

# CROWDSOURCING CONTESTS: A DYNAMIC STRUCTURAL MODEL OF THE IMPACT OF INCENTIVE STRUCTURE ON SOLUTION QUALITY

*Completed Research Paper*

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## Abstract

*A key challenge faced by firms that undertake crowdsourcing-contests to get solutions from crowds to their problems is to design an incentive structure which helps attract high quality solutions. We develop a structural model of user participation in crowdsourcing-contests and present empirical evidence on how incentive structure could affect the quality of solutions. Using data from Threadless.com, we find that participants exert less effort as competition for the reward increases. This indicates that increasing the reward may adversely affect the quality of the solutions produced as it will increase the competition. However, counter-intuitively the policy simulations indicate that increasing the reward increases both the quantity and quality of submitted solutions. This is because under the new policy of higher reward, individual equilibrium behavior is different. When the firm increases the reward, the additional utility from increase in the reward offsets the reduction in probability of winning due to intensified competition.*

**Keywords:** Crowdsourcing contests, User-generated-content, Structural Modeling, Learning curve, Econometric analyses, Economics of information systems, Utility

## **Introduction**

The importance of business innovation has been long recognized by practitioners. Technology has enabled methods of soliciting solutions to tasks from outside individuals via open calls to large-scale communities of the Internet. Jeff Howe (2006) named this new approach Crowdsourcing and defined the crowd as “the new pool of cheap labor: everyday people using their spare cycles to create content, solve problems, even do corporate R&D.” Crowdsourcing initiatives can be broadly categorized into crowdsourcing contests (Boudreau et al 2011; Jeppesen et al 2010) and non-competitive crowdsourcing ideation initiatives (Bayus 2010; Di Gangi et al. 2010; and Huang et al. 2012). In this paper, we focus on crowdsourcing contests.

In a typical crowdsourcing contest, an innovating firm (the seeker) facing a problem posts this problem to an open crowd (the solvers). A reward is provided to attract solvers. Solvers then compete with each other, and those who generate best solutions win the reward. Compared to traditional in-sourcing approach, crowdsourcing contest has several advantages: 1) Seekers have access to a larger pool of solvers, and thus may be able to find better solutions than the ones generated internally; 2) Seekers can evaluate designs or solutions using the same crowd; 3) Seekers only pay for successful innovations, but not for the failures, as the associated risks of failures are shifted to the solvers (Terwiesch and Xu, 2008); 4) The cost is generally lower for seekers. These advantages make crowdsourcing contests attractive to many firms, even those with long R&D traditions.

Although crowdsourcing contests have become popular in a variety of industries, little is known about how to design the rules of the contest to achieve the best efficiency. A key challenge faced by the firms that undertake crowdsourcing contests is to design an incentive structure which helps attract high quality solutions. Theoretical literature on tournaments (Glazer and Hassin 1988; Lazear and Rosen 1981; Rosen, 1986), which are similar to crowdsourcing contests, suggests a high monetary reward could affect the quality of solutions in two opposite ways which leads to two opposing policy recommendations. On the one hand, a higher reward would encourage individuals to put in more effort as there is higher return on winning increasing the quality of solutions. This would indicate that the firm should provide a high reward for the winning solution. On the other hand, a higher reward could encourage a lot of individuals to participate increasing the competition and reducing the chances of winning for everyone. As a result, each individual may put in lower effort reducing the quality of solutions. This suggests that the firm should provide a small reward for the winning solution. Hence, it is unclear what an optimal incentive structure for a crowdsourcing contest is. In this study, we present the first empirical evidence on how incentive structures can affect the quality of the solutions produced in crowdsourcing contests. Specifically, we answer the following question: How does the incentive structure of crowdsourcing contests affect the quality of the solutions produced by the crowd?

To answer this question, we propose a dynamic structural model to understand users<sup>1</sup> behavior in crowdsourcing contests, and use a unique dataset obtained from Threadless.com to empirically estimate the model. Our model captures two important characteristics of users' behavior: 1) competition among individuals and 2) experience based learning. We also explicitly model how users make decisions on how much effort to exert when facing the tradeoff between increasing the probability of winning and incurring higher cost. The structural model allows us to conduct several policy simulations to understand how incentive structure may affect quality of solutions produced by the crowd. Our analysis reveals several interesting findings. First, the more competitors individuals expect to be facing, the less effort they will exert in developing designs. This may indicate that increasing the reward may adversely affect the quality of the solutions produced by the crowd as it will invariably increase the competition. However, our first set of policy simulations show that when the reward increases, users are more likely to submit designs, and also tend to exert more effort. This suggests that in the case of Threadless.com, the additional utility users expect from the increase in the reward can offset the reduction in the probability of winning resulting from intensified competition. Therefore, both the quality and quantity of the designs the crowd produces will be improved. In another set of policy simulations, we introduce additional incentive for individuals to participate in the design contest and find that this policy will lead to more submissions, but reduced effort. These two sets of simulations suggest that when the firm associates the additional incentive with the reward for the winners, it is possible that they can receive higher quality solutions; if

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<sup>1</sup> Since individuals need to register to participate and they are not solving problems in the context of Threadless.com, we call the community members “users” rather than “solvers”. “Users” and “individuals” are used interchangeably in this paper.

the firm only provides incentive to encourage users to participate in the contest, intensified competition resulting from the additional incentive may lead to lower quality solutions.

Our study makes several contributions. First, this is the first study that proposes a structural utility driven model of crowdsourcing contest and estimates the model using real-world data. Most of previous researches on this topic use either theoretical or reduced-form methods to examine different aspects of crowdsourcing contest. Our work fills in the gap in the literature. Our proposed structural framework for crowdsourcing contests can be used to evaluate the impact of different policy interventions. Second, our model is one of the more comprehensive models of crowdsourcing contest as it models both individuals' submission decisions and effort decisions, and captures both the competition among users for the reward and the learning dynamics in users' behavior. Third, our policy simulations have important managerial implications. We show that the firm cannot improve the quality of the designs by simply encouraging more people to participate. Only when the firm associates the incentive with the reward for the winners and ensures the increase in the reward can offset the reduction in the probability of winning resulting from intensified competition, it will get higher quality designs/solutions from the crowd.

## Literature Review

Our paper is related to multiple streams of literature. First, it is related to the emerging literature on crowdsourcing contests. There have been several theoretical analyses on this topic and most of them are based on game-theoretical models. Terwiesch and Xu (2008) build an analytical model to examine what type of innovation problems are most suited to be solved by crowdsourcing contest and how to design the reward structure optimally. They argue that the seeker can benefit from a larger solver population because she obtains a more diverse set of solutions. They also find that switching from a fixed-price reward to a performance-contingent reward will encourage solvers to exert more effort. Two separate studies, conducted by DiPalantino and Vojnovic (2009) and Archak and Sundararajan (2009) respectively, are closely related. In both papers, crowdsourcing contest is modeled as all-pay auction with incomplete information about contestant skills. DiPalantino and Vojnovic (2009) focus on strategic trade-offs that risk-neutral contestants face when choosing between multiple simultaneous single-reward contests, and find that rewards yield logarithmically diminishing returns with respect to participation levels under situations in which different contests require similar or unrelated skills. Archak and Sundararajan (2009) investigate strategic behavior of both risk-neutral and risk-averse contestants in a single contest with multiple rewards. They conclude that when agents are risk-neutral, the principal should optimally allocate its entire budget to the top reward; while if agents are sufficiently risk-averse, the principal may optimally offer more rewards than the number of submissions it desires. There are also a few empirical papers on crowdsourcing contests. Jeppesen and Lakhani's research (2010) reveals that the provision of a winning solution is positively related to increasing distance between the solver's field of technical expertise and the focal field of the problem. In Boudreau et al. (2011), the authors use Topcoder.com data and show that greater rivalry reduces the incentives of all competitors in a contest to participate but increases the likelihood that at least one competitor will find an extreme-value solution. Boudreau and Lakhani (2011) conduct a field experiment on TopCoder.com, and find that participants who have a preference to work within the competitive TopCoder regime exert more effort and the performance of solutions is higher. Yang et al. (2009) use data obtained from TaskCN.com and empirically show that feedback provided by the seeker can encourage solvers to put in more effort. In another recent study, Mo et al. (2011) investigate the impact of rivalry and friendship in crowdsourcing contests on a solver's chance of winning and find that the triadic structures a focal solver is embedded in have significant effects on her winning chance. Most models in the studies discussed above are static, i.e., contests are one-shot games and solvers only care about their current period utility. However in cases where contests are run regularly, we can see significant evidence that individuals learn from their past experience and thus are forward-looking when making participation decisions. We contribute to the literature by proposing a dynamic game model to capture important characteristics of crowdsourcing contests and using a real-world dataset to estimate the model.

The second stream of relevant research relates to the design of contests and tournaments. This stream of research originated in economics literature (e.g. Glazer and Hassin 1988; Lazear and Rosen 1981; Rosen, 1986) and has been adopted to management disciplines such as the sales force domain. For example,

Gaba and Kalra (1999) show that a high quota level or a rank-order contest where only the top few win induce sales representatives to opt for high-risk prospects, whereas a low quota level or a rank-order contest where a high proportion win induce sales representatives to opt for low-risk prospects. In their paper on sales contest, Kalra and Shi (2001) model salespeople's behavior by considering utility of the reward from achieving one of the winning ranks in the contest and assessing incremental chances of winning by exerting more effort. Their theoretical analysis suggests that salespeople exert lower effort when there are larger numbers of participants or when sales uncertainty is high. Our model is built upon this set of papers. We incorporate several unique characteristics of crowdsourcing contest in our model. In addition, the model in this paper is also motivated by the classic learning curve literature (see Dutton and Thomas, 1984, for a full review), in which the cost of producing the  $k^{th}$  unit of product is assumed to decrease with  $k$ . We adopt the same structure in our model to capture individuals' learning process.

In terms of methodology, our paper is related to the literature on dynamic structural models. In this study, we use a dynamic game model to capture important characteristics of individuals' behavior in crowdsourcing contests. The dynamic game model has been widely applied in industrial organization research (e.g. Aguirregabiria and Ho 2009; Aguirregabiria and Mira 2007; Bajari et al. 2007; Ericson and Pakes 1995; Pakes and McGuire 1994) and marketing (e.g., Dube et al. 2005; Misra and Nair 2009; Ryan and Tucker 2008).<sup>2</sup> Dynamic game models in information systems field include: Huang et al. (2012) who investigate employees' blogging behavior in the internal blog setting; Lu et al. (2010) who study how individuals' social structure on a social media platform affects their willingness to share knowledge with peers; Tang et al. (2011) who examine how content providers on YouTube derive different amounts of payoffs from subscriptions and views. Another paper that is closely related to our work is by Chung et al. (2010), who construct a dynamic structural model to understand how different bonus structures will affect employees' effort level. The major difference between their model and ours is that in our case, individuals are competing with each other while in their case there is no competition among employees.

## **Research Context, Data and Preliminary Analysis**

The research context in this paper is Threadless.com, a community based e-commerce website. It sells T-shirts designed by its online community of artists and design enthusiasts. It was founded in 2000 and has been growing fast since then. According to an article in Inc. Magazine (2008), its annual sales are estimated to be \$30 million with an estimated 30% profit margin. Customers play a crucial role across almost all Threadless' operations: from idea generation, sales forecasting to even marketing. Threadless runs design competitions on its own website Threadless.com on weekly basis. Users submit designs for T-shirts and the designs are open for scoring (a scale from 0 to 5) by the community for seven days. After the scoring window, the staff reviews top scoring designs and pick about 5-10 designs to print. We do not know all factors the firm takes into account when selecting designs to print. However, we know that the score is used to gauge the quality of the designs<sup>3</sup>. The users whose designs are selected receive \$2,000 in cash and \$500 in Threadless gift cards, which can be redeemed for \$200 cash (Threadless.com). Most of its products are sold worldwide through the online store (it has only one physical retail store in Chicago, where its headquarter and warehouse are located). There are two major advantages in its business model: 1) Since it employs no professional designers, no fashion photographers, and little sales force, costs are very low; 2) Since designs are evaluated by the community members before they are printed, risks of product failure are very low. The T-shirt design competition is the core of Threadless' business model. Therefore, how to effectively design the contest is a very important question to the firm. In this study, we will try to address this question.

We collect data from Threadless website. We downloaded all submitted designs since the website was launched until early 2012. In this analysis, we focus our attention on users' activities in 2010. In 2010, a total of 33,175 designs were submitted. After eliminating designs with missing designer information, we are left with 31,359 designs. These designs were submitted by 11,409 users. When we look at individual users' behavior, we can easily see there are two types of users; we define them as "active users" and

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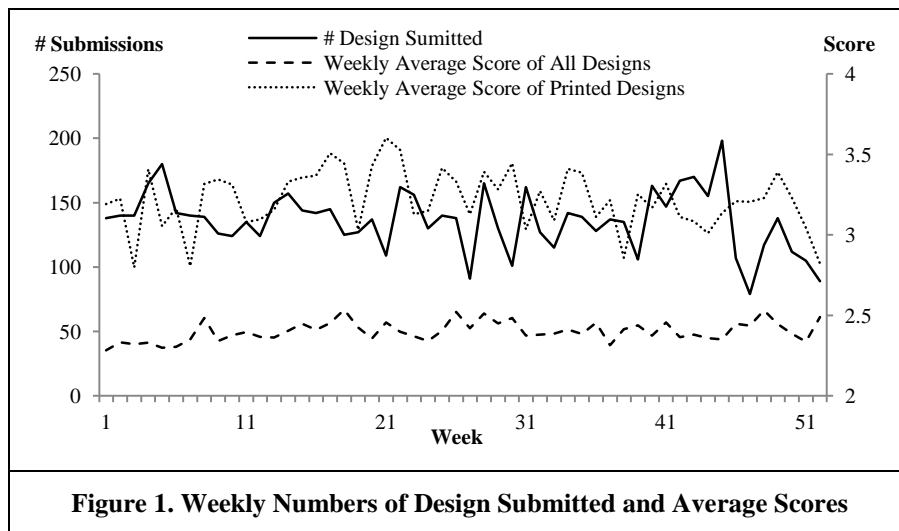
<sup>2</sup> For a complete review of the literature, see Dube et al. (2005).

<sup>3</sup> "We look at the top designs every week and pick out a few to print based off of the design's comments, score and general awesomeness factor, among other things. Ultimately the decision of which designs are made into shirts is left up to us. The scoring system helps give us a general idea of which designs our customers want. Sometimes we do print designs that we feel were underscored."—Threadless.com on April 26, 2010.

“casual users” respectively. Users who joined Threadless community before 2010, and continued to contribute after 2010 (at least submitted once in 2011 or 2012) are classified as “active users”; and the rest are classified as “casual users”. Table 1 compares the activities of the two groups of users. From the comparison, we can see that although active users are only about 12% of all registered users and their designs constitute only a little more than 31% of all designs submitted, more than 85% of the printed designs are from active users. Similarly, the success rate of their designs is 0.03, which is more than ten times higher than the success rate of designs submitted by casual users. We also see that the average score of designs submitted by active users is higher. In other words, active users contribute most of the high quality designs and compete most intensively with each other. Therefore, in this study, we focus on only active users’ behavior.

Group	Active	Casual
Number of user (Percentage %)	1354 (11.87)	10055 (88.13)
Submission (Percentage %)	9824 (31.33)	21535(68.67)
Printed (Percentage %)	298 (85.63)	50 (14.37)
Success rate	0.030	0.002
Average Score	2.226	1.967

	Mean	Standard Deviation	Max	Min
# Submission per week	136.15	23.37	198	79
# Printed per week	6.73	2.70	10	4
Score of all designs	2.39	0.48	4.53	1.00
Score of printed designs	3.24	0.37	4.53	2.02



**Figure 1. Weekly Numbers of Design Submitted and Average Scores**

The evaluation of designs takes place on a rolling basis. Therefore, it is important to define which designs compete against each other. We notice that in the 2010 data, no design was submitted on Sundays, and so it is likely that a weekly contest starts on Monday, and lasts until Saturday. As the firm picks designs to print from the set of scored designs, all the designs submitted in Week 1 (from Monday through Saturday) are evaluated on Sunday in Week 2. In other words, designs submitted in the same week compete with each other. This is how we assign designs to the weekly design contest.

Aggregate level summary statistics are shown in Table 2. On average, active users contribute about 136 designs per week (average total number of designs submitted per week by all users is about 600), and

weekly average score is centered at 2.39. From Figure 1, we can see that despite some fluctuations, the weekly number of submissions and average score are relatively stable. We run the following fixed-effect regression (Equation 1) to test the relation between score and the number of submissions.

$$score_{it} = \beta_0 + \beta_1 exper_{it} + \beta_2 (submission_t/1000) + \alpha_i + W_t + \varepsilon_{it} \quad (1)$$

In Equation (1),  $exper_{it}$  is the experience individual  $i$  has in period  $t$ , which is measured as the discounted cumulative number of designs individual  $i$  has submitted up to period  $t$ . We discount the cumulative experience over time because the experience people gained long time ago should have less impact than recent experience (the construction of experience will be discussed in detail later).  $submission_t$  represents the total number of designs submitted in period  $t$ ,  $\alpha_i$  is the individual level fixed-effect, and  $W_t$  is week dummy. The estimation results of Equation (1) are summarized in Table 3. The regression results suggest that after controlling for individual heterogeneity, we find significant negative correlation between score and the number of designs submitted in the current week. This suggests that when competition is more intense, users tend to produce low quality designs. This may indicate that any intervention by the firm, such as higher reward, to attract more participants may adversely affect the quality of designs submitted. This finding somewhat contradicts common sense, because people often think that the more contestants compete against each other, the more effort they exert, and thus the firm gets better designs from individuals. In addition, as individuals' experience increases, they produce higher quality designs. This empirical finding suggests that there is possibly learning dynamics present in users' behavior.

Table 3. Reduced-form: Dependent Variable-Score (Equation 1)	
Variable	Coefficient (Standard error)
$exper_{it}$	0.0126 (0.0037)***
$submission_t/1000$	-0.932(0.201)***
Individual Fixed Effects	Yes
Week Dummies	Yes
n=1354, N=9824, Adjusted R-Squared : 0.5831, Significance codes: '***' < 0.001	

We run a logistic regression (Equation 2) to explore how users make decisions on whether to submit a design or not. From Table 4, we can see that individuals with higher experience are more likely to submit designs. In addition, when the mean of the distribution of contestants' experience (denoted as *average experience<sub>t</sub>*) is larger, the probability that a certain individual will submit a design becomes lower. Given an individual's experience level, a larger average experience indicates that this individual is in a disadvantaged position. It is not surprising that in this case, the probability that this individual submits a design is lower.

$$X_{it} = \beta_0 + \beta_1 exper_{it} + \beta_2 average\ experience_t + \alpha_i + \zeta_{it}$$

$$\text{and } Submit_{it} = \begin{cases} 1 & \text{if } X_{it} > 0 \\ 0 & \text{if } X_{it} \leq 0 \end{cases} \quad (2)$$

Table 4. Reduced-form: Dependent Variable-Submission (Equation 2)	
Variable	Coefficient (Standard error)
$exper_{it}$	0.169 (0.020)***
$average\ experience_t$	-4.845 (0.905)***
Individual Fixed Effects	Yes
n=1354, N=70408, AIC: 19822, Significance codes: '***' < 0.001	

From the reduced-form analysis, we can see that as the number of contestants increases, individuals produce lower quality designs. This may indicate that the optimal policy for Threadless would be to have an incentive structure that reduces competition. However, as Lucas (1976) points out, the above analysis is limited in its ability to guide policy decisions. There is no variation in the reward or the incentive for participation in our data and so we cannot tell how different incentive structures will affect users' behavior. Even if we had such variations in the data, policy inferences from the reduced-form results can be misleading because any policy change that constitutes a major regime shift, which changes the key

elements of the decision process, can potentially lead to unstable responses (Lucas 1976). In other words, when a new policy, such as a higher reward, is introduced into the system, the coefficients in the reduced-form model may change. By delving into the underlying decision-making mechanism and explicitly modeling the decision primitives, one may be able to obtain a more reliable estimate of the effect of the new policies. Since reduced-form analysis is not sufficient to address our main research questions, we develop a structural model, which will be discussed in detail in the next session.

## The Structural Model

### Per-period Utility

Individuals’ per-period utility can be expressed as:

$$U_{it} = \alpha P_{it} - d_{it}[f_{it} + c(e_{it})] + \gamma_{it}(d_{it}) \tag{3}$$

In Equation (3),  $\alpha$  measures how users value the \$2000 reward and the \$500 gift card (for simplicity purposes, we do not consider any utility derived from rewards paid for reprints) as well as the reputation and “happiness” users gain when they win a contest.  $P_{it}$  represents the probability of individual  $i$ ’s submission in period  $t$  being printed and it equals 0 when individuals  $i$  does not submit anything in period  $t$ .  $d_{it}$  represents individual  $i$ ’s decision on submission in period  $t$ , which takes a value of 1 when she submits a design, and 0 otherwise.  $\gamma_{it}(d_{it})$  is idiosyncratic choice specific random shock, which only affects individuals decision on whether to submit designs, but not the decision on her effort level.  $\gamma_{it}(d_{it})$  is assumed to follow the standard normal distribution, i.i.d. with respect to time, choice and individuals.  $f_{it}$  represents the fixed cost user  $i$  incurs when she submits a design in period  $t$ .  $c(e_{it})$  captures the variable cost she incurs when she exerts  $e_{it}$  units of effort. Users incur cost only when they decide to submit designs ( $d_{it} = 1$ ). We will explain the cost function in detail in the next sub-section.

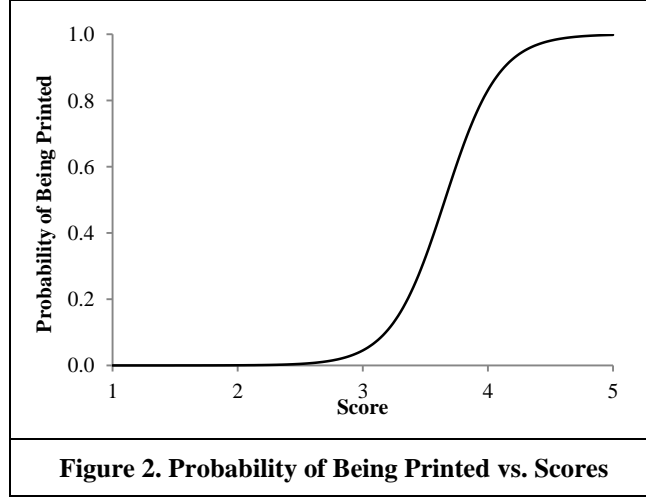
Since users are competing against each other,  $P_{it}$  is affected by both individuals’ own decision and other people’s decisions. It is not clear what factors the firm takes into account when selecting designs to print. The only thing we know is that the score is used to gauge the quality of the designs. Lacking this information, we cannot model the firm’s decision structurally. Here, we use a reduced-form logistic regression to explore factors that may affect the probability of a certain design being printed. In the following regression, we include score ( $score_{it}$ , score of the focal design), total number of submissions in the current week ( $submission_t$ ) and variables (moments) that capture the distribution of the scores the designs submitted in the current week receive, as explanatory variables. The random term  $\eta_{it}$  captures other unobserved factors that affect the probability of a certain design being printed.  $\eta_{it}$  is assumed to follow the standard logistic distribution. The estimation result shows that the standard deviation and the skewness of the scores do not significantly affect the probability of a design being printed. We further perform AIC-based stepwise model selection to confirm that the main predictors of whether a design will be printed are score ( $score_{it}$ ), total number of submission in the current week ( $submission_t$ ) and the average score of current week’s submissions ( $meanscore_t$ ) (Table 5).

$$Y_{it} = \delta_0 + \delta_1 score_{it} + \delta_2 (submission_t/1000) + \delta_3 meanscore_t + \eta_{it}$$

$$\text{and } Print_{it} = \begin{cases} 1 & \text{if } Y_{it} > 0 \\ 0 & \text{if } Y_{it} \leq 0 \end{cases} \tag{4}$$

Table 5. Reduced-form: Dependent Variable-Print (Equation 4)	
Variable	Coefficient (Standard error)
<i>Intercept</i>	-11.376 (2.657)***
<i>score<sub>it</sub></i>	4.641 (0.196)***
<i>submission<sub>t</sub>/1000</i>	-3.158(1.564)*
<i>meanscore<sub>t</sub></i>	-2.170(1.127) ·
N= 9824, AIC: 1673.5	
Significance codes: ‘***’ <0.001 ‘**’ <0.01 ‘*’ <0.05 ‘.’ <0.1	

Figure 2 shows how the probability of winning the reward increases with a design’s score ( $submission_t$  and  $meanscore_t$  are fixed at their average levels). As we can see, when a design’s score is below 2.5, there is little chance that it will be printed. The probability of one design being printed increases very fast when the score is between 3 and 4, and once a design gets a score higher than 4.5, it is almost certain that it will be printed. If we assume score linearly increases with effort, then cost cannot also be linearly increasing with effort. This is because in the data, most submissions’ scores are under 3. If cost is linearly increases with effort, users should have incentive to increase their effort level and reach higher scores. Therefore, we should expect that the cost increases faster than a linear relation would suggest.



### Effort and Costs

The biggest challenge in this model is that one of the decisions, effort level  $e_{it}$ , is not observed. To overcome this, we follow Chung et al. (2010) and assume that the score is determined by effort, with a random error term  $\mu_{it}$  (Equation 5). Equation (5) implies that the score can be used as a proxy for effort; or, from the users’ perspective, if they exert  $e_{it}$  units of effort in a design, they know the expected value of the score the design will receive is  $e_{it}$ .

$$S_{it} = e_{it} + \mu_{it} \tag{5}$$

$$f_{it} + c(e_{it}) = (f + \sum_{k=1}^K c_k e_{it}^k)(exper_{it} + 1)^{-b} \tag{6}$$

The cost term in the utility function can be extended as Equation (6). Consistent with the learning literature, we assume that as individuals gain experience, the cost they incur to produce one additional design of fixed quality will decrease. The most common formulation of learning model is the log-linear form. In Equation (6), the first factor  $f + \sum_{k=1}^K c_k e_{it}^k$  represents the baseline cost, which is the cost a user with no experience ( $exper_{it} = 0$ ) incurs if she submits a design on which she exerts an effort of  $e_{it}$ .  $b$  represents the learning (progress) rate. The larger the  $b$  is, the faster the individuals’ cost reduces. We name the second term  $(exper_{it} + 1)^{-b}$  “cost factor”.  $c(e_{it})$  represents the cost associated with effort, which we define as the variable cost. Since we do not have prior information about how variable cost and effort are related, we assume the baseline variable cost to be a flexible polynomial function (with no constant term) of  $e_{it}$ , which can be represented as  $\sum_{k=1}^K c_k e_{it}^k$ . Then we have  $c(e_{it}) = (\sum_{k=1}^K c_k e_{it}^k)(exper_{it} + 1)^{-b}$ . Similarly,  $f_{it} = f * (exper_{it} + 1)^{-b}$ .

### State Variable

Individuals’ state variable is experience ( $exper_{it}$ ). It evolves in the following way:

$$exper_{it+1} = 0.9exper_{it} + d_{it} \tag{7}$$

In the data, we do see very occasionally that users submit more than one designs in a single period. This happens less than 1% of the time. In these instances, we still count  $d_{it} = 1$ . We assume that individuals



gain experience from the submission because they can learn from the feedback their prior submissions receive from the voters. The experience gain from previous periods is carried over to future periods with a depreciation factor 0.9<sup>4</sup>. The depreciation factor reflects the fact that recent experience has greater effect on cost reduction than old experience, because of the forgetting effect. As experience affects the cost users incur when they submit designs, it should also affect users' per period utility. Hence, users' current submission decisions will affect their future utility through the evolution of the experience state.

### Individuals' Decision

In each period, users make two decisions. First, they need to decide whether to submit a design or not. Second, if they decide to submit designs, they need to decide how much effort to exert.

In the current model, we assume that individuals' experience evolves as they submit designs, and the efforts individuals exert have no impact on the evolution of experience. Therefore, individuals' decisions on effort level are static. Individuals who have already decided to participate in the current period contest will form expectation on who will compete with them and how much effort these competitors will exert. Then, they will select the optimal level of effort to maximize their current period utility. In contrast, individuals are forward-looking when making submission decisions because these decisions will affect their future utility through the evolution of experience. Hence, their submission decisions are dynamic.

To simplify the notation, we use  $a_{it}$  to denote the combination of  $d_{it}$  and  $e_{it}$ , and  $z$  to denote the experience state. Each individual would select the optimal action  $a_{it}$  to maximize the expected life time utility, which can be expressed as:

$$E[\sum_{\tau=t}^{\infty} \beta^{\tau-t} U_{it}(a_{\tau}, z_{\tau}) | z_{\tau}].$$

where  $z_{\tau}$  represents a vector of the all individuals' experience levels in period  $\tau$ ,  $\beta$  is the discount factor. The expectation is over all individuals' actions in the current period and future values of the state variables, actions, and private shocks. We assume individuals have rational expectation, meaning that their expectation matches the reality. Let  $\rho_i$  and  $\sigma_i$  denote user  $i$ 's policy functions for decisions on whether to submit designs and how much effort to exert respectively:  $\rho_i: Z \times \Gamma_i \rightarrow D_i$ ;  $\sigma_i: Z \rightarrow e_i$ .  $\rho_i$  is a mapping from all users' current state  $z$  and the user  $i$ 's current choice specific random shock  $\gamma_i$  to the decision  $d_i$ ; while  $\sigma_i$  is a mapping from all users' current state  $z$  to the effort decision  $e_i$ . One challenge we are facing to estimate the policy function is that we have too many individuals competing against each other. If we include all individuals' states, the model will be unmanageable. In addition, in reality, it is also unrealistic for individuals to keep track of all their competitors' states. Therefore, we reduce the opponents' state, denoted as  $z_{-it}$ , to the moments of the distribution of  $z_{-it}$ . Note that we have many individuals in our sample, we use the distribution of all individuals' state,  $z_t$ , to approximate the distribution of  $z_{-it}$ , in which individual  $i$  is excluded. Subscript  $t$  is dropped in  $\rho_i$  and  $\sigma_i$  because policies are time-invariant.  $\rho$  and  $\sigma$  are vectors of all individuals' policies:  $\rho: Z \times \Gamma_1 \times \dots \times \Gamma_n \rightarrow D$ ;  $\sigma: Z \rightarrow E$ . Then individual  $i$ 's ex-ante value function  $V_i(z)$  can be represented as:

$$V_i(z; \rho, \sigma) = E_{\gamma}[U_i(\rho(z, \gamma), \sigma(z), z) + \beta \int V_i(z'; \rho, \sigma) dP(z' | \rho(z, \gamma), \sigma(z), z) | z] \quad (8)$$

In Equation (8),  $P(z' | \rho(z, \gamma), \sigma(z), z)$  is the probability that all users' states will evolve to  $z'$  in the next period, given all users' current states are  $z$  and all users are following policies  $\rho(z, \gamma)$  and  $\sigma(z)$ .

### Equilibrium Concepts

As discussed above, users' decision on how much effort to exert is static, because effort decision will not affect individuals' future utility. This point will become clearer when we plug Equation (6) to Equation (3):

$$U_{it} = \alpha P_{it} - d_{it} [(f + \sum_{k=1}^K c_k e_{it}^k) (exper_{it} + 1)^{-b}] + \gamma_{it}(d_{it}).$$

<sup>4</sup> Here we fixed the depreciation factor. Ideally, we should try different depreciation factor such as 0.8, 0.95 or even 1 to see which one fit the data better.

Users make effort decisions only when they decide to submit designs. Hence, the components  $f_{it}$  and  $\gamma_{it}(d_{it})$  are fixed and thus are irrelevant to users' effort decisions. For those who decide to submit a design, they only need to select the effort level such that  $\alpha P_{it} - [(\sum_{k=1}^K c_k e_{it}^k)(exper_{it} + 1)^{-b}]$  is maximized. Remember that other people's decision will also affect one's utility through affecting  $P_{it}$ . Therefore, after all users decide whether to participate, contestants in the current week are playing a static game, in which the equilibrium policy is  $\sigma$  if the following inequality holds:

$$U_i(z; \sigma_i, \sigma_{-i}) \geq U_i(s; \sigma'_i, \sigma_{-i}) \quad (9)$$

The interpretation of the inequality is: given all other individuals are playing  $\sigma_{-i}$ , the utility individual  $i$  receives from playing  $\sigma_i$  is greater than or equal to the utility she receives from playing alternative policy  $\sigma'_i$ . Different from users' effort decision, users' submission decision is dynamic. Following Ericson and Pakes (1995) we focus on Markov Perfect Equilibrium (MPE) as a solution concept of the dynamic submission decision. In an MPE, users' decisions depend only on the current states and their current private shocks. A profile  $\rho$  is Markov Perfect Equilibrium if, given the opponent profile  $\rho_{-i}$ , each user  $i$  prefers its strategy  $\rho_i$  to all alternate strategies  $\rho'_i$ . That is, for  $\rho$  to be MPE

$$V_i(z; \rho_i, \rho_{-i}) \geq V_i(z; \rho'_i, \rho_{-i}) \quad (10)$$

### Sequence of Events

1. In the beginning of each period, individuals receive submission choice specific shocks  $\gamma_{it}(d_{it})$ .
2. Individuals observe both their own experience level and their competitors' experience levels and then predict who will be competing in the current period and what will be their scores. They then form expectations on the probability of a submission with a certain score being printed.
3. Based on their expectation, individuals decide whether to submit designs or not in a dynamic manner. Those who decide to submit designs also decide how much effort they want to exert in this period.
4. An idiosyncratic score shock  $\mu_{it}$  is realized. The effort and random score shock determine the score each submission receives. Individuals' own score and their competitors' scores, as well as the number of designs submitted in the period will determine the probability of each design being printed.
5. Individuals' experience evolves from current period to the next period.

### Estimation

The parameters we need to estimate are  $\theta = (\alpha, f, c_k, b)$ . We use the two-step estimation method proposed by Bajari, Benkard, and Levin (2007, BBL hereafter) to estimate the model.

#### First Step

Since in our model, state transition is deterministic, in the first step of the BBL estimation, we only need to recover the equilibrium policy functions for submission decision  $\rho$  and effort decision  $\sigma$ , i.e., estimate flexible non-parametric mappings between observed states and individuals' actions. Once we recover the policy functions, we can use forward simulation to approximate the value functions.

#### Effort Policy Function

Effort policy function can be written as:

$$e_i = \sigma_i(z)$$

One may notice that there is no random shock to individuals' effort decision. To see why we need to impose this assumption, plugging the equation above to Equation (5), we get:

$$S_{it} = \sigma_i(z) + \mu_{it} \quad (11)$$

If we include another random shock in  $\sigma_i(z)$ , we cannot distinguish the random shock from  $\mu_{it}$ . We first run a simple linear regression with individual specific fixed effects, in which the first few moments of  $z_t$  are included. The estimation result suggests that only the first moment, i.e. the mean of vector  $z_t$ , affects  $S_{it}$ . For model simplicity, we only keep the mean of  $z_t$  in individuals' effort policy function. Then we use

non-parametric method (a local linear regression in which  $S_{it}$  is the dependent variable and own experience state  $z_{it}$  and the average of  $z_t$  are independent variables) to recover individuals effort policy function.

### Submission Policy Function

Submission policy function  $\rho_i: Z \times \Gamma_i \rightarrow D_i$  is a mapping from all users' current state and user  $i$ 's choice specific shock  $\gamma_i(d_i)$  to the submission decision  $d_i$ . Since the utility function is additively separable, i.e.,  $U_i(a, z, \gamma_i) = \tilde{U}_i(a, z) + \gamma_i(d_i)$ , and the effort decision is static and deterministic conditional on experience state, we can construct the choice specific value functions:

$$v_i(d_i, z) = E_{\gamma_{-i}}[\tilde{U}_i(d_i, \rho_{-i}(z, \gamma_{-i}), \sigma(z), z) + \beta \int V_i(z'; \rho, \sigma) dP(z'|d_i, \rho_{-i}(z, \gamma_{-i}), \sigma(z), z)] \quad (12)$$

With this notation, action  $d_i$  is user  $i$ 's optimal choice when

$$v_i(d_i, z) + \gamma_i(d_i) \geq v_i(d'_i, z) + \gamma_i(d'_i), \forall d'_i \in D_i$$

Since  $\gamma_i(d_i)$  is assumed to follow standard normal distribution and is i.i.d across individuals, time and choices,  $P(d_i = 1|z) = \Phi([v_i(1, z) - v_i(0, z)]/\sqrt{2})$ . We first estimate  $P(d_i = 1|z)$  non-parametrically (a local linear regression in which  $d_i$  is the dependent variable and own experience state  $z_{it}$  and the average of  $z_t$  are independent variables), we can then recover the difference in the choice specific value functions,  $v_i(1, z) - v_i(0, z)$ , for any state  $z$ . Given the first difference  $v_i(1, z) - v_i(0, z)$  and choice specific random shocks (which can be simulated from drawing standard normal random variables), we can determine the optimal decision on  $d_i$  given  $z$ .

Given the policy rules  $\sigma$  and  $\rho$ , we can estimate  $U_i(z; \sigma_i, \sigma_{-i})$  ( $U_i(z; \sigma'_i, \sigma_{-i})$ ) from stage game simulations in which user  $i$  uses equilibrium policy  $\sigma_i$  (alternative policy  $\sigma'_i$ ), while all other contestants are playing equilibrium policy  $\sigma_{-i}$ . Similarly, we can estimate  $V_i(z; \rho_i, \rho_{-i})$  ( $V_i(z; \rho'_i, \rho_{-i})$ ) from simulations of a dynamic game of 70 periods in which user  $i$  uses equilibrium policy  $\rho_i$  (alternative policy  $\rho'_i$ ), while all other users are playing equilibrium policy  $\rho_{-i}$ .

### Second Step

In the second step, we use the estimates from the first step combined with the equilibrium conditions of the model to estimate the underlying structural parameters. We have two sets of equilibrium conditions. Let  $x_1 \in X_1$  index the equilibrium conditions related to the effort decision, so that each  $x_1$  denotes a particular  $(i, z; \sigma'_i)$  combination. Let us further define:

$$g_1(x_1; \theta, \varphi_1) = U_i(z; \sigma_i, \sigma_{-i}, \theta, \varphi_1) - U_i(z; \sigma'_i, \sigma_{-i}, \theta, \varphi_1).$$

Here,  $\sigma$  is parameterized by  $\varphi_1$ . The first set of equilibrium condition is satisfied at  $\theta$  and  $\varphi_1$  if  $g_1(x_1; \theta, \varphi_1) \geq 0$ . Similarly, let  $x_2 \in X_2$  index the equilibrium conditions related to the submission decision, so that each  $x_2$  denotes a particular  $(i, z; \rho'_i)$  combination.  $g_2(x_2; \theta, \varphi_2)$  is then defined as:

$$g_2(x_2; \theta, \varphi_2) = V_i(z; \rho_i, \rho_{-i}, \theta, \varphi_2) - V_i(z; \rho'_i, \rho_{-i}, \theta, \varphi_2).$$

The alternative policy for  $\sigma_i$  is introduced by adding a  $N(0,0.5)$  random variable to the optimal effort level, while the alternative policy for  $\rho_i$  is introduced by adding a  $N(0,3)$  random variable to  $v_i(d_i) - v_i(d'_i)$ . We apply forward simulation to approximate  $U_i(z; \sigma_i, \sigma_{-i}, \theta, \varphi_1)$ ,  $U_i(z; \sigma'_i, \sigma_{-i}, \theta, \varphi_1)$ ,  $V_i(z; \rho_i, \rho_{-i}, \theta, \varphi_2)$  and  $V_i(z; \rho'_i, \rho_{-i}, \theta, \varphi_2)$ . Given a state  $z$ , we simulate the random shocks users receive in each period and then use the equilibrium policy functions recovered in the first stage to determine all individuals' submission decisions and effort decisions. Once decisions are determined, states evolve accordingly. To estimate  $U_i(z; \sigma_i, \sigma_{-i}, \theta, \varphi_1)$ , we only need to simulate the stage game, because the effort decision is static; while to estimate  $V_i(z; \rho_i, \rho_{-i}, \theta, \varphi_2)$ , we simulate up to 70 periods and calculate the discounted sum of utility the focal user receives.  $U_i(z; \sigma'_i, \sigma_{-i}, \theta, \varphi_1)$  and  $V_i(z; \rho'_i, \rho_{-i}, \theta, \varphi_2)$  are estimated in a similar way, the only difference is that the focal user is now using the alternative policy ( $\sigma'_i$  and  $\rho'_i$ ), rather than the equilibrium policy. Once we have  $U_i(z; \sigma_i, \sigma_{-i}, \theta, \varphi_1)$ ,  $U_i(z; \sigma'_i, \sigma_{-i}, \theta, \varphi_1)$ ,  $V_i(z; \rho_i, \rho_{-i}, \theta, \varphi_2)$  and  $V_i(z; \rho'_i, \rho_{-i}, \theta, \varphi_2)$ , the empirical analogues of  $g_1(x_1; \theta, \varphi_1)$  and  $g_2(x_2; \theta, \varphi_2)$  can be calculated for each alternative policy. For

both effort policy and submission policy, we draw  $n_l = 500$  alternative policies and for each alternative policy, we simulate  $n_s = 500$  different paths. We can then define:

$$Q_n(\theta, \varphi_1, \varphi_2) = \sum_{m=1}^2 \frac{1}{n_l} \sum_{j=1}^{n_l} (\min \{ \hat{g}_m(x_{mj}; \theta, \varphi_m), 0 \})^2.$$

Denote the estimates for  $\varphi_1$  and  $\varphi_2$  we obtain in the first step as  $\hat{\varphi}_1$  and  $\hat{\varphi}_2$ , then the estimate for  $\theta$ , denoted as  $\hat{\theta}$ , is the set of  $\theta$  that would minimize the objective function  $Q_n(\theta, \hat{\varphi}_1, \hat{\varphi}_2)$ , or

$$\hat{\theta} = \arg \min_{\theta \in \Theta} Q_n(\theta, \hat{\varphi}_1, \hat{\varphi}_2)$$

## Results

### First Step

We first use local linear regression to non-parametrically estimate  $\sigma_i(z_{it}, z_{-it})$ . Figure 3 shows how the optimal effort level changes with individuals' own experience and average experience. In general, users with higher experience tend to exert more effort, which is probably because it costs them less to submit a design of certain quality. However, when the average experience is relatively high, the optimal effort increases more slowly with own experience. Users with low and median experience exert slightly more effort when average experience is high; while highly experienced users tend to exert less effort when the average experience is high. In addition, the standard deviation of  $\mu_{it}$  is estimated to be 0.452. This number is relatively big, indicating high uncertainty associated with the final scores users' designs receive.

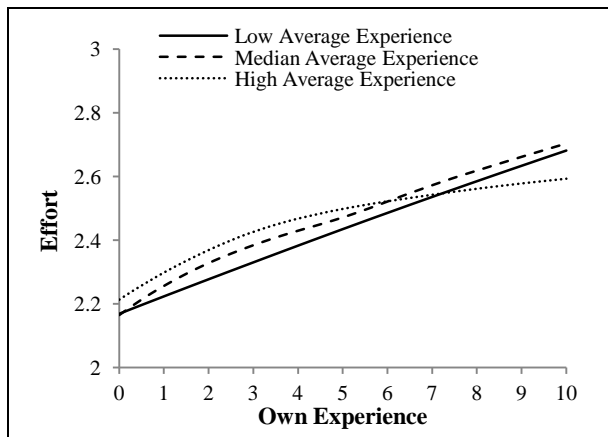


Figure 3. Effort vs. Own Experience

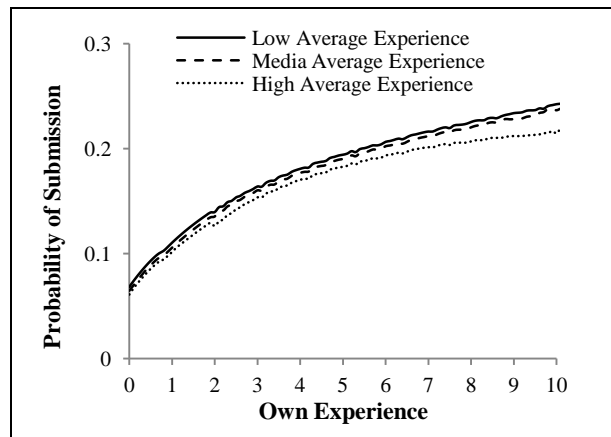


Figure 4. Prob. of Submission vs. Own Experience

We then use a similar method to recover  $\rho_i(z_{it}, z_{-it}, \gamma_i)$ . Unlike the estimation of  $\sigma_i(z_{it}, z_{-it})$ , where the policies depend only on states but not any random shocks,  $\rho_i(z_{it}, z_{-it}, \gamma_i)$  depends on both states and shocks. Figure 4 shows how the conditional choice probabilities  $P(d_i = 1|z)$  changes with own and average experience. Conditional choice probabilities are not exactly policy functions, but are closely related to the policy functions (see Estimation Section). Not surprisingly, users with higher experience are more likely to submit designs. However, when average experience is higher, users at all experience levels are less likely to submit.

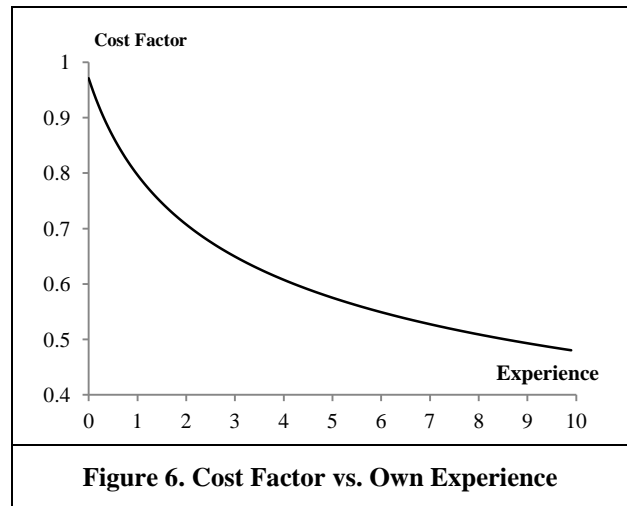
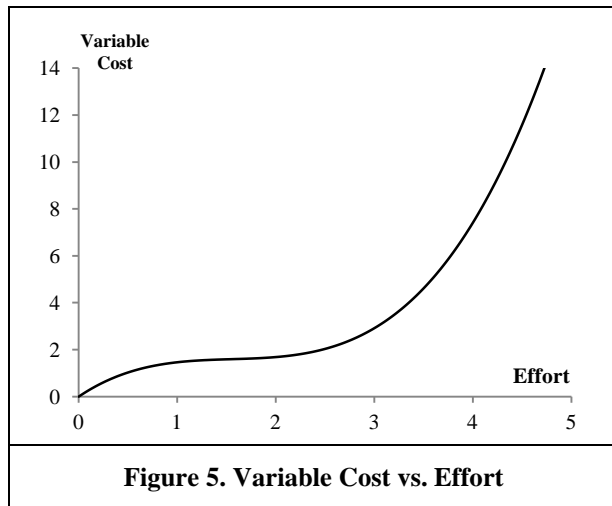
### Second Step

The structural parameter estimates are summarized in Table 6.  $\alpha$  is estimated to be 1.937, which indicates that users can get 1.937 utility if their designs are printed. The value is relative to the scale of the choice specific random shock (assumed to follow standard normal distribution). The baseline fixed cost of submitting a design, denoted as  $f$ , is estimated to be 1.201 (note that we impose a negative sign in front of cost terms in the utility function). Fixed cost seems to be relatively high, but it still makes sense because it includes the hassle cost of posting a design and the opportunity cost. The opportunity cost of submitting a design could be high because people may have many other important things to do in their life and so cannot always spend time designing T-shirts. As you can see in the table, we only have three  $c_k$  terms,  $c_1$ ,

$c_2$  and  $c_3$ . We actually include more than three  $e_{it}^k$  terms when we estimate the model but the higher order terms turn out to be insignificant. Therefore, we only keep  $e_{it}$ ,  $e_{it}^2$  and  $e_{it}^3$  in the variable cost function.

Notation	Parameter Estimates	Standard Error
$\alpha$	1.937	0.518
$f$	1.201	0.233
$c_1$	2.842	0.710
$c_2$	-1.751	0.356
$c_3$	0.376	0.074
$b$	0.306	0.085

The relation between effort and variable cost is shown in Figure 5. We can see that when effort is greater than 3, variable cost increases very fast as effort further increases. This is consistent with the observation that most of the scores are below 3. The learning rate parameter  $b$  is estimated to be 0.306, with a standard error of 0.085, indicating that the costs users incur decrease significantly as they gain more experience. The relation between cost factor  $((exper_{it} + 1)^{-b})$  and experience is displayed in Figure 6. As we can see, to submit a design with fixed expected score (effort), the cost a user whose experience is 10 incurs is only about 50% of the cost a user with no experience incurs. This explains why experienced users are more likely to submit designs and they tend to exert more effort.



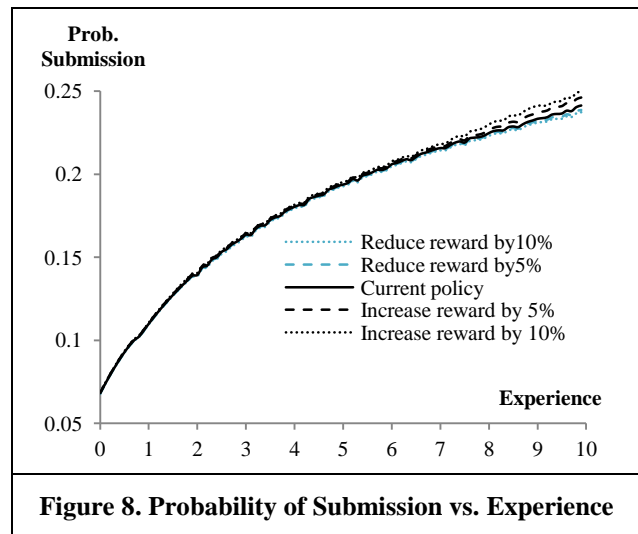
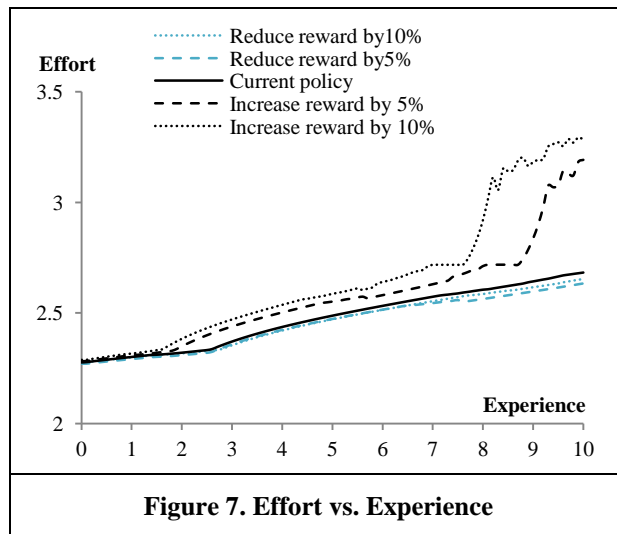
## Policy Simulations

As discussed earlier, one of the most important factors that determine whether a crowdsourcing contest will be successful is the design of the incentive structure. In this section, we conduct two sets of policy simulations to see how a firm can improve the overall performance of its crowdsourcing contest by accounting for the competition among users and users' learning from their past experience.

### Change the Reward

In the first set of policy simulations, we change the value of the reward slightly around the current level. An increase in the reward may have two effects. First, it will increase the payoff individuals receive when their designs are selected to print; second, it can also lead to more intense competition among users, because more users will be attracted to compete in the contest. As these two effects work in opposite directions, it is not clear how the participation and effort level will change as the reward changes. In this set of policy simulations, we look at 4 different alternative policies. We first reduced the reward by 5% and 10% and then increase the reward by 5% and 10%. We solve the new equilibrium under each policy. Figure 7 shows the optimal effort level for users at different experience levels under different policies. As

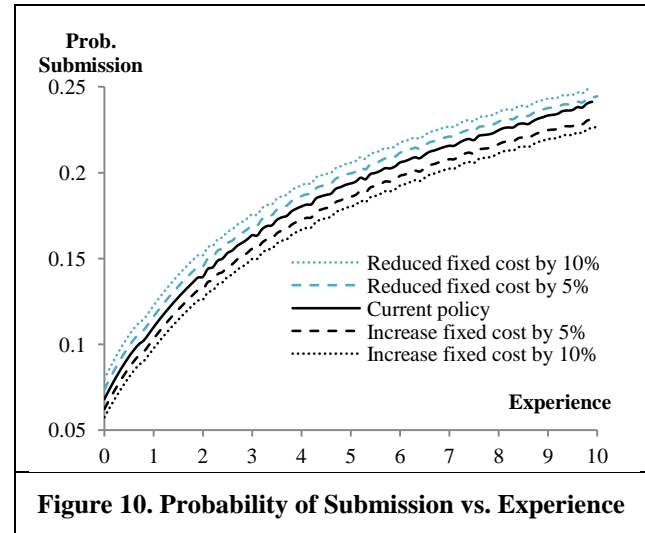
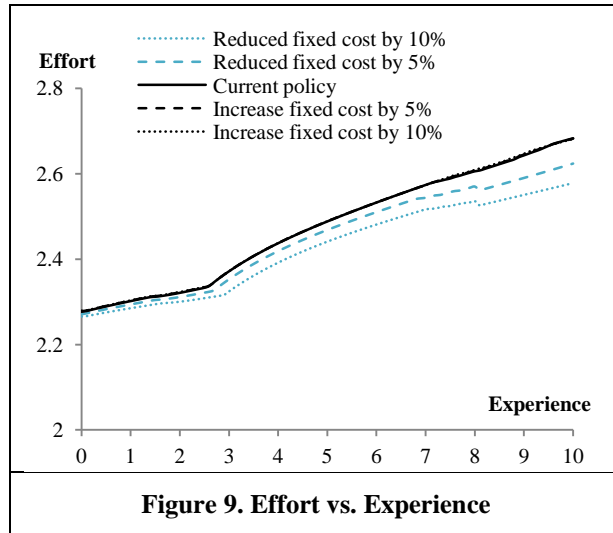
we can see from the figure, individuals' optimal effort level increases as the reward increases. This suggests that the first effect we discussed above dominates the second effect. In addition, we find the increment is larger for highly experienced users. There is a big jump in the optimal effort level from around 2.7 to 3.1. This is because when the score of a design passes 3, the probability of this design being printed ( $P_{it}$ ) increases very fast with effort. Recall that the expected payoff equals  $\alpha P_{it}$ . When the reward increases (and so does  $\alpha$ ), it is possible that the expected payoff can increase even faster than the cost in a certain effort range. In other words, the marginal benefit of increasing effort exceeds the marginal cost. Therefore, it is not optimal for individuals to exert any effort between 2.7 and 3.1; instead, they would be better off if they increase their effort even further to above 3.1. This jump occurs to individuals whose experience is above 9 when the reward is increased by 5%. And the jump starts at experience=8 when the reward is increased by 10%. Figure 8 shows how the probability of submitting designs is related to users' own experience under different levels of reward. Not surprisingly, we find that as the reward increases, the probability of submitting designs increases. Again, we find the increment is larger for experienced users. It seems that increasing reward is an effective policy because the firm will receive more designs and the users tend to exert more effort in their submissions. Of course, the firm incurs cost to implement this policy, because it has to pay more to the winners. To see whether this policy is worth implementing, the firm should convert the increase in the number of designs they get from users and the improved quality of the designs to monetary terms, and then compare the additional profit it can make with the additional cost it incurs.



### ***Provide Additional Incentive for Participation***

In the second set of policy simulations, we try to evaluate policies that encourage more individuals to participate in the contest but do not involve changes in the reward. One way to do it is to provide additional incentive for participation in the contest (e.g. Users earn points from submitting designs, which can be used as monetary discount later). From modeling perspective, providing additional incentive to participate is equivalent to reducing the fixed cost for individuals to submit designs. Hence, in this set of policy simulations, we introduce new policies by changing individuals' fixed cost in the utility function. Consistent with our intuition, when the fixed cost is reduced, the probability of submission increases for individuals at all experience levels; when the fixed cost is increased, the probability of submission decreases for individuals at all experience levels (Figure 10). As shown in Figure 9, we also find that when the fixed cost is reduced, the optimal effort level decreases, especially for highly experienced individuals. This is because the competition among individuals for the reward is intensified as more individuals participate in the contest. Consequently, the probability for each individual to win the contest is reduced. In other words, given the same effort level, the expected payoff is reduced, but the variable cost remains the same. As a result, the optimal effort level decreases. Somewhat surprisingly, the effect of changing the fixed cost on optimal effort level is not symmetric: When we increase the fixed cost, the optimal effort level does not change significantly, as the three black curves (current policy, increase fixed cost by 5% and increase fixed cost by 10%) almost overlap with each other. This set of policy simulations suggests that

while it is possible that the firm will be worse off if they provide additional incentives to attract more users to compete in the contest, it is unnecessary for the firm to increase fixed cost to reduce the competition on purpose.



## Discussion and Conclusion

Although crowdsourcing contests have become a popular approach of new product development and corporate R&D, little is known about how to design the rules of the contest to achieve the best efficiency. One of the most important questions for practitioners who are using crowdsourcing contests is how to design the incentive structure of the contests such that they can obtain better quality designs/solutions from the open crowd. Many practitioners believe that the firm can always be better off if they can attract more users/solvers to submit designs/solutions, because when the competition is intense, people have to exert more effort to win the contest. However, one important factor that practitioners may ignore is that individuals incur cost when they exert effort. When individuals are making decisions on whether to submit a design/solution or not, and how much effort they should exert, they are facing tradeoffs between increasing the expected payoff (the reward times the probability that they win) and incurring higher cost. When the firm increases the reward or provides additional incentive to attract more individuals to participate in the contest, it is possible that it will observe lower quality submissions. This is because when the number of contestants increases, the probability of winning decreases. If the increase in the reward, or additional incentive, cannot offset the decrease in the probability of winning, resulting in reduced expected payoff, individuals will exert less effort. Considering the additional cost the firm incurs when it increases the reward or introduces additional incentive, it is possible that the firm will be worse off. To address issues related to the incentive structure design of crowdsourcing contests, a deeper understanding of users' behavioral dynamics in crowdsourcing contests is urgently needed.

In this paper, we propose a dynamic structural model to capture users' behavioral dynamics in periodic crowdsourcing contests and estimate the model using a rich dataset obtained from Threadless.com. We find that individuals indeed incur both fixed cost and variable cost when they submit designs. In addition, the variable cost increases very fast as the effort goes beyond 3. We also confirm that users can learn from their participation experience and the learning speed is significant. Users whose discounted cumulative experience is 10 will only incur 50% of the cost the users whose discounted cumulative experience is 0 incur; therefore, highly experienced users have an advantage over their competition. Since experience brings the benefit of future cost reduction, individuals will take the future benefit into account when they decide whether to submit designs or not. Our policy simulations suggest that when the firm increases the reward and make sure that the increase in the reward can offset the reduction in the probability of winning as a result of intensified competition, such that the expected payoff will be higher, it will be able to improve both the quantity and the quality of the designs the crowd produces. If the firm can reasonably estimate the monetary value associated with the improvement of the quantity and quality of the designs

(which is beyond the scope of this study), it will be able to determine the optimal reward using our framework. Another finding in our policy simulations is that if the firm provides incentive to attract more individuals to participate in its contests and this incentive is not tied to the expected payoff individuals receive from winning the contest, the number of submissions will be larger; however, the effort individuals exert in their submissions will be lower. Firms should think twice before implementing this kind of policies.

Our paper also has some limitations. First, in this study, we only focus on active users who consistently submit designs on the website for the sake of tractability. We have not modeled individuals' decisions on entering and exiting the market yet. This is also an important research question to ask, because it will have implications on how the firms can attract more good designers and retain good designers. Second, we assume that the evolution of the experience state is affected by individuals' submission decision. We have not considered whether the effort will also affect the evolution of experience states. Third, we have not incorporated individual level heterogeneity in the current model. The baseline costs of submitting designs of certain quality could vary across individuals, which can potentially explain some of the dynamics in the data. Fourth, due to limited information, we cannot model the firm's decision about which designs to print structurally. Despite these limitations, our paper is the first study that provides a dynamic structural framework to analyze users' behavior in the context of crowdsourcing contests, which help both practitioners and researchers to better understand this new form of product development and corporate R&D. We hope our work can pave the way for future research on this important area.

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