + \eta_{st}, \tag{2}$$

where X_i is a vector of participant characteristics, Z_{st} is a vector of idea characteristics which includes variables such as idea length and sentiment, α is a parameter vector that reflects participant ability, β is a parameter vector that captures jury preferences for different idea characteristics, $\xi_{it} \sim N(0, \sigma)$ is a participant-contest specific quality unobservable iid across participants and contests, and η_{st} is an iid submission-specific quality shock that follows a standard logistic distribution. The jury assigns a rating $W_{st} = m$ if $\phi_{m-1} < u_{st} \leq \phi_m$ for $m = 1, ..., 5$, where $\phi_0 = -\infty$, $\phi_5 = \infty$, and $\phi_1, ..., \phi_4$ are parameters that characterize the thresholds for transitioning from one rating to another. All parameters of the jury rating model may vary across categories to capture differences in participant-category fit, unobserved heterogeneity, and quality thresholds for achieving each rating. The unobservable ξ_{it} allows for correlation in the unobserved components of quality of submissions made by the same participant in contest t. For example, a participant may submit ideas with a similar theme that cannot be explained by her X_i or by the idea characteristics Z_{st}.

Participant Entry Model

Risk-neutral participants form expectations of their contest payoffs. A total of I_t participants consider entering contest t. Participant i chooses to make $d_{it} \in \{0, 1, ..., D\}$ submissions in contest t, where D is the submission limit. Participants do not choose idea characteristics Z_{st} but rather draw them from the joint empirical distribution of idea characteristics conditional on contest category and total number of submissions - $F_Z(Z_{st,s\in S_{it}}|d_{it})$, where S_{it} is the set of submissions made by participant i in contest t. This assumption is required to ensure that I can simulate the characteristics of an incremental idea for both entrants and non-entrants in the estimation procedure described in Section 'Estimation'. In practice, participants may choose idea content in addition to how many ideas to submit. I focus on the number of submissions as the sole action for tractability and account for differences in idea content by drawing idea characteristics from their empirical distribution. In addition, I require that the distribution of idea characteristics depends on the number of submissions d_{it} but is independent of participant characteristics X_i to ensure that it is possible to draw from the empirical distribution of idea characteristics without making parametric assumptions on the relationship between Z_{st} and X_i. All participants have symmetric information about the contest and are uncertain about the same set of variables. I make 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. Participants 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.*

I require that participants cannot select into contests based on an unobservable (to the researcher) component of sponsor or jury preferences. In other words, participants have the same information as the researcher regarding unobserved components of submission quality. This assumption also rules out the possibility that participants submit only those ideas that are better based on an unobserved component of idea quality.[6] In addition, the assumption requires that participants know about competitor behavior. The platform does not reveal competitor information during a contest, but participants are able to obtain information about competitors either by investigating the winning submissions of past contests (which are publicly available for almost all past contests) or by examining a leaderboard of participants and their portfolios of submissions (this leaderboard contains information on over 2,000 ideators and 600 producers who made at least one submission). In addition, I allow for participants to make optimization mistakes when evaluating their expected returns. Nevertheless, the assumption that participants know about the behavior of their competitors is a simplification which reduces the simulation burden of estimating the participant entry model. I discuss these assumptions further in Section 'Discussion of Model Assumptions and Limitations'.

Expected payoffs are given by

$$\pi_{it} = R_t(d_{it}, d_{-it}; X_i, X_{-it}) - c_{it}(d_{it}). \tag{3}$$

The expected returns function $R_t(d_{it}, d_{-it}; X_i, X_{-it})$ captures the expected winnings of a participant with characteristics X_i who makes d_{it} submissions given competitor characteristics X_{-it} and actions d_{-it}. To further motivate the participant entry model, I first present several simplified cases of the expected returns function with 2 participants (labeled A and B) and 2 possible ratings (4 and 5). For the purpose of exposition, I set $g(m) = e^{\gamma_m}$ where γ_m is the parameter on rating m in the sponsor choice model (Equation 1).

Case 1: 1 Prize of \$$p$, Each Participant Makes 1 Submission

Consider a contest where both participants make one submission each. The jury assigns a rating of 4 or 5 to each submission according to a reduced version of the jury rating model (Equation 2) with only 2 possible ratings. The state space consists of four possible scenarios - $\{4, 4\}$, $\{4, 5\}$,

[6] A similar assumption is made in empirical contest models by Yoganarasimhan (2016) and Gross (2017). In two-stage entry and demand models such as Ishii (2008), Eizenberg (2014), and Wollmann (2018), the authors make a similar assumption regarding unobserved components of demand (labeled ξ in all of the above articles). It is assumed that these components are unknown to firms before making entry decisions.

$\{5,4\}$, and $\{5,5\}$, where the first number in braces is the rating of A's submission and the second number is the rating of B's submission. A's expected returns can be written as

$$R(1,1;X_A;X_B) = \Pr\{4,4\}\frac{g(4)p}{2g(4)} + \Pr\{4,5\}\frac{g(4)p}{g(4)+g(5)} + \Pr\{5,4\}\frac{g(5)p}{g(5)+g(4)} + \Pr\{5,5\}\frac{g(5)p}{2g(5)} \quad (4)$$

where $\Pr\{W^A, W^B\}$ is the probability of state $\{W^A, W^B\}$. Note that this probability depends on variables in the jury rating model which include participant characteristics X_i, idea characteristics Z_{st}, and a quality unobservable ξ_{it}. Idea characteristics are generated from their empirical distribution $F_Z(Z_{st,s\in S_{it}}|d_{it})$ for each participant. Equation 4 is a summation of the probabilities of being in each state multiplied by the expected payoffs to A from that state. Expected payoffs take on a logit form as they are derived from the sponsor choice model (Equation 1). In states where A receives a high rating, she is expected to win with higher probability.

Case 2: 1 Prize of \$$p$, A Makes 2 Submissions, B Makes 1 Submission

Now consider the case where participant A makes 2 submissions. The space of possible ratings enlarges to include the following - $\{(4,4),4\}$, $\{(4,5),4\}$, $\{(5,4),4\}$, $\{(5,5),4\}$, $\{(4,4),5\}$, $\{(4,5),5\}$, $\{(5,4),5\}$, $\{(5,5),5\}$, where the two numbers in parentheses are the ratings of A's first and second submissions, and the final number in braces is the rating of B's only submission. A's expected returns can be written as

$$R(2,1;X_A;X_B) = \Pr\{(4,4),4\}\frac{2g(4)p}{3g(4)} + \Pr\{(4,5),4\}\frac{(g(4)+g(5))\,p}{2g(4)+g(5)} + ... \quad (5)$$

and so on for each state. Just as in Equation 4, the expression is the sum of state probabilities multiplied by the expected chances of winning conditional on being in that state. A's expected returns can be written more succinctly as

$$R(2,1;X_A;X_B) = \sum_{W_1^A=4}^{5}\sum_{W_2^A=4}^{5}\sum_{W_1^B=4}^{5} \Pr\{(W_1^A, W_2^A), W_1^B\}\frac{\left(g(W_1^A)+g(W_2^A)\right)p}{g(W_1^A)+g(W_2^A)+g(W_1^B)} \quad (6)$$

where W_k^i is the rating assigned to submission k belonging to participant i. Note that the state space will grow as the number of participants, actions, and ratings increases. In addition, note that the ratings received by A may be correlated as they share a common unobservable component ξ_{it} and may have correlated idea characteristics Z_{st}.

Case 3: 2 Prizes of \$$p_1$ and \$$p_2$, A Makes 2 Submissions, B Makes 1 Submission

Now suppose that the contest offers 2 prizes, whereas the behavior of the participants remains as in Case 2. Although the space of possible ratings remains unchanged, the complexity of the expected returns function for participant A increases as she must now consider the possibility that she wins any combination of the available prizes.

First, consider the state $\{(4,4),4\}$. The returns of participant A take the form:

$$\left[\underbrace{\frac{2}{3}\left(\frac{1}{2}\right)\times(p_1+p_2)}_{\text{win both prizes}}+\underbrace{\frac{1}{3}\left(\frac{2}{2}\right)p_2}_{\text{lose 1st but win 2nd prize}}+\underbrace{\frac{2}{3}\left(\frac{1}{2}\right)p_1}_{\text{win 1st but lose 2nd prize}}\right] \tag{7}$$

. This expression includes the probability that A wins both prizes - the first with probability 2/3 as she makes 2 out of a total of 3 submissions, and the second with probability 1/2 as there remains only her and her competitor's submission after the first prize is won. She must also consider the probability of losing the first prize and winning the second, as well as the probability of winning the first prize but losing the second. Each of these will typically be a distinct probability expression depending on submission ratings.

Second, consider the state $\{(4,5),4\}$. Participant A must consider the possibility of winning any combination of prizes with any combination of submissions, thereby increasing the complexity of the expected returns expression. The returns of participant A in the state $\{(4,5),4\}$ are:

$$\begin{aligned}&\underbrace{\frac{g(4)}{2g(4)+g(5)}\left(\frac{g(5)}{g(4)+g(5)}\right)\times(p_1+p_2)}_{\text{win 1st prize with 1st sub., 2nd prize with 2nd sub.}}+\underbrace{\frac{g(5)}{2g(4)+g(5)}\left(\frac{1}{2}\right)\times(p_1+p_2)}_{\text{win 1st prize with 2nd sub., 2nd prize with 1st sub.}}+\\&\underbrace{\frac{g(4)p_2}{2g(4)+g(5)}}_{\text{lose 1st but win 2nd}}+\underbrace{\frac{g(4)}{2g(4)+g(5)}\left(\frac{g(4)}{g(4)+g(5)}\right)p_1}_{\text{win 1st prize with 1st sub., lose 2nd}}+\underbrace{\frac{g(5)}{2g(4)+g(5)}\left(\frac{1}{2}\right)p_1}_{\text{win 1st prize with 2nd sub., lose 2nd}}\quad.\end{aligned} \tag{8}$$

Note that the first line of Equation 8 includes two possibilities in which A wins both prizes. In the first case, her first submission wins the first prize. In the second case, her second submission wins the first prize. Distinguishing between these possibilities is important as each submission may have a different rating. Similarly, the case where A wins the first prize but loses the second also includes two possibilities - she may win the first prize with her first or second submission. The complete expression for participant A's expected returns must be derived as the sum of expected returns over all possible draws of submission ratings. Note that the complexity of the expected returns function increases considerably as more prizes are introduced.

Full Expected Returns Function

I now allow for the expected returns function to include an arbitrary number of participants, prizes, and submissions per participant. In a contest with one prize (as in Cases 1 and 2 above), the expected winnings of a participant making $d_{it} > 0$ submissions are

$$R_t(d_{it}, d_{-it}; X_i, X_{-it}) = \text{Prize}_t \times \int \frac{\sum_{k=1}^{d_{it}} g(W_{kt}^i)}{\sum_{j=1}^{I'_t} \left(\sum_{k=1}^{d_{jt}} g(W_{kt}^j) \right)} dF_{W_t}(W_t^1, ..., W_t^{I'_t}), \tag{9}$$

where Prize_t is the prize awarded in contest t, I'_t is the total number of participants who made at least one submission, W_{kt}^i is the rating assigned to submission number k belonging to participant i in contest t, $g(W) = e^{\sum_{m=1}^{5} \gamma_m 1\{W=m\}}$ is the exponential of the parameter assigned to a rating of W in the sponsor choice model, F_{W_t} is the distribution of ratings which is derived from the jury rating model, and $W_t^i = (W_{1t}^i, ..., W_{d_{it}t}^i)$. In contests with multiple prizes, the expression for expected returns becomes more complicated as illustrated in Case 3 above. In practice, I use simulation to evaluate expected returns.

I consider cost functions of the form

$$c_{it}(d_{it}) = (\theta_1 + \theta_2 d_{it} + \nu_{it}) d_{it}, \tag{10}$$

where ν_{it} is a mean-zero participant-contest specific cost unobservable and θ_1, θ_2 are cost parameters with $\theta = (\theta_1, \theta_2)$. Prior to entry, each participant observes her cost shock ν_{it} and chooses how many submissions to make to maximize expected payoffs π_{it}. She may also choose to make no submissions.

Cost functions of this form are considered in games with ordered choices by Lee and Pakes (2009), and allow for convexity in submissions as well as a linear source of unobserved heterogeneity.

6 Estimation

Estimation proceeds in three stages. In the first and second stages, I estimate the sponsor choice model and the jury rating model. Given the first and second stage results, I estimate the participant entry model using moment inequalities for ordered choices (Ishii, 2008; Pakes et al., 2015).

Sponsor Choice Model

I use data on sponsor ranking decisions and submission ratings to estimate the sponsor choice model. Variation in sponsor decisions given different sets of submission ratings identifies the parameters assigned to each rating. The likelihood of observing a ranking $s_{(1)}, ..., s_{(N_t)}$ is

$$L_t\left(s_{(1)}, ..., s_{(N_t)}\right) = \prod_{r=1}^{N_t} \left(\frac{g(W_{s_{(r)}t})}{\sum_{j=r}^{N_t} g(W_{s_{(j)}t}) + \sum_{k \in \emptyset} g(W_{kt})} \right), \tag{11}$$

where N_t is the number of ranked submissions and $\emptyset$ is the set of all unranked submissions. The likelihood corresponds to a rank-ordered logit model (Beggs, Cardell, and Hausman, 1981; Chapman and Staelin, 1982). I estimate the model separately for each category using maximum likelihood methods.

Jury Rating Model

Data on jury ratings and variation in participant and idea characteristics within a contest identify the parameters α, β, and $\phi_1, ..., \phi_4$. Note that idea characteristics are realized before the jury rates the ideas. As a result, observed idea characteristics can be used in estimation. The standard deviation of participant-contest specific quality unobservables σ is identified from instances where multiple submissions made by the same participant receive a similar rating that cannot be explained by idea or participant characteristics. The likelihood of observing a sequence of ratings $W^i_{1t}, ..., W^i_{d_{it}t}$

for participant i conditional on ξ_{it} is

$$M_t(W^i_{1t}, ..., W^i_{d_{it}t}|\xi_{it}) = \prod_{k=1}^{d_{it}} \prod_{m=1}^{5} \left(\frac{1}{1+\exp\{\alpha X_i + \beta Z_{kt} + \xi_{it} - \phi_m\}} - \frac{1}{1+\exp\{\alpha X_i + \beta Z_{kt} + \xi_{it} - \phi_{m-1}\}} \right)^{1\{W^i_{kt}=m\}}. \tag{12}$$

The likelihood of observing all of the ratings in a contest is

$$\int \prod_{i=1}^{I'_t} M_t(W^i_{1t}, ..., W^i_{d_{it}t}|\xi_{it}) dF_\xi, \tag{13}$$

where F_ξ is the distribution of ξ_{it}, parameterized by σ. I use simulated maximum likelihood with Gauss-Hermite quadrature to estimate model parameters separately for each category.

Participant Entry Model

I use moment inequalities to partially identify cost parameters for each contest category. Pakes et al. (2015) show how moment inequalities can be used to obtain upper and lower bounds on cost parameters for discrete choice games where agents make ordered choices. With moment inequalities, I need not explicitly specify an equilibrium selection mechanism. Furthermore, the methodology allows for a flexible distribution of cost unobservables and yields estimates that are robust to participant optimization and researcher simulation errors. However, parameters will typically be set identified and not point identified. In other words, moment inequalities yield a set of parameters as opposed to a point, and confidence bounds must be obtained taking this into account.

I introduce an error term $\omega_{itd_{it}}$ (which I refer to as "expectational error") into the payoff equation to allow for simulation error, as well as the possibility that participants make estimation errors when evaluating their expected returns. Then, the payoff equation can be written as

$$\pi_{it} = R_t(d_{it}, d_{-it}; X_i, X_{-it}) - c_{it}(d_{it}) + \omega_{itd_{it}}. \tag{14}$$

I require that participants are correct on average and, at this stage, place no additional restrictions on the distribution of expectational errors.

Assumption 2 $E[\omega_{itd_{it}}] = 0$.

Lower Bound

First, consider the derivation of the lower bound for marginal costs. Define a function of the difference in observable returns from making one additional submission as

$$\Delta R^*_{it}(d_{it}+1, d_{it}) = \begin{cases} R_t(d_{it}+1, d_{-it}, X_i, X_{-it}) - R_t(d_{it}, d_{-it}, X_i, X_{-it}), \text{ if } d_{it} < 5, \\ 0, \text{ if } d_{it} = 5, \end{cases} \tag{15}$$

and let $\omega_{itd_{it}+1,d_{it}} = \omega_{itd_{it}+1} - \omega_{itd_{it}}$. By revealed preference, for a participant who made less than 5 submissions,

$$\underbrace{\Delta R^*_{it}(d_{it}+1, d_{it}) + \omega_{itd_{it}+1,d_{it}}}_{\text{expected marginal return}} \le \underbrace{\theta_1 + \theta_2(2d_{it}+1) + \nu_{it}}_{\text{marginal cost}}, \tag{16}$$

as the expected marginal return from making one additional submission must be no greater than the marginal cost of making one additional submission. Otherwise, the participant would have made $d_{it}+1$ instead of d_{it} submissions. For a participant who made 5 submissions, the expected marginal return from making one additional submission is likely an overestimate of the marginal cost of doing so, as the participant may have chosen to make more submissions under a more lenient submission limit. I make the assumption that the marginal cost of making one additional submission is at least zero for entrants who made the maximum permitted number of submissions.

Assumption 3 *The condition* $\theta_1 + \theta_2(2d_{it}+1) + \nu_{it} \ge 0$ *holds for entrants with* $d_{it} = 5$.

Taking the expectation over participants, it must be the case that

$$E\left[\underbrace{\theta_1 + \theta_2(2d_{it}+1)}_{\text{marginal cost}} - \underbrace{\Delta R^*_{it}(d_{it}+1, d_{it})}_{\text{marginal return}}\right] \ge 0. \tag{17}$$

The expectational errors $\omega_{itd_{it}+1,d_{it}}$ average out to zero because of Assumption 2. The cost unobservables ν_{it} average out to zero because the expectation does not condition on the participant's action. The ability to take an expectation over cost unobservables for all participants, regardless of their action, is crucial for the estimation of bounds on cost parameters.

An empirical analogue for the lower bound for marginal costs can be written as

$$m^L(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\frac{1}{I_t}\sum_{i=1}^{I_t}\Delta r_{it}^*(d_{it}+1, d_{it};\theta), \tag{18}$$

where T is the total number of contests used in estimation and

$$\Delta r_{it}^*(d_{it}+1, d_{it};\theta) = \Delta R_{it}^*(d_{it}+1, d_{it}) - \theta_1 - \theta_2(2d_{it}+1). \tag{19}$$

Any θ that satisfies $m^L(\theta) \geq 0$ must lie in the identified set of cost parameters. In practice, $R_t(d_{it}, d_{-it}; X_i, X_{-it})$ is not analytically tractable (as illustrated in Case 3 in Section 'Participant Entry Model') but is required as an input to $\Delta r_{it}^*(d_{it}+1, d_{it})$ in the definition of $m^L(\theta)$. I use simulation to approximate the expected returns function for each participant in every contest.

Upper Bound

Next, consider the upper bound for marginal costs. For entrants i in $L_t = \{i : d_{it} > 0\}$, define the difference in observable returns from making one less submission as

$$\Delta R_{it}(d_{it}, d_{it}-1) = R_t(d_{it}, d_{-it}, X_i, X_{-it}) - R_t(d_{it}-1, d_{-it}, X_i, X_{-it}). \tag{20}$$

Then, by revealed preference, for $i \in L_t$,

$$\underbrace{\Delta R_{it}(d_{it}, d_{it}-1) + \omega_{itd_{it},d_{it}-1}}_{\text{expected marginal return}} \geq \underbrace{\theta_1 + \theta_2(2d_{it}-1) + \nu_{it}}_{\text{marginal cost}}. \tag{21}$$

In other words, the expected marginal return of increasing submissions from $d_{it}-1$ to d_{it} must have been greater than the associated marginal cost. Otherwise, entrants would have made one less submission than they actually did. The above condition holds only for participants who submitted at least once. I must take into account the possibility that non-entrants, or participants with $d_{it} = 0$, may have had particularly large cost unobservables. If an empirical analogue, only for entrants, is developed based on the above inequality, the estimated upper bound on costs may be too low. Pakes et al. (2015) suggest using symmetry of the ν_{it} distribution to obtain an upper bound on the ν_{it} for non-entrants. Intuitively, the negative of the lowest lower bound for ν_{it} can be used as the highest upper bound for the negative of the ν_{it} of non-entrants. This result holds as long as the ν_{it} density is not skewed left.

Assumption 4 *For each contest, the cost unobservables ν_{it} follow a mean-zero distribution that is not skewed left.*

For exposition, I derive all subsequent inequalities assuming that the ν_{it} follow a symmetric distribution, which will yield conservative bounds if the actual distribution is skewed right. Assumption 4 allows for the cost unobservables to correlate with participant characteristics but requires that contests do not differ in difficulty level, conditional on contest category. The symmetry property of the ν_{it} distribution can be used to implement the selection correction technique suggested by Pakes et al. (2015) and obtain upper bounds for the unobserved costs of non-entrants. As long as the number of entrants exceeds the number of non-entrants for a given contest, the negatives of the lowest lower bounds on cost unobservables over all participants can be used as upper bounds for the negatives of the cost unobservables of non-entrants.

For a given contest, the moment conditions can be developed as follows. First, rank all entrants by $r_{it} = -\Delta r^*_{it}(d_{it}+1, d_{it}; \theta)$ so that $r_{(1)t} \leq r_{(2)t} \leq ... \leq r_{(I_t)t}$. Next, construct a set of size equal to the number of non-entrants such that $U_t = \{i : r_{it} \geq r_{(n_t+1)t}\}$, where n_t is the number of entrants in contest t. The negative lowest lower bounds for ν_{it} become the upper bounds for the $-\nu_{it}$ of non-entrants. Define the moment

$$m^U(\theta) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{I_t}\left(\sum_{i\in L_t}\Delta r_{it}(d_{it}, d_{it}-1;\theta) - \sum_{i\in U_t}\Delta r^*_{it}(d_{it}+1, d_{it};\theta)\right), \tag{22}$$

where

$$\Delta r_{it}(d_{it}, d_{it}-1;\theta) = \Delta R_{it}(d_{it}, d_{it}-1) - \theta_1 - \theta_2(2d_{it}-1) \tag{23}$$

is the difference in observable profits from making one less submission.

Consider the expectational error $\omega_{itd_{it}}$. The lowest lower bounds on cost unobservables used as part of the selection correction technique originate from a selected subset of participants. I require an assumption on the joint density of expectational errors and cost unobservables to ensure that participants with the lowest costs do not consistently underestimate their expected marginal returns. Otherwise, the upper bounds I obtain for non-entrants may be too low. This assumption would only affect the observations used in constructing $m^U(\theta)$ for participants in U_t with $d_{it} < 5$ because the inequality condition for participants with $d_{it} = 5$ does not contain an expectational error term (Assumption 3). I find that this 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.[7]

Identified Set

The identified set for parameters $\theta = (\theta_1, \theta_2)$ is defined as

$$\{\theta : m^L(\theta) \geq 0 \text{ and } m^U(\theta) \geq 0\}. \tag{24}$$

Identification of the cost parameters follows naturally from the restrictions imposed by the moment inequalities. However, it is not possible to obtain lower and upper bounds for both θ_1 and θ_2 (a total of 4 bounds) using only 2 moment inequalities. Additional restrictions on the covariance of ν_{it} and participant characteristics X_i can generate additional inequalities. However, there is no reason to expect that characteristics that affect the quality of a participant's submissions do not also affect her costs. Instead, I choose to restrict the shape of the cost function.

Assumption 5 $\theta_1 = 0$ *so that* $c_{it}(d_{it}) = (\theta_2 d_{it} + \nu_{it})d_{it}$.

I find that a cost function with $\theta_1 > 0$ and $\theta_2 \leq 0$ is unlikely. Given the large number of participants in each contest, the marginal expected returns of each participant are almost linear in the number of submissions. If the cost function were also linear or concave, a small change in prize amount would lead all participants to submit either 0 or 5 times, which does not appear reasonable as over one-third of all participants in the data make an intermediate number of submissions.

Confidence Bounds

I obtain confidence bounds using a block-bootstrap procedure. I sample a dataset of size equal to the number of contests within a category (with replacement) and estimate the sponsor choice and jury rating models on the re-sampled set of contests. I repeat this procedure 200 times and

[7] I provide the exact condition for the joint density of expectational errors and cost unobservables in Web Appendix E. The proof that if $m^U(\theta) \geq 0$, then θ lies in the identified set of cost parameters follows naturally from the proof presented in Pakes et al. (2015).

recover the standard deviation of the parameter estimates across bootstrapped datasets. The confidence set for the cost parameter includes the true parameter 95% of the time and is obtained using a procedure suggested by Andrews and Soares (2010). Intuitively, the procedure consists of simulating via bootstrap the distribution of a criterion function that penalizes violations of the moment inequalities. This criterion function can be used to identify points that fall into the confidence set.[8] I use the bootstrapped datasets obtained for the sponsor choice and jury rating models to incorporate first-stage estimation error in the confidence sets for the cost estimates.

Discussion of Model Assumptions and Limitations

The current specification does not allow for participants to select into contests based on an unobserved component of idea quality (for example, interest in the contest topic). Although it is not possible to measure the extent of selection absent the outcomes of non-entrants, an advantage of this setting is that participants vary in their number of submissions and thereby their *intensity* of entry. Selection on unobservables implies that participants who submit more have a higher average rating within a contest. In Web Appendix B, I find limited evidence of this relationship. Additionally, I re-estimate the jury rating model using data only from participants who made 5 submissions to assess the potential impact of selection on the cost estimates but find no significant effect.

Absent data on consideration sets, I include participants who viewed the contest page more than once and were active in the past 3 months in the set of non-entrants. To evaluate the impact of this decision, I re-estimate the entry model assuming that there are no non-entrants as has been the default in prior research. The confidence bounds on cost estimates and resulting counterfactual outcomes shrink considerably. An increase in the number of non-entrants typically results in a widening of the confidence bounds. If the number of non-entrants exceeds the number of entrants, the upper bound on costs approaches infinity. Although I do not develop a perfect solution to account for non-entry, this research is one of the first to consider this possibility. I am able to track changes in the number of entrants in response to varying contest designs, which is not possible in models that assume away non-entry.

Throughout, I assume that participants face no dynamic incentives within or across contests. This assumption is primarily a simplification in line with the literature on contests. In Web Ap-

[8]The algorithm is provided in Web Appendix F.

pendix B, I provide support for this assumption within contests. I show that most participants submit their ideas on a single day, there is no evidence that submission timing affects ratings, and participants have no strategic reason to wait as they receive no information during a contest. Across contests, the jury is blind to participant identity. Although I am unable to measure the extent of reputation benefits outside of the platform, I am able to show that immediate incentives matter in the descriptive analysis in Web Appendix C.

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 Web Appendix G, I relax this assumption and propose a model which allows for participants to be uncertain about the quantity, characteristics, and actions of their competitors. The model requires that participants know the empirical distribution of competitor information conditional on contest structure. A participant's expected returns are calculated as the average of the expected returns she would have received had she replaced a random participant in each one of the contests with the same prize structure. I evaluate the impact of imposing a submission limit under asymmetric information and find that, on average across contests, it does not differ significantly from the implications of the current model. Outcomes for individual contests may differ more meaningfully depending on the informational assumption.

7 Structural Model Estimates

Sponsor Choice Model

Table 5 presents parameter estimates for the sponsor choice model. As expected, I find a significant and monotonic relationship between submission rating and chance of winning. The odds of winning first prize for a submission with a rating of 5 are several hundred times higher than for a submission with a rating of 1 and about 3 times higher than for a submission with a rating of 4, suggesting that a high rating is almost crucial for victory.

[Table 5 about here.]

Jury Rating Model

Table 6 presents parameter estimates for the jury rating model. The estimates point to evidence of participant heterogeneity within and across contests. For example, participants from the US with video production skills and a past victory tend to receive higher ratings in almost all categories. Participants in the toy category are most likely to receive a rating of 5, whereas participants in the food and female health categories have the most difficulty securing the highest rating. There is also significant evidence of unobserved heterogeneity in submission quality across participants as indicated by the estimates of σ, ranging from 0.872 to 1.334. Intuitively, ideas with less negative sentiment tend to receive higher ratings across almost all categories. Idea characteristics such as submission timing, idea length, and sentiment are overall helpful beyond participant characteristics and participant-specific unobservables in explaining jury ratings.[9]

[Table 6 about here.]

Cost Estimates

Table 7 shows estimates of the cost parameters. Participants incur a cost of $0.34-1.95 for producing their first submission on average, with some evidence of heterogeneity across categories.[10] This cost estimate captures the cognitive and mental effort required to think of a 140 character idea as well as the opportunity cost of time. Costs increase in a convex manner, with the average cost of making five submissions in the range of $8.60-48.67. For comparison, the median hourly salary of a writer, copywriter, or editor in the US is $29.44,[11] which falls in the range of costs required to think of five original ideas or 700 characters of text.

[Table 7 about here.]

[9] I provide further validation of the jury rating model estimates by correlating a participant's implied chances of winning with her observed number of submissions. The results, provided in Web Appendix H, suggest that participants with higher estimated chance of winning make more submissions, consistent with model assumptions.

[10] The average cost across categories is obtained by taking the weighted average of category-specific costs.

[11] www.bls.gov/oes/2016/may/oes273043.htm

8 Counterfactuals

I assume that participants play a Nash equilibrium in submission strategies and know the prize structure of the contest, sponsor and jury preferences, the number of potential competitors they face, their own characteristics, as well as competitor characteristics and actions as in Assumption 1. Formally, participant i's information set in contest t is given by $\mathcal{J}_{it}^{CI} = \{d_{it}, d_{-it}, X_i, X_{-it}, I_t, C_t, \delta_t\}$, where C_t represents the prize structure of contest t and includes the prize amount and number of prize spots, $\delta_t = (\alpha_t, \gamma_1, ..., \gamma_5, \phi_{1t}, ..., \phi_{4t}, \sigma_t)$, and $\delta_t = \delta_s$ for contests t and s within the same category. I introduce the subscript t on the parameters to reflect the notion that jury preferences may differ across categories. For a uniformly sampled point in the identified set, I recover bounds on cost unobservables for each participant. These bounds ensure that at the sampled parameter, the observed decisions constitute an equilibrium. I uniformly sample cost unobservables that satisfy the bounds for each participant and compute equilibrium actions under alternative contest designs using iterated best response. I repeat the procedure for different sample parameters and cost draws, and recover bounds on the outcome of interest across simulations.[12]

I focus on a number of outcome metrics. The total number of entrants $\sum_{i=1}^{I_t} 1\{d_{it} > 0\}$ and total submissions $\sum_{i=1}^{I_t} d_{it}$ are important metrics for contest designers. Increasing entry cultivates participant engagement with the platform. Quality outcomes matter if the goal of the sponsor is to implement the best idea or to incorporate information from all submitted ideas. I consider expected total quality, defined as $\int \left(\sum_{i=1}^{I'_t} \sum_{k=1}^{d_{it}} g(W_{kt}^i) \right) dF_{W_t}$. Expected maximum quality, defined as $\int \log \left(\sum_{i=1}^{I'_t} \sum_{k=1}^{d_{it}} g(W_{kt}^i) \right) dF_{W_t}$, will be related monotonically to expected total quality. As a result, I report only expected total quality. In contests that offer multiple prizes, the sponsor may also be interested in the expected quality of the winning submissions. Usually, as the number of prizes is small relative to the number of submissions (5 prizes on average), the impact of counterfactual designs on the expected quality of the top few submissions will be very similar to the impact on the expected quality of the top submission.[13]

[12] Details of the counterfactual simulation procedure are provided in Web Appendix I.

[13] In Web Appendix J, I also report the impact on the expected quality of the top 50 submissions for a sample contest with 50 prizes and show that it is in the same direction as the impact on expected total quality.

Designing a Contest

To develop intuition, I initially focus on a single contest. The contest offered 50 prizes of $100 for a total award of $5,000 and attracted a total of 254 participants, of whom 177 made 565 submissions. Table 8 shows the impact of counterfactual policies on contest outcomes.

[Table 8 about here.]

Doubling the Number of Prizes

Suppose that instead of offering 50 prizes of $100, the sponsor now offers 100 prizes of $50. Increasing the number of prizes may discourage stronger participants who have an increased incentive to rank lower while encouraging weaker participants who now have a chance of winning a lower ranking prize. Such a policy may have two countervailing effects. On the one hand, the increase in entry and submissions from weaker participants may lead to an overall increase in all outcome metrics. On the other hand, if there is not sufficient heterogeneity within the contest, the reduction in submissions from stronger participants may outweigh the benefits of more submissions from weaker participants. Figure 4 shows the difference at the observed levels of submissions between the current and counterfactual expected returns for participants with different levels of αX_i, which I refer to as the participant's observed *ability*. Participants with higher abilities receive greater expected returns under a policy that offers fewer prizes.

[Figure 4 about here.]

The row of Table 8 labeled "Double the Number of Prizes" illustrates the impact of doubling the number of prizes on contest outcomes. I compare the simulated entry outcomes to the entry outcomes observed in the data. I evaluate and compare expected total quality across scenarios before realization of the sponsor choice and jury rating model unobservables as is common in the literature (Eizenberg, 2014). Although the simulations do not reject the possibility that the counterfactual may change any of the outcome metrics, it appears that the number of entrants and submissions does not decrease, whereas quality does not appear to change. The number of entrants and submissions may increase as weaker participants have a higher chance of winning a lower ranking prize. However, increasing the number prizes discourages stronger participants which may lead to a reduction in the quality of each individual submission.

Offering a Single Prize

Instead of offering 50 prizes of \$100, suppose that the sponsor now offers 1 prize of \$5000. As discussed in the previous section, reducing the number of prizes encourages higher ability participants while discouraging lower ability participants. Although the impact is subtle, offering a single prize does not appear to improve the outcome metrics for this contest. The increased effort from higher ability participants does not compensate for the reduced effort from lower ability participants.

One Prize Per Participant

I simulate a scenario in which the total number of prizes is held fixed but each participant is allowed to win at most one prize. Equivalently, the sponsor removes all other submissions made by the same participant as soon as one of her submissions wins a prize.[14] The impact of this counterfactual policy on the expected returns of participants as a function of their ability does not appear too different from the illustration in Figure 4. Participants with a high ability are most negatively impacted by the restriction on the number of prizes they can win. The row labeled "One Prize Per Participant" shows the impact of the policy. Restricting the number of prizes a single participant can win may increase entry, submissions, and expected quality, but the effect cannot be distinguished from 0. As in the case when the total number of prizes is doubled, stronger participants submit less thereby creating opportunities for weaker participants to enter the contest and submit more. However, this policy has no significant impact if the total number of prizes is held at the observed level.

Doubling the Number of Prizes with One Prize Per Participant

As both increasing the number of prizes and reducing the number of prizes per participant act in the same direction by handicapping stronger participants and encouraging weaker participants, a combination of the two policies may have a stronger effect than implementing any one of the policies

[14] Section 'Reducing the Number of Prizes From 2 to 1' in Web Appendix K illustrates a simple example of how a the expression for a participant's expected returns may change in this scenario.

individually. The row labeled "Both (A) and (B)" in Table 8 shows the impact of implementing both policies simultaneously. All outcome metrics increase, but expected quality increases by less than the number of submissions in relative terms, suggesting that the increases in quality originate from a greater number of submissions rather than from more high quality submissions.

Offering Too Many Prizes

In this counterfactual, I explore the shortcomings of increasing the number of prizes by too much while offering at most one prize per participant. Suppose that instead of offering 50 prizes of $100 the sponsor offers 240 prizes of roughly $21 (the total number of participants is 254). This specific prize allocation is chosen to illustrate counterfactual outcomes when the number of prizes is almost equal to the number of participants. Offering too many prizes discourages almost all but the weakest participants as they are almost guaranteed to win one prize with a single submission. Whereas it may be possible to improve all outcome metrics by increasing the number of prizes and limiting the number of prizes per participant, increasing the number of prizes by too much may have adverse effects on all outcome metrics.

Additionally, I explore the impact of offering decreasing prizes such that the prize amount is proportional to rank. Such policies can encourage competition among participants at different ability levels (Moldovanu and Sela, 2001). However, given the large number of prizes available in the contests I study, re-scaling prizes according to rank has the same effect as reducing the number of prizes. For example, in a two-prize contest there exists a continuum of possible prize amounts between the case where two equal prizes are offered (say two prizes of $100 each) and the case where a single prize is offered (one $200 prize). As sponsors have the option of offering a large number of prizes, increasing the number of prize spots from say 50 to 51 almost mimics the effect of continuously redistributing a greater share of prize money to lower ranking participants. As a result, offering decreasing prize amounts discourages lower ability participants but encourages higher ability participants, just as decreasing the number of prizes does. I illustrate the impact of offering decreasing prizes by starting from the scenario where the sponsor offers 240 prizes and one prize per participant. From there, I implement a decreasing prize schedule. In the columns labeled "Decreasing Prizes," prizes are scaled such that the first prize is 2x, 1.2x, or 1.1x times its original amount and the last prize is 0, 0.8x, or 0.9x times its original amount. All intermediate prizes are linearly decreasing between these two points such that the total amount of prize money remains unchanged. The results show that the outcome metrics improve, as though the sponsor is decreasing the number of prizes away from their sub-optimal level.

Optimal Number of Prizes

By searching over all equally-distributed prize configurations in increments of 10, I find that the total quality outcome metric achieves its maximum value based on both the lower bound and upper bound estimates at 180 prizes. The row labeled "Optimal Number of Prizes" presents the impact of offering 180 equally-valued prizes on all outcome metrics. These results suggest that by increasing the number of prizes to 27-29% of the expected number of submissions (and roughly 71% of the total number of potential entrants) the sponsor can expect a 14-20% increase in entrants, an 11-16% increase in submissions, and a 8-11% increase in total quality.

Submission Limits

The platform requires that all participants submit at most five times to each contest. What if participants could submit at most four times? Higher ability participants would be restricted by a lower submission limit as they tend to make more submissions. The final row of Table 8 shows that the submission limit may increase the number of entrants quite significantly, by 1-17%, but reduces the number of submissions by 4-11%. Stronger participants no longer crowd out other potential entrants. However, by significantly reducing the number of submissions, the platform reduces expected total quality by 4-11%. In contrast to when prize structure is altered, a more stringent submission limit uniformly imposes a constraint on the action sets of all participants, including weaker participants who would have preferred to submit five times after the stronger participants are handicapped. This results in higher entry but considerably reduces total submissions, resulting in lower expected quality outcomes.

Counterfactual Outcomes Across Contests

I obtain bounds on the outcomes of all contests for several design counterfactuals. Table 9 shows the average impact across contests.

[Table 9 about here.]

Prize Structure

For most of the contests, doubling the number of prizes or offering a single prize while holding fixed total award does not have a substantial impact on outcomes. The change in expected marginal returns to participants is low as the number of prizes is usually small compared to the number of submissions (prizes usually comprise less than 1% of all submissions). As a result, few participants alter their actions. Increasing the total number of prizes while restricting the number of prizes per participant may be effective in cases when the sponsor is willing to increase the number of prizes to roughly 20% of the number of expected submissions. I investigate the potential impact of increasing the number of prizes to 50, 100, and 150 for all of the contests in the sample. The rows labeled "Offer 50 (100, 150) Prizes" show the impact of such policies, whereas the rows labeled "Both (A, B, C) and (D)" show the combined impact of increasing the number of prizes while restricting the number of prizes per participant. Consistent with the results in Section 'Designing a Contest', such policies may lead to improvements in entry, submissions, and quality.

Submission Limits

Submission limits have more profound implications than moderate changes to prize structure for the platform as a whole, as a significant number of participants would be affected by the restriction on their action set. In the row labeled "4 Submission Limit" in Table 9, I observe that a more stringent submission limit increases entry but reduces submissions and total quality, consistent with the results in Section 'Designing a Contest'.

The Role of Participant Heterogeneity

I examine the impact that participant heterogeneity within a contest has on the simulated impact of a change to the contest's prize structure. I focus on the counterfactual which offers 100 prizes while restricting the number of prizes per participant to 1. I calculate $\text{var}(\alpha X_i)$ for each contest to quantify the spread in the distribution of estimated participant abilities. Table 10 shows results for sets of regressions of the lower and upper bound for the predicted change in outcomes, respectively, on the variance of participant abilities as a proxy for heterogeneity, controlling for other determinants of the change in outcomes. All coefficients indicate a positive but insignificant relationship between impact and within-contest ability variance. As a result, although the results are in the same direction as the predictions of theoretical contest models, it is not possible to confirm that the effectiveness of the design is driven by heterogeneity in participant abilities. The effect of heterogeneity is dominated by the effects of the number of potential entrants and the total amount of prize money. The number of potential entrants determines the denominator in the percentage change in impact as well as the fraction of participants who expect to be rewarded with an increase in the number of prizes. These two factors imply that the policy has a smaller impact in larger contests. Contests with a greater prize amount benefit more from the policy as the change in prize structure is more salient to participants. Table 10 also shows that the economic impact of a one standard deviation change in heterogeneity is subtle, whereas the impact of a similar change in potential entrants and prize amount is more pronounced. However, the variation in heterogeneity across contests is not as large as the variation in the other variables, which may be mitigating the estimated economic impact.

[Table 10 about here.]

9 Conclusion

An appropriate contest design can improve the outcome of a contest by handicapping stronger participants. I empirically address the question of how a sponsor with a fixed budget may use design parameters such as prize structure and submission limits to improve contest participation and quality outcomes in the presence of participant heterogeneity. This research helps resolve ambiguities in the predictions of theoretical contest models. I rely on data from a popular innovation platform and present a structural model that allows for heterogeneity in participant submission quality and costs, endogenous entry, and multiple equilibria. Counterfactuals reveal that increasing the number of prizes to equal roughly 20-30% of the expected number of submissions while restricting the number of prizes per participant can improve all outcome metrics. Similarly, submission limits can be a powerful tool for encouraging entry but may reduce total submissions and idea quality.

References

Andrews, D. W. and Soares, G. "Inference for Parameters Defined by Moment Inequalities Using Generalized Moment Selection." *Econometrica*, Vol. 78 (2010), pp. 119-157.

Baye, M. R., Kovenock, D., and De Vries, C. G. "Rigging the Lobbying Process: an Application of the All-Pay Auction." *American Economic Review*, Vol. 83 (1993), pp. 289-294.

Baye, M. R., Kovenock, D., and De Vries, C. G. "The Solution to the Tullock Rent-Seeking Game when r > 2: Mixed-Strategy Equilibria and Mean Dissipation Rates." *Public Choice*, Vol. 81 (1994), pp. 363-380.

Beggs, S., Cardell, S., and Hausman, J. "Assessing the Potential Demand for Electric Cars." *Journal of Econometrics*, Vol. 17 (1981), pp. 1-19.

Boudreau, K. J., Lacetera, N., and Lakhani, K. R. "Incentives and Problem Uncertainty in Innovation Contests: An Empirical Analysis." *Management Science*, Vol. 57 (2011), pp. 843-863.

Boudreau, K. J., Lakhani, K. R., and Menietti, M. "Performance Responses to Competition Across Skill Levels in Rank-Order Tournaments: Field Evidence and Implications for Tournament Design." *RAND Journal of Economics*, Vol. 47 (2016), pp. 140-165.

Chapman, R. G. and Staelin, R. "Exploiting Rank Ordered Choice Set Data within the Stochastic Utility Model." *Journal of Marketing Research*, Vol. 19 (1982), pp. 288-301.

Che, Y.-K. and Gale, I. L. "Caps on Political Lobbying." *American Economic Review*, Vol. 88 (1998), pp. 643-651.

Che, Y.-K. and Gale, I. L. "Optimal Design of Research Contests." *American Economic Review*, Vol. 93 (2003), pp. 646-671.

Dahan, E. and Mendelson, H. "An Extreme-Value Model of Concept Testing." *Management Science*, Vol. 47 (2001), pp. 102-116.

Derbaix, C. M. "The Impact of Affective Reactions on Attitudes Toward the Advertisement and the Brand: A Step Toward Ecological Validity." *Journal of Marketing Research*, Vol. 32 (1995), pp. 470-479.

Dohmen, T. and Falk, A. "Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender." *American Economic Review*, Vol. 101 (2011), pp. 556-590.

Eizenberg, A. "Upstream Innovation and Product Variety in the US Home PC Market." *Review of Economic Studies*, Vol. 81 (2014), pp. 1003-1045.

Eriksson, T., Teyssier, S., and Villeval, M.-C. "Self-Selection and the Efficiency of Tournaments." *Economic Inquiry*, Vol. 47 (2009), pp. 530-548.

Fullerton, R. L. and McAfee, R. P. "Auctioning Entry into Tournaments." *Journal of Political Economy*, Vol. 107 (1999), pp. 573-605.

Gross, D. P. "Creativity Under Fire: The Effects of Competition on Creative Production." *Review of Economics and Statistics* (forthcoming).

Gross, D. P. "Performance Feedback in Competitive Product Development." *RAND Journal of Economics*, Vol. 48 (2017), pp. 438-466.

Ishii, J. "Compatibility, Competition, and Investment in Network Industries: ATM Networks in the Banking Industry." Working Paper, Stanford Graduate School of Business, Stanford University, 2008.

Kalra, A. and Shi, M. "Designing Optimal Sales Contests: A Theoretical Perspective." *Marketing Science*, Vol. 20 (2001), pp. 170-193.

King, C., Silk, A. J., and Ketelhöhn, N. "Knowledge Spillovers and Growth in the Disagglomeration of the US Advertising-Agency Industry. *Journal of Economics & Management Strategy*, Vol. 12 (2003), pp. 327-362.

Lazear, E. P. and Rosen, S. "Rank-Order Tournaments as Optimum Labor Contracts." *Journal of Political Economy*, Vol. 89 (1981), pp. 841-864.

Lee, R. S. and Pakes, A. "Multiple Equilibria and Selection by Learning in an Applied Setting." *Economics Letters*, Vol. 104 (2009), pp. 13-16.

Loch, C. H., Terwiesch, C., and Thomke, S. "Parallel and Sequential Testing of Design Alternatives." *Management Science*, Vol. 47 (2001), pp. 663-678.

Mohammad, S. M. and Turney, P. D. "Crowdsourcing a Word-Emotion Association Lexicon." *Computational Intelligence*, Vol. 29 (2013), pp. 436-465.

Moldovanu, B. and Sela, A. "The Optimal Allocation of Prizes in Contests." *American Economic Review*, Vol. 91 (2001), pp. 542-558.

Pakes, A., Porter, J., Ho, K., and Ishii, J. "Moment Inequalities and Their Application." *Econometrica*, Vol. 83 (2015), pp. 315-334.

Stein, W. E. "Asymmetric Rent-Seeking with More Than Two Contestants." *Public Choice*, Vol. 113 (2002), pp. 325-336.

Szymanski, S. and Valletti, T. M. "Incentive Effects of Second Prizes." *European Journal of Political Economy*, Vol. 21 (2005), pp. 467-481.

Taylor, C. R. "Digging for Golden Carrots: An Analysis of Research Tournaments." *American Economic Review*, Vol. 85 (1995), pp. 872-890.

Teixeira, T., Wedel, M., and Pieters, R. "Emotion-Induced Engagement in Internet Video Advertisements." *Journal of Marketing Research*, Vol. 49 (2012), pp. 144-159.

Terwiesch, C. and Xu, Y. "Innovation Contests, Open Innovation, and Multiagent Problem Solving." *Management Science*, Vol. 54 (2008), pp. 1529-1543.

Tullock, G. "Efficient Rent Seeking." In J. M. Buchanan, R. D. Tollison, G. Tullock, eds., *Toward a Theory of the Rent-Seeking Society* Texas: Texas A&M University Press, 1980.

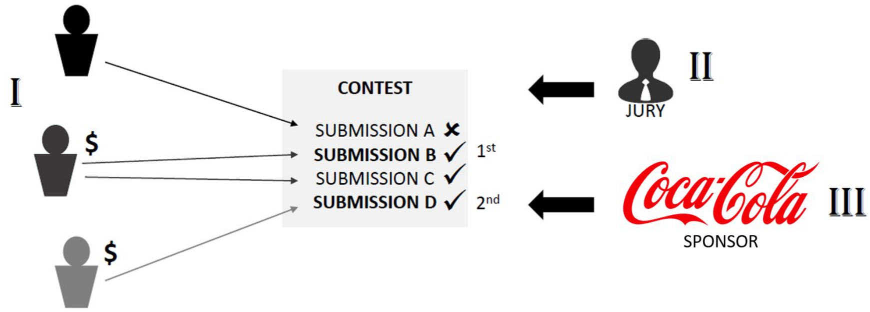
Wollmann, T. G. "Trucks Without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles." *American Economic Review*, Vol. 108 (2018), pp. 1364-1406.

Wooten, J. O. and Ulrich, K. T. "The Impact of Visibility in Innovation Tournaments: Evidence from Field Experiments." Working Paper, The Wharton School, University of Pennsylvania, 2015.

Wooten, J. O. and Ulrich, K. T. "Idea Generation and the Role of Feedback: Evidence from Field Experiments with Innovation Tournaments." *Production and Operations Management*, Vol. 26 (2017), pp. 80-99.

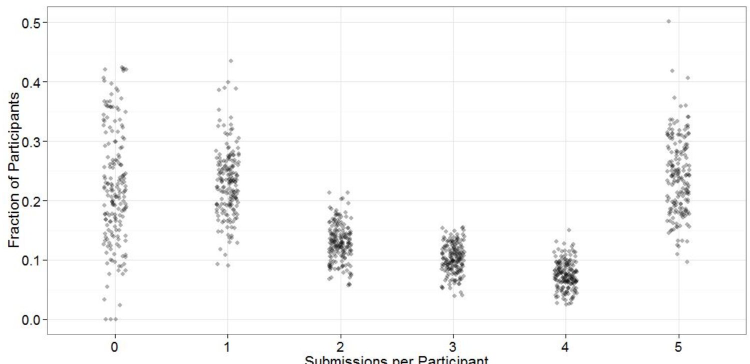
Yoganarasimhan, H. "Estimation of Beauty Contest Auctions." *Marketing Science*, Vol. 35 (2016), pp. 27-54.

Figure 1: Sequence of Choices within a Contest



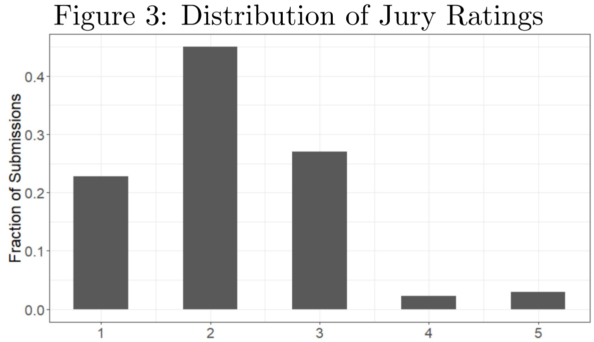
Note: Figure shows sequence of choices made after a fictional contest sponsored by Coca-Cola is posted on the platform: (I) Participants make submission decisions; (II) A jury reviews the submissions - giving a low rating to submission A (cross) but high ratings to submissions B, C, and D (check); (III) Sponsor makes final ranking decisions and winners receive prize money.

Figure 2: Distribution of Submissions within Contests



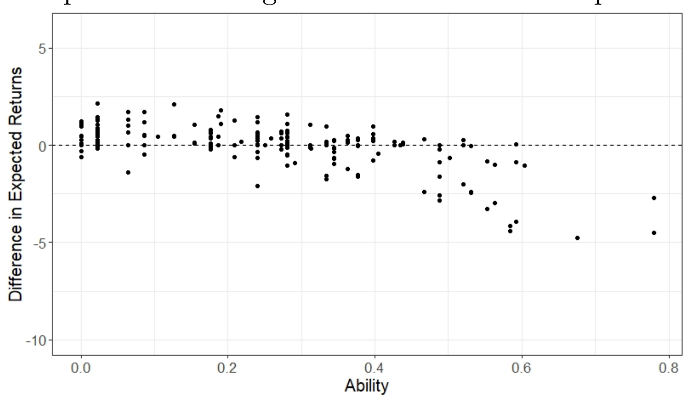
Note: An observation is a contest. Plot shows the fraction of participants who made d submissions within each contest, where $d \in \{0, ..., 5\}$ and is plotted on the horizontal axis.

Figure 3: Distribution of Jury Ratings



Note: Figure shows the distribution of jury ratings across all submissions. Although less than 3% of all submissions receive a rating of 5, roughly 41% of all winning submissions have a rating of 5, suggesting that a high rating is a strong determinant of victory.

Figure 4: Impact of Doubling Number of Prizes on Expected Returns



Note: Figure shows the difference in expected returns between the scenario where the number of prizes is doubled and the observed scenario for participants of different ability levels within an example contest. Expected returns are evaluated by simulation of $R_t(d_{it}, d_{-it}; X_i, X_{-it})$ at the observed levels of d_{it} and d_{-it}. Ability is defined as αX_i at the estimated parameters α. Participants with higher abilities experience lower expected returns under a policy that offers a larger number of prizes, suggesting that they may revise their submissions downwards.

Table 1: Contest Categories

Category	Description	Number of Contests
Consumer	Consumer packaged goods	22
Food	Food and beverages: snacks, ingredients, soft and alcoholic drinks	45
Utility	Hardware: tires, tools, paint, etc.	12
Health	General and male personal care and medical products	21
Health(F)	Female personal care products	18
Tech	Electronics and internet services	19
Toy	Toys and games	20
Other	Sporting goods, clothing, social cause, professional services	24

Note: Table shows contest categories, their descriptions, as well as the number of contests in each category. Table 6 in Section 'Structural Model Estimates' presents estimates that show evidence of heterogeneity in participant-category fit.

Table 2: Summary of Contest Characteristics

Per-Contest Characteristics	Min	Median	Mean	Max
Non-Entrants	0	48	54	124
Entrants	58	187	193	499
Submissions	178	551	572	1,875
Number of Prizes	1	4	5	50
Prize Amount per Spot	\$100	\$250	\$323	\$1,250
Total Award	\$500	\$1,000	\$1,450	\$10,000

Note: Table shows summary statistics for contest characteristics. Contests tend to attract a large number of entrants and submissions relative to the number of prizes offered.

Table 3: Description of Participant Characteristics

Variable	Definition	(%) Participants	Submissions	Prize
Demographics				
Age_i	1 if participant i was born after 1984 and 0 otherwise	37	40	39
Country_i	1 if participant i is from the US and 0 otherwise	81	84	87
Gender_i	1 if participant i is female and 0 otherwise	25	24	24
Participant-Platform Characteristics				
Paid_i	1 if participant i was paid prior to 2011 and 0 otherwise	5	14	28
Producer_i	1 if participant i has video production skills and 0 otherwise	23	46	69
Referred_i	1 if participant i was referred to the platform and 0 otherwise	21	21	15

Note: Table shows percentage of participants, submissions, and prize money attributable to each characteristic. Participants with $\text{Paid}_i = 1$ or $\text{Producer}_i = 1$ win disproportionately more prize money than other participants. In addition, Table 6 in Section 'Structural Model Estimates' presents estimates that show evidence of heterogeneity in participant-category fit based on demographic variables.

Table 4: Description of Idea Characteristics

Variable	Definition	Min	Median	Mean	Max
First_Day$_s$	1 if submission s was made on the first day of the contest and 0 otherwise	0	0	0.144	1
Last_Day$_s$	1 if submission s was made on the last day of the contest and 0 otherwise	0	0	0.285	1
Length$_s$	Number of characters in submission s divided by maximum permitted length	0.007	0.943	0.897	1
Positive$_s$	Fraction of words in submission s associated with positive sentiment	0	0.083	0.109	1
Negative$_s$	Fraction of words in submission s associated with negative sentiment	0	0	0.046	1
Joy$_s$	Fraction of words in submission s associated with joy	0	0.055	0.054	1
Surprise$_s$	Fraction of words in submission s associated with surprise	0	0	0.026	1

Note: Table shows summary statistics for idea characteristics. The total number of ideas in the data is 103,554. Sentiment is calculated using the NRC Word-Emotion Association Lexicon (Mohammad and Turney, 2013).

Table 5: Sponsor Choice Model Parameter Estimates

	γ_1	γ_2	γ_3	γ_4	γ_5
Rating	-2.932***	-1.938***	-0.004	1.941***	3.064***
	(0.259)	(0.176)	(0.298)	(0.217)	(0.239)
Contests	181				
Observations	905				

Note: Table shows estimates of rating-specific parameters from the sponsor choice model. The model specification is given by $q_{st} = \sum_{m=1}^{5} \gamma_m 1\{W_{st} = m\} + \epsilon_{st}$ with further details in Section 'Sponsor Choice Model'. Bootstrapped standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6: Jury Rating Model Parameter Estimates by Category

	Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Age	-0.045	0.042	0.051	0.004	-0.085	-0.092*	0.001	-0.055
	(0.055)	(0.031)	(0.057)	(0.048)	(0.054)	(0.062)	(0.073)	(0.047)
Country	0.279***	0.311***	0.157*	0.241***	0.175**	0.316***	0.098	0.241***
	(0.082)	(0.049)	(0.084)	(0.071)	(0.078)	(0.090)	(0.073)	(0.071)
Gender	0.013	0.040	-0.053	0.067	-0.008	-0.091	0.121**	0.029
	(0.062)	(0.037)	(0.066)	(0.055)	(0.058)	(0.074)	(0.059)	(0.054)
Paid	0.391***	0.168***	0.277***	0.011	0.189**	0.299***	0.273***	0.240***
	(0.079)	(0.050)	(0.093)	(0.070)	(0.077)	(0.087)	(0.070)	(0.073)
Producer	0.153***	0.221***	0.196***	0.179***	0.258***	0.175***	0.157**	0.154***
	(0.058)	(0.034)	(0.063)	(0.050)	(0.058)	(0.064)	(0.052)	(0.049)
Referred	-0.090	0.033	0.003	-0.026	-0.071	-0.229***	-0.078	-0.023
	(0.070)	(0.040)	(0.073)	(0.058)	(0.070)	(0.075)	(0.062)	(0.060)
First Day	-0.005	0.141***	-0.200*	0.679***	0.219**	0.144	-0.530***	-0.208***
	(0.072)	(0.046)	(0.113)	(0.060)	(0.085)	(0.091)	(0.091)	(0.068)
Last Day	-0.269***	-0.163***	-0.328***	0.146***	-0.225***	-0.274***	-0.060	-0.409***
	(0.060)	(0.039)	(0.071)	(0.055)	(0.065)	(0.064)	(0.064)	(0.057)
Length	0.957***	0.852***	0.033	-0.267	1.286***	0.912***	1.095***	0.770***
	(0.218)	(0.140)	(0.122)	(0.223)	(0.192)	(0.237)	(0.186)	(0.206)
Positive	1.273***	0.500**	0.254	-0.199	1.026***	-1.111***	-0.104	0.321
	(0.318)	(0.210)	(0.292)	(0.323)	(0.345)	(0.363)	(0.331)	(0.299)
Negative	-1.702***	-0.871***	-0.345	-0.970***	-1.101***	-1.073**	-1.726***	-0.153
	(0.348)	(0.225)	(0.323)	(0.346)	(0.399)	(0.421)	(0.358)	(0.313)
Joy	-1.092**	-0.310	-0.417	0.679	-0.425	1.426**	0.590	-0.212
	(0.468)	(0.300)	(0.486)	(0.438)	(0.470)	(0.560)	(0.501)	(0.430)
Surprise	0.025	-0.082	-0.254	-0.933**	0.517	0.530	-1.055*	-0.577
	(0.545)	(0.321)	(0.534)	(0.469)	(0.611)	(0.630)	(0.571)	(0.493)
ϕ_1	-0.481***	-0.474***	-1.360***	-0.555***	-0.002	-0.381*	-0.526***	-0.861***
	(0.219)	(0.141)	(0.140)	(0.223)	(0.197)	(0.235)	(0.185)	(0.207)
ϕ_2	2.019***	2.186***	1.153***	1.635***	2.484***	1.990***	1.606***	2.032***
	(0.220)	(0.142)	(0.139)	(0.223)	(0.198)	(0.236)	(0.186)	(0.208)
ϕ_3	4.599***	5.005***	3.900***	4.084***	4.857***	4.383***	3.584**	4.653***
	(0.225)	(0.146)	(0.151)	(0.228)	(0.205)	(0.242)	(0.191)	(0.214)
ϕ_4	5.216***	5.507***	5.033***	4.530***	5.652***	5.176***	4.295***	5.164***
	(0.228)	(0.148)	(0.167)	(0.230)	(0.211)	(0.246)	(0.195)	(0.217)
Std. Dev. (σ)	1.147	1.239	1.334	0.988	1.082	1.158	0.872	1.191
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	11875	29974	8910	12472	9041	9685	8319	13278

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. 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 7: Ideation Cost Estimates by Category

Cost Function		Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Quadratic	LB	0.287	0.247	0.231	0.387	0.392	0.348	0.629	0.321
($\theta_1 = 0, \theta_2 \neq 0$)	UB	1.232	0.832	0.770	1.469	2.698	1.474	6.746	1.509

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'. I restrict the parameter θ_1 to zero for identification purposes as discussed in Section 'Identified Set' and Web Appendix B.

Table 8: Counterfactual Design Outcomes for a Sample Contest

	Entrants LB	Entrants UB	Submissions LB	Submissions UB	Total Quality LB	Total Quality UB
Actual	177		565		1	
Double the Number of Prizes (A)	177 (1.00)	189 (1.07)	565 (1.00)	575 (1.02)	1.00	1.00
Single Prize	176 (0.99)	177 (1.00)	557 (0.99)	565 (1.00)	0.99	1.00
One Prize Per Participant (B)	177 (1.00)	185 (1.05)	565 (1.00)	585 (1.04)	1.00	1.02
Both (A) and (B)	183 (1.03)	209 (1.18)	580 (1.03)	610 (1.08)	1.02	1.04
Too Many Prizes and (B)	147 (0.83)	168 (0.95)	453 (0.80)	525 (0.93)	0.77	0.90
Decreasing Prizes$^{\times}$ (1.1x to 0.9x)	168 (0.95)	172 (0.97)	491 (0.87)	528 (0.93)	0.84	0.91
Decreasing Prizes$^{\times}$ (1.2x to 0.8x)	168 (0.95)	180 (1.02)	531 (0.94)	555 (0.98)	0.92	0.94
Decreasing Prizes$^{\times}$ (2x to 0)	201 (1.14)	211 (1.19)	613 (1.08)	637 (1.13)	1.05	1.08
Optimal Number of Prizes and (B)	202 (1.14)	212 (1.20)	626 (1.11)	658 (1.16)	1.08	1.11
4 Submission Limit	179 (1.01)	207 (1.17)	505 (0.89)	543 (0.96)	0.89	0.96

Note: Table shows the bounds on counterfactual outcomes for each design policy. Bounds are calculated using the algorithm in Web Appendix I. Expected total quality normalized to 1 for actual outcome. $^{\times}$: In the "decreasing prizes" scenario, prizes are scaled such that the first prize is 2x, 1.2x, or 1.1x times its original amount and the last prize is 0, 0.8x, or 0.9x times its original amount. All intermediate prizes are linearly decreasing between these two points such that the total amount of prize money remains unchanged. The counterfactuals are implemented in combination with offering 240 prizes and one prize per participant. Changes relative to Actual are indicated in parentheses for the number of entrants and submissions.

Table 9: Average Counterfactual Design Outcomes Across Contests

	Entrants LB	Entrants UB	Submissions LB	Submissions UB	Total Quality LB	Total Quality UB
Double the Number of Prizes	0.0	0.1	0.0	0.2	0.0	0.1
Single Prize	0.0	0.0	0.0	0.0	0.0	0.0
Offer 50 Prizes (A)	0.0	1.2	0.0	1.5	0.0	1.1
Offer 100 Prizes (B)	0.0	1.4	0.0	1.7	0.0	1.5
Offer 150 Prizes (C)	0.0	1.8	0.0	2.5	0.0	1.9
One Prize Per Participant (D)	0.0	0.0	0.0	0.0	0.0	0.0
Both (A) and (D)	0.0	1.8	0.0	2.1	0.0	1.8
Both (B) and (D)	0.2	2.6	0.2	3.8	0.2	3.3
Both (C) and (D)	1.2	6.2	1.3	7.4	1.2	6.5
4 Submission Limit	0.4	4.3	-11.2	-6.9	-11.0	-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 Web Appendix I.

Table 10: Impact of Changing Prize Structure Across Contests by Ability Heterogeneity

DV:	Entrants LB	Entrants UB	Submissions LB	Submissions UB	Total Quality LB	Total Quality UB
Heterogeneity	0.161	0.131	0.243	0.058	0.112	0.046
	(0.334)	(0.158)	(0.187)	(0.093)	(0.163)	(0.082)
	[0.102%]	[0.083%]	[0.155%]	[0.037%]	[0.071%]	[0.029%]
log(Potential Entrants)	-0.108***	-0.029***	-0.114***	-0.038***	-0.095***	-0.033***
	(0.020)	(0.010)	(0.011)	(0.006)	(0.010)	(0.005)
	[-2.897%]	[-0.778%]	[-3.058%]	[-1.019%]	[-2.549%]	[-0.885%]
log(Prize Amount)	0.024**	0.016***	0.026***	0.012***	0.019***	0.010***
	(0.011)	(0.005)	(0.006)	(0.003)	(0.005)	(0.003)
	[1.319%]	[0.879%]	[1.429%]	[0.659%]	[1.044%]	[0.550%]
R^2	0.263	0.187	0.511	0.373	0.475	0.361
Category Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	181	181	181	181	181	181

Note: Table shows the output for a series of regressions described in Section 'The Role of Participant Heterogeneity'. Standard errors in parentheses. Square brackets indicate the economic impact of a one standard deviation change in the dependent variable relative to its mean. For heterogeneity, this is an increase of 0.006 in the variance of abilities (relative to a mean of 0.040). For log(Potential Entrants), this is an increase of $\log(247 + 76) - \log(247)$. For log(Prize Amount), this is an increase of $\log(1450 + 1062) - \log(1450)$. This implies that, for example, a \$1062 increase in prize amount over the mean value of \$1450 corresponds to an additional 1.319% increase in lower bound on the number of entrants relative to the baseline scenario. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.