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Open Innovation: An Empirical Study of Online Contests

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OPEN INNOVATION: AN EMPIRICAL STUDY 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. By examining large-scale data from an online contest marketplace, we find that a contest with higher award, longer duration, shorter description, lower time cost, and higher popularity will attract more solvers. Specifically simple and ideation based projects are the most efficient in capturing solvers.

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, Proctor 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). In September 2008, Google funded a $10M launch of an open innovation contest. The project was called Project 10^100 and was looking for new ideas. During a 2-month period, Google had received over 154,000 submissions from all over the world. In the future, we expect that more firms will adopt open innovation to mitigate the risks of internal projects and identify solutions from across the globe.

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[1]. 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 will a contest have? How do duration and award impact the contest performance? How should a seeker collaborate with solvers? Our study aims to give answers to these 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. At last we get a prediction model for the emerging number of solvers and shows that a contest with higher award, longer duration, shorter description, lower time cost, and higher popularity will have more emerging solvers. Naming projects, which have low expertise requirement and low time cost, are most efficient in the marketplace. Both duration and project type can moderate the impact of award to number of solvers. Marketplace maturity also matters, although our result indicates that the marketplace we have studied shows negative network effect or negative solver population growth.

The rest of this paper is organized as follows. First, we give an introduction to the process of real world online contests and identify some key differences between online contests and traditional contests. Second, we present our performance model including feedback impact. Next, we develop hypotheses and a model to predict the number of solvers which is a proxy measure of contest performance. Then we test the hypotheses with data. Finally, discussion

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[1] According to Terwisech and Xu's definitions, *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.

and implications are given. Limitations and future research is also discussed.

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 Table 1.

Table 1. Work Flow of Online Contests

Step	Innovation Seekers	Solvers	Marketplace
Posting	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	Expertise-matched solvers are notified if appropriate new projects are published. Solvers can browse or search for qualified projects.	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.
Bidding	Wait for solvers to join the contest. Invite solvers.	Review project, and decide if join the contest. Once joining, solvers can contact seekers by email or private message system.	
Feedback	Provide qualitative feedbacks to preferred submissions.	Submit solutions, get feedback and make improvement. Some solvers fail to submit anything finally.	Undesirable submissions such as totally wrong or empty submissions are eliminated.
Awarding	Choose winners Projects end once the winners are chosen.	Winners receive award. The rest participated solvers can report to the CSR, if any awarding is suspicious. (e.g. the winner is an alias of seeker)	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.
Extending	If a seeker is not satisfied with all submissions, she[2] has the option of extending this project for more days by adding awards. Then goes back to step 2.	Go back to step 2.	Evaluate the extension request and extend the project.
Evaluating	Seekers have option to give evaluation feedback to the performance in scales of negative, neutral or satisfied.	Winners can leave feedback to the seeker.	If no feedback is given, and if a winner is selected, the system will create the feedback as “satisfied” mutually.

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

Due to distinct differences between the online world and offline world, the same application may be executed differently. For instance, Gregg and Walczak (2003) have identified the features of online auctions which are different from traditional auctions, such as user's information retrieval behavior, bidding behavior and etc. Similarly, by comparing with traditional contests, we have identified three 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. Those solvers whom enter the process later, may perceive less probability of winning than early entered solvers, and may be less likely to enter the contest. As a result, the final number of solvers is an emerging result of a natural selection process.
2. Submission observability. Previous studies assume that all submissions are unobservable to competitors. However, in many marketplaces such as TaskCN and TopCoder, nearly all submissions are open to public. One obvious incentive for marketplace to do so is to make the site more attractive to new seekers.
3. 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. Qualitative feedback appears to encourage solvers to contribute more efforts. As a result, the contest performance can be improved.

These differences make our research background significantly different from previous studies.

Modeling Online Contest

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:

$$V = \rho \max_{i=1,\ldots,n}\{v_i\} + (1-\rho)\frac{\sum_{i=1,\ldots,n} v_i}{n}, \qquad (1)[3]$$

where $0 \le \rho \le 1$. 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 $i=1\ldots n$. The performance of solver i is given in linear format:

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

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

[3] 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.

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.

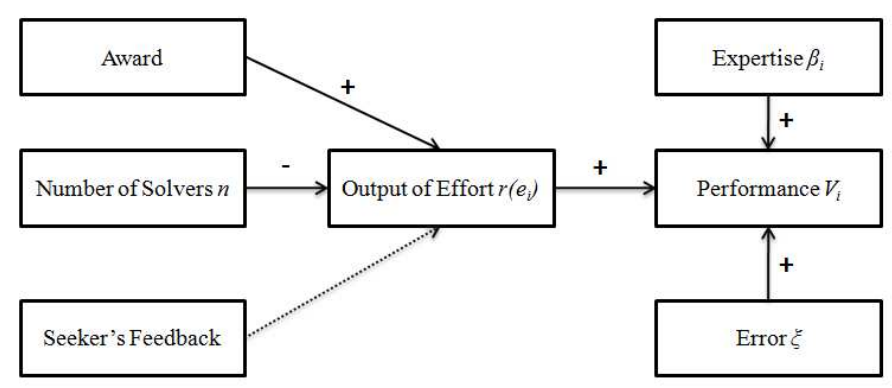

Figure 1. Individual Solver's Performance Model without Feedback

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 (as shown in Figure 1).

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.

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 2). 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:

$$r = r(\vec{e}_i) = r[e_i(fe_i, n), fit_i(fe_i)] \quad (3)$$

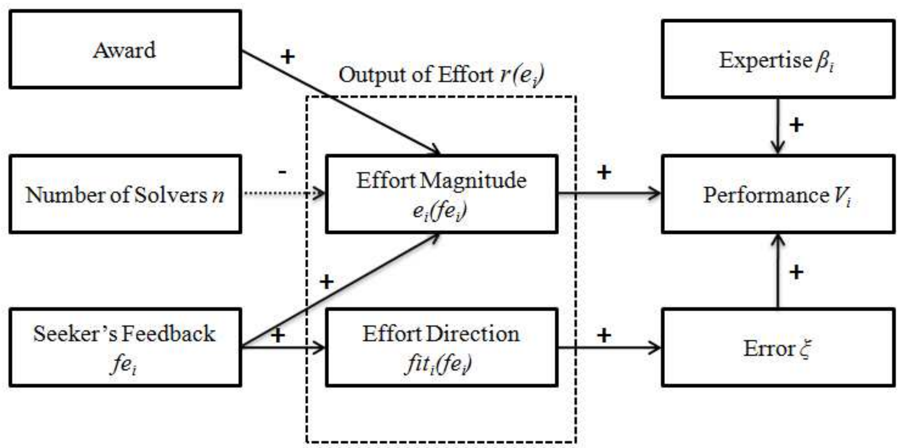

Figure 2. Individual Solver's Performance Model with Feedback

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. Finally equation 1 suggests that the overall performance of a contest can be simply measured by counting number of solvers of the contest. Since this performance is based on assumption that overall feedback effort $\sum fe_i$ can maximize all preferred solvers' effort which is an ideal situation, we call it *potential performance* V_p, which is always not lower than *real performance* V. So we have:

$$V_p = Number\ of\ Solvers \geq V \quad (4)$$ [4]

By reviewing our one-stage contest process with feedback impact, the contest is more like a two-stage one. At the first stage, solvers submit initial submissions. At the second stage, the seeker will send feedbacks to preferred solvers and these solvers are competing in the second round.

The emerging number of solvers now is a proxy measure of contest performance. We are interested to know how this number is impacted by contest settings and project characteristics such as award, duration, time cost and etc. Especially considering the limitation of a seeker's capability, attracted solvers are not always the more the better, so

[4] This equation is also based on the assumption that expertise distribution in constant.

seekers may be interested to know how to predict this number with limited resources. Next we are going to develop a prediction model for the emerging number of solvers.

Prediction Model and Hypotheses

In order to develop a prediction model, we consider all the potential independent variables that a seeker may know or control before launching a contest, including award, contest duration, time cost, project description, and etc. 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 numbers of contests to enter. So contest projects are competing with each other in the same pool. To capture more solvers, a seeker should make her contest more competitive than other contests. Whether a project is more competitive can be explained by switching cost theory (Klemperer1995, Chen and Hitt 2005, and etc). Switching cost theory has been widely used to analyze the competitive power of firms or products. 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 lowest switching cost. 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. Switching cost theory suggests that higher award provide better compensation to the transaction cost or production time cost, thus the switching in cost is lower, and should be able to attract more solvers. It is also found that in a reverse auction, higher value will attract more solvers (Snir and Hitt 2003). So we have:

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

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

Hypothesis 2: A contest with higher time cost will attract fewer solvers.

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

Hypothesis 3: A contest with longer description will attract fewer solvers.

The learning cost of a contest 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 join 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 solvers. So we have:

Hypothesis 4: The project type of a contest will impact number of solvers.

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. To our knowledge, no contest study has paid attention to this variable. Snir and Hitt (2003) consider duration effect in their reverse auction study and find that with longer duration an auction can attract more solvers. Similarly, a contest with longer duration will has exposure to more potential solvers. Thus, we expect more solvers in a contest with longer duration. So we have:

Hypothesis 5: A contest with longer duration will attract more solvers.

Marketplace maturity is the overall age of a specific marketplace. The maturity of marketplace may also impact the number of solvers. It captures the changes in market structure over time, such as positive network effects and growth in the solver population. Snir and Hitt (2003) also find this variable can impact the number of bidders of online auctions. So we have:

Hypothesis 6: Marketplace maturity can impact number of solvers that a contest can attract.

Except above main effects, we are also interested in some interaction effects. We want to know whether duration can moderate the award main effect such as whether a higher award with longer duration can attract even more solvers. So we propose:

Hypothesis 7: a contest with higher award and longer duration will attract more solvers

Category represents project types, and it also captures the common features of a bunch of projects. For instance, naming projects are usually easier and less time consuming than other types of projects, so naming projects should be more sensitive to award or duration than other types of projects. We are interested to know which types of projects are most sensitive to award and duration. So we have:

Hypothesis 8: different types of projects response different to award.

Hypothesis 9: different types of projects response different to duration.

All above hypotheses are shown in Figure 3.

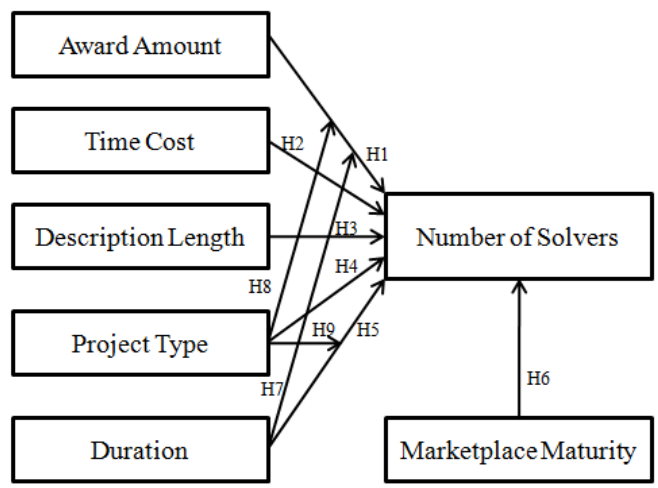

Figure 3. Research Model for Number of Solvers

Data and Measurement

Data Collection

The unique aspect of our analysis is the opportunity to evaluate large-scale data of open innovation contests in the real world. 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 pursing 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.

  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. So we choose naming category as our reference category.

  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.
- *Marketplace 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.

The dependent variable *Number of Solvers* is directly available from the website. We use the natural log of this variable. The descriptive analysis and correlation matrix is given in Table 2.

Result and Analysis

Model

All variables are skewed, so we have them natural log-transformed. Also with natural log transforming, we can capture the higher order behaviors of variables. Since some hypotheses are for the interaction effects related to categorical variables, we test the hypotheses with two regression models. In model 1, we only keep main effects. In model 2, we include interaction terms. The interaction terms with category have included the main effects of award and duration in each category, so we don't list the main effect of award and duration in model 2.

Model 1:

$$Ln(No.SOLVERS) = \beta_0 + \beta_1 Ln(AWARD) + \beta_2 Ln(TIME\ COST) + \beta_3 Ln(DESCRIPTION) + \beta_4 CATEGORY + \beta_5 Ln(DURATION) + \beta_6 Ln(MATURITY) + \xi$$

Model 2:

$$Ln(No.SOLVERS) = \beta_0 + \beta_2 Ln(TIME\ COST) + \beta_3 Ln(DESCRIPTION) + \beta_4 CATEGORY + \beta_6 Ln(MATURITY) + \beta_7 Ln(AWARD) * Ln(DURATION) + \beta_8 Ln(AWARD) * CATEGORY + \beta_9 Ln(DURATION) * CATEGORY + \xi$$

where *No. SOLVERS* is the number of solvers that have been attracted by a contest; *AWARD* is the award amount for a contest; *TIME COST* is the production time cost defined in time cost measurement. *DESCRIPTION* is the description length of a contest; *CATEGORY* is a categorical variable to indicate the project type of each contest; *DURATION* is the contest duration of each contest. ξ is a random error.

Table 2. 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
Number of Solvers	128.3	359.36	4029	5

Category	Subcategory	Number of Observations	Percent (%)
Category	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	Award	Duration	Description	Time Cost	Maturity
No.Solvers	1.000	0.107***	0.289***	-0.005	-0.466***	-0.106***
Award	0.107***	1.000	0.299***	0.185***	0.148***	-0.066**
Duration	0.289***	0.299***	1.000	0.097***	0.085***	-0.094***
Description	-0.005	0.185***	0.097***	1.000	0.051*	0.084***
Time Cost	-0.466***	0.148***	0.085***	0.051*	1.000	-0.066**
Maturity	-0.106***	-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.

Results and Analysis

We use software SAS 9.2 to do our regression analysis. For categorical term, naming category is used as our reference category. With data collected from the marketplace, two models are tested and the results are summarized in Table 3.

Table 3. Regression Results

Variable	Coefficient	Main Model	Interaction Model
Constant	β_0	5.307***(0.153)	6.075***(0.535)
Ln(AWARD)	β_1	0.278***(0.019)	--
Ln(TIME COST)	β_2	-0.363***(0.014)	-0.361***(0.014)
Ln(DESCRIPTION)	β_3	-0.028* (0.013)	-0.029* (0.013)
CATEGORY	β_4		
• *Graphic Design*		-2.461***(0.058)	-2.451*** (0.400)
• *Naming*		0.000	0.000
• *Website Development*		-3.137***(0.079)	-3.627***(0.547)
• *Software Development*		-3.425***(0.083)	-3.145***(0.530)
• *Creative Writing*		-2.530***(0.087)	-3.714***(0.631)
• *Other*		-2.669***(0.071)	-2.196***(0.477)
Ln(DURATION)	β_5	0.269***(0.019)	
Ln(MATURITY)	β_6	-0.159***(0.017)	-0.156***(0.017)
Ln(AWARD)*Ln(DURATION)	β_7	--	0.050* (0.023)
Ln(AWARD)*CATEGORY	β_8	--	
• *Graphic Design*			0.141* (0.070)
• *Naming*			0.161* (0.101)
• *Website Development*			0.265** (0.095)
• *Software Development*			0.067 (0.094)
• *Creative Writing*			0.215* (0.115)
• *Other*			-0.028 (0.086)
Ln(DURATION)*CATEGORY	β_9	--	
• *Graphic Design*			-0.019 (0.127)
• *Naming*			-0.040 (0.129)
• *Website Development*			-0.096 (0.149)
• *Software Development*			0.018 (0.131)
• *Creative Writing*			0.274* (0.147)
• *Other*			0.133 (0.133)
Number of observations	2453		
R^2		0.675	0.680

Notes. Dependent variable—Ln(Number of Solvers). Standard errors in parentheses.
*p <0.1; **p <0.05; ***p <0.001.

Regression result of model 1 shows that award has positive impact to number of solvers. Thus hypothesis 1 is supported. β_2 and β_3 are significant and negative in both regression results, which means longer project descriptions and more time consuming projects will have fewer solvers. Thus hypothesis 2 and 3 are supported. The coefficients of categories are all significant. So project types influence the number of solvers, which is consistent with hypothesis 4. Especially naming category has the highest positive coefficient, which suggest that naming project or simple ideation project is the most efficient in capturing solvers in the marketplace. Complicated projects such as website development and software development are capturing fewer solvers than other projects. The result of model 1 shows that β_5 is significant and positive, which means longer duration can help to capture more solvers, so hypothesis 5 is supported. β_6 is significant, which means the marketplace maturity also influences the number of solvers. However the negative sign shows that this marketplace doesn't have positive network effect or solver population growth. β_7 is significant and positive, which tells that longer duration contest with higher award can attract more solvers, so hypothesis 7 is supported. β_8 is mostly significant except for category software development and "other" category. The two exceptional categories don't have many projects, so the insignificance may be due to small sample size. β_8 is measuring the award sensitivity of projects in each category. It's surprising to see that β_8 for naming category is not the highest, although the main effect of naming category is stronger than any other category. This is out of our expectation. This result suggests that naming projects are the most efficient in capturing solvers is due to its largest solver population and low time cost, not because of its award sensitivity. The result shows that website development and creative writing are actually the most award sensitive types. β_9 is mostly not significant, so hypothesis 9 is not supported. That means duration effect is not different between categories.

Both models explain about 68% variance of number of solvers. Model 2 can help us to understand more details, but for prediction purpose these two models are almost the same. We summarize all valid hypotheses and the feedback impact to performance in Figure 4.

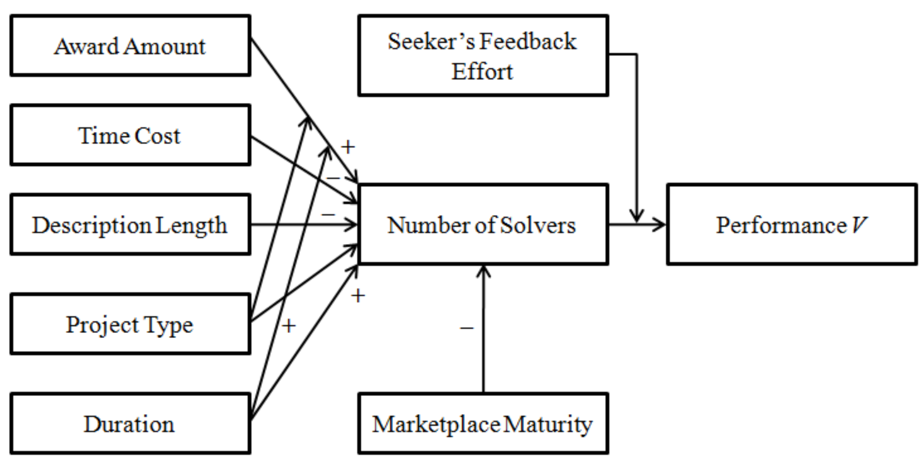

Figure 4. Online Contest Performance Model

Discussion and Conclusions

Open innovation is a very 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. To lift the veil of real world online contests, we have studied a large online marketplace and examined several variables which may impact the potential contest performance with field data. 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 we observe that the participation of an online contest is usually a dynamic process. 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 impact of feedback, these contests are more like two-stage ones. At first stage, solvers submit initial submissions. At 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 each 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 in order to do that, it's better for seekers to send feedback to each solver privately.

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.

Actually, the number of solvers itself is very interesting. In previous studies, this variable is usually taken as a given number. In an online marketplace, this number is an emerging result of a series of initial setting and project characteristics. With more solvers entering, the later players perceive less probability of winning until no incentive to join, thus the emerging number of solvers is finally balanced by some constraints. Besides, considering the limitation of a seeker's capability, attracted solvers are not always the more the better, so seekers may want to control the solver population by changing settings of contests. All these are calling for a prediction model for emerging number of solvers. Finally we find that a contest with higher award, lower time cost, shorter project description, longer duration and higher popularity will capture more solvers. If a seeker is short of budget, she can get more solvers by extending the duration. Both duration and project type can moderate the impact of award to number of solvers. However duration impact to each category doesn't show significant difference. Surprisingly the most award-sensitive project types are website development and creative writing, not naming. Naming projects are the most efficient in capturing solvers because they are the most popular projects to heterogeneous solvers. Maturity of marketplace can also impact the emerging number of solvers. How it will impact is depending on the marketplace network effect and user population growth. To innovation seekers, if they are targeting diversified and creative ideas, they should try their best to make the project easy enough to allow any solvers enter.

Limitations and Future Research

There are several limitations for this study. First, most of our observations are having small amount of award, comparing to the projects of InnoCentive. TaskCN and several other marketplaces require seekers to deposit full award in advance and the award is never-refundable. This policy gives solvers guarantee that they will be paid if win, so it is embraced by solvers. However, under this payment policy, seekers will have to bear the risk of failure, even for receiving no submission. As a result, seekers are not willing to launch cutting-edge and high value projects in this kind of marketplaces due to high risk. Unfortunately, the cutting-edge and high value innovation projects are the most important ones to large firms and most profitable ones to marketplace owners. How to get a tradeoff between solver's benefit and innovation seekers by designing appropriate payment policies for different types of projects is an interesting question for future research.

Another limitation of our study is the assumption of constant expertise distribution in all contest projects. This assumption is widely used by previous studies. However whether it is hold in real world is not clear. In a reverse auction study, Snir and Hitt (2003) find that higher value projects will attract higher proportion of low skilled solvers. Whether the expertise impacts solvers' choices of solvers is also an interesting question.

We find that longer duration can attract more solvers. However, being different from reverse auction, duration of contest clearly tells the solvers how long it will take before they may receive the award if they make submission immediately. A reward comes after executing effort will bring two problems: procrastination (Akerlof 1991) and delayed award discounting (Green and Myerson 2004). Procrastination theory suggests that longer duration will make high procrastinating solvers do the project later, which is not expected by the seekers. Discounting theory suggests that longer duration will make solvers perceive lower incentive, which is also not expected by the seekers. How to mitigate the procrastination due to longer duration is an interesting question. Also how duration discounts solvers' perceived value of award is very interesting. The answer to this question may tell the optimal setting of contest duration.

Giving the existing marketplaces are still very young, it's hard to foresee how such kind of marketplaces will evolve in the future. Any change in pattern or rules can make the contest process different.

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