Information Spillovers and Strategic Behaviors in Open Innovation Crowdsourcing Contests: An Empirical Investigation

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Abstract

Designing optimal contests is crucial to the success of online crowdsourcing markets that seek to attract a diverse crowd of high quality participants. While there has been some theoretical work examining the design of different types of contests, there are hardly any empirical studies on the effectiveness of different types of contests for crowdsourcing. This study analyzes data from a large online crowdsourcing market for design tasks, to examine the strategic behavior of participants faced with a trade-off between two competing forces in open innovation contests. Open innovation contests typically, make information about contestants and their submissions visible to all participants, thereby allowing later contestants to imitate or learn from earlier entries, favoring later submissions. On the other hand, early entries are more likely to get valuable feedback from the contest holder – feedback that can help these early entrants to significantly revise their solutions and resubmit. Timing of entry, thus, becomes an important strategic choice for contestants. Our findings show that open innovation contests are subject to significant informational spillovers relating to submissions that benefit later entrants. More interestingly, we find that the benefits of informational spillovers from feedback provided to early entries depend on the type of feedback provided. We contrast these findings with the outcomes of blinded contests that prevent informational spillovers. Our findings have interesting implications for the design of innovation contests, as well as for market makers, and for contest holders in online crowdsourcing markets.

1. Introduction

The ability of online markets to efficiently bring together individuals and businesses has redefined and transformed traditional ways of conducting business. More recently, there has been an explosion of new business models that leverage online interactions and the "wisdom of the crowds". In particular, firms have increasingly begun to leverage online crowdsourcing marketplaces to seek solutions to business problems as well as to undertake research – activities that were traditionally performed within the boundaries of the organization. Lego, for instance, encourages its most fanatical customers to redesign its famous sets (Rodgers, 2011). Other big corporations such as Dell, have turned customer complaints into increased profit margins by tapping the crowd for solutions to their problems (Bensen, 2013). An important objective of these crowdsourcing markets is to attract high quality solvers, and to obtain good, diverse solutions (Terwiesch & Ulrich, 2009; Terwiesch & Xu, 2008). The effectiveness and success of a crowdsourcing marketplace depends largely on the market's ability to not only incentivize participants to submit high quality solutions, but also deter strategic gaming by the participants.

Most online crowdsourcing markets use "contests", with anonymous users ("the crowd") submitting solutions to the contest holder's problem and competing for prize money. Contest design plays a crucial role in the success of the marketplace. It is widely recognized that contestants' incentive to exert effort depends largely on the competitive environment as defined by the rules of the contest. While offline and online contests share a number of similarities, a key characteristic of several online contests is the increased availability of information – in particular, information relating to other contestants. Two broad categories of contests are popular in online crowdsourcing markets – open contests, wherein information about other contestants are made visible to all participants, and closed (also known as blind) contests, wherein the visibility of such information is limited. Open contests in particular, such as the one used in the marketplace we study, make information about a contestant as well as her submissions visible to all other contestants. While this encourages greater participation, open contests also suffer from a number of drawbacks.

Participants in these online crowdsourcing markets are faced with a number of strategic choices – an important choice being the order of submission or timing of entry in a contest. While early movers (i.e., contestants who submit early) may enjoy some benefits and also be able to deter entry of later contestants, late movers might benefit from their ability to learn from early entrants. However, another critical feature of online innovation contests is the provision of feedback to contestants by the contest holders. Given the uncertainties surrounding the contest holder's requirements and tastes, feedback provided by the contest holder on the submissions can be very helpful to the contestant in refining their solutions. In particular, early submissions have a higher likelihood of obtaining valuable feedback that can help early entrants to refine and resubmit their solutions. While early entrants are more likely to benefit from feedback provided on their submission, the visibility of such feedback information to all contestants can provide later entrants valuable information that increases their chances of winning the contest. Poorly designed contests can dissuade potential submissions, while well-designed contests that deter strategic gaming by participants and can stimulate participation and growth of online crowdsourcing markets. Understanding how informational spillovers in open innovation contests impact the entry behaviors of contestants and their likelihood of winning can provide valuable insights into the effectiveness of open innovation contests.

This study analyzes data from a large online crowdsourcing market for design to examine the strategic behavior of contestants and their impact on outcomes. The marketplace we study allows individuals or businesses to setup contests for the design of logos, graphics, and websites. Contestants are usually individual designers who compete to provide solutions, with the winner being financially rewarded. The marketplace uses two types of contests (a) an open contest, where all submissions by contestants as well as the associated feedback provided by the contest holder are visible to all the participants, and (b) a blind contest, where information about a submission is not available to other contestants. The presence of these different types of contests enables us to study the role of informational spillovers relating to submissions as well as feedback on the strategic entry decisions of contestants as well as its impact on their likelihood of winning.

More specifically, we seek to investigate the following questions.

1) *How do informational spillovers relating to submissions (i.e., the ability to see earlier submissions) influence a focal contestant's behavior (timing of entry) and her likelihood of winning?*
2) *How do informational spillovers relating to feedback (i.e., the ability to see the feedback provided by the contest holder to earlier submissions) influence a focal contestant's behavior (timing of entry) and her likelihood of winning? Further, how does the type of feedback (specific versus generic) impact these outcomes?*

We find that contest design, particularly relating to information visibility, significantly influences contestant's behavior as well as outcomes. Both early submissions as well as late submissions are more likely to win a contest compared to submissions at other times during the contest. In examining the impact of informational spillovers relating to the submissions, we find that late submissions are more likely to win in open contests. However, in blind contest where there are no informational spillovers and when no feedback is provided by the contest holder, there are no specific submission times that perform better than others. Only a contest holder's expertise, experience, and skill are associated with her likelihood of winning the contest. We also find evidence of informational spillovers relating to feedback. Interestingly, in both open as well as blind contests, when feedback is provided by the contest holder to contestants, we find that early submissions are more likely to win, particularly when these early contestants make a resubmission.

We also find that the benefits from informational spillovers differ depending on the type of feedback provided by the contest holder. In open contests with feedback, the more specific the feedback given to others in a contest, the higher the chances of late submissions winning the contest. However, in blind contests where users cannot see each other's submissions, specific feedback given to a contestant does not benefit other contestants, while generic feedback increases the likelihood of late submissions winning the contest.

Finally, in examining the role of skill, experience, and expertise, we find that in the case of open contests, contestants with high skill, experience, or expertise that submit late are more likely to win. However, in the case of blind contests with feedback, we find that high skilled contestants who submit early are more likely to win.

Our findings suggest that contestants in these markets strategically time their submissions to increase their chances of winning the contest. Interestingly, it is the contestants with higher skills, experience, and expertise that are more likely to act strategically and win the contest. Our results have interesting implications for the design of innovation contests. While feedback provided by the contest holder to a contestant could benefit that contestant, we find that when this feedback is very specific, the informational spillovers are higher and other contestants that submit later tend to benefit from such feedback. Such information spillovers might not be detrimental to the contest holder; however they could discourage contestants from participating in such open contests. While informational spillovers relating to submissions as well as feedback could help later contestants converge to a winning solution more quickly, they could have an unintended side effect of reducing variety. Blind contests, on the other hand, could promote greater variety by reducing information spillovers from earlier submissions.

Our study makes a number of contributions. It is one of the first studies to examine the role of informational spillovers in open innovation contests and the consequences of such informational spillovers. Using data on open as well as blind contests with and without feedbacks, we are able to tease out the differing impacts of informational spillovers relating to submission and feedbacks. While a few recent studies have examined the role of the feedback process on the idea generation (Wooten et al., 2011), this is the first study to identify the effects of informational spillovers that occur when such feedback is made visible to other contestants. Our study also contributes to the vast stream of research in marketing, economics, and strategy on the role of timing of entry and its implications for market outcomes. Most of the studies examining the timing of entry of market participants examine the strategic behavior of firms. This study is among the first to examine strategic entry behavior of individuals in a decentralized marketplace. Finally, and most importantly, this study contributes to the emerging literature on online crowdsourcing markets and the design of online contests.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the research context and Section 4 describes the data and methodology. The results are presented in Section 5. Section 6 discusses the implications of the study. Section 7 describes the limitations and future research.

2 Related Research

This study draws upon research relating to the optimal design of contests, the timing of entry of competitors, and the impacts of information spillovers.

2.1 Design of Contests

Most of the work relating to contest design is analytical in nature. Prior work has examined a number of contest-related factors to examine their impact on outcomes. One stream of literature (see for instance, Kalra and Shi, 2001, Glazer and Hassin, 1988, Moldovanu and Sela, 2001, and Liu et al., 2007) has focused on the optimal prize structure, including how many prizes should be offered and how the total award should be allocated among them. Researchers (see for instance, Gradstein and Konrad, 1999, and Baik and Lee, 2000, Fu and Lu, 2006) have also examined the design of an optimal contest that generates the highest revenue, as well as contest structures that maximize the effort exerted by contestants.

While there is a growing body of theoretical research examining the impact of different contest parameters, empirical research on the impact of contest design is scant, and has been limited to examining the impact of prize on effort exerted. For example, Maloney and McCormick (2000), analyze responses of individual runners to different prizes, and find a significant relation between the performance and the prize value and that higher prize values are associated with higher effort levels. Lynch and Zax (2000) examine data on road races in the United States and find that the larger prize spreads produce better performance not because they encourage all runners to run faster but because they attract faster runners. A recent experimental study by Sheremeta (2011) compares the performance of four simultaneous lottery contests and the effort levels exerted. Most of the empirical studies of contest design focus on contests in offline settings. An exception is a recent study by Huang et al. (2012), where the authors examine the effect of incentive prize structure design of online crowdsourcing contests on the solutions produced by the crowd. They find that participants exert less effort as competition for the prize increases, indicating that the prize may adversely affect the quality of the solutions produced by the crowd.

While the "prize structure" as well as the "contest structure" are important determinants of a number of outcomes of interest, there are hardly any studies that have examined the differences in "information structures" – in particular, information visibility – within contest and their impacts on outcomes. This study is among the first to empirically examine the role of different information visibility regimes on the behavior of contestants as well as contest outcomes in online settings.

2.2 Timing of Entry

There is substantial theoretical and analytical research that highlights the importance of timing of entry for market participants (for instance see, Lieberman & Montgomery, 1988; Urban & Star, 1991). First movers, for instance, have been shown to deter entry of later entrants by locking in consumers (Lieberman & Montgomery, 1988; Klemperer, 1987; Dewan et al., 2003; Lee & Grewal, 2004). Other studies have explored additional benefits of early entry including the evidence of scale effects (Rao & Rutenberg, 1979), experience effects (Smiley & Ravid, 1983), asymmetric information about product quality and risk averse buyers (Conrad, 1983), and reputational effects (Bain, 1956; Krouse, 1984), among others. In contrast to these studies of early mover advantages, other studies find that late movers have an advantage when they can lower their uncertainty and costs by learning from the experiences of early movers (Reinganum, 1981; Fudenberg & Tirole, 1985; Dutta et al., 2005; Hoppe, 2000; Hoppe & Lehmann-Grube, 2004). The main disadvantage of pioneers is that it is generally more costly to be a pioneer than to be an early follower or a late entrant since product innovation tends to be more costly than product imitation (Mansfield et al., 1981; Levin et al., 1987). Other studies have explored how a later entrant can diminish the impact of the first movers by moving away from the first mover, and by developing a more desirable position (Carpenter & Nakamoto, 1989; Hauser & Shugan, 1983).

Findings of empirical studies examining the impacts of timing of entry are mixed (for reviews of empirical findings see, Kerin et al., 1992; Robinson et al., 1994; Kalyanaram et al., 1995; Zahra et al., 1995; Mueller, 1997; Lieberman & Montgomery, 1998). While some studies (for instance, Robinson and Fornell, 1985, Robinson,1988, Lilien & Yoon, 1990; Cooper, 1979; Parry & Bass, 1990) have found support for first mover advantages, others (for instance, Shankar, Carpenter and Krishnamurthi, 1998, Huff and Robinson, 1994, Kalyanaram & Wittink, 1994, Brown & Lattin, 1994, Sullivan, 1992, Mascarenhas, 2006) have found support for later mover advantages. Most of this empirical research on timing of entry to market has been limited to offline settings and have focused on the firm as the primary unit of analysis.

More recently, there has been growing number of empirical studies on timing of entry of individual participants in online auction marketplaces. Studies on online bidding behavior suggest that early and late bidding could affect outcomes in opposite ways leading to opposing conclusions. On the one hand studies have found that a significant amount of bidders bid early in the auction (Bajari & Hortacsu¸ 2003; Hasker et al., 2004), while on the other, studies have found that a substantial fraction of bidders submit their bids towards the end of an auction (Ockenfels & Roth, 2002, 2006; Roth & Ockenfels, 2002). Early bidding can lower a bidder's cost of searching for alternatives, at the same time making other competitors less interested in competing (Vadovic, 2009). On the other hand, late bidding is considered to be a best response strategy at times for informed bidders to protect their information (Roth & Ockenfels, 2002) and prevent learning (Nekipelov, 2007).

Despite the recent growth of crowdsourcing marketplaces, little attention has been paid to timing of entry in online crowdsourcing contests. The findings from a few recent studies have shown mixed results. Archak (2010) examines a crowdsourcing software development website TopCoder.com, and finds that high rated contestants face tougher competition in the contest phase. Yet they strategically play Stackelberg leaders in the registration phase of the contest by committing early to particular projects, thus deterring entry of opponents to that contest. Yang et al. (2011) use Taskn.com to show that winners are more likely to be those who submit early or later during the submission period as opposed to those submit in the middle.

Thus far most of the empirical research examining timing of entry has been at the firm level of analysis and in offline settings. Our study is among the first to empirically examine the impact of different information visibility regimes on individual contestants' timing of entry and their related outcomes in an online crowdsourcing marketplace.

2.3 Information Spillovers

The impact and value of information spillover or information externalities have been examined in wide variety of fields, including economics, IT and finance. There are various strands of research relating to information spillover in different literatures; however, the main idea is that the lack of information about some essential variable that is of public interest can be compensated for, at least partially, by looking at what other similar agents do. For example, if the information that is privately available to agent A to form his decision has some value for agent B (a neighbor of A) the observation of A's actions can help B make a better decision since A's actions will partly reveal his information.

In general information spillover occurs when each agent has some private piece of information which, if combined with the others' would increase the information available to each about some relevant common variable. If pooling is ruled out, each agent's private information will be embedded in his decisions. The other agents' choices become an alternative source of information. As a consequence, individual agents' decisions are affected both by their private information and by other agents' actions. Specifically, private information spills over through individual actions. In an open innovation contest, information about the taste of the contest holder is a key variable of interest for all contestants. Visibility of certain information can provide insights into the taste of the contest holder which can be harvested by each contestant.

Most of the work relating to information spillovers is analytical in nature. Prior theoretical work has examined how information spillover occurs, and how it affects related outcomes of interest. Given the nature of information spillover, it is hard to empirically isolate and test for information spillovers (Chang & Gurbaxani, 2012). Consequently, empirical studies have been scarce and most are experimental studies conducted in offline settings. Cheng and Nault (2007) focus on industry-level spillover benefits that result from IT investments made by upstream industries. Chang and Gurbuxani (2012) examine the effects that result from IT related spillovers on firm level productivity. Experimental studies, mostly in the finance, have found that the disclosure of information about a firm presented in different ways affects the valuations and trades of investors and even experienced financial analysts (Hirst & Hopkins, 1998; Dietrich et al., 2001; Hopkins et al., 2000). There is also evidence that individuals fail to make use of all publicly available information (Lipe, 1998).There is other evidence suggesting that investors' and analysts' assessments are influenced by the format and salience with which public signals are presented (Hand,1990).

Thus far research on information spillovers has been largely theoretical, and the few empirical studies conducted in offline settings have focused on industries or firms. Our study extends this stream of research by examining information spillovers at the individual level in an online crowdsourcing marketplace.

3 Research Context

In this study we use data from a large crowdsourcing contest design marketplace to examine the role of information externalities and their impact on the strategic behavior of participants. The community is a design crowdsourcing website where contests are held and users submit logos or website designs.

The following section describes the process of the contest.

3.1 Contest Launch

To launch a contest, a contest holder provides the following information:

- Contest Prize (the marketplace used in this study has a minimum prize of $299).
- Design Description. The contest holder needs to provide project details, which usually includes the objective, slogans, and any other information sought by the contest holder.
- The contest type, whether open or blind. Blind contests are contests where the submitted solutions (i.e., logos) are not visible to anyone in the contest except to the contest holder. Open contests are contests where the submissions are visible to all contestants.
- The contest can then be launched and displayed in the design marketplace. Logo designs contests are open for 7 days. The contests are displayed based on their ending dates.

3.2 Submissions

Designers (contestants) who wish to enter a contest view and evaluate the contest. Figure 1 illustrates how contests are displayed in an open design contest. Designers can view several contests, the type of the contest (open or blind), the title of each contest, the end date, the number of entries, the prize amount, the contest holder, and details about the contest and contest holder. Figure 2 displays the publicly available information about the contest holder. Users can not only view current open contests of a contest holder, but also see a contest holder's past activity such as the total contests held, total prizes awarded, and average feedback. Users can obtain more information on the contest requirements by viewing the design brief as shown in Figure 3. In addition, users are able to see the current submissions in a contest. Figure 4 shows submission entries of contestants along with the star feedback given by the contest holder. Users are able to obtain additional information on contestants by clicking on their profiles. Figure 5 displays a contestant profile, which lists the total contests entered and won by the contestant, as well as her portfolio of designs.

Designers can submit a solution at any time before the end of the contest. If the contest is open, designers can see the submissions of other contestants; however, if the contest is blind, designers cannot see the submission of other contestants. A key decision for a contestant is when to submit, (that is, early or late in the contest). Figure 6 shows the submission order frequency during the lifetime of the contests.

3.3 Feedback

After contestants begin submitting solutions, the contest holder is encouraged by the community to send feedback to solvers about their solutions by communicating her average feedback % score. A contest holders average feedback (%) score depends on the amount of feedback given in previous contests. Feedback by a contest holder to contestants is through (a) star rating of one to five stars, and (b) text feedback. Contestants usually prefer to submit improved solutions after receiving feedback. Although the community encourages feedback there are quite a large number of contest holders that do not provide any feedback. Figure 7 displays the text feedback frequency, and Figure 8 shows the star feedback frequency. On average, both figures show that feedback is primarily given at the early stages of the contest timeline, decreasing in frequency towards the end of the contest.

3.4 Announcing the Winner

Once the contest duration ends, the contest holder then announces a winner who is awarded the prize.

4. Data and Methodology

We collect data in 3 time periods, namely (a) Nov 2010, (b) April 2011, and (c) Nov 2011- Oct 2012. The sample is composed of 3,893,221 designer participations (or submissions) in 16,645 contests. 13,225 are open contests (of which 6091 have feedback and 7134 do not), and 3420 are blind contests (of which 2417 have feedback and 1003 do not). Table 1 lists the variables and their descriptions. Table 2a reports the descriptive statistics of the variables used in this study. On average, contest holders have held around 3 contests, have awarded around $718, and have provided an average of 70% feedback. Contestants on average have been on the crowdsourcing community for around 422 days, have an average of 13 wins, and have entered an average of 287 contests. Contests on average have 211 entries, 69 designers, and a prize of $517.

Table 2b reports the descriptive statistics of the variables in terms of the different contest designs and information regimes - namely, (a) open contests with feedback, (b) open contests with no feedback, (c) blind contests with feedback, and (d) blind contests with no feedback. Table 2b shows that on average, there are more submission entries for open contests with feedback (267) than for open with no feedback (228), and fewer for blind contests (197, with feedback, and 151, with no feedback). A similar pattern is also seen in terms of the number of designers. Furthermore, in all contest designs, on average early submitters (defined as the first 20 percentile of submissions) have the highest number of resubmissions. In addition, for open contests, the averages reported for late submitters in terms of skill is higher than the averages reported for early and middle submitters. Yet for blind contests, the averages reported for early submitters in terms of skill is higher than the averages reported for late and middle submitters. The reported averages suggest that contestants with different skills are likely to have different entry times.

4.1 Variables

The following sections describe the variables used in this study. The data is in panel form and the unit of analysis is the contestant *i* in contest *t*.

4.1.1 Dependent Variable

The main dependent variable in this study is a binary variable *winner_dummy*, indicating whether or not the contestant *i* won the contest *t*.

4.1.2 Independent Variables

To examine the impact of information spillover on contestant time of entry and contest outcome, we explore the following categories of explanatory variables related to the contestant *i* in contest *t*: (1) Submission order, (2) Feedback to others in a contest, (3) Direct feedback to a contestant, (4) Resubmissions, and (4) Expertise and past experience.

To capture timing of entry behavior we measure c*_suborder*, the order of the first submission of a contestant *i* in contest *t*, along with submission order squared *c_subOrder2* to capture any late strategic behavior.

Feedback by a contest holder to a contestant is provided through stars or text. Both types of feedback (stars and text) are visible to others in a contest. To capture information spillovers of star feedback given to others, we measure the following metrics (a) *c_maxstar_prior:* the maximum star rating given in a contest *t* at the time of entry of a contestant *i*, (b) *c_avgstar_prior:* the average star rating given in a contest *t* at the time of entry of a contestant *i*, and (c) *c_ttlnumuserswithstars_prior:* the total number of users that were given stars in a contest *t* at the time of entry of a contestant *i*. To examine textual feedback, we use a text mining program - Linguistics Inquiry and Word Count (LIWC) - to categorize the type of feedback given in a contest. We find that feedback is either given to a specific submission, for example, the feedback contains a callout to a submission number or a username, or is general with no reference to any particular submission (see Figure 9 for examples). We construct *contest_SpecificFdbk* to measure the total count of the specificity of the feedback given to others in the contest *t* at the time of contestant *i*'s entry, and *contest_GenericFdbk*, to measure the total count of generic feedback given in a contest *t* at the time of a contestant *i*'s entry.

To examine the impact of direct feedback given to a contestant *i*, we construct two metrics to quantify both types of feedback. The first metric c*_feedback_dum*, measures whether or not the contestant was given text feedback in contest *t*. The second metric c*_max_star*, measures the maximum star rating given to the contestant at a particular time in contest *t*.

We construct two metrics to measure resubmissions of a contestant *i* in contest *t*. *c_ttl_resubs*, measures the total number of resubmissions of a contestant *i* in contest *t*, and *c_timeToResubmit* measures the lag between one resubmission and the next of a contestant *i* in contest *t*.

Lastly, we construct three different metrics to measure contestants *i*'s expertise and past experience: (a) *c_skill* –measures of past wins of contestant *i* divided by the total number of contest participations, (b) *c_experience*- measures the total number of contest participations of contestant *i* in the community, and (c) *c_expertise_dum*- a binary variable that indicates whether contestant *i* participates in other contests within the community (for example, website designs, banner design, t-shirt design, etc.).

4.1.3 Controls

We include several additional controls. In particular, we control for (a) Contestant-Related Factors: Total number of days in the community, total number of contests currently participating in (b) Contest-Related Factors: total number of entries, the contest prize money, contest design description length, and (c) Contest Holder - Related Factors: total number of matches held, total prize awarded, and average feedback. (See Table 1 for further description of control variables).

4.2 Empirical Model

The main objective of this study is to measure the effect of information spillovers on the contestant's timing of submission and the probability of her winning the contest. We examine different contest designs in particular open contests and blind contests. We examine the probability of winning a contest based on the submission order, the feedback given in a contest whether to the contestant herself or to other contestants in a contest, along with other variables such as contestant expertise, and resubmissions in a contest. We also control for contestant variables, contest controls and contest holder controls as described in section 4.1. The data is in panel form, and the unit of analysis is the contestant (*i*) in contest (*t*), in particular, in its simplest form we estimate the following model:

$$Prob(Winning_{it} = 1 \mid x) = F(x, \beta)$$

where x is the full set of explanatory and control variables and β are the coefficients of interest, in particular,

$$P(Winning_{it} = 1 \mid x) = F(Contestant\ Submission\ Order_{it}, Feedback\ to\ Others\ in\ Contest_{it}, Direct\ Feedback\ to\ Contestant_{it}, Contestant\ Expertise_{it}, Contestant\ Resubmissions_{it}, Contestant\ Controls_{it}, Contest\ Controls_{t}, Contest\ Holder\ Controls_{t}) + \varepsilon_{it} \quad \textbf{(1)}$$

Given the complexity and difficulty in controlling for all omitted variable bias in terms of contestants choice of participation in contests, we need to control for individual effects. A standard modeling choice when faced with bias caused by missing variables is fixed effects (Agarwal et al., 2009). More specifically, we observe the submission order and whether the contestant won at the individual contestant level, for 16,645 different contests. This panel data allows us to estimate a model that controls for omitted bias with individual fixed effects,

$$Win_{it} = X_{it}\beta + \gamma S_{it} + \alpha_{it} + \varepsilon_{it} \quad \textbf{(2)}$$

where i indicates the contestant, t denotes the time in contests, Win_{it} is the observed winning dummy for contestant i in contest t such that variable *Winit* is 1 if contestant i is the winner, while *Winit* = 0 for all others in the contest, X_{it} is a vector of time varying explanatory variables that includes feedback and the above specified variables and controls in equation (1), S_{it} is the submission order for individual i in contest t, α_{it} is the unobserved individual effects, and ε_{it} is the disturbance.

The above equation (2) can be estimated using a simple panel data fixed effects model. However, one concern is that the time of entry or submission order may be correlated with some unobservable contestant-specific characteristics that may influence outcome of winning the contest. If some explanatory variables are correlated with errors, then ordinary least-squares regression gives biased and inconsistent estimates. The Wald test of exogeneity (chi2 (1) = 5.48; p<0.05) for submission order points to the presence of endogeneity, implying that the parameter of interest γ will be estimated with a positive bias and underscoring the need for an instrumental variable (IV) approach. To account for this, we use a Two Stage Least-Squares (2SLS) regression with IV's. Under the 2SLS approach, in the first stage, each endogenous variable is regressed on all valid instruments, including the full set of exogenous variables in the main regression. We instrument for submission order with the average submission order of contestant *i* in previous contests, as her past submission behavior would be a good predictor of her submission behavior in the current contest. In addition, we also use the average star rating received by the contestant *i* in prior contests, to instrument for her submission order in the current contest.

(1) $S_{it} = X_{it}\beta + Z_{it} + \alpha_{1it} + \varepsilon_{1it}$ ***(3)***

(2) $Win_{it} = X_{it}\beta + \gamma S'_{it} + \alpha_{2it} + \varepsilon_{2it}$ ***(4)***

where Z_{it} is the full set of instruments. As denoted earlier, X_{it} entails the rest of the explanatory and control variables (for example, contestant expertise, contestant resubmissions, contestant controls, contest controls and contest holder controls). The first stage estimation is the submission order and the second stage is the probability of winning the contest. We estimate the probability of winning the contest for the various types of contests: (a) open contests with feedback (b) open contests with no feedback (c) blind contests with feedback and (d) blind contests with no feedback. The first-stage F statistic is highly significant and much higher than the minimum value of 10, alleviating weak instrument concerns (Staiger & Stock, 1997).

Variance inflation factors across all models range from 1.18 to 3.37, suggesting that the estimates obtained are not biased because of multicollinearity. The main drawback of the Fixed Effects estimator is that it prevents the use of any explanatory variables that do not change on the individual level over time. We therefore also conduct a two stage Random Effects model to mitigate this drawback.

5. Results

Table 3 illustrates the estimation results for each explanatory parameter of interest (namely, submission behavior, feedback to others, direct feedback to user, and expertise). The key research objective is to investigate the role of different information visibility regimes on the behavior of contestants as well as contest outcomes. Therefore, for each parameter of interest, we discuss the Fixed Effects coefficients for the different contest design regimes visibility (open with feedback, open with no feedback, blind with feedback, blind with no feedback). Note that both fixed effects and random effects are consistent in terms of sign and significance.

5.1 Submission Behavior of Contestants

Columns 1 and 2 of Table 3 show the results for open contests with feedback using the fixed effects model and random effects model respectively. In this type of contest**,** both the design submissions and feedback is visible. The results for the fixed effects model are in column 1. The coefficient on *c_subOrder* is negative and significant ($\beta_{\text{(c\_subOrder)}} = -0.1223$) and the coefficient on *c_subOrder^2* is positive and significant ($\beta_{\text{(c\_subOrder\^{}2)}} = 0.1667$), indicating that those who submit either early or late are more likely to win. The coefficients on the interaction of the expertise variables and *c_subOrder* is positive, implying that users with higher skill, expertise or experience *and* who submit late have a higher probability of winning.

Columns 3 and 4 of Table 3 show the results for open contests with no feedback using the fixed effects model and random effects model respectively. Referring to column 3, the coefficients on *c_subOrder* and *c_subOrder^2* ($\beta_{(c\_subOrder)} = 0.1634$; $\beta_{(c\_subOrder\hat{}2)} = 0.0076$) are positive and significant, implying that the later the submission the higher the probability of winning. This indicates that although there is no feedback from the contest holder, users are able to benefit from the information spillover of the design visibility of their competitors.

Columns 5 and 6 in Table 3 report the regression coefficients for blind contests with feedback, where design submissions are not visible, and only feedback is visible. Note that the signs of the coefficients of the submission order variables are in accordance with what one would expect for both fixed effects model (column 5) and random effects model (column 6). As shown in column 5, the coefficients on both *c_subOrder* and *c_suborder^2* ($\beta_{(c\_subTime)} = -0.2544$; $\beta_{(c\_subOrder\hat{}2)} = -0.0302$) are negative and significant, implying that earlier submission entries have a higher probability of winning the contest. The coefficients on the interaction of the expertise variables and *c_subOrder* is negative, implying that users with higher skill, expertise or experience *and* who submit early have a higher probability of winning. This suggests that when design submissions are not visible, users do not benefit from late submissions. However they benefit from the feedback provided by the contest holder and hence, are more likely to receive feedback and win the contest when they submit early.

Lastly, columns 7 (fixed effects model) and 8 (random effects model) of Table 3 report the regression coefficients for blind contests with no feedback, where there is no visibility of design or feedback. Referring to column 7, the coefficients on both *c_subOrder* and *c_suborder^2* are insignificant, showing no evidence of strategic behavior related to timing of entry and probability of winning. Only the coefficients of *c_skill, c_expertise_dum*, and *c_experience* are positive and significant, indicating that when there is no information spillover, contestants do not benefit from waiting, and only benefit from their own skill and expertise.

5.2 Feedback to Others

We examine the impact of feedback in two ways**.** First, we explore the impact of the visibility of feedback (stars and text), and also analyze the impact of the type of textual feedback provided by the contest holder.

5.2.1 Visibility of Feedback

We examine the impact of feedback visibility given to others on one's submission behavior and the probability of winning in open and blind contests. In open contests where design submissions of others are visible, information contained in the feedback can spillover, whereas in blind contests feedback has no information spillover effects since the design submissions of others are not visible, and, thus, feedback may not have much value.

Referring to the regression coefficients for open contests with feedback, (see column 1), we find that the coefficients on *c_maxstar_prior*, *c_avgstar_prior*, and *c_ttlnumuserswithstars_prior* ($\beta_{c\_maxstar\_prior}$= -0.0007; $\beta_{c\_avgstar\_prior}$ = -0.0035; $\beta_{c\_ttlnumuserswithstars\_prior}$ = -0.0050) are negative and significant, implying that higher the feedback given to others at the time of a contestant's first submission, the lower the probability of a focal contestant winning the contest. However, the coefficients of the interactions with *subOrder* are positive and significant ($\beta(_{c\_maxstar\_prior*subOrder)}$=0.1284; $\beta(_{c\_avgstar\_prior*subOrder)}$= 0.1174; $\beta(_{c\_ttlnumuserswithstars\_prior*subOrder)}$ = 0.1055), implying that the higher the feedback given to others and the later the submission of a focal contestant, the higher the probability of winning the contest.

Regression coefficients for blind contests with feedback in column 5 are as anticipated. The regression coefficients for feedback to others are negative and significant ($\beta_{c\_maxstar\_prior}$= -0.0896; $\beta_{c\_avgstar\_prior}$ = -0.0507; $\beta_{c\_ttlnumuserswithstars\_prior}$ = -0.1126), indicating that the higher the feedback given to others at time of a contestant's first submission, the lower the probability of winning the contest. Yet, in contrast to open contests with feedback, we find that in blind contests, the coefficients for the interaction of feedback given to others variables and *c_subOrder* are negative and significant (β $(_{c\_maxstar\_prior*subOrder})$ = -0.0054; $\beta(_{c\_avgstar\_prior*subOrder})$= -0.0139; $\beta(_{c\_ttlnumuserswithstars\_prior*subOrder})$ = -0.0729), implying that the higher the feedback given to others and the later the submission, the lower the probability of winning the contest. Since later contestants are not able to benefit from the spillover of information contained in the feedback given to other contestants, late submitters are unable to outperform early entrants.

5.2.2 Type of feedback

We further examine how the different types of textual feedback impact outcomes. We compare the specificity of the text feedback in open contests and blind contests. In open contests, we find that the regression coefficient in column 1 for *contest_SpecificFdbk* is positive and significant ($\beta_{(contest\_SpecificFdbk)}$ = 0.2421), implying that the higher the specificity of the feedback to other contestants in a contest, the higher the likelihood of a focal contestant winning the contest. The coefficient on the interaction of submission order and the specificity of the feedback is positive and significant, ($\beta_{(c\_subOrder *contest\_SpecificFdbk)}$ = 0.2841), indicating that the later the submission and the higher the specificity of the feedback, the higher the likelihood of winning the contest. Interestingly, the regression coefficient for generic feedback is not significant predictor of the outcome of interest.

In blind contests, we observe that the regression coefficient in column 5 for *contest_SpecificFdbk* is negative and significant ($\beta_{(contest\_SpecificFdbk)} = -0.1052$), showing that the higher the specificity of the feedback given to others, the lower the probability of winning. In addition, the coefficient on the interaction of submission order and the specificity of the feedback is also negative and significant, ($\beta_{(c\_subOrder*contest\_SpecificFdbk)} = -0.1931$), denoting that the later the submission and the higher the specificity of the feedback, the lower the likelihood of winning. These findings show that specific feedback to other contestants is not very useful to a contestant when the designs are not visible. However, the coefficient for generic feedback is positive and significant ($\beta_{(contest\_GenericFdbk)} = 0.0344$), implying that the higher the generic feedback given to others, the higher the likelihood of winning for a focal contestant. The coefficient for the interaction of submission order and generic feedback is negative ($\beta_{(c\_subOrder*contest\_GenericFdbk)} = -0.2152$) suggesting that the earlier the submission and the higher the generic level of the feedback, the higher the likelihood of winning.

When design submissions of others are visible, the more specific the feedback, the greater the benefits from information spillovers relating to the feedback; thus, later submissions have a higher probability of winning. However, when design submissions of others are not visible, the specific feedback is less valuable to others, and we find no benefit in late submissions – i.e., early submissions have a higher likelihood of winning the contest.

5.3 Direct Feedback to User

We also examine the impact of direct feedback to a contestant and resubmission in both open and blind contests with feedback.

In open contests with feedback, we find that the regression coefficients in column1 on direct feedback are both positive and significant ($\beta_{(c\_maxstars)} = 0.0751$; $\beta_{(feedback\_dum)} = 0.0624$), indicating that the higher the star rating feedback of a contestant, the higher the probability of winning the contest. Also, contestants that get feedback are more likely to win the contest as compared to contestants that do not get feedback. The positive and significant coefficient on the total number of resubmissions ($\beta_{(c\_ttl\_resubs)} = 0.0557$), shows that the higher the number of resubmissions, the higher the likelihood of winning the contest. Further examining the impact of direct feedback; the regression coefficient for the interaction of star feedback and time to resubmit is negative and significant ($\beta_{(c\_maxstars*timeToResubmit)} = -0.0976$), denoting that the higher the star rating feedback a user gets and the earlier the resubmission, the higher is the likelihood of winning the contest. In addition, the coefficient for the interaction of total resubmissions and feedback dummy is positive and significant ($\beta_{(c\_ttl\_resubs*feedback\_dum)} = 0.0835$), indicating that users that get feedback and resubmit are more likely to win the contest as compared to users that do not get feedback and resubmit

Results for blind contests are also similar to open contests. The coefficients in column 5 on direct feedback are also both positive and significant ($\beta_{(c\_maxstars)} = 0.2011$; $\beta_{(feedback\_dum)} = 0.1319$), indicating that the higher the feedback a user gets, the higher is the likelihood of her winning. Similarly, the positive significant coefficient on total resubmissions ($\beta_{(c\_ttl\_resubs)} = 0.1043$), implies that the higher the number of resubmissions, the higher is the likelihood of being a winner. The interaction coefficient for star feedback and time to resubmit is negative ($\beta_{(c\_maxstars*timeToResubmit)} = -0.0339$), showing that the higher the star rating feedback a user gets and the earlier the resubmission, the higher is the likelihood of being a winner. Lastly, the interaction coefficient for the total resubmissions and feedback dummy is positive and significant ($\beta_{(c\_ttl\_resubs*feedback\_dum)} = 0.1721$), denoting that users that get feedback and resubmit are more likely to win as compared to users that do not get feedback and resubmit

We also find that users resubmit when there is no feedback in the contest. In open contests with no feedback, the coefficient in column 3 on the total number of resubmissions is positive and significant ($\beta_{(c\_ttl\_resubs)} = 0.0089$), implying that higher number of resubmissions increase likelihood of winning. In blind contests with no feedback, the number of resubmissions is not a significant predictor winning the contest.

5.4 Skill, Expertise, and Experience

In all types of contests**,** the regression coefficients for all expertise variables are positive and significant, implying that contestant with high skill (or high rate of past wins), experience, and expertise are more likely to win. Interestingly, in open contests (with and without feedback) where designs are visible, the coefficients for the interaction of *c_subOrder* and expertise variables are positive and significant, showing that contestants that submit late and have high skill, design expertise, or experience, are more likely to win. However, in blind contests with feedback, the coefficients for the interaction of *c_subOrder* and expertise variables are negative, indicating that contestants that submit early and have high skill, design expertise or experience are more likely to win. However, when there is no feedback spillover in blind contests (blind with no feedback), we do not find any significant results for the interaction of *subOrder* and expertise variables on the probability of winning the contest.

5.5 Controls

Results for the control variables align well with expectations. For all types of contests, the regression coefficients for total contest entries, contest prize amount, contest description length, contest holders average feedback and contest holder total prizes awarded are negative and significant. More entries, a higher prize, a more detailed description, a more attractive contest holder all imply competition, and therefore negatively impact the probability of winning a contest. As expected, the coefficient of a member's age is positive and significant, showing that contestants that have been in the online marketplace for longer have a higher probability of winning the contest.

5.6 Robustness Checks

To ensure the robustness of the findings, we conduct a series of additional tests.

5.6.1 Selection Bias

An issue of concern is whether there is selection bias in terms of contestants' choice in selecting an open versus a blind contest. We use a t-test to test the difference of means on contestants' skill, experience, expertise and membership age in terms of choice of open contest and blind contests. We find no significant difference in either skill p =0.203; experience p = 0.186; expertise p = 0.843; or member age p = 0.102, indicating no self-selection bias in choice of open versus blind contests relating to these variables.

In addition, we examine whether or not contest holders provide different prizes for open versus blind contests and find no significant different in the prizes awarded for these contests.

5.6.2 Additional Specifications

To further validate the findings, we estimated alternative model specifications. We estimated a two stage random effects model as shown in Table 3 using the same fixed effects IV's as instruments. We also estimated a Probit and a Logit model for the probability of winning the contest. Furthermore, we estimated at a two stage Probit with IV using the same instrumental variables (average submission order and average star rating). All three models provided highly consistent results in terms of sign and significance.

6. Implications and Conclusions

Crowdsourcing markets have emerged as viable alternative to insourcing as well as traditional outsourcing mechanisms. A wide variety of crowdsourcing markets – including crowdsourcing markets for labor, for innovation for creative tasks, etc have witnessed rapid growth in the last few years. Most of these markets use open contests to encourage participation as well as to promote competition. However the open nature of these contests, while encouraging participation and competition as in the case of open auctions, also lead to strategic behavior among contestants. Such strategic behaviors could have important implications for market outcomes and calls for a systematic understanding of the implications of contest designs. This study is among the first to examine the information spillovers resulting from the open nature of innovation contests and their implications for contestant behaviors and outcomes. Using data from one of a large online crowdsourcing marketplace for design tasks, we compare different information visibility regimes - open and blind contests - to examine the impact of information spillovers relating to contestants' submissions as well as the contest holder feedbacks, on contestants' behaviors and outcomes.

Our findings indicate that contestants in this market strategically time their submissions to take advantage of information spillovers and increase their chances of winning the contest. Interestingly, it is the contestants with higher skills, experience, and expertise that are more likely to act strategically as well as win open contests. However, in blind contest where there are no informational spillovers, there are no significant late mover advantages. Only a contestant's expertise, experience, and skill are associated with her likelihood of winning the contest. In examining the impact of spillovers of information contained in the contest holders' feedback, we find that when this feedback is very specific, the informational spillovers are higher and other contestants that submit later tend to benefit from such feedback. Overall, we find that contest design, particularly relating to information visibility, significantly influences contestants' behaviors as well as outcomes. Information spillovers from both design as well as feedback visibility has econometrically identifiable impacts on contestant's behavior and contest outcome.

Such information spillovers might not be detrimental to the contest holder in the short run; however they could discourage contestants from participating in such open contests. While informational spillovers relating to submissions as well as feedback could help later contestants converge to a winning solution more quickly, they could have an unintended side effect of reducing variety. To the extent that information spillovers foster imitation, the loss of variety in itself could be a detrimental outcome. Blind contests, on the other hand, could promote greater variety by reducing information spillovers from earlier submissions. However, to the extent that blind contests make it difficult for the contestants to infer the intentions of the contest holder, they could lead to inferior outcomes for the contest holder as well as deter contestants in the long run. Our findings indicate the need for a more balanced approach to the design of crowdsourcing contests – one that better balances the needs of the contest holder for diversity and that of the contestants for more information about the contest holder's needs.

7. Limitations and Future Research

Although this study controlled for experience and expertise of the designers, we were not able to obtain demographic information. Demographics such as gender, age, education, and profession may potentially impact outcomes. While the fixed effects models used in this study accounted for omitted variable bias, future studies can replicate this study and control for such demographic information.

Our study indicates that contestants behave strategically; however, the precise mechanism through which strategic behavior exerts itself in this specific context is less understood. We have identified information spillovers and their effects on submission behaviors, but there may be others, and our study does not examine them. More qualitative data via interviews or surveys may shed further light on this issue. In addition, future studies can also survey designers to further investigate whether designers learn specific types of strategies with time and whether their strategies change overtime.

Our analysis of the textual comments is one of the first efforts to study the effect of textual feedback on strategic behavior of contestants. Though we identified the main feedback categories of text (specific versus generic), future studies could undertake a more nuanced analyses of textual feedback and how they impact outcomes.

Lastly, since this study was limited to a single open innovation marketplace for a specific logo contest, additional corroboration of these novel findings by subsequent research that examine other types of design contests as well as other crowdsourcing markets would be useful. This is especially so as the imitation costs of different types of contests and the value of information spillovers is likely to be contingent on the nature of the contest and the marketplace.

Figure 1 Examples of contests in the Crowdsourcing Marketplace

Contest Type	Contest Title	Contest Holder	Ends	Entries	Prize
Open	Help Community Care with a new logo	***	14mins, 28 secs	116	295
Blind	Help Chils Play Qid with a new logo	***	18mins, 48 secs	92	$495
Open	Huniu Photography needs a new logo	***	35mins, 16 secs	124	$295
Open	New logo wanted for Football Die hards	***	42 mins, 43 secs	73	$395
Blind	Logo redesign for 76 year old company	***	47 mins, 23 secs	128	$495

Figure 2 Contest Holder's Profile

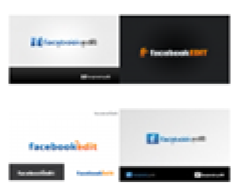
Contest Holder X

PROFILE

Open Contests

Activity

Contests Held	2
Contests Active	1
Contests Awarded	2
Prizes Awarded	$595
Average Feedback	100%



LOGO needed for new web application!

Figure 3 Sample Contest Description

Design Brief

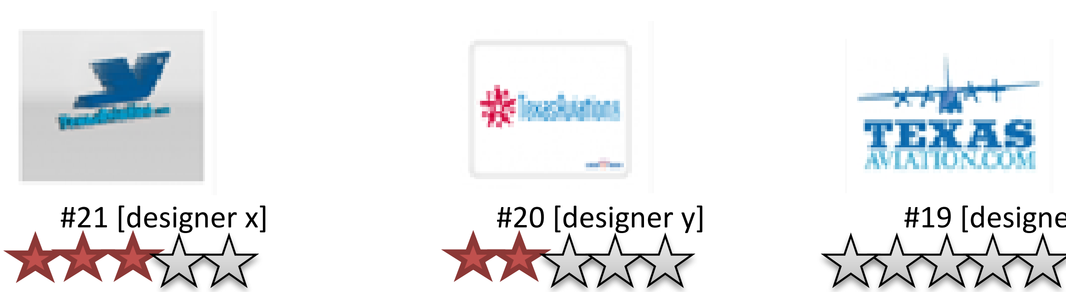
For Contest : New Logo for Avaiation Company , Held by : *** , in the logo design community

Open	**Entries**	**Prize**
Contest accepting entries 6 days, 8 hours remaining	20	$600

Brief Overview	We are a new aviation company. Our goal is to provide the premier club for aviation enthusiasts in the stage of Texas. We will be hosting events for owners of aircraft, and also provide a complete resource for all kinds of aviation information for the state of Texas.
Brand Name	***
Target Audience	We are targeting Aviation enthusiasts for the state of Texas. Pretty much anyone that is interested in flying.
Requirements	Please include .com in the logo. I am looking for something professional and also creative. You are free to be creative on this logo.

Figure 4 Contestants and their Submissions to a Contest

Entries (most recent first)



Notes: This figure is adapted from an open innovation marketplace. It shows a few submission entries for a contest along with the star rating for each submission. A star is given by the contest holder to a submission. Star ratings are out of 5. For example, submission #21 has a star feedback of 3 out of 5. Submission #20 has a star feedback of 2 out of 5, and submission #19 has no star feedback.

Figure 5 Contestant's Profile

Profile for Designer X

Activity	
Contests Entered	230
Contests Won	16
Contests Participating	2

Bio

Portfolio by request.

Folio Highlights all folio >

Recent Wins all wins >

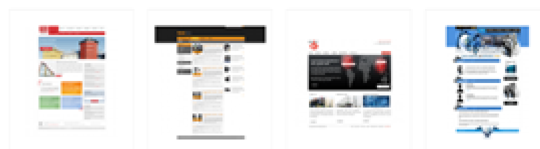


Figure 6 Submission Order Frequency

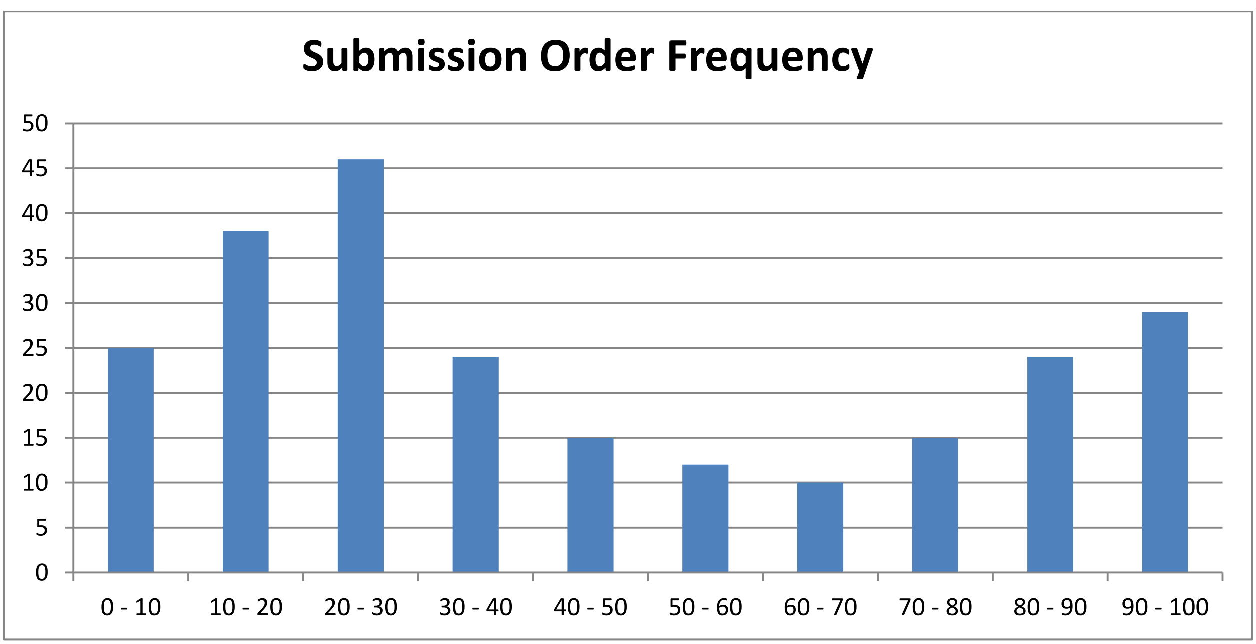


Figure 7 Text Feedback Frequency

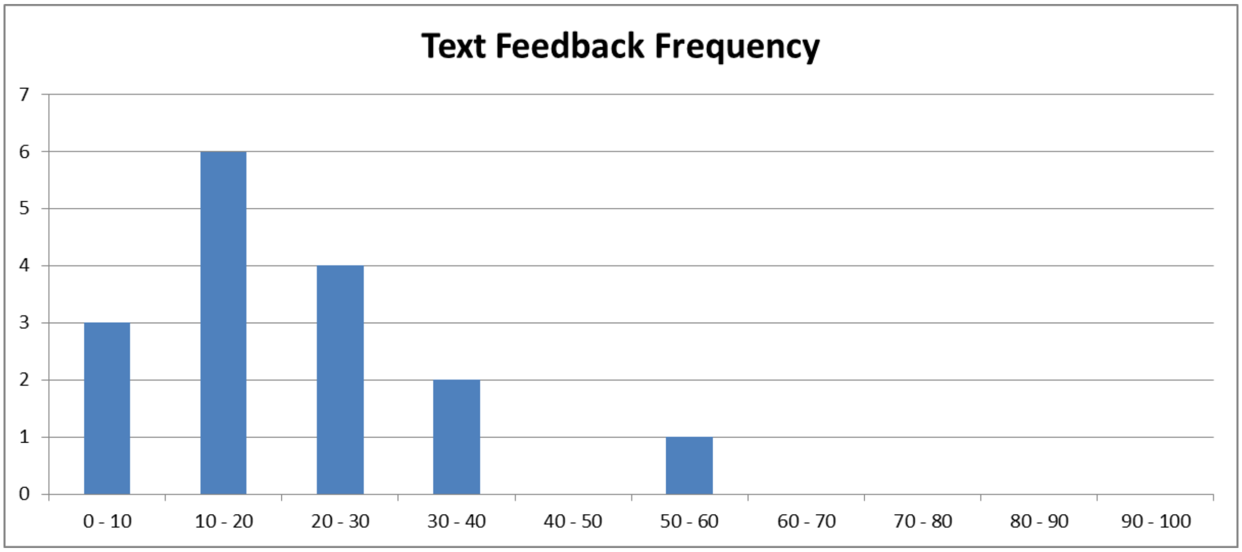


Figure 8 Star Feedback Frequency

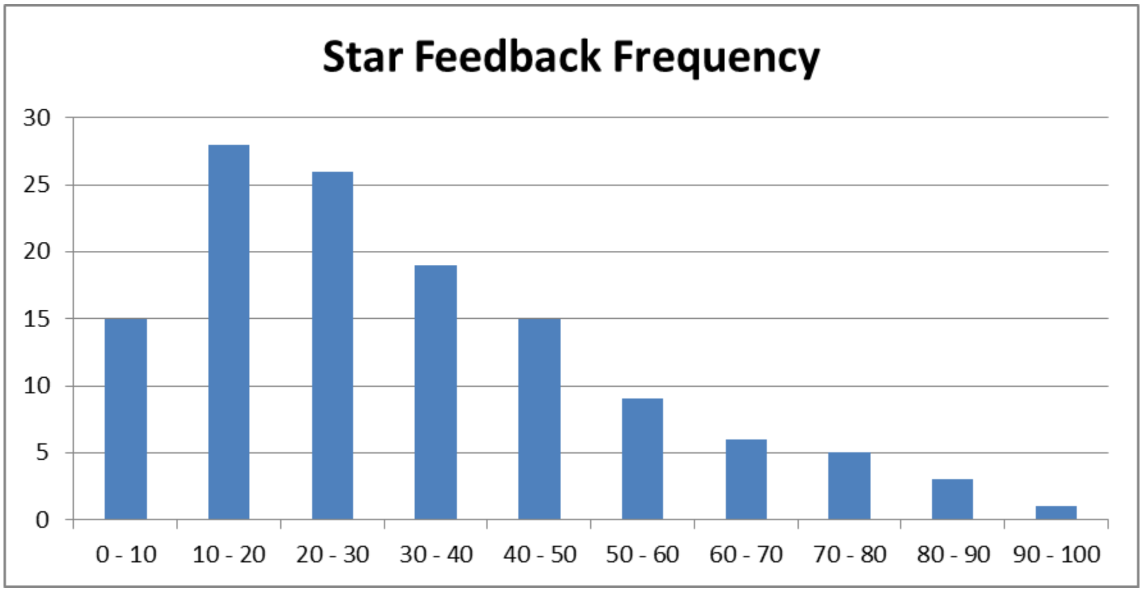


Figure 9 Feedback Categorization

(1) Generic Feedback	**(2) Specific Feedback**
Overall Feedback for all, with no specific callouts.	Specific callout to a submission (Use of submission number or username).
Examples:	*Examples:*
Hi again everyone, thanks for all the designs. The designs are great however many are either more masculine or more feminine. The primary target is female (they will likely be the purchaser of the gifts) however they will buy for both males and females. This means the logo on the packaging will need to be more gender neutral and not too feminine. Female buyers might be turned off if they think the product looks too girly and not suitable for a male. I hope this makes sense and helps with your designs.	*Did we lose BigBaldBeard? We liked number #305...*
Hi everyone thanks for the designs so far. We're looking for something pretty simple with more emphasis and refinement on the typography. It looks like the device we asked for might be a bit difficult to crack so we would prefer you concentrate on making the typography look simple and premium. If you have a great idea for a device/mark by all means submit it. Thanks again everyone.	*#82, #68 and #59 are the leading designs. #59 is the only contender for the logo but it is still not quite perfect. Some additional shaping to the G to make it look more smiley is desired. I would also like to see the text in different colors for $59. For #68 - I love this but it needs a body. #82is the most fun body because of the attire. His shirt is open and the collar is outside of his lapel. He's a bit "cooler" and less formal. He is having fun, which is important for my character to portray. I don't know what the rules are with merging designs, but I feel like the purple head of #68 is much more elaborate and higher quality, so if anything, I would like to see that design adopt a better body / outfit. #82 really only has the attire correct. Everything else is not something I care for too much.*
Try put signal strength, globalization, and tower within the text of the logo.	*We like #71 #52. But we would like to some more bright colors in both.*

Table 1 Variables and Descriptions

	Variable name	Description
Dependent Variable	Winner_dum	Binary variable that indicates whether the contestant won the contest.
Independent Variables		
Contestant Skill & Expertise	c_skill	Contestant skill = (Total number of previous wins) / (Total number of previous contest participation)
	c_expertise_dum	Binary variable that indicates whether contestant participates in other contests within the community.
	c_experience	Contestant total contests entered.
Strategic Behavior	c_subOrder	Time of contestant's first submission in contest X, as a percentage of total entries in contest X.
Direct Feedback to Contestant	c_maxstar	For contests with Feedback : Maximum star rating of the contestant received by the contest holder (out of 5) in contest X.
	c_feedback_dum	Dummy whether the contestant was given feedback through stars or through text.
Feedback to Others		
Text- Type of Feedback	contest_SpecificFdbk	For contests with Feedback: Total count of the specific feedback given in a contest at time of contestant entry.
	contest_GenericFdbk	For contests with Feedback: Total count of the generic feedback given in a contest at time of contestant entry.
Star	c_maxstar_prior	Max star rating given in a contest at time of contestant entry to contest.
	c_avgstar_prior	Average star rating given in a contest at time of contestant entry to contest.
	c_ttlnumuserswithstars_prior	Total number of users given a star rating at time of contestant entry to contest.
Resubmission	c_ttl_resubs	Total number of resubmissions of contestant in contest X.
	c_timeToResubmit	The average lag in number of submissions from one submission to next for a contestant in contest X.
Control Variables		
Contestant Controls	c_participating_in	Total number of contests the user is participating in, at time of submission in contest X.
	c_membershipAge	Total number of days the contestant has been in the marketplace.
Contest Controls	contest_entries	Total number of entries in contest X.
	contest_prize	Prize awarded ($) in contest X.
	contest_ttldescription_length	Count of the total number of words in the design description.
Contest Holder Controls	ch_matchesHeld	Contest Holder total number of matches held.
	ch_matchesPrizes	Contest Holder total number of prizes awarded.
	ch_avgfdbk	Contest Holder average feedback.

Table 2a Descriptive Statistics

Unit	**Variable**	**Description**	**Mean**	**Std.Dev**	**Min**	**Max**
Contestant *i*						
	c_subOrder	First submission order of contestant *i*.	0.5698	0.3888	0	1
	c_maxstar	Max star rating of contestant *i*.	1.9656	1.8223	0	5
	c_won	Total number of contests won for contestant *i*.	13.3417	21.1542	0	352
	c_experience	Total number of contests entered for contestant *i*.	287.0228	319.4493	2	6043
	c_skill	Contestant *i*'s skill = Won/Entered.	0.0405	0.0545	0	1
	c_participating_in	Contestant *i* total number of contests currently participating in.	1.2349	2.3983	0	72
	c_ttl_resubs	Contestant *i*'s total number of resubmissions.	1.8375	3.2347	0	14
	c_membershipAge	Contestant *i*'s total number of days in community.	422.0544	612.7567	102	3102
Contest Details						
	contest_Entries	Total number of Entries in a contest.	211.1656	354.0386	20	4531
	contest_Designers	Total number of Designers in a contest.	69.2919	76.9834	5	1523
	contest_prize	Total USD Prize of Contest.	517.4523	201.9317	100	1945
	contest_tt_comments	Total number of comments in a contest.	10.5048	12.9505	0	145
	contest_ttldescription_length	Count of the total number of words in the design description	223.2715	162.1385	38	1793
Contest Holder						
	ch_matchesheld	CH -Total number of matches held.	2.8316	3.36956	1	156
	ch_matchesPrizes	CH -Total USD awarded as Prizes.	718.6134	1275.0500	0	32412
	ch_AvgFdbk	Average Feedback of CH.	0.7013	0.3311	0	1
	ch_Lastseen	CH - Number of days last seen.	286.2236	485.7173	0	2103
	ch_DaysSinceLastFeedback	CH - Number of Days since last feedback.	689.4185	478.0628	0	2413

Note: CH denotes Contest Holder.

Table 2b Descriptive Statistics of Different Contests

Parameter	**Open With Feedback** Mean (stdev)	**Open With No Feedback** Mean (stdev)	**Blind With Feedback** Mean (stdev)	**Blind With No Feedback** Mean (stdev)
Resubmissions				
Early	6.2511 (2.9281)	2.5012(0.5101)	4.1231(0.8165)	0.8283(0.3102)
Middle	4.3221(3.4010)	0.5129(0.9371)	2.1232(0.5774)	0.1023(0.2938)
Late	0.5281(0.8210)	0.2574(0.5023)	0.3984(0.5012)	0.0023(0.0109)
Skill				
Early	0.0425(0.04102)	0.0368(0.03483)	0.0432(0.03979)	0.0423(0.04321)
Middle	0.0382(0.02307)	0.0375(0.03401)	0.0388(0.03521)	0.0402(0.04117)
Late	0.0432(0.03918)	0.0401(0.04032)	0.0415(0.04019)	0.0416(0.04123)
Experience				
Early	280.1923(340.3910)	276.3918(376.1920)	289.1920(411.3201)	293.1029(417.1927)
Middle	275.1263(382.4263)	273.2837 (401.2371)	295.2736(421.2929)	290.1139(411.2039)
Late	293.1249(312.3010)	285.1029(412.1029)	301.2394(370.1820)	292.1298(428.3098)
Membership Age				
Early	417.2707(687.1982)	415.2380(632.1028)	434.1039(589.2981)	431.2983(597.4126)
Middle	414.1923(662.9247)	409.2938(640.2038)	410.2981(620.1092)	411.2931(610.2986)
Late	426.9810(680.1725)	421.2981(664.2081)	438.1029(601.2091)	435.2827(593.1092)
Contest Details				
Contest Entries	267.4165 (363.9745)	228.5493 (231.5256)	197.3981(221.3382)	151.2983 (215.0192)
Designers	94.7061 (73.2588)	71.7773 (49.2803)	63.4918 (50.2983)	47.1923 (52.3948)
Prize	520.2096 (290.8650)	473.3077 (148.0056)	584.1201 (262.9384)	512.1717 (200.8537)
Contest Description Length	215.2093 (166.2981)	220.1837 (170.2721)	222.3948 (171.2481)	235.2985 (150.2938)
Contest total comments/Feedback	8.6181 (18.6417)	0	12.39155 (22.2726)	0

Notes: Early, Middle and Late are defined as, the time of submission as a percentage of total entries; Early: 0-20%, Middle: 20-80%, and Late: 80-100%.

Table 3 Regression Analysis

	Open With Feedback	Open With Feedback	Open With No Feedback	Open With No Feedback	Blind With Feedback	Blind With Feedback	Blind With No Feedback	Blind With No Feedback
Variable	**(1) FE-IV**	**(2) RE-IV**	**(3) FE-IV**	**(4) RE-IV**	**(5) FE-IV**	**(6) RE-IV**	**(7) FE-IV**	**(8) RE-IV**
c_subOrder	-0.1223***	-0.1455***	0.1634***	0.2176***	-0.2544***	-0.3246***	-0.2321	-0.2551
	(0.0187)	(0.0173)	(0.0166)	(0.0146)	(0.0432)	(0.0328)	(0.7241)	(0.6394)
c_subOrder^2	0.1667***	0.1976***	0.0076***	0.0084***	-0.0302***	-0.0306***	-0.0864	-0.0869
	(0.0419)	(0.0402)	(0.0012)	(0.0013)	(0.0077)	(0.0080)	(0.6741)	(0.6743)
contest_SpecificFdbk	0.2421***	0.2822***			-0.1052***	-0.1053***		
	(0.0543)	(0.0512)			(0.0282)	(0.0283)		
contest_GenericFdbk	-0.0052	-0.0053			0.0344***	0.0352***		
	(0.3011)	(0.3015)			(0.0093)	(0.0091)		
c_subOrder*GenericFdbk	0.0283	0.0285			-0.2152***	-0.2777***		
	(0.1071)	(0.1062)			(0.0343)	(0.0317)		
c_subOrder*SpecificFdbk	0.2841***	0.4647***			-0.1931***	-0.2233***		
	(0.1001)	(0.1020)			(0.0465)	(0.0455)		
c_skill	0.4666***	0.4959***	0.4841***	0.5269***	0.5066***	0.5787***	0.5684***	0.6188***
	(0.1264)	(0.1213)	(0.1034)	(0.1029)	(0.0964)	(0.0952)	(0.0634)	(0.0626)
c_experience	0.2583***	0.2921***	0.2733***	0.3337***	0.3361***	0.3462***	0.3428***	0.3530***
	(0.0693)	(0.0667)	(0.0733)	(0.0724)	(0.0831)	(0.0822)	(0.0808)	(0.0789)
c_expertise_dum	0.1159***	0.1467***	0.0718***	0.0727***	0.1513***	0.1567***	0.2113***	0.2417***
	(0.0267)	(0.0214)	(0.0177)	(0.0179)	(0.0428)	(0.0429)	(0.0310)	(0.0304)
c_skill*c_subOrder	0.4953***	0.5062***	0.5236***	0.5429***	-0.2563***	-0.2711***	-0.1650	-0.1652
	(0.0829)	(0.0816)	(0.0664)	(0.0641)	(0.0429)	(0.0426)	(0.4323)	(0.4325)
c_experience*c_subOrder	0.3123***	0.3430***	0.3239***	0.3347***	-0.1601***	-0.1604***	-0.1287	-0.1289
	(0.0624)	(0.0617)	(0.0834)	(0.0836)	(0.0341)	(0.0344)	(0.6472)	(0.6457)
c_expertise_dum*c_subOrder	0.2043***	0.2059***	0.1302***	0.1310***	-0.1087***	-0.1092***	-0.0247	-0.0251
	(0.0441)	(0.0425)	(0.0165)	(0.0158)	(0.0212)	(0.0205)	(0.7566)	(0.7568)

c_maxstars	0.0751***	0.0973***			0.2011***	0.2034***		
	(0.0245)	(0.0246)			(0.0380)	(0.0289)		
c_timeToResubmit	-0.0134***	-0.0157***	-0.0015	-0.0016	-0.0341***	-0.0392***	-0.0342	-0.0347
	(0.0024)	(0.0034)	(0.0532)	(0.0543)	(0.0074)	(0.0071)	(0.7213)	(0.7215)
c_maxstars*c_timeToResubmit	-0.0976***	-0.0991***			-0.0339***	-0.0361***		
	(0.0201)	(0.0197)			(0.0079)	(0.0071)		
c_ttl_resubs	0.0557***	0.0533***	0.0089***	0.0115***	0.1043***	0.1144***	0.0438	0.0439
	(0.0128)	(0.0121)	(0.0012)	(0.0025)	(0.0113)	(0.0107)	(0.0322)	(0.0324)
c_ttl_resubs*feedback_dum	0.0835***	0.0846***			0.1721***	0.1922***		
	(0.0209)	(0.0214)			(0.0135)	(0.0128)		
feedback_dum	0.0624***	0.0628***			0.1319***	0.1328***		
	(0.0151)	(0.0146)			(0.0143)	(0.0144)		
c_maxstar_prior	-0.0007***	-0.0009***			-0.0896***	-0.0902***		
	(0.0002)	(0.0003)			(0.0221)	(0.0227)		
c_maxstar_prior*suborder	0.1284***	0.1321***			-0.0054***	-0.0067***		
	(0.0322)	(0.0314)			(0.0014)	(0.0013)		
c_avgstar_prior	-0.0035***	-0.0038***			-0.0507***	-0.0518***		
	(0.0009)	(0.0008)			(0.0123)	(0.0117)		
c_avgstar_prior*suborder	0.1174***	0.1181***			-0.0139***	-0.0144***		
	(0.0320)	(0.0327)			(0.0031)	(0.0029)		
c_ttlnumuserswithstars_prior	-0.0050***	-0.0067***			-0.1126***	-0.1148***		
	(0.0008)	(0.0007)			(0.0135)	(0.0137)		
c_ttlnumuserswithstars_prior*subOrder	0.1055***	0.1073***			-0.0729***	-0.0732***		
	(0.0155)	(0.0154)			(0.0108)	(0.0113)		
c_participating_in	0.0000	0.0000	0.0000	0.0000	-0.0008	-0.0012	-0.0001	-0.0009
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0212)	(0.0203)	(0.0012)	(0.0011)
contest_entries	-0.0005**	-0.0008**	-0.0006***	-0.0009***	-0.0008***	-0.0009***	-0.0001**	-0.0001**
	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0000)	(0.0000)
contest_prize	-0.0026***	-0.0027**	-0.0011***	-0.0012***	-0.0019**	-0.0019**	-0.0010***	-0.0011***

	(0.0009)	(0.0012)	(0.0003)	(0.0004)	(0.0007)	(0.0007)	(0.0002)	(0.0003)
ch_matchesHeld	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0008	-0.0009
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0020)	(0.0021)
ch_matchesPrizes	-0.0401***	-0.0408**	-0.0040***	-0.0040***	-0.0000***	-0.0003***	-0.0000***	-0.0002***
	(0.0064)	(0.0186)	(0.0003)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ch_avgfdbk	-0.0000***	-0.0002***	-0.0176***	-0.0172***	-0.0007***	-0.0007***	-0.0104***	-0.0107***
	(0.0000)	(0.0000)	(0.0018)	(0.0019)	(0.0001)	(0.0001)	(0.0013)	(0.0015)
c_membershipAge	0.0218***	0.0241***	0.0421***	0.0448***	0.0545	0.0579	0.0240	0.0253
	(0.0057)	(0.0069)	(0.0076)	(0.0112)	(0.1152)	(0.1143)	(0.0845)	(0.1153)
contest_ttldescription_length	-0.0112***	-0.0148***	-0.0094***	-0.0109***	-0.0124***	-0.0132***	-0.0127***	-0.0138***
	(0.0011)	(0.0014)	(0.0021)	(0.0024)	(0.0031)	(0.0036)	(0.0032)	(0.0033)
_cons	0.1551***	0.2682***	0.3151***	0.3353***	0.6422***	0.6249***	0.4285***	0.4376***
	(0.0095)	(0.0588)	(0.0824)	(0.0775)	(0.1467)	(0.1143)	(0.1185)	(0.1041)
R-sq between	0.1063	0.1085	0.0141	0.0187	0.0061	0.0083	0.1047	0.1145
R-sq within	0.1116	0.2101	0.0261	0.0298	0.0115	0.1108	0.1246	0.1358
R-sq overall	0.1389	0.1969	0.0871	0.0945	0.0376	0.0964	0.1189	0.2104
F-Stat	22.64***		25.53***		24.48***		27.43***	
N	1630457	1630457	1632492	1632492	477427	477427	152845	152845

*p< 0.10, **p< 0.05, ***p< 0.005. Standard errors shown in parentheses

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