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

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Abstract

Contests are a popular mechanism for the procurement of innovation. In marketing, design, and other creative industries, firms use freelance marketplaces to organize contests and obtain high-quality ideas for ads, new products, and even business strategies from participants. A central question faced by contest sponsors is how to appropriately structure prizes and entry regulations. I develop an empirical model of idea generation (ideation) contests and investigate the impact of the number of prizes, prize amount, and submission limit on participation and quality outcomes using data from a popular marketing ideation platform. The model explains participant submission decisions, jury ratings, and sponsor rankings of winning submissions. Counterfactuals reveal the impact of design parameters on outcomes and provide guidance for the optimal design of ideation contests and platforms.

Keywords: idea generation; crowdsourcing; contest design; structural estimation.

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1 Introduction

Contests have a rich history as a mechanism for the procurement of innovation in design and technology. With the growth of the internet, firms have begun using contests to procure ideas for advertising, new products, and marketing strategies. For example, when motorcycle manufacturer Harley-Davidson split with its ad agency of 31 years, it turned to the crowd to create its next generation of advertising (Klaassen 2011). With the help of a crowdsourcing firm, Harley organized an *ideation contest* - fans of the brand could submit short ad ideas for a chance to win a cash prize. The winning submissions motivated a series of popular Harley marketing campaigns. Contests carry many advantages over the traditional ad agency model of advertising procurement: brands can expect a large number of ideas at a relatively low cost; participants tend to be actual end users of the product; and contests build awareness by engaging consumers in conversation with the brand (Kirby 2013).

Harley is not alone in adopting the contest model of ideation. Government agencies and firms in the private sector across a variety of industries have implemented ideation contests. For example, Challenge.gov, a government operated ideation platform, solicits ideas from participants for projects organized by different federal agencies such as DARPA and NASA. Innocentive, a popular platform for scientific innovation, hosts ideation contests for companies such as Ford, GlaxoSmithKline, and MasterCard. The crowdsourcing studio Tongal organizes advertising ideation contests for AT&T, General Electric, Google, Lego, P&G, and Unilever, among others.[1]

The success of an ideation contest hinges on its design - the choice of how to structure prizes and contest entry regulations. In this research, I empirically examine the impact of three broadly applicable design decisions - how many prizes to award, how much money to award per prize, and how many submissions to accept per participant - on contest participation and idea quality outcomes such as expected total and maximum submission quality.

Prior research has explored how incentives affect ideation from an agency theory perspective (Toubia 2006, Girotra et al. 2010), but few papers have empirically examined the use of contest mechanisms for the procurement of ideas. I develop and estimate a structural model of ideation

[1] Some of the earliest ideation contests in marketing date back to the 1950s and 1960s (Kirby 2013). Popular brands would organize contests through newspapers and specialized publications to obtain ideas for ads, commercial jingles, and new product names from consumers.

contests to assess the impact of different design parameters on contest outcomes. 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 Tongal jury assigns a quality rating to all submissions. The sponsor then ranks submissions and rewards the winners.

Participants may differ in their *abilities* and *costs*. Ability heterogeneity reflects the notion that idea quality may differ across participants. Ideation contests attract a wide array of entrants with different backgrounds and experiences. Certain participants may submit higher quality ideas than others. For example, we may expect a Harley veteran to generate higher quality ideas for a motorcycle ad than someone with limited riding experience. Cost heterogeneity allows for participants to differ in how easy or difficult it is for them to think of ideas for a particular contest. For example, individuals with more outside commitments may have less time to participate in online contests, increasing their costs of making submissions. I allow for abilities and costs to differ by participant and contest. Moreover, participants can select into contests based on an unobservable (to the researcher) component of costs.

I use data from crowdsourcing platform Tongal to estimate the model in three stages. First, data on sponsor rankings of winning submissions identify sponsor preferences as a function of observable participant characteristics and a rating assigned to the submission by a jury. Second, jury ratings assigned to all submissions identify the distribution of ratings conditional on observable and unobservable participant characteristics. 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. 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 different specifications of participant information sets. I estimate the model separately by industry of the contest sponsor.

Counterfactual simulations reveal the impact of alternative prize allocation and submission limit decisions on contest outcomes under different assumptions about the information sets of participants. I experiment with two information structures, which I label complete and incomplete information. In the complete information scenario, participants know their own characteristics, as well as sponsor and jury preferences, and the characteristics of their competitors. In the incomplete

information scenario, participants do not know sponsor or jury preferences, or competitor characteristics, but are aware of the joint density of these variables conditional on contest structure. I find that both information structures imply similar counterfactual outcomes on average across contests. However, the outcome of each individual contest may differ depending on the informational assumption.

First, I investigate the impact of offering a single prize instead of multiple prizes. I find that although multiple prizes motivate weaker (low ability, high cost) participants and demotivate stronger (high ability, low cost) participants, the number of prizes, holding fixed total award, has a negligible impact on participation and quality - the change in expected marginal returns to most participants is small compared to submission costs. Second, I explore the impact of increasing prize money. I find that a strong response from stronger participants leads to an increase in idea quality but may not lead to a substantial increase in the total number of entrants. Finally, I examine the effect of reducing the maximum number of submissions allowed per participant. This policy benefits weaker participants who would have otherwise been discouraged from entry by the presence of stronger participants who submit multiple times to the same contest. A more stringent submission limit restricts stronger participants, increasing the number of entrants but reducing expected quality outcomes.

The remainder of this paper is organized as follows. Section 2 summarizes the relevant theoretical and empirical literature on contest design. Section 3 presents the data and Section 4 presents descriptive evidence of the importance of prize allocation. Section 5 outlines the structural model, Section 6 details the estimation routine, and Section 7 presents the estimates. Section 8 examines the impact of counterfactual contest designs and presents practical implications. Section 9 concludes.

2 Contest Design

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. Effort in the contest literature is typically

viewed as a non-negative continuous decision variable. I view effort as the discrete number of idea *submissions* a participant makes to a given contest.[2]

Traditionally, contests have been modeled as either imperfectly discriminating (Tullock 1980), all-pay auctions (Baye et al. 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. In all-pay auctions, highest effort typically guarantees victory. Ideation contests share similarities with imperfectly discriminating contests and rank-order tournaments - participants who submit the most ideas are not guaranteed to win, and in contests with multiple prizes, submissions are ranked in order of the sponsor's preferences.

A key aspect of ideation contests is participant heterogeneity. Participants, with different levels of skill and experience, can freely join the platform and enter contests. Although a greater number of entrants improves the sponsor's chances of obtaining an extreme-value, high quality idea, especially in contests with significant participant uncertainty about sponsor preferences (Boudreau et al. 2011), increased participant asymmetries typically result in reduced effort (Baye et al. 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 from all types. However, an appropriate choice of prize allocation can mitigate this concern.[3]

Theory literature has examined the impact of prize allocation on the effort of heterogeneous participants. Moldovanu and Sela (2001) explore the impact of multiple prizes on effort in all-pay auctions. The authors show 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. On the other hand, stronger participants exert less effort, as with multiple prizes, the payoff from "losing" increases. The optimality of offering multiple prizes depends on participant heterogeneity and the convexity of their costs of effort. If costs are sufficiently convex, a smaller number of prizes will not

[2]The ideation contests I study require participants to submit 140 character ideas for ads. Each participant can submit at most 5 ideas to a single contest. Section 4 show evidence that the number of submissions is a good measure of participant effort - submissions react in expected ways to changes in prize allocation.

[3]Fullerton and McAfee (1999) argue that restricting entry can also benefit sponsors. By imposing an appropriate entry auction mechanism that encourages stronger participants to enter, the sponsor can expect greater effort while minimizing the costs of procurement.

encourage stronger participants to increase effort by enough to compensate for the reduced effort of weaker participants, and the sponsor may find it optimal to offer multiple prizes. Szymanski and Valletti (2005) argue that stronger participants may increase effort in response to multiple prizes in imperfectly discriminating contests. The added uncertainty of winning may motivate stronger participants to react to increasing competition from weaker participants. Few papers have examined the impact of prize allocation on outcomes other than effort. Terwiesch and Xu (2008) consider expected maximum and average quality outcomes in imperfectly discriminating innovation contests and all-pay auctions. The authors similarly show that multiple prizes may be optimal in contests with heterogeneous participants, but a single prize works best for contests with ex-ante identical participants.[4] Overall, the effect of multiple prizes on effort is ambiguous and depends on participant heterogeneity and cost function shape.[5] I contribute to the literature by presenting estimates of different prize allocation policies on participation and quality outcomes, and suggesting practical implications for ideation contest design.

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. I investigate the impact of restricting the number of submissions per participant - a relevant and easy to implement policy in the context of ideation contests. My results show that submission limits constrain stronger participants and increase overall entry. However, I find that a more stringent submission limit may reduce expected total and maximum idea quality.

Substantial progress in the empirical literature on contests has been achieved with the increasing availability of online data. Boudreau et al. (2016) examine the impact of competition on the effort

[4] See Sisak (2009) for a survey of the theoretical literature on multiple prizes in contests.

[5] Apart from heterogeneity, participant risk-aversion may also motivate sponsors to adopt multiple prizes. Kalra and Shi (2001) show that in rank-order sales contests with sufficiently risk-averse homogeneous participants, multiple prizes may increase effort. However, experimental research suggests that risk-averse participants are less likely to enter contests altogether (Eriksson et al. 2009, Dohmen and Falk 2011). Throughout, I focus on settings with risk-neutral heterogeneous participants and show further evidence in support of this model tenet in Section 4.

of heterogeneous participants in the context of the popular TopCoder platform for programming contests. The authors examine a number of contest design policies but do not focus on the question of how many prizes to award or how many submissions to accept per participant. Yoganarasimhan (2016) presents a model of beauty contest auctions, or procurement auctions with uncertain outcomes. The author applies the model to a freelance marketplace where each auction can have at most one winner and selection on unobserved components of cost is less of a concern as participants do not invest costly effort to enter. In the setting of online design contests, research has explored the impact of feedback and entry visibility on participation and submission quality (Wooten and Ulrich 2015a,b, Gross 2016) as well as the effects of competition on experimentation (Gross 2014). Gross (2016) presents a structural model to study the impact of performance feedback on submission quality in logo design contests but does not study prize allocation and submission limits or allow for non-entry in estimation. I contribute to the empirical literature by presenting estimates of the impact of a number of key design parameters, such as the number of prizes, prize amount, and submission limit, on participation and quality outcomes in ideation contests organized by popular brands. I suggest an empirical model of contests with multiple prizes, participant heterogeneity, and the possibility of selection into contests based on unobserved costs of effort. Furthermore, I address a recent call in literature to allow for more flexibility in the information structures of empirical games (Borkovsky et al. 2015) and derive contest outcome predictions that are robust to different informational assumptions.

3 Data and Setting

I use data from Tongal, a popular crowdsourcing platform. Major brands such as AT&T, General Electric, Google, Lego, P&G, and Unilever use the platform to organize ideation contests. Brands typically use the obtained ideas to develop advertising content, either independently or through Tongal.

Ideation contests on Tongal operate as follows. Tongal 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 allocation, 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. After the contest ends, a Tongal 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.

I focus on a sample of 181 ideation contests that ran from 2011 to 2015 (the platform was founded in 2009) 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 of the 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 further describes the classification criteria and shows the distribution of contests by category.

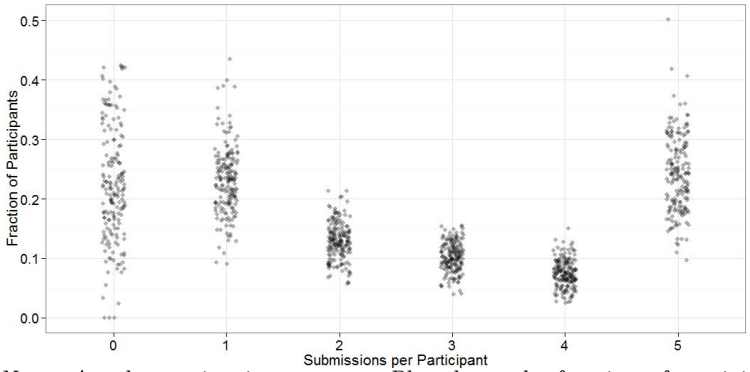
Table 1: Contest Categories

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

An important aspect of many contests is that not all participants who consider entering choose to do so. I use browsing data to define the set of likely non-entrants, or participants who considered entering a contest but chose not to. 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. Figure 1 presents a plot of the distribution of submissions per participant

within a contest for all 181 contests in the data. A significant proportion of participants does not enter, submits once, or makes the maximum number of submissions allowed. For each one of the participants, I observe a set of characteristics collected by the platform, which is further summarized in Section 6.

Figure 1: 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.*

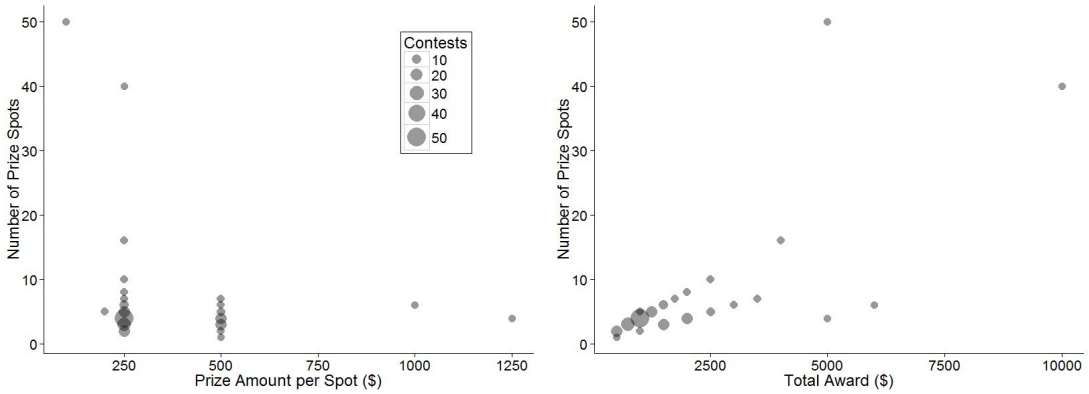
Table 2 presents summary statistics for the contests considered. The contests tend to attract a high number of entrants and submissions, with the average contest securing 193 entrants and 572 submissions. There is also substantial variation in prize allocation across contests, with the number of prizes ranging from 1 to 50 and prize amount per winning spot ranging from \$100 to \$1,250. Figure 2 shows that contests predominantly offer a \$250 or \$500 prize per spot and that contests with more prizes tend to have a higher total award.

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

Approximately 0.9% or 950 out of a total of 103,554 submissions win a prize. I observe the rating assigned to each submission by a Tongal jury. Ratings are assigned on a 5-point scale and based on the jury's perceived quality of the submission. Submissions receiving below a 3 are considered inadequate by the jury but may still win if sponsor preferences differ significantly from the jury's. I

Figure 2: Scatter of Contest Characteristics



refer to a rating below 3 as a low rating. Otherwise, the submission is said to have received a high rating. Of all submissions, 68% receive a low rating. A submission with a low rating has a 0.1% chance of winning and less than 10% of all winning submissions have a low rating. A high-rating submission has a 2.4% chance of winning and roughly 90% of all winning submissions have a high rating. Jury ratings are a strong predictor of a submission's success.

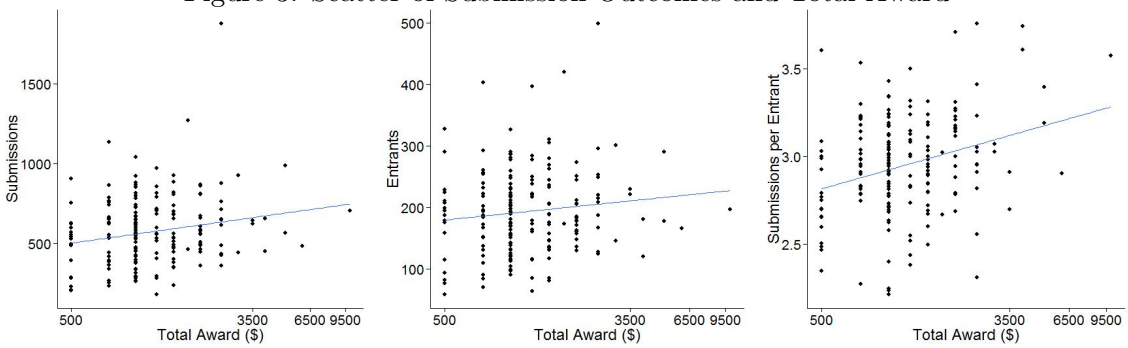
4 Descriptive Evidence

Is there evidence in the data that participants respond to prizes? Such evidence would suggest that prize allocation is an important design parameter that can alter behavior.

First, consider the impact of prize amount on submissions. Figure 3 shows the raw correlation between total award and three outcomes: the total number of submissions a contest receives, the number of entrants, and the number of submissions made by each entrant. Contests that award a higher prize attract more entrants and receive more submissions in total and more submissions per entrant. I regress the outcome metrics on the logarithm of total award and include fixed effects to control for differences in contest category, sponsor, and the number of prizes. Identifying variation comes from differences in the outcome across contests that share the same set of fixed effects but offer different prizes. Table 3 shows the estimated coefficients on the logarithm of total award. All columns show positive coefficients, consistent with the notion that a larger total award increases entry and effort.

Next, consider the impact of the number of prizes on submission behavior. Table 4 shows

Figure 3: Scatter of Submission Outcomes and Total Award



Note: An observation is a contest. Line shows best-fitting linear model.

Table 3: Contest-Level Regressions of Outcomes on log(Total_Award$_t$)

DV: log(Submissions$_t$)	0.154	0.187	0.350	0.260	0.238	0.555
	(0.053)	(0.025)	(0.058)	(0.061)	(0.069)	(0.112)
R^2	0.045	0.071	0.319	0.050	0.055	0.377
DV: Submissions$_t$/Entrants$_t$	0.156	0.166	0.129	0.147	0.097	0.060
	(0.039)	(0.051)	(0.074)	(0.095)	(0.065)	(0.075)
R^2	0.082	0.090	0.071	0.032	0.015	0.012
Category Fixed Effects	N	Y	N	N	Y	N
Sponsor Fixed Effects	N	N	Y	N	N	Y
Number of Prizes Fixed Effects	N	N	N	Y	Y	Y
Observations	181	181	78	178	167	40

Note: Robust standard errors in parentheses.

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

To further investigate the impact of the number of prizes on submission behavior, I draw on individual participant-level submission patterns. Theory (Moldovanu and Sela 2001, Terwiesch and Xu 2008) predicts that stronger participants prefer a smaller number of prizes, holding fixed total award, whereas the reverse is true for weaker participants. I classify participants into segments based on their participation frequency, defined as the number of contests they viewed. I expect that participants who view a large number of contests either have a low cost of participation or a high expected probability of winning. Each segment contains a similar number of participant

Table 4: Contest-Level Regressions of Outcomes on log(Number_of_Prizes$_t$)

DV: log(Submissions$_t$)	-0.296	-0.306	-0.175
	(0.096)	(0.116)	(0.118)
R^2	0.034	0.032	0.018
DV: Submissions$_t$/Entrants$_t$	-0.085	-0.068	-0.078
	(0.089)	(0.099)	(0.061)
R^2	0.006	0.002	0.004
Category Fixed Effects	N	Y	N
Sponsor Fixed Effects	N	N	Y
Total Award Fixed Effects	Y	Y	Y
Observations	179	158	33

Note: Robust standard errors in parentheses.

decision instances. Contests are grouped based on their observable characteristics. I compare the number of submissions made by the same participant across contests offering a different number of prizes within the same contest group. The regression equation is given by

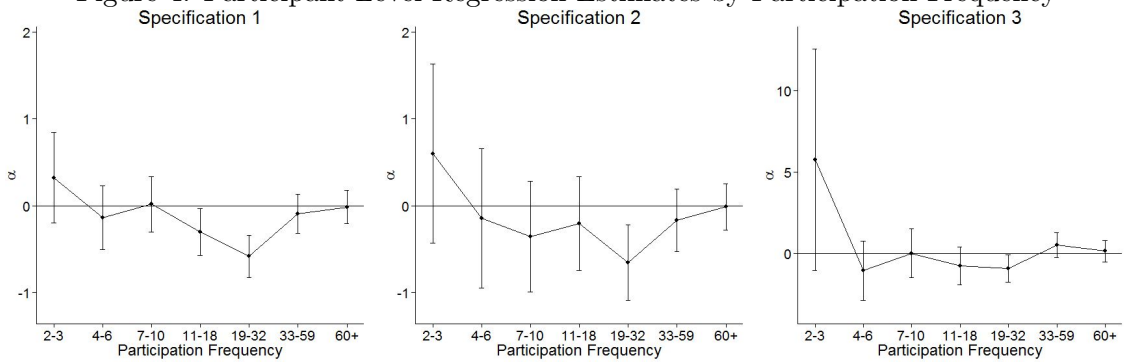
$$\text{Submissions}_{it} = \alpha \log(\text{Number\_of\_Prizes}_t) + \xi_{iG(t)} + \epsilon_{it}, \tag{1}$$

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

Figure 4 illustrates the estimate of the coefficient α when Regression 1 is applied separately to each segment of participants. Participants who view a small number of contests appear to prefer multiple prizes, but participants who view a moderate number of contests show a distaste for multiple prizes. No effect is found for the most frequent participants. Further inspection reveals that participants who consider over 33 contests tend to submit near the maximum number of times to each contest, perhaps because of low costs or high abilities. As a result, there is limited variation in their submission behavior, resulting in a near-zero coefficient for the most frequent participants. Figure 4 shows evidence consistent with the theoretical prediction that stronger participants may prefer fewer prize, holding fixed total award, but is not consistent with explanations that rely solely on risk-aversion or unobserved contest difficulty level.

The descriptive evidence presented in this section suggests that submission decisions respond to changes in prize allocation. Furthermore, the evidence supports models with risk-neutral het-

Figure 4: Participant-Level Regression Estimates by Participation Frequency



Note: Plots show estimates and robust 95% confidence intervals for α in Regression 1. Participants segmented based on the number of contests they viewed. Specification 1 groups contests by total award. Specification 2 groups contests by category and total award. Specification 3 groups contests by sponsor and total award.

erogeneous participants such as Moldovanu and Sela (2001), Stein (2002), and Terwiesch and Xu (2008). I proceed to derive a structural model motivated by these theoretical contributions. A structural model of sponsor preferences is required to assess the impact of contest design on quality, a variable not observed in the data. Furthermore, a model of participant submission decisions would enable an analysis of the impact of submission limits, a variable that remains unchanged across contests in the data. Finally, structure would allow for the investigation of the impact of participant information sets on contest outcomes.

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. I consider a trial-and-error model of ideation, whereby participants sample from a quality distribution with each submission in an attempt to generate an idea of high quality for the sponsor. This approach is common in models based on the statistical view of innovation in new product design (Dahan and Mendelson 2001, Loch et al. 2001) and in models of research contests with uncertain outcomes (Taylor 1995, Fullerton and McAfee 1999, Terwiesch and Xu 2008). Second, a Tongal jury assigns a binary quality rating to all submissions. Finally, the sponsor reviews all submissions and ranks the top submissions by its perception of submission quality. Most sponsors in the data offer only one contest. Sponsors who offer multiple contests tend to focus on different products and ideation

topics across contests. I use sponsor and contest interchangeably and denote both by t.

The model will capture three key features of ideation contests. First, participant abilities may differ across contests. If two participants make the same number of submissions, the participant with the higher ability has a larger expected payoff. Ability heterogeneity captures the notion that the "fit" between a participant and a contest may depend on the participant's background and the contest ideation topic. Second, participants exhibit cost heterogeneity and may select into contests they find most convenient based on an unobservable component of costs. If two participants have the same ability but different costs, the participant with the lower cost may increase her expected payoff by making a larger number of submissions. Cost heterogeneity accounts for the possibility that certain participants may be busier than others at different times or find it more difficult to think of ideas for certain contests. Third, participants may view their own abilities, the number of competitors, competitor abilities, and competitor actions with uncertainty and form expectations of their own expected payoffs given their information sets.

I work backwards and first present the model for the final stage sponsor decision (Section 5.1), followed by the model for jury ratings (Section 5.2). I present the model for participant entry decisions in Section 5.3. The empirical implementation of the two stages is presented in Section 6. A discussion of key model assumptions is presented in Section 6.5.

5.1 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 quality

$$q_{st} = \beta X_i + \gamma W_{st} + \epsilon_{st},$$

where X_i is a vector of participant characteristics, W_{st} is the rating assigned to submission s, β and γ are sponsor preference parameters, which I assume are common to all sponsors within a category, and $\epsilon_{st} \sim T1EV$ is an iid submission-specific quality shock.

The interaction of sponsor preferences β and participant characteristics X_i reflects the differences in participant submission quality that can be explained by observed participant characteristics. The parameter γ captures the effect of the rating assigned to the submission. The rating

W_{st} may explain unobserved components of submission quality that are not captured by X_i. The shock ϵ_{st} captures all heterogeneity in submission quality that cannot be explained by participant characteristics or submission rating.

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 $s_{(1)}, ..., s_{(N_t)}$.

5.2 Jury Rating Model

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

$$u_{st} = \alpha X_i + \xi_{it} + \eta_{st},$$

where X_i is the same vector of participant characteristics used in the sponsor choice model, α is a parameter that reflects jury preferences and is assumed constant within a category, $\xi_{it} \sim N(\phi, \sigma)$ is a participant-contest specific quality unobservable, distributed iid across participants and contests, and η_{st} is an iid submission-specific quality shock that follows a standard logistic distribution. If $u_{st} > 0$, the jury assigns a high rating and $W_{st} = 1$. Otherwise, the submission receives a low rating and $W_{st} = 0$.

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 level of humor that cannot be explained by her X_i. This source of variation in ratings will be explained by her quality unobservable ξ_{it}.

Note that correlation in jury and sponsor preferences is captured by allowing the jury's rating W_{st} to enter directly into the sponsor's perceptions of quality q_{st}. Alternatively, one may exclude W_{st} from q_{st} but allow for correlation in the unobserved components ϵ_{st} and η_{st}. I use the former approach as the sponsor has access to and may be directly influenced by the jury's ratings when it makes ranking decisions.

5.3 Participant Entry Model

Risk-neutral participants form expectations of their contest payoffs with respect of the distribution of jury ratings conditional on X_i, the distribution of quality shocks, and participant perceptions of competitor actions and characteristics. Participants know their own X_i and the contest prize structure but may view sponsor and jury preferences, the number of competitors, competitor characteristics, and competitor actions as random variables because of incomplete information. I further make the following assumption:

Assumption 1 *Participants do not know the realizations but do know the distributions of ϵ_{st}, η_{st}, and ξ_{it} before making submission decisions.*

I require that participants cannot select into contests based on an unobservable (to the researcher) component of sponsor preferences or jury rating. In other words, participants have the same information as the researcher regarding unobserved components of submission quality.[6]

Suppose that 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. Expected payoffs are given by

$$\pi_{it} = E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it}) | \mathcal{J}_{it}\right] - c_{it}(d_{it}).$$

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}. For example, in a contest with one prize, the expected winnings of a participant making $d_{it} > 0$ submissions are

$$R_t(d_{it}, d_{-it}; X_i, X_{-it}) = \int \frac{\sum_{k=1}^{d_{it}} \exp\{\beta X_i + \gamma W_{kt}^i\}}{\sum_{j=1}^{I_t'} \left(\sum_{k=1}^{d_{jt}} \exp\{\beta X_j + \gamma W_{kt}^j\} \right)} dF_{W_t}(W_t^1, ..., W_t^{I_t'}),$$

where 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, F_{W_t} is the distribution of

[6] A similar assumption is made in empirical models of contests by Yoganarasimhan (2016) and Gross (2016), and in two-stage entry and demand models in industrial organization such as Ishii (2008), Eizenberg (2014), and Wollman (2014). In Section 6.5.2 and Appendix A.1, I show evidence that supports this assumption.

ratings and $W_t^i = (W_{1t}^i, ..., W_{d_{it}t}^i)$. To determine her optimal action, the participant must form an expectation of her expected returns $R_t(.)$ with respect to her information set $\mathcal{J}_{it}$, which will vary depending on what the participant knows about her competitors.

I consider cost functions of the form

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

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 and obtain zero payoffs.

6 Estimation

Estimation proceeds in two stages. In the first stage, I estimate the sponsor choice model and the jury rating model. Given the first stage results, I estimate the participant entry model using moment inequalities. The underlying game is likely to have multiple equilibria because of the discrete action space. The moment inequalities methodology allows for multiple equilibria, does not require explicit specification of participant information sets, and permits a flexible distribution of cost unobservables. In the second stage, I follow the estimation procedure for discrete games with ordered choices suggested by Ishii (2008) and Pakes et al. (2015).

6.1 Sponsor Choice Model

I use data on sponsor ranking decisions, participant characteristics, and submission ratings to estimate the sponsor choice model. Identification relies on rankings data and heterogeneity in participant characteristics and submission ratings. Variation in sponsor decisions given different sets of submission characteristics identifies the sponsor preference parameters. The likelihood of

observing a ranking $s_{(1)}, ..., s_{(N_t)}$ is

$$L_t\left(s_{(1)}, ..., s_{(N_t)}\right) = \prod_{r=1}^{N_t} \left(\frac{\exp\{\beta X_{s_{(r)}} + \gamma W_{s_{(r)}t}\}}{\sum_{j=r}^{N_t} \exp\{\beta X_{s_{(j)}} + \gamma W_{s_{(j)}t}\} + \sum_{k \in \emptyset} \exp\{\beta X_k + \gamma W_{kt}\}} \right),$$

where N_t is the number of ranked submissions, $\emptyset$ is the set of all unranked submissions, and $X_s = X_i$ if submission s belongs to participant i. The likelihood of the data corresponds to the likelihood of a rank-ordered logit model. Prior research has used rank-ordered logit models (also known as exploded logits) to recover preferences from rankings in consumer survey data (Beggs et al. 1981, Chapman and Staelin 1982). In my setting, a structural model of sponsor choice generates a statistical rank-ordered logit model that can be estimated using data on sponsor rankings of contest winners. I estimate the model separately for each category using maximum likelihood methods.

6.2 Administrator Rating Model

Data on jury ratings and variation in participant characteristics within a contest identify jury preference parameters α and ϕ. 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 the participant's observed 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

$$M_t(W^i_{1t}, ..., W^i_{d_{it}t} | \xi_{it}) = \prod_{k=1}^{d_{it}} \left(\frac{\exp\{\alpha X_i + \xi_{it}\}}{1 + \exp\{\alpha X_i + \xi_{it}\}} \right)^{W^i_{kt}} \left(\frac{1}{1 + \exp\{\alpha X_i + \xi_{it}\}} \right)^{1 - W^i_{kt}}.$$

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

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

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

6.3 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 different specifications of participant information sets. 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.

The participant entry model can be rewritten as follows. I define the expectational error $\omega_{itd_{it}}$ as the difference between a participant's expected and actual returns: $\omega_{itd_{it}} = E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})|\mathcal{J}_{it}\right] - R_t(d_{it}, d_{-it}; X_i, X_{-it})$. Sources of expectational error may include participant uncertainty about competitor actions (as a function of costs) and characteristics, and may also incorporate optimization mistakes made by the participant in evaluating her expected returns. Then, the payoff equation can be written as

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

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

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

Note that Assumption 2 holds trivially if participants have correct expectations as

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

However, participants may have incorrect expectations (perhaps because of incorrect perceptions about equilibrium action distributions) as long as they are correct on average.

I proceed by first deriving a lower bound for marginal costs, where I take into account the possi-

bility that participants who made the maximum number of submissions may have had particularly low costs. Then, I derive an upper bound for marginal costs, where I use a selection correction technique to account for the possibility that non-entrants may have had particularly large costs. Additional assumptions about the distributions of $\omega_{itd_{it}}$ and ν_{it} are introduced as they become relevant.

6.3.1 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

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

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,

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

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 $\theta_1 + \theta_2(2d_{it}+1) + \nu_{it} \geq 0$ holds for entrants with $d_{it} = 5$.*

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

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

The expectational errors $\omega_{itd_{it}+1,d_{it}}$ average out to zero because participants are correct on average. 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

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

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

$$\Delta r^*_{it}(d_{it}+1, d_{it};\theta) = \Delta R^*_{it}(d_{it}+1, d_{it}) - \theta_1 - \theta_2(2d_{it}+1).$$

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 but is required as an input to $\Delta r^*_{it}(d_{it}+1, d_{it})$ in the definition of $m^L(\theta)$. To obtain expected returns, it is necessary to consider the probability of observing all possible combinations of winning submissions from the set of all submissions. For contests with multiple prizes and hundreds of submissions, this expression can be analytically intractable. I use simulation to obtain an approximation of the expected returns function for each participant in every contest.[7]

6.3.2 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

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

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

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

[7] It can be shown that simulation error averages out in the moment inequalities framework.

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

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

where

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

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. I provide the exact condition for the joint density of expectational errors and cost unobservables in Appendix A.2. 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) and is reproduced in Appendix A.2 for completeness.

6.3.3 Identified Set

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

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

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.

6.4 Confidence Bounds

I obtain confidence bounds using a block-bootstrap procedure. The procedure is applied separately to each category. 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 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. The simulated distribution is used to obtain a critical value, which is compared to the actual value of the criterion function in the observed sample. Points where the value of the criterion function falls below the critical value are included in the confidence set. The above procedure, first described by Chernozhukov et al. (2007), may produce very conservative confidence sets, primarily because of the influence of very positive moments that satisfy the inequality restrictions by a wide margin. Andrews and Soares (2010) suggest a moment selection procedure that yields more precise coverage by excluding very positive moments before simulating the criterion function. I use the bootstrapped datasets obtained in the inference procedure for the sponsor choice and jury rating models to incorporate first-stage estimation error in the Andrews and Soares (2010) criterion function.

6.5 Discussion of Model Assumptions

6.5.1 Selection and Participant Heterogeneity

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

The model does not allow for persistent unobserved heterogeneity in the quality of a participant's submissions. Participants cannot choose how many submissions to make based on an unobserved component of expected submission quality. I include an indicator in X_i for whether or not a participant won money from Tongal prior to her first ideation contest to allow for persistent differences in skill and submission quality across participants. Participant submissions may depend on a quality unobservable ξ_{it} which is iid across participants and contests and not known to participants before entry. The quality unobservable may explain correlation in the quality of submissions made by the same participant in the same contest. A similar assumption on the role of unobservable components of demand is made in recent empirical work on contests (Yoganarasimhan 2016, Gross 2016) and two-stage entry models (Ishii 2008, Eizenberg 2014, Wollman 2014) to allow for two-step estimation. Incorporating unobserved components of demand known to participants in entry games with multiple equilibria is an active area of research.

6.5.2 Submission Order

I test for the importance of unobserved components of submission quality by exploiting data on submission order. Participants may choose to submit their best idea first. Evidence of a relationship between submission quality and order may suggest that participants have private information about the quality of their submissions that cannot be explained by participant characteristics alone. In addition, it would provide evidence of decreasing returns to submissions resulting from quality deterioration. I run a series of regressions to test for a relationship between jury rating and submission order. In Appendix A.1, I show that there does not appear to be a strong connection

between the two variables.

6.5.3 Cost Function Shape

Incorporating non-linearities in the cost function requires instruments for participant actions, restrictions on the distribution of cost unobservables, or covariance restrictions between observable characteristics and cost unobservables. Note that d_{it} cannot be used as an instrument to construct additional inequalities unless ν_{it} is assumed to be zero as $E[\nu_{it}|d_{it}] \neq 0$. In Section 7.3, I present estimates of θ_1 under the assumption that $c_{it}(d_{it}) = (\theta_1 + \nu_{it})d_{it}$ and estimates of θ_2 under the assumption that $c_{it}(d_{it}) = (\theta_2 d_{it} + \nu_{it})d_{it}$. I find that the assumption of constant marginal costs is unlikely to hold as small perturbations in a contest's prize would lead all participants to submit either 0 or 5 times given the approximate linearity of participant marginal expected returns. It is possible that the expected returns function is not sufficiently concave as it does not incorporate risk-aversion or deteriorating submission quality. However, the descriptive evidence in Section 4 does not support risk-aversion and the analysis presented in Appendix A.1 does not show significant evidence of submission quality deterioration for participants who make multiple submissions.

7 Structural Model Estimates

7.1 Sponsor Choice Model

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. Variables in the set of characteristics X_i include the participant's age, country, gender, an indicator for whether or not the participant won a contest on Tongal prior to the first contest she considered entering in my sample, an indicator for whether or not the participant has video production skills, and an indicator for whether or not the participant was referred to the platform. Table 5 presents the definitions for all variables used in estimation. The set of observable characteristics is deliberately discretized to ensure that there exists only a finite number of participant types, which facilitates simulation of expected payoffs and counterfactuals.

Table 6 presents parameter estimates for the sponsor choice model by category. As expected, I find a significant effect of submission rating on chance of winning. Conditional on rating, esti-

Table 5: Description of Participant Characteristics

Variable	Definition	Share of Participants
Demographics		
Age_i	1 participant i was born after 1984 and 0 otherwise	0.373
Country_i	1 if participant i is from the US and 0 otherwise	0.814
Gender_i	1 if participant i is female and 0 otherwise	0.252
Participant-Platform Characteristics		
Paid_i	1 participant i was paid prior to her first contest and 0 otherwise	0.047
Producer_i	1 if participant i has video production skills and 0 otherwise	0.232
Referred_i	1 if participant i was referred to the platform and 0 otherwise	0.210

mates of the remaining parameters should be interpreted either as discrepancies between sponsor preferences and jury ratings, or as additional determinants of submission quality that cannot be explained by the rating alone, perhaps because of the coarseness of the rating measure. For example, participants with past success and with experience producing video have a higher chance of winning in many categories, conditional on rating, suggesting that rating alone does not fully capture differences in submission quality for these participants. I find heterogeneity in the effects of age and country but no significant effect of gender. Heterogeneity of coefficients across contests points to differences in the variance of unobserved components of quality and idiosyncrasies in the sponsor's choice process, as well as discrepancies between sponsor choice and jury rating patterns.

Table 6: Sponsor Choice Model Parameter Estimates by Category

	Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Age	-0.703	-0.066	0.170	-0.009	0.001	0.144	0.073	0.294
	(0.211)	(0.158)	(0.290)	(0.207)	(0.205)	(0.229)	(0.178)	(0.173)
Country	-0.442	0.283	0.494	-0.540	0.279	0.391	-0.420	0.062
	(0.233)	(0.274)	(0.525)	(0.252)	(0.338)	(0.378)	(0.240)	(0.255)
Gender	-0.008	-0.204	0.131	0.043	0.169	-0.460	0.115	-0.179
	(0.213)	(0.194)	(0.347)	(0.241)	(0.212)	(0.307)	(0.211)	(0.204)
Paid	0.525	0.274	0.093	-0.181	0.474	0.342	0.655	0.324
	(0.218)	(0.188)	(0.370)	(0.284)	(0.249)	(0.279)	(0.201)	(0.205)
Producer	0.390	0.800	0.977	0.482	-0.028	-0.117	0.369	0.600
	(0.214)	(0.181)	(0.338)	(0.222)	(0.225)	(0.242)	(0.230)	(0.187)
Referred	-0.489	-0.683	-0.037	0.043	-0.538	0.221	-0.067	-0.484
	(0.288)	(0.245)	(0.373)	(0.243)	(0.352)	(0.279)	(0.244)	(0.248)
Rating (γ)	3.214	2.212	3.904	2.767	4.042	4.845	5.155	3.046
	(0.357)	(0.195)	(0.617)	(0.292)	(0.463)	(0.707)	(0.694)	(0.263)
Contests	22	45	12	21	18	19	20	24
Choice Instances	120	172	49	100	101	82	133	148
Log-Likelihood	-657	-998	-267	-561	-508	-412	-636	-810

Note: Bootstrapped standard errors in parentheses.

I examine the model's explanatory power by testing its ability to predict characteristics of the set of winning submissions. The model successfully predicts 4.4% of winning submissions and can

predict the identity of the winning participant correctly 6.1% of the time. In 11.6% of the contests, the model is able to predict at least one winner correctly. Note that these prediction tasks are very difficult as only 0.9% of submissions ever win a prize.

7.2 Jury Rating Model

Table 7 presents parameter estimates for the jury rating model by category. I find that participants from the US with past success and video production skills tend to receive higher ratings in all categories. Female participants appear to receive higher ratings in the toy and other categories, and a slightly higher rating in the category dedicated to female health and personal care products. Older participants perform better in the female health, technology, and other categories. I also find evidence of unobserved heterogeneity in submission quality across participants as indicated by the estimates of σ, ranging from 1.116 to 1.553. Estimates of the variance of participant-level quality unobservables are higher in the consumer, food, hardware, and toy categories but lower in the health categories.

Table 7: Jury Rating Model Parameter Estimates by Category

	Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Age	-0.035	0.007	0.040	-0.021	-0.114	-0.085	0.008	-0.101
	(0.039)	(0.025)	(0.047)	(0.039)	(0.046)	(0.045)	(0.047)	(0.039)
Country	0.292	0.289	0.207	0.224	0.202	0.299	0.213	0.293
	(0.056)	(0.036)	(0.063)	(0.055)	(0.064)	(0.062)	(0.062)	(0.055)
Gender	0.053	0.010	-0.070	0.046	0.088	0.061	0.257	0.125
	(0.044)	(0.029)	(0.055)	(0.046)	(0.049)	(0.053)	(0.055)	(0.044)
Paid	0.367	0.101	0.390	0.169	0.177	0.417	0.225	0.177
	(0.055)	(0.037)	(0.069)	(0.056)	(0.064)	(0.060)	(0.063)	(0.057)
Producer	0.079	0.175	0.219	0.152	0.195	0.149	0.170	0.101
	(0.041)	(0.026)	(0.050)	(0.041)	(0.049)	(0.047)	(0.049)	(0.040)
Referred	-0.082	0.031	0.082	-0.017	-0.145	-0.207	-0.018	-0.044
	(0.051)	(0.031)	(0.058)	(0.047)	(0.061)	(0.055)	(0.057)	(0.049)
Mean (ϕ)	-1.006	-1.098	-1.119	-1.039	-1.078	-1.113	-0.873	-1.191
	(0.059)	(0.039)	(0.066)	(0.059)	(0.069)	(0.066)	(0.067)	(0.058)
Std. Dev. ($\log \sigma$)	0.408	0.350	0.440	0.153	0.110	0.284	0.399	0.220
	(0.034)	(0.022)	(0.040)	(0.038)	(0.049)	(0.041)	(0.041)	(0.035)
Contests	22	45	12	21	18	19	20	24
Choice Instances	4006	10161	2966	4170	2971	3221	2893	4623
Log-Likelihood	-7096	-17819	-5165	-7540	-5370	-5744	-5161	-7654

Note: Bootstrapped standard errors in parentheses.

The model is able to correctly predict 71% of all jury ratings. The bulk of the model's explanatory power can be attributed to the mean and standard deviation of the participant-specific quality unobservable. Observable characteristics such as participant country, past success, and producer

status help explain a portion of the remaining variance in jury ratings.

7.3 Cost Estimates

Table 8 shows estimates of the cost parameters. First, I assume that $c_{it}(d_{it}) = (\theta_1 + \nu_{it})d_{it}$ and obtain a confidence set for θ_1. Subsequently, I assume that $c_{it}(d_{it}) = (\theta_2 d_{it} + \nu_{it})d_{it}$ and obtain a confidence set for θ_2. The cost parameters are estimated separately for each category. As discussed previously in Section 6.3.3 and Section 6.5.3, I focus on the quadratic cost function in the remainder of the analysis.

Table 8: Ideation Cost Estimates by Category

Cost Function		Consumer	Food	Hardware	Health	Health(F)	Tech	Toy	Other
Linear	LB	1.575	1.492	1.407	2.246	1.767	1.979	3.231	1.951
$(\theta_1 \neq 0, \theta_2 = 0)$	UB	3.136	2.436	2.025	3.917	4.597	3.502	6.886	3.197
Quadratic	LB	0.279	0.257	0.242	0.391	0.322	0.352	0.623	0.358
$(\theta_1 = 0, \theta_2 \neq 0)$	UB	1.197	0.793	0.664	1.379	2.559	1.443	6.694	1.472

Note: Bootstrapped 95% confidence bounds.

The estimated cost parameters suggests that, on average, participants incur a cost of \$0.33-1.30 for producing a single submission.[8] 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 that could have been spent elsewhere. Costs increase in a convex manner, with the average cost of making five submissions in the range of \$8.30-32.43. For comparison, the median hourly salary of a writer, copywriter, or editor in the US is \$28.71 (Bureau of Labor Statistics 2016), which falls in the range of costs required to think of five original ideas.[9]

I find heterogeneity in costs across categories. For example, contests in the hardware category appear less costly for participants than contests in the toy category. Differences in costs may arise for several reasons: participants may find it easier to think of ideas for certain topics; contests within a category may be scheduled at times that are inconvenient relative to contests in a different category; the set of participants who typically consider entering into a contest within a category may differ in their availability from other participants.

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

[9] Assume that writers incur a cost of effort less than their wage and that the wage estimate for writers applies to Tongal creatives. Then, an upper bound for the time spent per 140 character idea falls in the range of 3-14 minutes, or 16-76 seconds per word (assuming 11 words per idea).

8 Counterfactuals

Although moment inequalities allow for flexible information sets in estimation, I require an explicit specification of the information sets of participants to simulate counterfactuals. I experiment with two specifications, which I refer to as *complete information* and *incomplete information*.

In the complete information setup, 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 competitors they face, their own characteristics, as well as competitor characteristics and actions. Formally, participant i's information set in contest t is given by $\mathcal{J}_{it}^{CI} = \{d_{it}, d_{-it}, X_i, X_{-it}, I_t, M_t, \delta_t\}$, where M_t represents the prize structure of contest t and includes the prize amount and number of prize spots, $\delta_t = (\alpha_t, \beta_t, \gamma_t, \phi_t, \sigma_t)$, and $\delta_t = \delta_s$ for contests t and s within the same category. I introduce the subscript t on β and γ to reflect the notion that sponsor and 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. Details of the counterfactual simulation procedure are provided in Appendix A.3.1.

The complete information assumption may require a high level of participant sophistication. Tongal reveals neither the identities nor the submissions of competitors. Furthermore, participants may not have a good sense of sponsor or jury preferences. In the incomplete information scenario, I focus on a subset of contests with the same prize structure and allow for participant uncertainty with regards to sponsor and jury preferences, and the quantity, characteristics, and actions of competitors. Participant i's information set in contest t is given by $\mathcal{J}_{it}^{II} = \{d_{it}, X_i, M_t\}$, and the participant knows the conditional joint density of the number of participants and sponsor/jury preferences $H(I_t, \delta_t | M_t)$, and the conditional joint density of competitor actions and characteristics $G(d_{-it}, X_{-it} | I_t, M_t, \delta_t)$. I assume that participants use an iterative updating procedure, described further in Section 8.1 and Appendix A.3.2, to converge to a new equilibrium from their current state. The procedure can be interpreted as a learning algorithm that participants use to find a new

equilibrium under a different contest structure.

Equipped with parameter estimates and an assumption about the information structure of the game, I run simulations of alternative contest designs. 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 the data provider. Increasing entry cultivates participant engagement with the platform and allows for sponsors to communicate with a large number of potential consumers and build brand awareness. Quality outcomes are also important if the goal of the sponsor is to implement the best idea or to incorporate information from all submitted ideas into its marketing strategy. I consider expected total quality, defined as $\int \left(\sum_{i=1}^{I'_t} \sum_{k=1}^{d_{it}} e^{\beta_t X_i + \gamma_t W_{kt}^i}\right) dF_{W_t}$, and expected maximum quality, defined as $\int \log \left(\sum_{i=1}^{I'_t} \sum_{k=1}^{d_{it}} e^{\beta_t X_i + \gamma_t W_{kt}^i}\right) dF_{W_t}$. A sponsor may be interested in total quality if it wishes to combine data from all submissions to create an ad or improve its product offerings. Maximum quality becomes more important for a sponsor interested in implementing only the best idea.

8.1 The Impact of Incomplete Information

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

To understand the impact of incomplete information on behavior, I recover participant expectational errors, which capture the difference between a participant's expected returns under incomplete information and her expected returns under complete information. To do so, I draw a large sample of contests of size B from $\mathcal{W}$ (with replacement) and label these contests $b = 1, ..., B$. Then, assuming that the cost unobservables ν_{it} are independent conditional on X_i for all participants i within a contest t and letting j_b denote a random participant in contest b, the expected

returns $E\left[R_t(d_{it}, d_{-it}; X_i, X_{-it})|\mathcal{J}_{it}\right]$ can be approximated by

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

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

I find that participants who make higher quality submissions tend to underestimate their expected returns ($\hat{\omega}_{itd_{it}} < 0$) as they do not know with certainty that they are the most skilled participants in their contests. Similarly, participants who make lower quality submissions tend to overestimate their expected returns ($\hat{\omega}_{itd_{it}} > 0$) as they do not know with certainty that they fall in the lower range within the contests they participate in. Given their observed actions, this implies that participants with higher quality submissions will have lower cost unobservables ν_{it} than had they had complete information. Similarly, participants with lower quality submissions will have higher cost unobservables than in a complete information scenario. A counterfactual simulation analysis is required to compare equilibrium outcomes under complete and incomplete information.

8.2 Counterfactual Outcomes Across Contests

I obtain bounds on the outcomes of all contests for each one of the three design counterfactuals under the assumption of complete information. For the 49 contests in $\mathcal{W}$, I also obtain counterfactual outcomes under the assumption of incomplete information using an iterative procedure described in Appendix A.3.2. Figures 5, 6, and 7 show the impact of counterfactual design policies on different contests, and Table 9 shows the average impact across contests.

8.2.1 Single Prize

For most of the contests, reducing the number of prizes 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. As a result, few participants alter their actions.

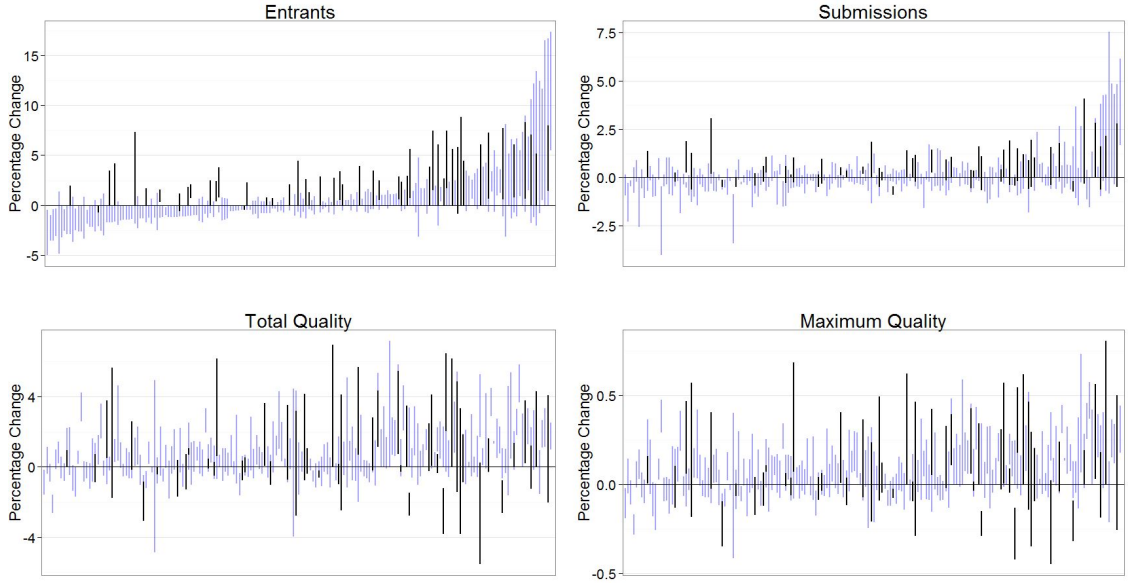
For certain contests with very low heterogeneity in the expected marginal returns and costs

Table 9: Average Counterfactual Design Outcomes Across Contests

	Entrants		Submissions		Total Quality		Max Quality	
	LB	UB	LB	UB	LB	UB	LB	UB
Complete Information (all contests)								
Single Prize	0.2	3.9	-0.2	1.1	-0.8	2.3	-0.1	0.3
20% Prize Increase	1.1	8.7	2.1	8.9	3.3	12.8	0.4	1.3
3 Submission Limit	0.7	6.9	-9.3	-5.0	-10.1	-3.9	-1.3	-0.5
Incomplete Information (49 contests offering four $250 prizes)								
Single Prize	-0.9	1.8	-0.6	0.7	-0.2	1.8	0	0.2
20% Prize Increase	0.8	4.9	1.7	5.5	6.5	13.5	0.7	1.5
3 Submission Limit	0.5	4.0	-9.5	-6.9	-8.4	-3.7	-1.0	-0.4

Note: Average lower bound (LB) and upper bound (UB) of percentage change in counterfactual outcomes reported.

Figure 5: Impact of Reducing the Number of Prizes Across Contests



Note: Each segment represents the range of counterfactual outcomes for a single contest under complete information (light) and incomplete information (dark). Contests ordered by increasing impact on the number of entrants in the complete information scenario.

of participants, a single prize may significantly increase entry but only under the assumption of complete information. In a setting with limited participant heterogeneity, there is no longer a reason to motivate participants with a lower chance of winning, and a single prize reduces the incentive for all participants to achieve a worse rank. However, in a setting with incomplete information, participants do not know the extent of heterogeneity within their contest. As a result, they average over possible states and do not react as strongly to a reduction in the number of prizes in contests with limited participant heterogeneity.

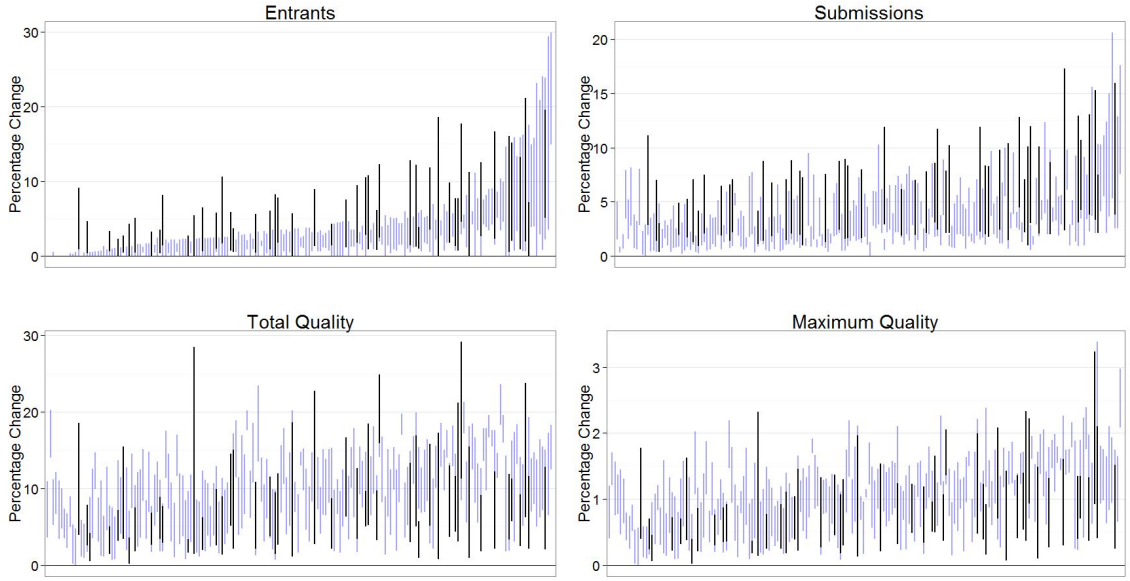
I find that the counterfactual simulation results are in line with the implications of the regres-

sion estimates in Table 4. In particular, I fail to find a significant effect of prize allocation on submission behavior in both models. This is encouraging validation of the structural model as the regressions and the structural model rely on different assumptions and different sources of variation for identification.[10]

8.2.2 Prize Increase

A 20% prize increase improves the outcome metrics, especially expected total quality, but may not lead to as significant an increase in entry in a complete information scenario if there is substantial participant heterogeneity. The added prize incentive predominantly encourages participants with a higher chance of winning to submit more, limiting the benefits of making more submissions for participants with a lower chance of winning. If the contest is highly asymmetric, the prize increase will only significantly affect the behavior of a small number of participants with high expected marginal returns and low costs, which will increase quality outcome metrics but may not lead to a significant increase in entry.

Figure 6: Impact of a 20% Prize Increase Across Contests



Note: Each segment represents the range of counterfactual outcomes for a single contest under complete information (light) and incomplete information (dark). Contests ordered by increasing impact on the number of entrants in the complete information scenario.

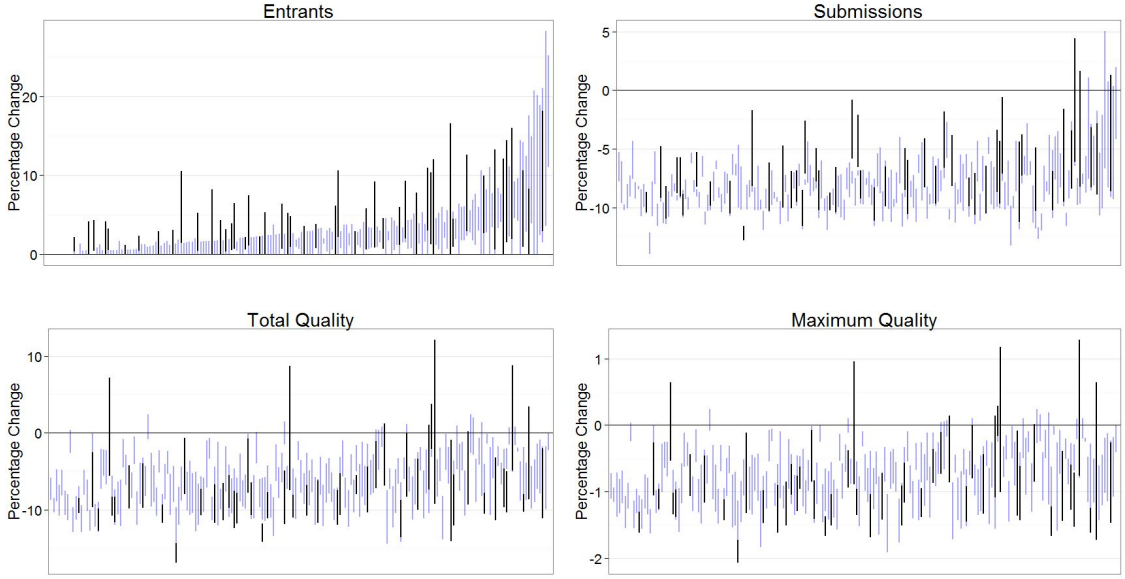
[10]Regressions leverage variation in the number of submissions across contests offering different prize structures, whereas the structural model recovers the costs that rationalize participant submission decisions and then simulates a counterfactual outcome for each contest individually. The structural model does not require variation in prize structure for identification.

I compare the implied elasticity of submissions with respect to prize to the elasticities obtained from the regression results in Table 3. The counterfactual simulations imply a prize elasticity of submissions in the range of 0.105-0.445 for the complete information scenario and 0.085-0.275 for the incomplete information scenario, whereas the estimates in Table 3 suggest elasticities of 0.154-0.555. It is encouraging that both sets of elasticities fall within the same range.

8.2.3 Submission Limit

The platform requires that all participants submit at most five times to each contest. What if participants could submit at most three times? Participants with a higher chance of winning would be restricted by a lower submission limit as they tend to make more submissions, creating an opportunity for participants with a lower chance of winning to enter the contest and make more submissions. Higher ability participants with low costs no longer crowd out other potential entrants. A more stringent submission limit encourages entry but restricts participants with higher expected marginal returns and lower costs, reducing expected total and maximum quality across both complete and incomplete information scenarios.

Figure 7: Impact of a 3 Submission Limit Across Contests



Note: Each segment represents the range of counterfactual outcomes for a single contest under complete information (light) and incomplete information (dark). Contests ordered by increasing impact on the number of entrants in the complete information scenario.

8.2.4 Comparison of Complete and Incomplete Information

In the complete information scenario, the impact of a design parameter depends crucially on the extent of participant heterogeneity in expected marginal returns and costs within a contest. For example, a prize increase will be more effective if participants know that they are competing in a contest with limited participant heterogeneity. Under incomplete information, participants must form an expectation of their expected returns by averaging over states (contests). Building on the previous example, participants who are engaged in a contest with limited participant heterogeneity do not know the extent of this heterogeneity, and hence, will not react as strongly to a prize increase under incomplete information.

Interestingly, many other contest-based freelance marketplaces (such as 99designs for graphic design) offer sponsors the option to organize a contest where participants can see the submissions of their competitors. Research has considered the impact of visibility and free-riding on entry incentives and submission quality (Wooten and Ulrich 2015b). My results suggest that offering contests with complete information can have an impact beyond free-riding that directionally depends on the extent of participant heterogeneity.

8.3 Practical Implications

These findings have a number of practical implications for ideation contest and crowdsourcing platform design. First, the choice of how many prizes to offer does not substantially affect the outcome of the contest, as long as the contest attracts a large number of submissions. The choice of how many prizes to offer should be driven by institutional considerations. For example, in many ideation contests, the sponsor retains intellectual property of the winning submissions. In these settings, the sponsor would benefit from offering more prizes, without significantly altering the outcome of a contest. Only in complete information settings where the sponsor expects to receive submissions from a very homogeneous set of participants does a single prize appear preferable. Second, if a sponsor's intention is to increase the number of entrants, increasing prize award may not have as strong an impact if there is no limit on the maximum number of submissions a participant can make. Third, a submission limit can be used as an effective strategy to encourage entry but may come at the cost of expected total and maximum idea quality. If a sponsor seeks to attract a

large number of entrants and use the contest as a mechanism for engaging potential consumers, it should implement a more stringent submission limit.

9 Conclusion

Firms across a range of industries use ideation contests to procure ideas for ads, new products, and marketing strategies. An appropriate design can improve the outcome of a contest. Moreover, different firms may care about different outcome metrics. Brands interested in engaging consumers may focus on increasing entry, whereas a manufacturer interested in designing a new product may value the maximum quality of submitted ideas.

I empirically investigate the impact of three design parameters - number of prizes, prize amount, and submission limit - on contest participation and quality outcomes, using data from a popular crowdsourcing studio that runs ad ideation contests for major brands. I present a structural model of ideation contests that allows for multiple equilibria, incomplete information, and heterogeneity in participant submission quality and costs. Counterfactual simulations reveal the impact of different contest designs. The results show that, on average, the number of prizes does not significantly affect contest outcomes, prize amount increases submissions and all expected quality metrics but may not necessarily increase entry, and submission limits encourage entry but significantly reduce expected total and maximum quality.

I make several simplifying assumptions to ensure the model remains feasible. First, I assume that each contest is an independent game. Participants face no dynamic incentives and do not have constraints that prevent them from entering multiple contests at the same time. Future research may examine the implications of dynamics and competing contests on the optimal design of contest platforms. Second, I assume that participants choose the quantity but not the quality of submissions to make. Future research may allow for participants to choose not only how many submissions to make but also how much effort to invest into each individual submission. Finally, I do not observe the actual applications of ideas obtained through the contests. Absent these data, quality is inferred from jury ratings and sponsor rankings, and does not necessarily represent the market's perception of idea quality. Future work may incorporate post-contest outcomes to assess the impact of contest design on the true value of winning ideas.

An appropriately designed ideation contest can yield interesting concepts and spur innovation. Crowdsourcing platforms, sponsors, and contest designers must carefully consider the effects of different design parameters on outcomes.

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A Appendix

A.1 Do Participants Submit Their Best Idea First?

I estimate the difference between the rating of the first submission made by a participant and the ratings of her subsequent submissions, controlling for the total number of submissions made by the participant. For the set of entrants, I estimate the regression

$$\text{Rating}_{sit} = \alpha + \beta \text{First\_Submission}_{sit} + \epsilon_{sit}, \tag{2}$$

where Rating_{sit} is the rating of submission s made participant i in contest t, $\text{First\_Submission}_{sit}$ is an indicator for whether or not submission s was participant i's first submission, and ϵ_{sit} is an error term. Regression 2 is estimated for all cases where participants made d submissions, where $d \in \{2, 3, 4, 5\}$. Table 10 shows the resulting estimates of β. I find evidence that whenever participants make 5 submissions, the rating assigned to the first submissions tends to be higher than the rating assigned to subsequent submissions, although the difference is not economically significant. For all other categories, I fail to find a significant effect of submission order on submission rating. Similar results hold when I compare the rating of the first submission to the last submission and when I use a linear or logarithmic function of submission order instead of an indicator for first submission in Regression 2. I conclude that there is limited evidence of a relationship between submission order and rating.

Table 10: Regression of Rating on Submission Order

Total Number of Submissions	2	3	4	5
Relative Rating of First Submission	0.008	0.014	0.010	0.015
	(0.009)	(0.08)	(0.009)	(0.005)
R^2	0.000	0.000	0.000	0.000
Observations	11650	13761	13364	54250

Note: An observation is a submission. Standard errors in parentheses.

A.2 Deriving an Upper Bound on Marginal Costs

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

First, let $\Delta r_i = -\Delta r_i^*(d_i + 1, d_i; \theta)$ and use order-statistic notation to rank participants by ν_i

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

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

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

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

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

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

where the first inequality follows from the definition of the set U. The second inequality follows from the assumption that participants take the optimal action given their information sets. Note that

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

The distributional assumption on ν_i (Assumption 4) ensures that

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

Furthermore,

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

Expectational errors are mean-zero for entrants because the action d_i is an element of the participant's information set. I also require the following assumption:

Assumption 6 $E\left[\frac{1}{I}\sum_{i\in U_\nu}\omega^*_{id_i+1,d_i}\right] \geq 0.$

In other words, participants in U_ν cannot consistently underestimate their expected marginal returns. Note that this applies only to participants in U_ν with $d_i < 5$, as otherwise, $\omega^*_{id_i+1,d_i} = 0$.

As a result,

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

A.3 Counterfactual Simulation Procedure

A.3.1 Complete Information

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

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

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

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

4. Compute equilibrium actions according to the following procedure:

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

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

$$d_{it}^s = \arg\max_{d_{it}} \left[R_t(d_{it}, d_{-it}^s; X_i, X_{-it}) - (\theta_1^s + \theta_2^s d_{it} + \nu_{it}^s) d_{it} \right]$$

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

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

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

Steps 1-5 are repeated S times. In Figures 5-7, I report the lower bound on the counterfactual outcome as $V_t^L = \min(V_t^s)$ and the upper bound as $V_t^U = \max(V_t^s)$. To obtain the average outcome across contests, as shown in Table 9, I use $V^L = \frac{1}{T} \sum_{t=1}^{T} V_t^L$ for the lower bound and $V^U = \frac{1}{T} \sum_{t=1}^{T} V_t^U$ for the upper bound.

A.3.2 Incomplete Information

The procedure described in Appendix A.3.1 can be modified as follows to incorporate incomplete information. First, in Step 2, all instances of $R_t(d_{it}, d_{-it}; X_i, X_{-it})$ must be replaced with $ER_{it}(d_{it})$, which can be obtained using the procedure described in Section 8.1. Then, the resulting cost intervals $\left[\nu_{it}^{Ls}, \nu_{it}^{Us}\right]$ will take into account that participants had incomplete information when choosing their actions. Second, Step 4 must be modified to capture the change in the density of the number of competitors, participant actions, and characteristics when the structure of the contest changes. Formally, Step 4 can be modified as follows, assuming that $\left[\nu_{it}^{Ls}, \nu_{it}^{Us}\right]$ have been obtained for all participants in the contests in $\mathcal{W}$ in a previous step.

4. Compute equilibrium actions according to the following procedure:

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

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

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

where

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

for $d_{it} \in \{0, 1, ..., D\}$, where D is the counterfactual submission limit, $R_b(.)$ is the counterfactual contest expected returns function, and j_b denotes a random participant in contest b as in Section 8.1.

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

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