

OPEN INNOVATION: STRATEGIC DESIGN OF ONLINE CONTESTS

Completed Research Paper

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Abstract

Online contests for open innovation – seekers posting innovation projects to which solvers submit solutions – have been developed into a new online commerce model. This study is one of the first to lift the veil of online contests. We identify that real world online contests are very different from what is assumed by previous studies. A real world online contest has uncertain number of solvers due to dynamic participation process. Feedback can encourage solvers to contribute more than the equilibrium effort. With a given award, if the seeker's feedback effort is high enough, the emerging number of solvers is a proxy measure of contest performance. More solvers can increase potential performance, however

attention based theories suggest that a seeker is optimal to have an appropriate number of solvers to fit her capability of exploiting knowledge of solvers.

To predict the emerging number of solvers of a contest, we have developed a two-stage model. By examining data from a large online contest marketplace, we find that emerging number of solvers is influenced by award amount, project time cost, description length, contest duration, project type and marketplace maturity. It's surprising that higher award can attract more solvers to enter the contest, but will also reduce the completion rate for all types of projects. As a result, for all types of projects, multi-award structure has the potential to do better than only have one winner. Specifically multi-award structure is more effective to expertise based projects than ideation based projects. Ideation projects are the most effective in capturing solvers due to the largest population of potential solvers and the lowest time cost in average. In a marketplace with over-saturated number of solvers, market maturity has negative impact to both number of subscribed solvers and completion rate.

Keywords: online contest, open innovation, feedback, contest, online marketplace

Introduction

Investment returns in R&D and innovation are one of the most important sources of future market value for firms today (Hall et al. 2005). Accordingly, the firm's investment strategy for R&D and innovation is very important. The most common approach is *internal R&D projects*, by which teams of developers within the firm seek solutions for innovation projects as

scheduled. However, since the success of internal R&D projects cannot be guaranteed, firms are exposed to the risk of R&D failures. Also due to the team scale limitation, efficiency and outcome is difficult to be largely improved. In recent years, another approach called *open innovation* has emerged (Chesbrough 2003, von Hippel 2005, Terwiesch and Ulrich 2008). This approach to open innovation relies on the undefined public from the outside world for solutions. An appealing feature of this open approach is that innovation seekers only need to pay for the success, not the failure of innovation projects. So investment returns could be much higher. Besides, a potentially larger pool of innovators (solvers) may facilitate faster and better innovation outcomes with lower cost than internal projects. Since the winning solution is typically the best one that survives after a highly intensive competition in the real world, the outcome is naturally very competitive in the market. During recent years, many large firms are adopting open innovation to better leverage R&D expenditures. For instance, in September 2007, Procter and Gamble (P&G) launched an open innovation contest and finally “at least one of the final four who made it to the Procter and Gamble presentation has discovered a breakthrough in the fabric care marketplace that has got P&G very excited. If it comes to market it will be a win, win scenario for P&G, the design firm and millions of consumers” (Horn 2008).

By taking advantage of the Internet, open innovation seekers can reach large pool of potential solvers with low cost and possibly better solutions. *InnoCentive*, founded in 2001, is the first online marketplace in the world to host open innovation projects, in form of contests (Allio 2004). It was originally built to facilitate seeking for innovative medicine solutions. For now, as an emerging result, a variety of projects are posted there, ranging from website LOGO design, algorithm design to complex project such as construction design. The potential seeker could be

an individual, a firm, or any parties. Numerous marketplaces, such as Topcoder, and TaskCN are using online contests for open innovation projects.

A contest is a type of game in which several agents spend resources in order to win one or more prizes (Moldovanu and Sela 2001). The first contest model was done by Lazear and Rosen (1981). They propose a simple contest model with only two competitors in the pool to see how to set the optimal prize structure to stimulate the best output. In most contest studies, information is complete, contest is one-stage, and the contest performance is evaluated in one dimension such as quality or quantity (Lazear and Rosen 1981, Moldovanu and Sela 2001, Terwiesch and Loch 2004, and etc). One important finding is that having many solvers work on an innovation contest will lead to a lower equilibrium effort for each solver in the contest model, which is undesirable by seekers. Recently, Loch et al. (2006) discuss different problem types in product development and suggest that performance evaluation should be modeled with multi-dimensions instead of one dimension. Terwiesch and Xu (2008) may be the first to expand contest research scope to open innovation field. Their uniqueness is dividing projects into three dimensions: ideation based, expertise based and trial-and-error projects. *Ideation* based projects are problems looking for innovative ideas. It could be as simple as a name to a new company, or designing a LOGO for a website. *Expertise* based project usually requires some specific expertise which is not common. Software development is a typical expertise based project. *Trial-and-error* projects are innovative problems with very “rugged” solution landscape. Solvers couldn’t know the result without trials. They find that seekers will benefit from having more solvers due to more diversified solutions, which can mitigate and sometimes outweigh the effect of underinvestment from each solver.

Until now, most studies of contests have been theoretical ones and have mainly focused on the

optimal design of award structure. Especially compared to research of other Internet based transactional activities such as online shopping, online auction and reverse auction, the field understanding of online contests is very limited. For an online contest, the seeker needs to make decisions more than just award structure design. For instance, a seeker also needs to consider duration, start date, project description details and collaboration strategies before launching a contest. Every variation of these factors can impact the final performance. Unfortunately most of these influential factors have not been studied yet. For example, how many solvers should and will a contest have? Should a seeker make the duration longer or shorter? How does award impact the contest performance? How should a seeker collaborate with solvers? Which type of projects are the most efficient with online contests? Our study aims to give answers to these kinds of questions and to provide instructions to innovation seekers pertaining to how to set up an online contest to maximize innovation performance.

The uniqueness of this study is that we have an opportunity to examine open innovation contest with large-scale empirical data from an online marketplace. We find that real world online contests are very different from traditional ones or the ones assumed by previous studies. A real world online contest has uncertain number of solvers due to dynamic participation process and publicly observable submissions. Especially when seekers collaborate with solvers by providing feedbacks, the award probabilistic discounting effect can be largely reduced, and solvers would like to pay much more efforts than the equilibrium effort. With a given award, if the seeker's feedback effort is enough to cover all preferred solvers, the performance can be measured by the emerging number of solvers. However due to constraint of a seeker's capability, a seeker is optimal to have an appropriate number of solvers to fit her capability of exploiting knowledge of solvers. To predict the emerging number of solvers of a contest, we have developed a two-stage

model. By examining data from a large online contest marketplace, we find that emerging number of solvers can be impacted by award amount, project time cost, description length, contest duration, project type and marketplace maturity. It's surprising that higher award can attract more solvers to enter the contest, but will also reduce the completion rate for all types of projects. For all types of projects, multi-award structure has the potential to do better than only have one winner. Especially multi-award structure is more effective to expertise based projects than ideation based projects. Ideation projects are the most effective in capturing solvers due to the largest population of potential solvers and the lowest time cost in average. However a project based on expertise and ideation is the most sensitive to award and duration when capturing solvers. In a marketplace with over-saturated number of solvers, market maturity has negative impact to both number of subscribed solvers and completion rate

Real World Online Contest

Previous studies are mostly assuming the situation of traditional or offline contests. Although some studies talk about online contests, most assumptions are still based on traditional cases (Terwiesch and Xu 2008 and etc). Before proceed to our study, it's necessary for us to introduce the process of online contests in the real world and the key differences compared to traditional contests. In a third party hosted online contest, there are usually three parties: an innovation seeker, many solvers, and the marketplace. A typical work flow of a one-stage online contest is as showed in Appendix.

By comparing with traditional contests, we have identified two key differences which are important to our study:

1. Dynamic entering process. Nearly all previous studies assume that a known number of solvers will compete simultaneously. However, for real world online contests, this assumption is usually not hold. In an open environment, each solver receives information and responses dynamically and differently, thus the emerging number of solvers a contest can finally have is quite uncertain.
2. Feedback process. Most previous studies assume a process where solvers enter and participate without feedback, and seekers simply select a winner without any interaction. However, our research suggests that feedback happens very often.

Optimal Design of Online Contests

Performance evaluation is always the core for optimal design. In this part, we follow previous studies of contest to approach a modified model according to our different online contest scenario.

Previous Theoretical Approach

Terwiesch and Xu (2008) are one of the first to look into the contest for open innovation. They propose a performance evaluation model for a one-stage contest:

$$V = \rho \max_{i=1, \dots, n} \{v_i\} + (1 - \rho) \frac{\sum_{i=1, \dots, n} v_i}{n}, \quad (1)^1$$

¹ The easiest way to evaluate project performance in empirical research is using user generated evaluation score. The marketplace gives every seeker the opportunity to provide feedback about the performance of the contest. However, only around 10% seekers offer feedback. In our record during January 1st, 2008 ~ March 31st, 2009, there are 1,621 feedback received from contest seekers. Among all feedback, 1,594 seekers feel satisfied, 14 seekers feel neutral, and 13 feedbacks are negative. In other words, over 98 percent of feedbacks are positive. As a result, this data is not helpful due to the small variance.

where $0 \leq \rho \leq 1$. In the left-hand-side, V is the overall performance. In the right-hand-side, n is the number of solvers; ρ is the weight of best solution performance among all solutions. If a seeker only cares the best solution, then $\rho=1$. If a seeker cares all submissions equally, such as sales force contest where maximization cumulative performance of all submissions is pursued (Chen and Xiao 2005), then $\rho=0$. The variable v_i is the performance evaluation of submission from solver i , where $i=1 \dots n$. The performance of solver i is given in linear format:

$$v_i(\beta_i, e_i, m_i, \xi_i) = \max_j \{v_{ij} = \beta_i + r(e_i) + \xi_{ij}, j = 1, 2, \dots, m_i\} \quad (2)$$

Here β_i is the expertise level of solver i . Previous studies assume that the distribution of expertise is known and fixed. $r(e_i)$ is the output of effort when solver i execute effort e_i . j marks an experiment of solver i . Solver i has done m experiments. ξ_{ij} is a random error term of each experiment. This random error also includes the ideation output. Since β_i is fixed, the variance of performance is mainly based effort e_i and random error.

Obviously award is positively associated with effort e_i , which is not interesting. Previous studies prove that effort e_i is related to the number of solvers too. Larger population of solvers will bring more diversified ideations, but will also lower each solver's equilibrium effort e_i . In other words, having more solvers can increase the chance of having better ideas, but does not guarantee better performances due to lower equilibrium effort. This result is based on the assumption that there is no feedback from seekers or that the feedback doesn't impact the effort that each solver would contribute.

Feedback Impact

As indicated in section 2, we observe that seekers provide feedback to solvers quite frequently. Many marketplaces provide feedback software agents to encourage feedback. During this

process, seekers gather information from all submissions and send feedbacks to preferred solvers.

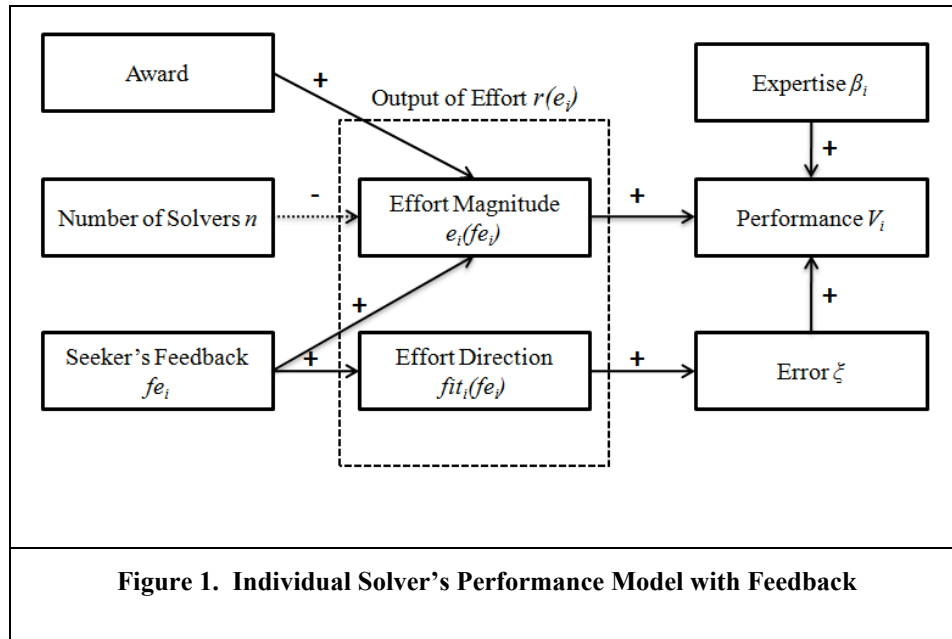
How does feedback impact the performance or the effort that a solver would like to pay? To directly understand the impact in real world, we posted a contest project to a marketplace as a field experiment. The project was pursuing a LOGO design for a website with a common award amount. After posted the project, the contest started to receive submissions from the first day. Taking advantage of submission review board, a software agent provided by the marketplace, we gave timely feedbacks to some preferred submissions. For instance, we indicated the elements we favor or not, and we gave suggestions of how to make the designs look better.

Finally after duration of 15 days the contest had attracted 46 subscribed solvers and 34 of them have submitted at least one prototype. Before we sent any feedback, each solver submitted only one prototype. Within the contest duration, we had provided feedback to 38 solvers and then received 43 improved prototypes. The response rate is 100 percent. Every submission feedback generated 1.13 improved prototypes in average. The winner had received feedback on 4 occasions and he contributed 5 prototypes. In other words, feedback from the seeker appears to increase the effort that a solver would like to contribute.

By reviewing our one-stage contest process with feedback impact, the contest is more like a two-stage one. In the first stage, solvers submit initial submissions. All solvers are receiving the same information. In the second stage, the seeker will send feedbacks to preferred solvers and these solvers are competing in the second. Solvers now are receiving different information.

Why solvers would like to pay far more efforts than equilibrium effort could be explained by probabilistic reward discounting theory (Ainslie 1992, Green and Myerson 1993, Kagel and et al. 1995, Green and Myerson 2004, and etc). Before receiving feedback from the seeker, solvers

only perceive a discounted award due to having many competitors. Once feedback is given, a solver receives the hint that his submission is preferred and has higher chance to win than before. As a result, each solver has incentive to pay more effort. If a solver refuses to make improvement, he will probably lose all what he has done for the project, while making improvement will increase his winning chance. If the award is enough to cover his total cost, his best response is to make improvement. From seeker's perspective, it will be optimal for her to give feedback with a purpose of minimizing the discounting effect. Ideally, with no probabilistic discounting, a preferred solver could perceive incentive of the full award.



Solver's effort \vec{e}_i is a vector which has two dimensions: magnitude e_i and direction fit_i (As shown in Figure 1). Our field experiment and analysis show that seeker's feedback effort fe_i can impact a solver's effort in both dimensions. So both e_i and fit_i are functions of seeker's feedback effort fe_i . In Terwiesch and Xu's model, effort magnitude e_i is also impacted by number of solvers n . Including all these, we have:

$$r = r(\vec{e}_i) = r[e_i(f, \zeta, n), fit_i(f, \zeta)] \tag{3}$$

Solvers making improvement according to feedback means that seeker's feedback effort will encourage solvers to pay more effort in magnitude. Making improvements according to seeker's feedback means the effort direction fit_i is matching better to seeker's preference, or solvers are allocating effort certainly in the right way. Ideation based performance is modeled as a stochastic process (Terwiesch and Xu 2008). With a better fit, the stochastic output can be improved, and the variance of random error variance can be reduced. As a result, if a solver has made improvement according to seeker's feedback, both effort-based output $r(e_i)$ and stochastic output ξ_i are increased. In other words, to a solver, the lower effort equilibrium caused by a larger population of solvers is broken by seeker's feedback. In this situation, n plays a very weak role and could be neglected when fe_i is high. Substituting equation 3 into equation 2, and assuming that seekers can provide enough overall feedback effort $\sum fe_i$ which is far from limit, all preferred solvers will perform their best in output. Expertise distribution is fixed and won't affect the overall performance in general. In this study, we don't consider sales force projects, so the seekers concern the performance of one or several best solutions. Hence ρ is close to 1. Plus, allocating feedback effort to preferred submissions also requires ρ close to 1. Now equation 1 suggests that the overall performance of a contest can be simply measured by counting the number of emerging solvers of the contest. We call it *potential performance* V_p :

$$V_p = \text{Number of Solvers} \geq V \quad (4)^2$$

Capability Constraint

Potential performance model suggests that having more solvers can do better. However in the real world, performance is constrained by limited resources and ideal situation is hard to reach.

² This equation is also based on the assumption that expertise distribution is constant.

One of the most critical constraints is the seeker's limited capability. To reach potential performance, overall feedback effort $\sum f e_i$ needs to be high enough to maximize all preferred solvers' effort. However, even the largest firms in the world are also having limited attentions. No matter evaluating a submission or sending a feedback, a minimum effort is required. So it's not reasonable for a seeker to expect to have too many solvers. Attention-based theories of the firm (Simon 1997, Ocasio 1997) suggest that managerial attention or capability of exploiting external sources is the most precious resource inside the firm and allocating limited attention to weighted activities is very important. These theories imply that attention allocation problem is the key element of firm performance.

With large-scale dataset of open innovation, Laursen and Salter (2005) find that open innovation performance is positively associated with the number of outside sources when firm's capability of exploiting external knowledge is enough. Also, they find that "searching widely" and "deeply" is "curvilinearly" (inverted U shape) related to open innovation performance. In other words, more outside sources can improve performance, but excessive outside sources will bring negative impact to open innovation performance, due to a lack of capability of exploiting external knowledge in depth. In analogue to our study, "searching widely" means having more solvers, and "searching deeply" means giving feedback and encouraging solvers to pay more efforts.

The attention-based theories are universally hold, no matter online or offline. Although by taking advantage of Internet, the searching cost and communication cost have been largely reduced, every evaluation and feedback process still requires a minimum cost for seekers. Since a seeker's capability is always limited, when the number of solvers is excessive, she will have to pay less effort to evaluate and give feedback to each submission in average; giving too much feedback to

each submission will make seeker lacking of attention to evaluate more submissions. To our study, attention based theories suggest that pursuing optimal performance of a contest, the seeker needs an *optimal number of solvers* which can just fit firm's max capability of exploiting external knowledge, not too “wide” or too “deep” (Figure 2).

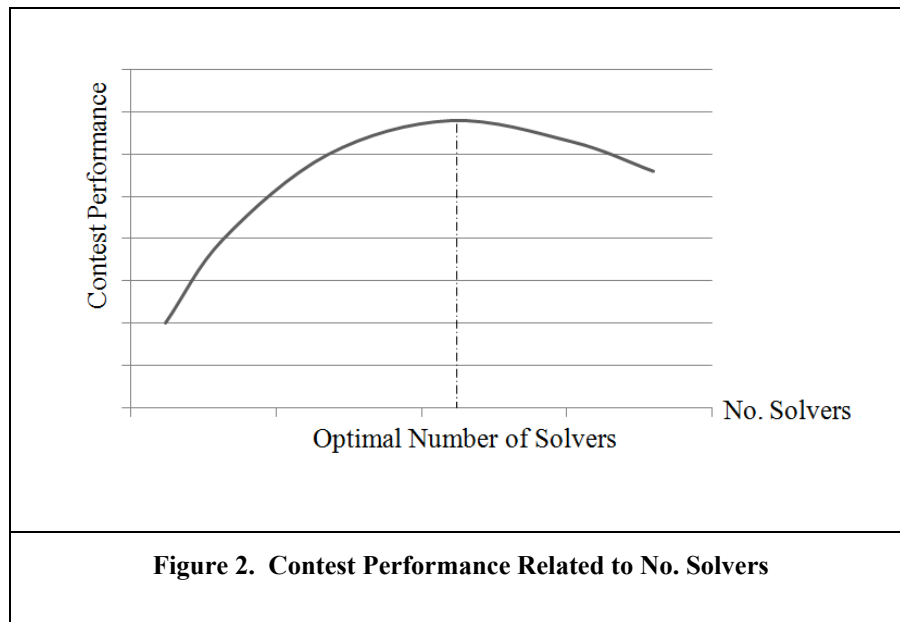


Figure 2. Contest Performance Related to No. Solvers

Strategy Based Contest Design Process

Above analysis suggest that optimal design of contests should be conducted in two steps: First, a seeker need to decide her optimal number of solvers. It is common knowledge that the seeker knows her attention limit, and the project evaluation and feedback cost for specific project based on her path dependent experience. With this common knowledge, the seeker could estimate approximately how many solvers that she could handle. For instance, if the project evaluation cost is low, such as LOGO design or naming project, seekers can handle large number of solvers. However for complicated projects such as data mining or website development, which require high evaluation and feedback cost, seekers should better have small number of solvers and put more attentions to evaluation and feedback. Second, seekers design the contests based on the

optimal number of solvers and resources. It's common knowledge that a seeker knows her resources such as budget and timeline, and project characteristic. To target optimal number of solvers, a prediction model is needed in order to help the seeker to decide how to input settings of resources and project information.

After all, no matter to estimate the potential performance of a launched contest or to launch a contest in an optimal design by allocating limited resources, a prediction model for emerging number of solvers is needed. So our next job is to develop a prediction model for emerging number of solvers.

Two-Stage Prediction Model for Number of Solvers

From solvers' perspective, each solver needs to go through a contest in two stages. In the first stage, each solver needs to decide whether to enter the contest after he evaluates the project information. If yes, he will need to subscribe as announcing "I am in". With having more solvers entered, the later players will perceive less probability of winning as incentive to enter. Finally no solvers will enter until there is no incentive to join. So the number of subscribed solvers is finally balanced by some constraints. We call these subscribed solvers as *subscribers*. In the second stage, the subscribers start to do the project and submit. Due to variety of reasons, some subscribers couldn't finish the project and fail to submit anything. In this study, we are interested in those solvers who have submitted at least one submission. They are the real solvers of current contest. In this article, the *number of solvers* always means the number of real solvers that have contributed at least one submission. According to this process, we can calculate a *completion rate* for each contest:

$$\text{Completion Rate} = \frac{\text{Number of Solvers}}{\text{Number of Subscribers}} \quad (5)$$

And the prediction function for number of solvers is:

$$\text{Number of Solvers} = \text{Number of Subscribers} \times \text{Completion Rate} \quad (6)$$

If we take natural log-transform to both sides of equation 6, we will have:

$$\ln(\text{Number of Solvers}) = \ln(\text{Number of Subscribers}) + \ln(\text{Completion Rate}) \quad (7)$$

After log transfer, we can predict the number of solvers by predicting the number of subscribers and the completion rate separately. Next we will develop two sub-models in two stages according to equation 7.

First Stage: Prediction Model for Number of Subscribers

In the first stage, we only concern a solver's behavior of entering. Once entered, he is a subscriber but not yet the real solver before he submit any solution. In a marketplace, every innovation seeker is capturing solvers. However, there are many contest projects open to public with free entry at the same time. Each solver has many contests to choose. Due to limited attention, he can only choose a small number of contests to enter. So contest projects themselves are also competing against each other in the same pool for capturing subscribers. To capture more subscribers, a seeker should make her contest more competitive than other contests.

Whether a project is more competitive can be explained by switching cost theory (Klemperer 1995, Chen and Hitt 2006, and etc). Switching cost theory has been widely used to analyze the competitive power of firms and products in market. Switching cost is the real cost that users perceive when they need to make decisions on whether to switch in or switch out providers, brands, and etc. According to switching theory, when establishing a new relationship, a rational consumer will choose the alternative with the lowest switching cost. We consider all the potential and independent variables that a seeker may know or control before launching a

contest, including award, contest duration, time cost, project description length, project type, and market maturity. In a marketplace, entering a contest means a solver is starting a new relationship, so we can estimate solvers' choices by evaluating the switching cost, or more accurately the switching in cost. Lower switching in cost of a contest, more solvers will come to enter to be subscribers.

Switching cost theory suggests that higher award provides better compensation to the transaction cost or production time cost, thus the switching in cost is lower, and should be able to attract more subscribers. This has been proved that in a reverse auction, higher value will attract more bids (Snir and Hitt 2003). So we have:

Hypothesis 1a: A contest with higher award will attract more subscribers.

A project requiring higher time cost will result higher transaction cost, thus the switching in cost is higher and will attract fewer subscribers. Besides, time cost is also related to project complexity (Banker et al. 1998). Experiment proof shows that people are less likely to choose more complex projects (Sonsino and et al. 2002). So we have:

Hypothesis 1b: A contest with higher time cost will attract fewer subscribers.

Switching cost theory also suggests that a contest with higher learning cost will have higher switching in cost, thus fewer subscribers will be captured. A contest with longer project description of a project has higher learning cost. So we have:

Hypothesis 1c: A contest with longer description will attract fewer subscribers.

The learning cost of a project also has another tier. Considering every project requires specific expertise. Expertise is hard to develop in short time, so the instant learning cost is large. This kind of learning cost prevents a solver to enter the contests with which he has no required

expertise. In a large-scale marketplace, the distribution of solvers with specific expertise is very stable. This suggests that project type matters number of solver and subscribers. So we have:

Hypothesis 1d: The project type of a contest will impact number of subscribers.

Duration is also a potential variable. Since the participation process of contest is dynamic, online contest duration is very different from duration of traditional contest. A contest with longer duration is exposed to more potential solvers. Snir and Hitt (2003) consider duration effect in their reverse auction study and find that with longer duration an auction has more bids. Similarly, we expect more subscribers for in a contest with longer duration. So we have:

Hypothesis 1e: A contest with longer duration will attract more subscribers.

Market maturity is the overall age of a specific marketplace. The maturity of a marketplace captures the changes in market structure over time, such as positive network effects and growth in the population of solvers (Snir and Hitt 2003). We have:

Hypothesis 1f: Market maturity can impact number of subscribers that a contest can attract.

Except above main effects, we are also interested the factor impacts to different types of project. For instance, naming projects are usually easier and less time consuming than other types of projects, so naming projects may be more sensitive to award and duration than other types of projects. So we have:

Hypothesis 1g: different types of projects response positively and differently to award variation when attracting subscribers.

Hypothesis 1h: different types of projects response positively and differently to duration variation when attracting subscribers.

Second Stage: Prediction Model for Completion Rate

Table 1. Impacts to Completion Rate		
Variable	Positive Impact	Negative Impact
Award	Higher award, higher incentive to complete.	Higher award, more subscribers, so lower probability of winning.
Time Cost	Higher time cost, fewer competitors, more likely to complete.	Higher time cost, more likely to procrastinate, so less likely to compete (Akerlof 1991); Higher time cost, more complicated, higher uncertainty of choice, so less likely to complete (Sonsino et al. 2002).
Description Length	Longer description, fewer competitors, more likely to complete.	N.A.
Project Type	N.A.	
Duration	Longer duration, more time to complete the project, more likely to complete.	Longer duration, more competitors, less likely to compete.
Maturity	N.A.	

When a solver decided to enter a contest, he was probably willing to complete the job. However due to variety of reasons, some of them failed to submit anything. One cause is procrastination behavior (Akerlof 1991). Procrastination theory suggests that long duration will make high procrastinating solvers do the project later or fail to do, which is not expected by the seekers. The procrastination hazard is positively related to task cost. Higher the cost, less likely the solver will complete. Another cause is the dynamic probabilistic discounting of award (Ainslie 1992, Green and Myerson 1993, Kagel and et al. 1995, Green and Myerson 2004, and etc). Because the participation process is dynamic, an early subscribed solver will feel less probability of winning after more solvers entered. Probabilistic discounting theory suggests that having more competitors will lower each subscriber's perceived value of award. As a result, if there are more competitors, a solver is less likely finish a solution. In the first stage, we have analyzed all potential variables that can impact number of subscribers, so all these variables may also impact the completion rate. In this stage, the variations of several variables will cause opposite impacts at the same time, and which direction is dominant is hard to say. We list all these impacts in Table 1.

Adding award amount will directly make each solver perceive higher value of the job, thus the completion rate will increase. However, higher award will also result more competitors in the pool, thus each solver will perceive less incentive and are less willing to complete the job. These two impacts are opposite and mitigate each other. Intuitively seekers would set higher award with expectation that solvers can perceive higher incentive, so we suppose that positive effect would be dominant. So we have:

Hypothesis 2a: a contest with higher award will have higher completion rate.

The impact of time cost is ambiguous too. From one side, higher time cost will prevent more solvers to enter. As a result, subscribers feel lower competition intensity and higher probability of winning. From the other side, higher time cost will result higher probability of procrastination (Akerlof 1991), thus subscribers are less likely to finish. Besides, time cost is also part of complexity (Banker et al. 1998). The definition of completion rate is actually measuring the uncertainty of choice of subscribers. Sonsino et al. (2002) have done an experiment and shows that choice uncertainty is negatively related to complexity of tasks. It's hard to say which impact is stronger. Intuitively we feel that negative effect is dominant. So we have:

Hypothesis 2b: a contest with higher production cost will have lower completion rate.

Longer description only brings positive impact in the second stage, which will result fewer subscribers and less probabilistic discounting effect. So we have:

Hypothesis 2c: a contest with longer description will have higher completion rate.

Project type is a categorical variable. It is related to the potential solvers' population of a specific category and can impact the number of subscribers, so it should also influence the completion rate due to dynamically probabilistic discounting of award. For instance, naming projects are usually easier and less time consuming than other types of projects, so naming projects are probably have the highest completion rate. So we have:

Hypothesis 2d: the project type of a contest will impact completion rate.

Longer duration will also result opposite impacts to completion rate. With longer duration, subscribers have more time to make a solution, thus will increase the completion rate. By the other side, long duration will bring more subscribers to compete, thus the higher probabilistic

discounting effect may decrease the completion rate. Intuitively we feel the negative effect is dominant. So we have:

Hypothesis 2e: a contest with longer duration will have lower completion rate.

Compared to the discussion of maturity in subscriber prediction model, the impact of maturity to the completion rate is very different. In attracting subscribers, the impact of market maturity measures website's changes of network effect and growth of solvers population. However, here the impact of market maturity records solvers' behavior changes. Especially for a young market, it records the inconsistency of subscribers' decision making in average. There are many latent variables can impact the direction of this time inconsistency behavior, so we don't do any guess and only propose:

Hypothesis 2f: marketplace maturity can impact completion rate.

We are interested to know the completion rate sensitivity to award and duration of each project type. We expect that a naming project with a higher award can increase completion rate the largest compared to other categories. Considering our discussion of hypothesis 2a and 2e, we propose:

Hypothesis 2g: In the impact to completion rate, different types of projects response positively and differently to higher award.

Hypothesis 2h: In the impact to completion rate, different types of projects response negatively and differently to longer duration.

Data and Measurement

Data Collection

Our data was collected from TaskCN.com, which is one of the largest online service marketplaces in China founded in 2005. By the end of 2008, it has over 2.4 million registered solvers. This marketplace allows anyone to start a contest with award deposit. Solvers can enter any contest for free. By the end of 2008, the site had hosted over 13,000 contests.

Our data was collected during September 2007 ~ September 2008. In total, there are about 3,700 contest projects. Around 20% of the projects are multi-winner projects. We eliminated these projects since the optimal design of award structure is not the core of this study. In addition, since people may contribute in an online community for non-monetary incentives (Wasko and Faraj 2005), we eliminated all projects with award amount lower than ¥50.00 Chinese Yuan (□1 Chinese Yuan is around \$0.15 USD). Sales force contests were also eliminated since sales force contests are pursuing maximizing the overall performance of all solutions, not just one or several best solution (Chen and Xiao 2005). After these adjustments, 2,453 contests remain in our sample.

Variables Measurement

To test our hypotheses and get prediction models for number of subscribers and completion rate, we need to measure the values of all potential variables defined in section 4. In this part, we give the measurement method that we use for each variable.

- *Award Amount.* This number is the money amount to be paid by the seeker as reward to the winner. The marketplace is having an award-never-refundable policy. To any contest, a full

amount of award is paid to the marketplace before this contest can start. The marketplace charges 20% as service fee for every contest, so the winner of each contest will receive 80% of total award. Since 20% service fee is a constant rate, we can still use the total award as our award amount. We use the natural log of this variable.

- *Time Cost.* In the marketplace it's difficult to directly measure the production time cost for each contest. Instead, we use the duration between contest start time and the submit time of first submission as production cost. Here we assume the duration between start time and the time that first submitter read the project is very short compared to production time cost, and can be neglected. We use the natural log of this variable.
- *Description length.* This number measures how many Chinese characters that a seeker used in project description of a contest. From our observation, this size varies considerably. We measure the description length by counting the number of characters. We use the natural log of this variable.
- *Type of Project.* Seekers need to choose the project category before launching contests. We use project category as project type which is a categorical variable. In this marketplace, the main categories are:

Graphic design. The most common case is a LOGO design contest, where a seeker needs a LOGO for a website, a company or a business card. This kind of projects requires the solver to have some design expertise. For example, solvers usually need to be good at using PHOTOSHOP, which is one of the most popular graphic design software. Although some level of expertise is required, usually creativity plays very important role. Because most of our observations are in this category, we choose graphic design as our reference category.

Naming. A contest in this category is very simple. A typical case is to give name to a new company. This type of projects does not need expertise or much effort, only diversified ideas. Naming projects are pure ideation projects, which is very good for research study.

Website Development. A website development project is not simple. It usually not only requires specific expertise like mastering of html, ASP, PHP or JAVA, but also creativity in design and much more effort.

Software Development. Similar to website development, software development projects requires high level of specific expertise like C++, Perl and etc. Usually these projects do not need creativity.

Creative Writing. Similar to naming, here writing projects need creative ideas in writing articles. Expertise is required. Compared to naming project, it requires more effort.

Other. The rest projects are classified into this category.

- *Contest Duration.* We measure the duration of contests by counting the days between start time and end time set by seekers. The start time and end time are available from TaskCN. We use the natural log of this variable.
- *Market Maturity.* We measure this variable by counting the days from the September 1st 2007 to the start date of each contest. We use the natural log of this variable.
- *Number of Solvers.* Data for this variable of each contest is available in the marketplace. We use the natural log of this variable.
- *Number of Subscribers.* Data for this variable of each contest is available in the marketplace. We use the natural log of this variable.

- *Completion Rate.* For each contest, we know the number of solvers and the number of subscribers. With equation 5, we can calculate completion rate for each contest. We use the natural log of this variable.

The descriptive analysis and correlation matrix is given in Appendix.

Regression Models

All variables are skewed, so we have all of them natural log-transformed. Another benefit of log-transform is that prediction model of number of solvers now equals the linear addition of two sub-models. Also with natural log transforming, we can capture the higher order relationships.

Hypothesis 1a-1f, and 2a-2f are made to test main effects for all categories. Hypothesis 1g-1h, and 2g-2h are made to test several main effects in different project categories. So we need to test all hypotheses with four models: A, B, C and D.

$$\begin{aligned} \ln(\text{No. Subscribers}) = & \beta_1 + \beta_{1a}\ln(\text{Award}) + \beta_{1b}\ln(\text{Time Cost}) + \beta_{1c}\ln(\text{Description Length}) + \beta_{1d}\text{Category} \\ & + \beta_{1e}\ln(\text{Duration}) + \beta_{1f}\ln(\text{Maturity}) + \xi \end{aligned} \quad (\text{A})$$

$$\begin{aligned} \ln(\text{No. Subscribers}) = & \beta_1 + \beta_{1b}\ln(\text{Time Cost}) + \beta_{1c}\ln(\text{Description Length}) + \beta_{1d}\text{Category} + \beta_{1f}\ln(\text{Maturity}) \\ & + \beta_{1g}\ln(\text{Award}) * \text{Category} + \beta_{1h}\ln(\text{Duration}) * \text{Category} + \xi \end{aligned} \quad (\text{B})$$

$$\begin{aligned} \ln(\text{Completion Rate}) = & \beta_2 + \beta_{2a}\ln(\text{Award}) + \beta_{2b}\ln(\text{Time Cost}) + \beta_{2c}\ln(\text{Description Length}) + \beta_{2d}\text{Category} \\ & + \beta_{2e}\ln(\text{Duration}) + \beta_{2f}\ln(\text{Maturity}) + \xi \end{aligned} \quad (\text{C})$$

$$\begin{aligned} \ln(\text{Completion Rate}) = & \beta_2 + \beta_{2b}\ln(\text{Time Cost}) + \beta_{2c}\ln(\text{Description Length}) + \beta_{2d}\text{Category} + \beta_{2f}\ln(\text{Maturity}) \\ & + \beta_{2g}\ln(\text{Award}) * \text{Category} + \beta_{2h}\ln(\text{Duration}) * \text{Category} + \xi \end{aligned} \quad (\text{D})$$

Result and Analysis

Regression Result

Table 2. Regression Results						
Variable	Dependent Variable: No. Subscribers			Dependent Variable: Completion Rate		
	Coef	Model A	Model B	Coef	Model C	Model D
Intercept	β_1	2.988***(0.145)	2.989***(0.158)	β_2	0.602***(0.021)	0.597***(0.023)
Ln(Award)	β_{1a}	0.356***(0.017)	--	β_{2a}	-0.024***(0.002)	--
Ln(Time Cost)	β_{1b}	-0.279***(0.013)	-0.275***(0.013)	β_{2b}	-0.028***(0.002)	-0.028***(0.002)
Ln(Description Length)	β_{1c}	-0.035** (0.012)	-0.037** (0.012)	β_{2c}	0.002 (0.002)	0.002 (0.002)
Category						
• <i>Graphic Design</i>		0.000	0.000		0.000	0.000
• <i>Naming</i>		2.272***(0.053)	2.412***(0.378)		0.081***(0.007)	0.049 (0.055)
• <i>Website Development</i>	β_{1d}	-0.634***(0.054)	-1.139** (0.390)	β_{2d}	-0.018** (0.007)	-0.024 (0.057)
• <i>Software Development</i>		-1.062***(0.063)	-0.790** (0.364)		0.028***(0.009)	0.088* (0.053)
• <i>Creative Writing</i>		-0.020 (0.069)	-1.586** (0.489)		-0.027***(0.010)	0.115 (0.071)
• <i>Other</i>		-0.103* (0.048)	0.348 (0.296)		-0.035***(0.007)	-0.024 (0.043)
Ln(Contest Duration)	β_{1e}	0.249***(0.018)	--	β_{2e}	0.006** (0.003)	--
Ln(Market Maturity)	β_{1f}	-0.147***(0.016)	-0.145***(0.016)	β_{2f}	-0.006** (0.002)	-0.006***(0.002)
Ln(Award)*Category						
• <i>Graphic Design</i>			0.371***(0.022)			-0.025***(0.003)
• <i>Naming</i>			0.361***(0.071)			-0.014 (0.009)
• <i>Website Development</i>	β_{1g}	--	0.478***(0.062)	β_{2g}	--	-0.021** (0.009)
• <i>Software Development</i>			0.312***(0.070)			-0.038***(0.010)
• <i>Creative Writing</i>			0.490***(0.090)			-0.036***(0.013)
• <i>Other</i>			0.181***(0.016)			-0.018** (0.007)

Ln(Duration)*Category						
• <i>Graphic Design</i>			0.219***(0.023)			0.010***(0.003)
• <i>Naming</i>			0.195***(0.064)			0.001 (0.009)
• <i>Website Development</i>	β_{1h}	--	0.176** (0.068)	β_{2h}	--	0.004 (0.010)
• <i>Software Development</i>			0.225***(0.056)			0.011 (0.010)
• <i>Creative Writing</i>			0.578*** (0.087)			-0.021* (0.012)
• <i>Other</i>			0.415***(0.056)			-0.007 (0.008)
Number of observations	2453					
R^2		0.660	0.665		0.236	0.241
ΔR^2			+0.005			+0.005

p < 0.1; **p < 0.05; ***p < 0.001

Result Analysis for First Stage Model

The Pearson correlations between all independent variables are less than 0.3, so they are low correlated. Especially, except the correlation between award and contest duration which is 0.299 and very significant (p value < 0.001), all the other correlations are very low (less than 0.2). This means although seekers can choose award and duration values arbitrarily, when award is higher, a seeker does have the intention to make duration longer.

β_{1a} in model A is positive and significant. It means higher award will attract more subscribers. So hypothesis 1a is supported. Also β_{1g} is positive and significant for each category. Especially projects of creative writing category show the highest award sensitivity. This is a little surprising because we thought that naming projects would be the most award-sensitive project type due to requiring the most common expertise and low time cost. Both projects of naming and creative writing are ideation based projects, but creative writing projects require higher level of expertise

and ideation. It's also interesting to notice that software development projects, which require high level of expertise but low level of ideation, are the lowest in award-sensitivity.

Both β_{1b} and β_{1c} are significant and negative in model A and model B. That means a contest project with longer project description and higher time cost will have fewer subscribers. Thus hypothesis 1b and 1c are supported.

β_{1e} in model A is positive and significant. β_{1e} captures the duration sensitivity for each category, so this result means a longer duration can attract more subscribers, which is consistent with hypothesis 1e. Consistently, β_{1h} is positive and significant for all categories. Specifically creative writing has the highest duration sensitivity, which is similar to the result of β_{1h} . However website development projects show the lowest sensitivity to duration changes. Naming projects don't show the highest duration sensitivity maybe because naming projects usually get saturated number of solvers very soon due to having the largest population of potential solvers.

β_{1d} for most categories are mostly significant. That means project types do influence the number of subscribers, which is consistent with hypothesis 1d. In model A and B, naming category always has the highest and positive coefficient, which suggest that naming projects or simple ideation projects are the most efficient in capturing subscribers in the marketplace. However as discussed above, naming projects are not the most award-sensitive projects. Besides, β_{1h} shows that naming projects are also not the most duration-sensitive projects. So the only reason to explain why β_{1d} for naming is the highest in model A is because naming projects require the most common expertise and the lowest time cost in average, or naming projects have the largest potential population of solver. Complicated projects such as website development and software development are capturing fewer solvers than other projects.

β_{1f} , which measures the changes of market structure, especially the network effect and the growth of number of solvers of the marketplace, is significant but negative. This means fewer solvers can be attracted by each contest as time goes by. According to the marketplace record, the overall population of this marketplace is increasing. Thus the network effect of this marketplace is negative. Considering one fact is that in the whole marketplace, the average number of subscribers that a contest can attract is 193. In other words, the average winning chance for a subscribed solver is around 0.5%. This is extremely low from a solver's point of view. So our explanation to the negative sign is that the marketplace is having over-saturated number of solvers, relative to the number of contest projects. The extremely low probability of winning has stopped many participated solvers to continue playing in the marketplace.

Result Analysis for Second Stage Model

It's very surprised to see that β_{2a} is negative although significant, which means with higher awards, a subscriber are less likely to submit a solution. So our hypothesis 2a is rejected. Based on our analysis given in Table 2, this result means that adding award will attract more solvers, however, the negative impact of deeper probabilistic discounting of award dominates the added award incentive. In other words, each solver perceives less incentive now. This is definitely not expected by the seekers. And this result is also a sign that the marketplace is having over-saturated population of solvers. To mitigate this unexpected result, multi-award structure is suggested. β_{2g} shows that this impact is negative to all categories. Thus for all categories, multi-award structure has the potential to do better. Specifically the result shows that β_{2g} is the lowest and negative for software development category, while the highest and also negative for naming category (significant at p value = 0.15 level). Thus multi-award structure is more effective for software development projects than for naming projects. Naming is a project type which is

purely ideation based, while software development is a project type requires high to specific expertise but not necessary for diversified ideas. Terwiesch and Xu (2008) find that ideation based projects are optimal to have single award structure but expertise based projects may or may not to be optimal to have multiple awards. However our result suggests that in a marketplace with over-saturated population of solvers, all types of projects are optimal to have multiple awards. Especially ideation based projects are least necessary to do that; while expertise based projects are the most necessary to have multiple award structure.

β_{2b} is negative and significant, so a contest with higher time cost will have lower completion rate. This is consistent with hypothesis 2b.

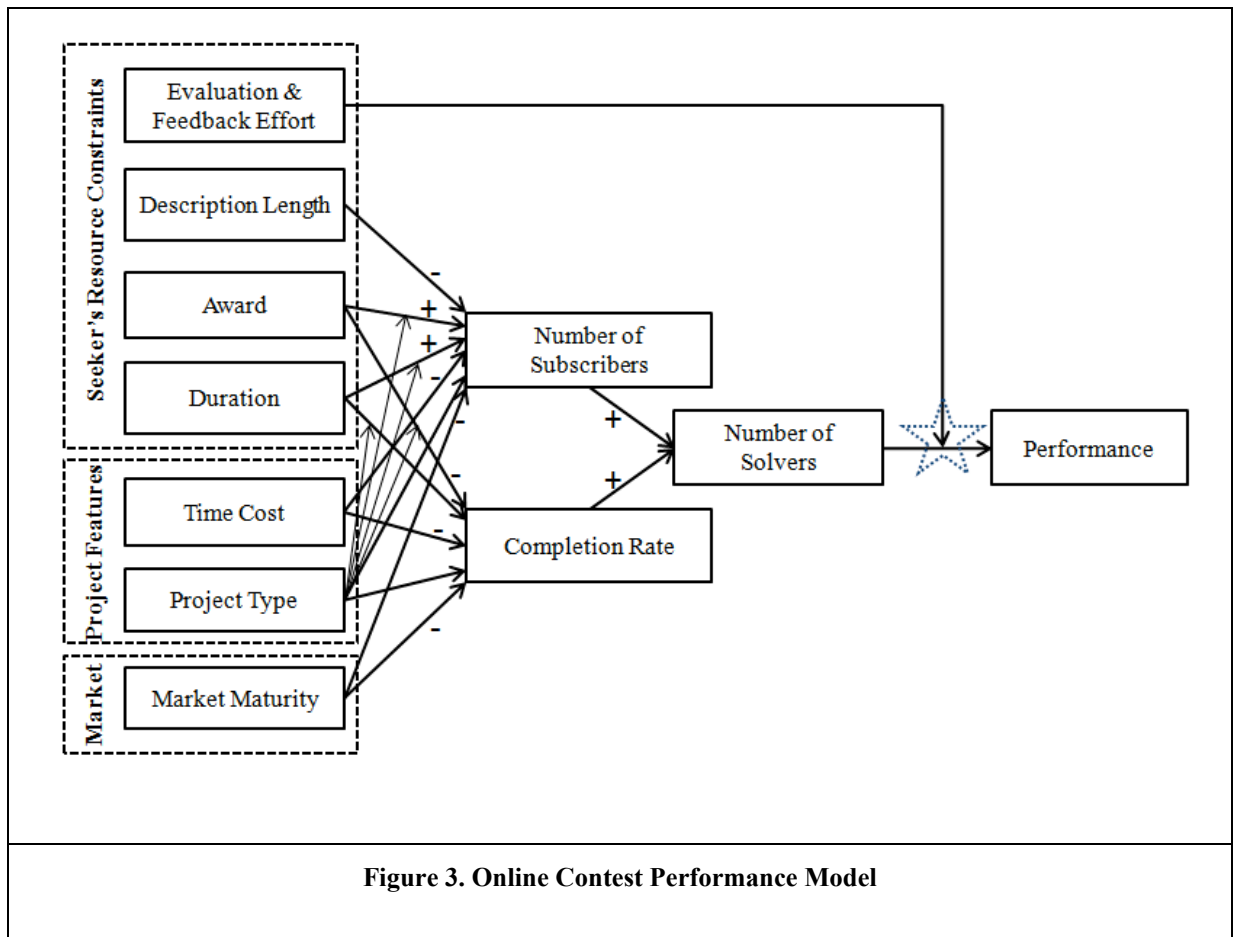
β_{2c} is not significant, so description length has no significant impact to project completion rate. Hypothesis 2c is not supported. Considering the significance of β_{1c} , we can conclude that description length can only impact a solver's decision of whether to enter a contest. Once entered, the description length won't impact a solver's willingness of completing the project.

β_{2d} is significant for all categories in model C, which means the completion rate is representing some characteristics of a specific project type of projects. So hypothesis 2d is supported. Specifically naming projects have higher completion rate than other types of projects, which is consistent with our expectation. Naming is also the most efficient project type in the first stage, so naming projects are the most efficient in the whole process of capturing real solvers.

β_{2e} is positive and significant. This result is slightly different from our expectation and suggests that positive impact is dominant. In other words, for most projects such as graphic design, solvers prefer to have more time to complete a project. However the coefficient is very small, so seekers don't need to consider duration too much for lifting completing rate purpose. The overall p value of β_{2h} is significant. However for each category, only the coefficients of graphic design

and creative writing are significant. And it's interesting that one is positive and another is negative. So graphic design projects with longer duration will have higher completion rate, but creative writing projects with longer duration will have lower completion rate.

β_{2f} is negative and significant. So as time goes by, solvers are somehow less likely to submit a solution. This can also be explained by the over-saturated population of solvers. Since participated solvers perceive very low chance of winning, they are more likely to quit than before.



Model Fitness

Model A and model B can explain 66.0% and 66.5% variance of number of subscriber accordingly. The R square improved by model B is only 0.5%. For prediction purpose, these two models are not much different.

Model C and model D can explain 23.6% and 24.1% variances of completion rate accordingly. The R square improved by model D is only 0.5%. For prediction purpose, model C and model D are not much different. However, R square values of both models are not high. Without category and time cost, R square is only 3.7%. This implies that completion rate is an endogenous variable, although it's derived with two dependent variables.

We summarize all valid hypotheses of our two-stage prediction model and the feedback impact to performance in Figure 3.

Discussion and Conclusions

Open innovation is a promising approach for innovation seekers due to foreseeable high investment returns and outstanding performance. By taking advantage of the Internet, launching an open innovation contest online becomes easy and convenient. Especially, in a contest marketplace with millions of potential solvers, a newly launched online contest can reach lots of solvers in a very short time with nearly no cost. During recent years, online contest for open innovation is becoming popular and has been adopted by more and more firms. However, the emerging marketplaces of online contest are still very young. Due to a lack of data, very little was known about this kind of marketplaces and real world online contests. To lift the veil of real world online contests, we have studied a large online marketplace and examined the typical participation process of online contests. With support of large-scale empirical data from an

online contest marketplace, our study contributes to the research of contest by providing a optimal strategy design for innovation seekers, a two-stage prediction model for number of solvers and many interesting findings.

First, we identify that the online contest process in the real world is very different from what is assumed by previous studies. Previous studies assume that solvers are competing simultaneously. However the participation process of an online contest is usually a dynamic. Previous studies assume that submission content is private to other solvers. However in several marketplaces, nearly all submissions are open to public due to a variety of reasons. Most previous contest studies of contest are assuming a one-stage contest process, which means solvers take the project information and finish the job mutually. Although all our observations are also one-stage online contests, due to the impact of feedback, these contests are more like two-stage ones. In the first stage, solvers submit initial submissions. In the second stage, the seeker will provide feedbacks to preferred solvers and these solvers will compete again with more information.

Moreover, our field experiment shows that seekers can encourage solvers to pay much more efforts by providing qualitative feedbacks. When a solver makes his initial submission, the perceived value of contest is discounted by the perceived probability that he can win, so his effort is only the equilibrium effort. However, with provided feedbacks, a solver's perceived probability of winning can be largely increased. Since feedback information is different to every individual, the equilibrium is broken. The optimal strategy that seekers should take is to maximize solver's perceived probability of winning by giving according hint in feedback. Also it's better for seekers to send feedback to solvers privately to break the equilibrium.

For a given award, if seekers have enough capability to evaluate all submissions and send feedbacks to preferred solvers, the emerging number of solvers can be used as a proxy measure

of performance or the potential performance that a contest can reach ideally. More solvers, higher potential performance will be. However, due to the constraint of a seeker's limited capability, attracted solvers are not always the more the better. Attention based theories suggest that a contest should have an optimal number of solvers, which should fit seeker's capability of exploiting external knowledge such as evaluation and feedback. To reach the best performance, seekers should estimate her optimal number of solvers based on her experience and all constraints.

To capture the optimal number of solvers, seekers need help from a prediction function. In previous studies, the number of solvers is taken as given. However in an open marketplace with free entry, this number is an emerging result of a two-stage participation process. In the first stage, a combination of initial settings and project characteristics decides how many solvers may subscribe to the contest. We find that a contest with higher award, lower time cost, shorter description, longer duration, more popular expertise will attract more subscribers. Specifically naming projects are the most efficient in attracting solver due to the largest population of potential solvers and low time cost. However ideation based projects with some specific expertise requirement are the most sensitive to award and duration. In the second stage, due to variety of reasons, only part of subscribers will submit a solution. In summary, a contest with lower award, lower time cost will have higher completion rate. Higher award will result lower completion rate, which is not expected by seekers. To mitigate this unexpected impact, a multi-award scheme is applicable, and may be most effective to expertise based projects, but less effective for ideation based projects. However the contest settings have very small impact to the completion rate in the second stage. The completion rate is mainly reflecting some endogenous characteristic of a contest project, such as the general difficulty level.

Finally we find that the marketplace is having over-saturated population of solvers, relative to the number of contest projects. As a result participated solvers may perceive extremely low probability of winning and are unlikely to continue to play in the future.

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Appendix

Work Flow of Online Contests			
Step	Innovation Seekers	Solvers	Marketplace

<p>Posting</p>	<p>Give project description, set number of winners, award amount, open duration (how long the contest will be open to accept submissions); Make full award deposit</p>	<p>Expertise-matched solvers are notified if appropriate new projects are published. Solvers can browse or search for qualified projects.</p>	<p>A specific customer service representative (CSR) is assigned to each contest. The CSR will help list the project in an appropriate category or re-organize the project; Confirm full payment of awards and initiate the contest.</p>
<p>Bidding</p>	<p>Wait for solvers to join the contest. Invite solvers.</p>	<p>Review project, and decide if join the contest. Once joining, solvers can contact seekers by email or private message system.</p>	
<p>Feedback</p>	<p>Provide qualitative feedbacks to preferred submissions.</p>	<p>Submit solutions, get feedback and make improvement. Some solvers fail to submit anything finally.</p>	<p>Undesirable submissions such as totally wrong or empty submissions are eliminated.</p>

Awarding	<p>Choose winners</p> <p>Projects end once the winners are chosen.</p>	<p>Winners receive award.</p> <p>The rest participated solvers can report to the CSR, if any awarding is suspicious. (e.g. the winner is an alias of seeker)</p>	<p>Review the selected winners, checks suspicious report, sends 80% payment(s) to selected winner(s), and transfer IPR to the seeker. 20% award is deducted as profit.</p>
Extending	<p>If a seeker is not satisfied with all submissions, she³ has the option of extending this project for more days by adding awards. Then goes back to step 2.</p>	<p>Go back to step 2.</p>	<p>Evaluate the extension request and extend the project.</p>
Evaluating	<p>Seekers have option to give evaluation feedback to the performance in scales of</p>	<p>Winners can leave feedback to the seeker.</p>	<p>If no feedback is given, and if a winner is selected, the system will create the feedback as “satisfied”</p>

³ In this paper, for convenience of statement, we call a seeker “she”, and a solver “he”.

	negative, neutral or satisfied.		mutually.
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Descriptive Statistics				
Variable	Mean	Std Dev.	Max	Min
Award Amount (¥)	347.95	376.84	5500	50
Time Cost (hours)	7.05	18.49	294.87	0.02
Description Length (char)	1092.59	963.6	12318	10
Contest Duration (days)	22.97	16.08	104	1
Market Maturity (days)	205.92	109.40	421.71	6.48
Number of Subscribers	193.08	443.07	4860	5.0
Number of Solvers	128.26	349.21	4029	5.00
Completion Rate	0.56	0.17	1.00	0.14
Category	Subcategory	Number of Observations		Percent (%)
	Graphic design	1651		67.3

	Naming	208	8.5					
	Website development	160	6.5					
	Software development	123	5.0					
	Creative writing	99	4.0					
	Other types	212	8.7					
Number of Observations	2453							
Correlation Matrix								
Variable	No. Solvers	No. Subscribers	Completion Rate	Award	Duration	Description	Time Cost	Maturity
No. Solvers	1.000	0.964***	0.443***	0.107***	0.289***	- 0.005	- 0.466***	- 0.106***
No. Subscriber	0.964***	1.000	0.192***	0.191***	0.318***	0.005	- 0.402***	- 0.111***
Completion Rate	0.443***	0.192***	1.000	- 0.249***	- 0.011	- 0.036**	- 0.365***	- 0.018
Award	0.107***	0.191***	- 0.249***	1.000	0.299***	0.185***	0.148***	- 0.066***
Duration	0.289***	0.318***	- 0.011	0.299***	1.000	0.097***	0.085***	- 0.094***
Description	- 0.005	0.005	- 0.036**	0.185***	0.097***	1.000	0.051**	0.084***
Time Cost	- 0.466***	- 0.402***	- 0.365***	0.148***	0.085***	0.051**	1.000	- 0.066***
Maturity	- 0.106***	- 0.111***	- 0.018	- 0.066**	- 0.094***	0.084***	- 0.066**	1.000

Notes. The correlations are calculated after natural log transformed. *p <0.1; **p <0.05; ***p <0.001.