Heterogeneous Problem-Solving Behavior and its Implications for Success in Unblind Innovation Contests

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Abstract

Innovation contests are increasingly adopting an "unblind" format where contest submissions and feedback are viewable by all contestants and the information structure changes dynamically during the contest. In such a format, contestants must weigh the cost of revealing their submissions against the benefits of learning and improvement of their submissions through emerging contest information. We seek to understand how contestants solve problems in unblind innovation contests and what the implications of their problem-solving behavior on contest outcomes are. We analyze problem-solving behavior among contestants in terms of how they make submissions to a contest—i.e., when does a contestant begin participation, how many submissions does a contestant make, what is the number of submissions over which a contestant actively participates, and how are a contestant's submissions distributed through her active participation. The econometric analysis of a large dataset of unblind innovation contests and participating contestants indicates that, despite the potential for intellectual property loss from revealing of submissions, contestants who make their first submission earlier are more likely to succeed in the contest as their number of submissions increases. We also find that increasing the length of participation in a contest has a strong positive effect on a contestant's likelihood of success. More importantly, our results indicate that contestants whose submission patterns in a contest exhibit greater positive skewness, mimicking the traditional innovation funnel process, have a higher likelihood of success. Departing from prior studies on "blind" formats, our study provides new evidence that the process of problem solving has significant implications for a contestant's success, above and beyond her prior experience and success in contests characterized by visible and dynamic information structure.

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1. Introduction

With growing competitive pressures to cut R&D costs and become more innovative, firms are increasingly looking beyond their organizational boundaries to seek new ideas and manage the creative process for developing goods and services (Chesbrough 2007, Bayus 2013). Toward this end, innovation contests that are conducted online on platforms such as 99designs.com, InnoCentive.com, and Logomyway.com have become a popular and a cost-effective business model for firms to generate new ideas and identify solutions to business problems (Terwiesch and Ulrich 2009, Jeppesen and Lakhani 2010). Broadly defined, an innovation contest describes a model for solving business problems that harnesses ideas from individuals through an open call for solutions (Erat and Krishnan 2012). The central advantage of such contests is their ability to decentralize the creative process across a large and diverse set of contestants (often dispersed globally) through competition for prizes. As a result, innovation contests can often dramatically lower the R&D costs for firms seeking solutions without compromising quality (Poetz and Schreier 2011).

The emerging literature on innovation contests has primarily focused on understanding an individual's motivation to participate in such contests (e.g., Brabham 2008, Jeppesen and Lakhani 2010), identifying optimal contest design parameters (i.e., award structures, problem characteristics, nature of feedback) from a contest holder's standpoint (e.g., Terwiesch and Xu 2008, Erat and Krishnan 2012, Wooten and Ulrich 2012), and determining contestant characteristics (i.e., problem familiarity, demographics) that influence their likelihood of developing a successful solution (e.g., Jeppesen and Lakhani 2010, Archak et al. 2010). However, with a few notable exceptions (e.g., Wooten and Ulrich 2013, Bullinger et al. 2010), much of the prior work in this area is based on a "blind" contest format where submitted contest solutions can only be viewed by the contest holders and not by other contestants. Typically, these contests allow one submission per contestant with limited or no intermediate feedback during the contest; contestants, therefore, rely primarily on the details of the problem specification provided by the contest holder and their likelihood of success is assumed to be a function of their intrinsic problem-solving skills, independent of other contestants (Terwiesch and Xu 2008).

Such assumptions, however, may not reflect the dynamics of competition in what we call "unblind" innovation contests, a distinct format (e.g., 99designs.com, Logomyway.com, and Taskcn.com). Unblind contests are becoming an increasingly popular format for innovation contests, particularly for those involving creative design tasks and contests related to the design of information goods.[1] These contests differ from traditional blind contests in three key ways (see Table 1): first, the solution(s) submitted by a contestant are viewable by other current and potential contestants; second, a contestant can make multiple submissions; and third, any intermediate feedback that is received on the submissions in the contest, either from the contest holder (e.g., rankings, comments) or from other contestants (i.e., comments) is also viewable by current and potential contestants. These dissimilarities result in significantly different information structure in the contest environment than what has been previously identified and studied in the innovation contest literature (Wooten and Ulrich 2013). In particular, in a blind contest, all information is available at the beginning of the contest and any additional information is private and gained through an individual contestant's efforts. Conversely, in an unblind contest, the information structure changes throughout the contest as the total number of submissions increases and feedback occurs. This emergent information is publicly available and due to the dynamic information structure, the assumption that the problem-solving process for a contestant is independent of other contestants (as assumed in much of the prior literature) is no longer reasonable. Contestants can incorporate emerging information from a contest environment into the creation and revision of their own solutions. Although this can reduce repetition in solutions and redundancy in effort (Kornish and Ulrich 2011), it can also create a perception of intellectual property loss from a contestant's standpoint. Contestants who participate in an unblind contest, thus, must weigh the cost of revealing their solutions against the benefits of continuous learning and improvement of their submissions through feedback and the possibility of a monetary prize. These characteristics of unblind contests are likely to have a significant impact on how contestants solve problems in such contests and influence the outcomes from their participation. To that end, our study investigates the following research question: *In what way, and to what extent, does a contestant's problem-solving behavior in an unblind innovation contest influence her likelihood of success in the contest, above and beyond her prior experience and success in the problem domain?*

[1] For example, 99designs.com, since its launch in February 2008, has become one of the fastest growing online platforms for graphic design contests (e.g., logo design, website design, mobile app design) with approximately 205,000 contests hosted to date, involving more than 218,000 contestants and total awarded prize money exceeding $50 million (Source: 99designs.com). Similarly, Logomyway.com, an online platform that specializes in logo-design contests has hosted more than 7,500 contests involving approximately 15,000 contestants with total awarded prize money estimated to be around $3 million, since its launch in April 2009 (Source: logomyway.com).

Table 1: Differences between Blind and Unblind Innovation Contests and their Implications

	Contest Type		Impact
	Blind	**Unblind**	
Submissions & Contestants	Not visible/not shared	Visible/shared	• Reveals ideas, risk of intellectual property loss
	Typically single submission	Multiple submissions	• Allows testing of multiple ideas • Allows contestants to incorporate emergent information into submissions • Submissions are not independent • Increases burden on contest holder
Feedback	If given, not visible/not shared If given, at end of contest	If given, visible/shared If given, during contest	• Reveals contest holder preferences
Information Structure	All information given in problem statement	Dynamically increasing information due to visibility of submissions and feedback	• Learning and solution improvement may occur

We address this research question by first characterizing problem-solving behavior in unblind innovation contests in terms of how contestants make submissions to a contest—i.e., when does a contestant begin participation in a contest *(position of first submission)*, how many submissions does a contestant make in a contest *(number of submissions)*, what is the number of submissions in a contest over which a contestant actively participates *(length of participation)*, and how are a contestant's submissions distributed through her active participation *(skewness of submissions)*. Next, we examine whether variations in problem-solving behavior among contestants across each of these dimensions impact their likelihood of success in a contest. Prior work has shown that in addition to contest characteristics such as prize amount, a contestant's prior experience and success in a contest domain may influence their likelihood of success in a blind contest (Bayus 2013, Jeppesen and Lakhani 2010). Therefore, in our analysis we control for variables such as these that have been shown to influence outcomes in blind contest environments, while introducing new variables related to contestant problem-solving behavior that are operative in unblind contest environments.

Hypotheses related to these dimensions of problem-solving behavior are tested using an integrated dataset comprised of detailed archival data from 1,024 contests and 2,626 unique contestants from a popular unblind logo-design contest platform, Logomyway.com. The pooled, cross-sectional nature of the data set allows us to control for unobserved heterogeneity across contestants. The empirical analysis is carried out using a two-stage estimation procedure that accounts for the endogenous nature of problem-solving behavior in the analysis. The results indicate that contestants' problem-solving behavior plays a significant role in their success in an unblind innovation contest. In particular, we find that, despite the potential for intellectual property loss from revealing of submissions, contestants who make their first submission earlier in a contest are more likely to succeed in the contest (i.e., place in the top three) as their number of submissions increases. We also find that the increased length of participation of a contestant in a contest has a strong positive effect on her likelihood of success as it enables greater learning from the contest environment. More importantly, contestants whose submission patterns in a contest exhibit greater positive skewness, mimicking the traditional innovation funnel approach (Ulrich and Eppinger 2011), have a higher likelihood of success. By conceptualizing the problem-solving behavior in unblind innovation contests in terms of granular submission activity in such contests, and by linking such behavior to contest outcomes, our study provides new evidence that the process of problem solving matters above and beyond prior experience and success in contest settings characterized by submission and contestant visibility. These findings lead to useful insights for the effective design and refinement of unblind innovation contests in practice.

2. Related Literature

The literature on innovation contests has its roots in the research stream relating to economics of R&D tournaments (e.g., Taylor 1995, Fullerton and McAfee 1999, Che and Gale 2003). Given the distinctive differences in the format and organization of internal firm-based R&D tournaments from innovation contests (Poetz and Schreier 2011), we focus primarily on studies examining innovation contests. To that end, the two key aspects of unblind innovation contests we examine in our study are the information structure of the contest environment and the resulting impact on heterogeneous problem-solving behavior of contestants. We discuss the existing literature on these aspects, identify the key gaps in our understanding of these aspects and highlight how our study contributes toward addressing these gaps.

Much of the prior innovation contest literature has studied blind, single submission settings with limited or no provision of intermediate feedback. Prior research on blind contests has primarily examined how heterogeneity across contests as measured by broad contest characteristics (e.g., size and number of awards, number of contestants, or the specificity of contest problems) influences contest participation and outcomes (e.g., Terwiesch and Ulrich 2009, Erat and Krishnan 2012, Chao and Erat 2012). The limited number of studies that have focused on heterogeneity within contests have primarily examined contestant level factors, such as contestant prior experience and skills in the contest problem domain, and their implications for contest outcomes (Terwiesch and Xu 2008, Jeppesen and Lakhani 2010). For instance, Terwiesch and Xu (2008) model problem solving in blind innovation contests as a set of parallel experiments where the performance of a submission by a contestant is a function of her expertise, effort, and random error. In an empirical study of InnoCentive, a science-focused blind innovation contest platform, Jeppesen and Lakhani (2010) find that contestants offering a different view on the problem (i.e., those that come from a different professional domain relative to the problem domain) have a higher chance of winning.

The notion that unblind contests provide a distinct environment for problem solving compared to blind contests and merit greater research can be seen from Wooten and Ulrich's (2013) recent work on unblind contests. Specifically, in a field experiment, they compare blind versus unblind contests in a logo-design setting similar to ours, and find that unblind contests have a greater total number of submissions than blind contests do, but have fewer submissions per contestant and a lower overall quality of submissions (based on external ratings). While other studies do not explicitly compare unblind contests with blind contests, they do examine various unique characteristics of the unblind contest format (e.g., visibility of contestants, intermediate feedback by contest holder) and their implications for problem solving (e.g., Yang et al. 2010, Archak 2010, Boudreau et al. 2012, Wooten and Ulrich 2012).[2] For example, using data from TopCoder, a platform for computer programming contests upon which contestant identity is visible but not their submissions, Archak (2010) and Boudreau et al. (2012) examine distinct effects of contestant expertise and visibility on the dynamics of the contests. Specifically, Archak (2010) finds that highly rated coders sign up for contests to signal that others should not enter, while Boudreau et al. (2012) find that highly skilled competitors who are at the top of the "ability distribution" exhibit higher effort and greater performance in the presence of superstars (well known, best-of-the-best competitors). Highlighting the implications of the dynamic information structure in an unblind contest environment, Wooten and Ulrich (2012), find that the quality of submissions by a contestant improves in

[2] The literature on online auctions also provides valuable insights into heterogeneous participant behavior in the presence of information visibility. Studies have shown that experienced participants use different bid strategies, including timing of bids and number of bids (e.g., Roth and Ockenfels 2002, Bapna et al. 2004), and that inexperienced bidders learn over time (e.g., Srinivasan and Wang 2010, Wang and Hu 2009). Furthermore, research has shown that for common value English auctions, it is in the best interest of sellers in an auction to make bidding information public since it decreases information asymmetry and promotes more aggressive competition among bidders, which results in increased revenues for the seller (e.g., Milgrom and Weber 1982).

an unblind contest due to increased total submissions in the contest and feedback from the contest holder, as contestants learn from the contest environment. In sum, the above studies support the notion that the visible and dynamic nature of the information structure in unblind contest environments have important implications for the problem-solving behavior of contestants. However, we know little about how problem solving behavior differs across contestants in an unblind contest and whether such systematic differences allows contestants to make use of the contest's visible and dynamic information structure to develop successful solutions.

Our study attempts to address the above questions by taking a closer look inside the "black box" of contestant problem solving in unblind innovation contests. We conceptualize observed differences in problem solving across contestants in terms of how contestants make submissions to a contest, as represented through multiple underlying dimensions, namely position of first submission, number of submissions, length of contest participation, and skewness of submissions. Such a multi-dimensional conceptualization of problem-solving behavior allows us to develop a set of hypotheses linking each of its underlying dimensions to a contestant's likelihood of success. Further, our study explicitly recognizes and empirically models problem-solving behavior as endogenous and driven by both contest and contestant characteristics. Such an estimation strategy allows us to get closer to causal explanations for the link between problem-solving behavior and contestant's likelihood of success. Developing robust explanations of the implications of problem-solving behavior in unblind contests can provide deeper insights into the nature of competition in such environments and potentially lead to contest design refinements (Jeppesen and Lakhani 2010).

3. Hypotheses Development

3.1. Problem-Solving Behavior in Unblind Contests

Problem-solving behavior may vary across contestants in an unblind contest because of the information structure and the opportunity for contestants to submit multiple times. We have identified four dimensions along which problem-solving behavior can potentially vary in such contests.

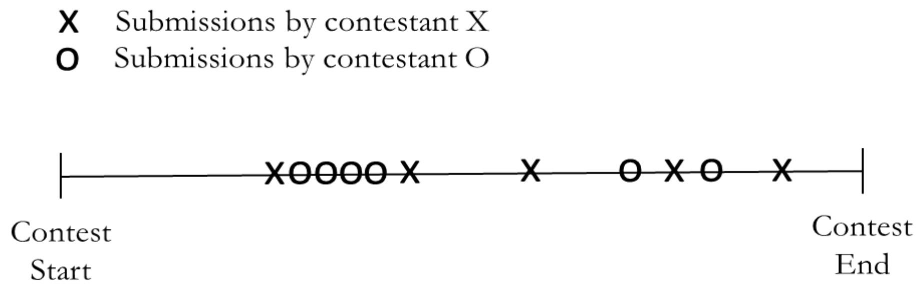
First, contestants are likely to differ in terms of their *position of the first submission* in the sequence of all submissions to the contest. The *lower* the position of the first submission, the *earlier* is a contestant's first submission into a contest relative to other contestants.[3] There are potential tradeoffs associated with this problem-solving behavior dimension. Although submitting early in a contest relative to other contestants may reduce the available time for a contestant to observe the competitive environment prior to submission and possibly lead to idea imitation, submitting late can restrict the amount of time available for the contestant to make revisions to her prior submission and/or make a new submission to the contest. Notwithstanding these tradeoffs, the first submission by a contestant signals the start of active participation by a contestant in a given contest. Following their first submission in a contest, contestants may differ in terms of their *number of submissions* in the contest as well as their *length of participation* in the contest. Length of participation represents the total number of submissions to the contest, by all contestants, between a contestant's first and last submission. This dimension is important because it is an indicator of the information structure changes in the contest (i.e., number of observable submissions) during a contestant's active participation. Both number of submissions and length of participation may depend on the contestant's understanding of the problem and the information available from the contest environment. Finally, a key distinguishing dimension of problem-solving behavior is the manner in which a contestant's submissions are distributed throughout her active participation in the contest (i.e., the *skewness of submissions*). For example, a contestant may make submissions uniformly or, alternatively, make more submissions early on and then focus on refining one or two concepts in the later stage of the contest.

In Figure 1, we provide a graphical representation of these four dimensions, where two hypothetical contestants (X and O) have submitted multiple submissions in the contest. Contestant X has made her first submission to the contest earlier than contestant O, made five submissions in total, and uniformly spaced the submissions in the contest. Contestant O has submitted six times and has concentrated the majority of his submissions at the beginning of his activity in the contest (i.e., has greater positive skewness of submissions). Further, contestant O's submissions are distributed over a shorter length of participation

[3] Since we are studying unblind contests and focusing on how information structure impacts contestant behavior, we use the position of the first submission relative to other submissions instead of the absolute time of the first submissions in the contest. Absolute time does not capture information about the information structure in the contest environment. For example, knowing that a contestant made her first submission 24 hours into a contest does not provide us information about the state of the contest environment, but knowing that the contestant's first submission was the 20th overall submission to the contest, indicates that there were 19 other submissions for the contestant to observe prior to her first submission in the contest.

compared to contestant X's submissions. Obviously, these are only two examples of contest problem-solving behavior in an unblind innovation contest. What is important is that problem-solving behavior across contestants can be characterized along these four dimensions. We now examine how systematic variations in such behavior along these dimensions can influence a contestant's likelihood of success.

Figure 1. Examples of Problem-Solving Behavior in an Unblind Innovation Contest



3.2. Problem-Solving Behavior and its Implications for Success

A number of studies in the new product development literature (e.g., Wheelwright and Clark 1992, Ulrich and Eppinger 2011) emphasize the importance of involving users early in the product development process as it reduces uncertainty in user requirements and enables the users to clearly articulate their expectations of new product performance. Extending these findings to the context of unblind innovation contests, we argue that contestants who make their first submission to a contest earlier have greater opportunities to engage with the contest environment, elicit feedback on their submissions, and, in general, participate more actively in a process that generates valuable information on the tastes of the contest holder. The likelihood of experiencing greater engagement and obtaining valuable contest holder feedback is higher early in the contest because a contestant's submission can be viewed in an environment where fewer contestants are competing against one another. Thus a contest holder's ability to effectively evaluate each submission and provide feedback is higher. Further, given the taste-based nature of logo-design contests, early submission in a contest increases a contestant's ability to shape the contest holder's taste toward her own submission. The above arguments have found support in an analogous stream of literature on market entry by firms (e.g., Lieberman and Montgomery 1988, Sørensen and Stuart 2000) where it has been shown that initial entrants in a product market receive disproportionate attention in the consumer's mind, whereas late entrants would need to have a significantly superior product in order to gain the consumer's attention.

In addition, submitting to a contest early allows contestants to actively monitor other submitted solutions over a greater period of time and revise their understanding of the contest holder requirements. However, the potential benefits of submitting early are more likely to manifest as contestants make additional submissions. This is due to the fact that by making additional submissions, following an early first submission, contestants are able to make use of the emerging information from the contest environment and make improved submissions (Wooten and Ulrich 2012). While a single early submission by a contestant may potentially help shape the contest holder's preferences, the usefulness of additional information from the contest environment is *not* realized by the contestant when further submissions are not made and the likelihood of success is significantly reduced in such a scenario. These arguments are consistent with prior literature on user involvement in new product development (e.g., Clark and Fujimoto 1991, Baldwin and Von Hippel 2011), where the benefits from involving users result only when feedback from such involvement is taken into account in making improvements.

There is a potential downside associated with making a first submission early. Specifically, contestants run the risk of revealing their ideas early on to other contestants and increase their likelihood of intellectual property loss. This in turn can reduce the payoffs to a contestant for her efforts. By delaying her first submission, a contestant can continue to learn about other submissions and revise her ideas without running the risk of revealing her ideas. However, prior studies that have examined how intellectual property rights are allocated within user innovation communities find the risks of free information revelation to be lower than anticipated (Harhoff et al. 2003, von Hippel 2005). These studies argue that free revelation of information allows an innovator to exercise greater monopoly and claim credit for her innovation. Von Hippel (2005) further notes that although free revelation of information allows competitors to better understand the problem specification, it also forces them to generate solutions that represent a distinct configuration of the problem specification. Additionally, unblind innovation contest platforms typically employ mechanisms for reporting and dealing with blatant copyright violations and intellectual property issues.[4] Therefore, we expect the benefits associated with

[4] For example, Logomyway.com uses a Logo Dispute Center, where potential copyright violations and issues are reviewed by the design community.

making a first submission early to outweigh the potential risks associated with intellectual property loss. We posit the following hypothesis.

> **HYPOTHESIS 1**: *Contestants who make their first submission to an unblind contest earlier are more likely to succeed in the contest as their number of submissions increases.*

From a purely mathematical standpoint, a contestant making more submissions is likely to have a higher likelihood of success in a contest, all else being equal (Simonton 2003). Toward this end, there is an established quantity-quality relationship in the idea generation literature (Osborn 1953, Girotra et al. 2010). Osborn (1953, p. 131) specifically notes "*it is almost axiomatic that quantity breeds quality in ideation. Logic and mathematics are on the side of the truth that the more ideas we produce, the more likely we are to think up some that are good.*" Consistent with this logic, we propose that in an unblind contest environment, the likelihood of success in a contest compounds as a contestant makes more submissions, since it provides contestants with greater opportunities to learn from the contest environment and incorporate such learning into their submissions. As much of the prior literature on individual learning (e.g., Cohen 1991, Argote et al. 1999) indicates however, such learning effects are likely to exhibit diminishing returns. This is because with an increasing number of submissions, contestants develop a better understanding of the problem specification and the contest holder tastes. Thus the marginal knowledge gained about the problem specification and the contest holder tastes from each additional submission decreases as the number of submissions increases.

We conjecture that some intermediate number of submissions will allow a contestant to best learn from the environment as well as focus her efforts to create high quality submissions. Making additional submissions may reflect a contestant's inability to identify and focus on a promising, high quality submission. For instance, Terwiesch and Xu (2008) have shown that the effort per contestant has an optimal level given a contestant's assessment of her probability of winning and the costs of participating. Making more submissions beyond this optimal level may lead to cannibalization of effort across submissions, thus resulting in an overall decrease in the quality of submissions. Similarly, in the context of creative problem solving, Reynolds (2010) notes that having a lot of competing design ideas can increase the cognitive burden associated with problem solving, making it difficult for the designer to distinguish between promising ideas and less promising ideas. Often, the designer may end up mixing elements of the prior ideas to arrive at a final design that may represent a lack of focus and a "diluted" message being communicated, resulting in a lower likelihood of success. Therefore, we posit the following hypothesis.

> **HYPOTHESIS 2:** *A contestant's number of submissions in an unblind contest exhibits a curvilinear relationship with likelihood of success, such that increasing the number of submissions is initially related to an increasing likelihood of success up to a certain point after which it is related to a decreasing likelihood of success.*

As contestants stay active in a contest over a greater length of participation, they have a greater opportunity to observe other contestants' submissions as well as feedback (on others and their own submissions). A contestant's observation of the evolving information structure in the contest can lead to learning and refinement of her own solutions. We note here that the notion of "active" participation by a contestant, which starts when the contestant makes her first submission, is central toward understanding the benefits of increasing the length of participation in a contest. It is plausible that such observational learning by a contestant may also occur without her making an initial submission to the contest (i.e., contestants can continue to observe submissions without yet participating in a contest). However, the benefits of such observational learning for the contestant are significantly reduced in the absence of an initial starting point for problem solving, which an initial submission provides (Kavadias and Sommer 2009). By actively participating, contestants can "learn by doing," which typically leads to better outcomes as compared to learning by observation (von Hippel and Tyre 1995). The potential result of increased learning by doing is a better understanding of the contest holder's requirements and their interdependencies, which are often difficult to predict through observation only.

Subsequent to their first submission, increasing the length of participation in a contest allows contestants to triangulate their ideas with information generated from other submissions and feedback from the contest holder, which can lead to a better understanding of the gap between their current performance and expected performance (Wooten and Ulrich 2012). Specific ideas or solution concepts submitted that have led to positive responses are reinforced, while the propensities to engage in actions that have led to negative responses are diminished (Gavetti and Levinthal 2000). Contestants can use this information to develop more promising solutions, which enhances their likelihood of success in the contest. In addition, increasing length of participation provides contestants with a more updated understanding of the contest holder's requirements. The context of logo design provides an example of contests characterized as "changing-use" environments where contest holders' requirements typically evolve as contests progress (Terwiesch and Xu 2008). Therefore, by actively keeping track of a contest holder's emerging requirements through feedback and other submissions, contestants can propose solutions that more closely match those requirements and succeed in the contest.[5]

> **HYPOTHESIS 3**: *As the length of participation of a contestant in an unblind contest increases, the contestant is more likely to succeed in the contest.*

The distribution of a contestant's submissions is potentially a reflection of her problem-solving process, which has commonly been modeled using the performance landscape or NK model in the innovation literature (e.g., Kauffman et al. 2000, Gavetti and Levinthal 2000, Kavadias and Sommer 2009, Kornish and Ulrich 2011). More recently, this prior representation has been used in the context of innovation contests (e.g., Terwiesch and Xu 2008, Erat and Krishnan 2012) where the required solution in a contest often cannot be fully specified *ex ante* and often evolves as the contest progresses.

A review of the literature indicates two key approaches to problem solving on rugged performance landscapes: selectionism (i.e., parallel testing) and trial and error (i.e., sequential testing) (Loch et al. 2006, Sommer et al. 2009). Selectionism involves generating several alternative solutions simultaneously and selecting the one that works best *ex post*. Such an approach is likely to be particularly useful for problem solving in ideation contests as it allows a contestant to test several points on the solution landscape by making multiple submissions in quick succession with various permutations and combinations. However, it can result in the identification of a sub-optimal peak if uncertainty in the solution landscape is high (i.e., the contest holder's preferences and the problem specifications that define a "good" solution change over time). The trial and error approach, on the other hand, involves actively searching for new information and making frequent adjustments to the most promising solution based on the new information. Such an approach is useful as it allows problem solvers to account for emergent information and revise their submissions. However, because the trial and error approach focuses on creating improvements to an existing solution, its effectiveness depends largely on the quality of the existing solution. Accordingly, this approach frequently leads to an inferior peak on a rugged landscape.

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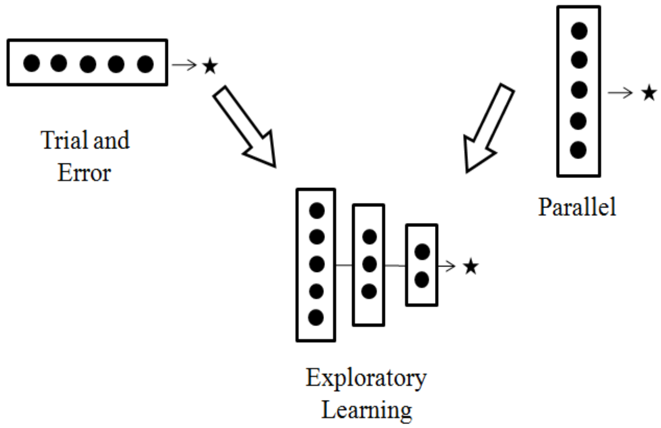
[5] We note here that the length of participation is not synonymous with the *duration* (in absolute time) of participation by a contestant. Consider for instance, two contestants, A and B. Over a period of two days, contestant A observes 50 submissions between her first and last submissions while contestant B observes 10 submissions between her first and last submissions. It is likely that, on average, contestant A will learn more from her participation as compared to contestant B because of a greater exposure to the evolving information. Note that this difference in learning may occur even though the duration of active participation is the same for both contestants.

Given the benefits and limitations associated with each problem-solving approach, a hybrid approach referred to as "exploratory learning" that combines parallel trials with trial and error may be better for problem solving in unblind innovations contests (McGrath 2001, Loch et al. 2006).

Figure 2. Exploratory Learning Approach in Unblind Innovation Contests



As Figure 2 indicates, in exploratory learning contestants follow a parallel process initially and submit several designs early, which provides them with an opportunity to obtain feedback on their submissions, identify those designs that are viewed more favorably, and then iterate. This approach is similar to the classic funnel process in new product development (Ulrich and Eppinger 2011), where the funnel in the early stages of product development is wide with many possibilities, then narrowed to a few or a single promising concept. In an unblind innovation contest, exploratory learning would manifest in the form of a positive skew in a contestant's problem-solving behavior wherein the contestant enters multiple submissions in close succession first followed by an increasing gap between submissions. A positive skew in a distribution indicates that the right side tail is longer than the left side tail and the bulk of the values in the distribution lie to the left of the mean. In our context, if the submissions of a contestant are more concentrated toward the beginning of her active participation in a contest, then her submission distribution will be positively skewed. We hypothesize that an increase in skewness (i.e., becoming more positively skewed) would increase her likelihood of success in the contest.

HYPOTHESIS 4: *Contestants whose submissions in an unblind contest are more positively skewed are more likely to succeed in the contest.*

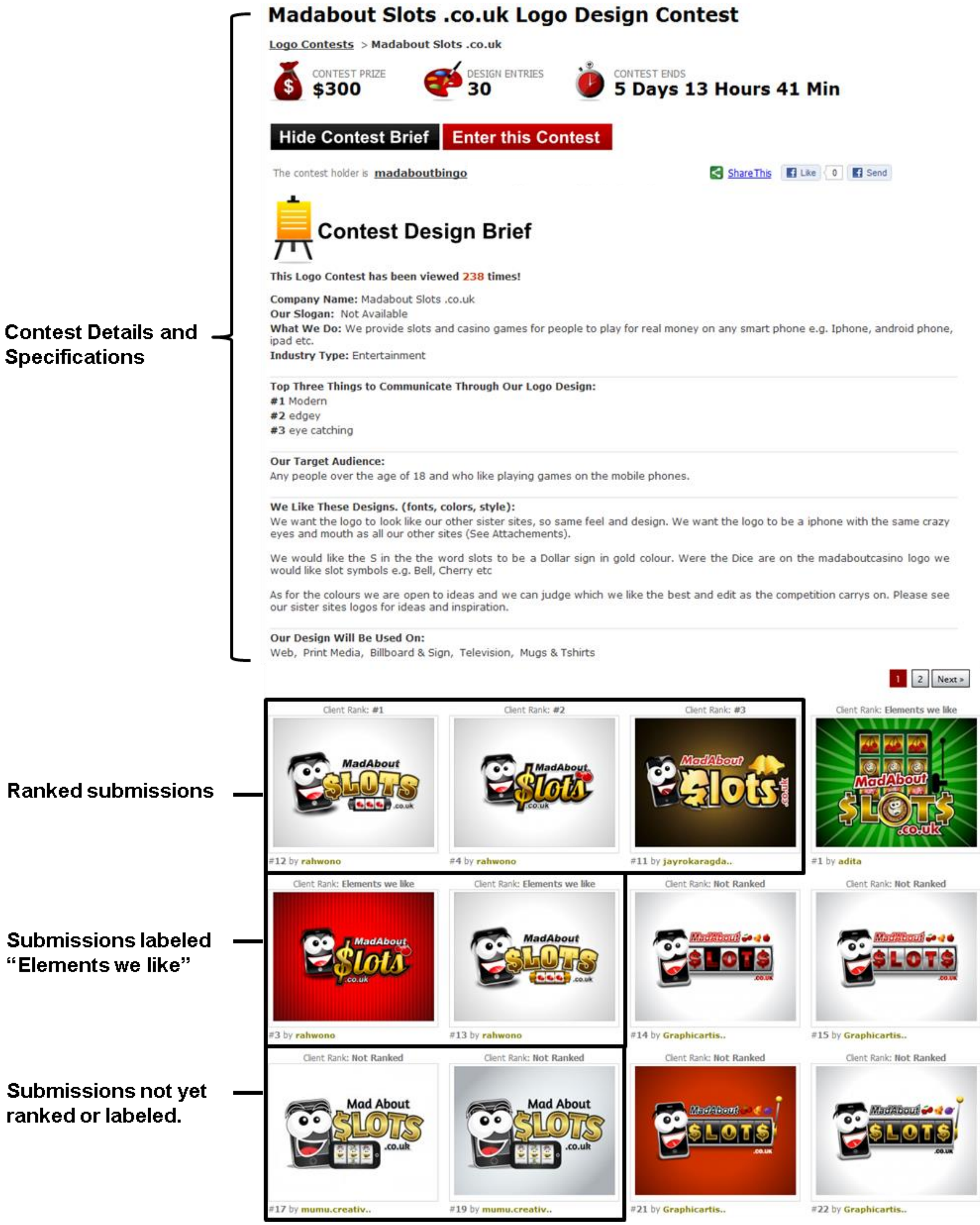
As noted from prior studies on innovation contests, it is likely that contestants' prior experience and success in the contest platform may influence their ability to generate a solution (Archak et al. 2010, Boudreau et al. 2011). For instance, prior participation experience in the contest platform may influence a contestant's evaluation of the contextual characteristics associated with a contest (i.e., industry context associated with the contest, the target audience for the contest solution, the expected levels of participation in the contest, and the tacit requirements of the contest holder). Further, a contestant's prior success in the contest platform may not only represent the contestant's intrinsic problem-solving skills, but also may reflect experiential wisdom that is the outcome of learning and selective retention of prior behaviors that yielded success (Srinivasan and Wang 2010, Hsu and Wolf 1999). Given our focus on the role of problem-solving behavior, we control for prior participation and prior success in our analysis, in addition to controlling for a number of contest- and contestant-specific characteristics.

4. Research Design

4.1. The Empirical Context: Logomyway.com

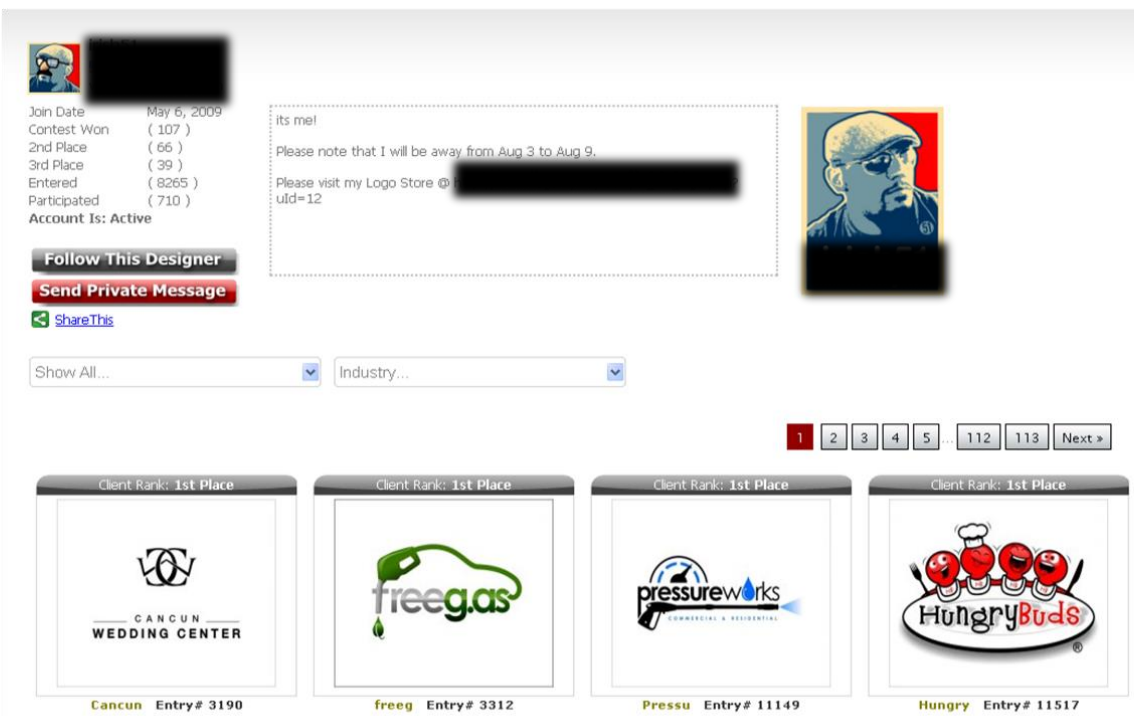
To test the above hypothesis, we collected data from a popular unblind innovation contest website, Logomyway.com, which matches graphic designers with organizations in need of new logos. The contest process on Logomyway.com begins when a contest holder (typically a business or organization) creates a new contest by indicating their preferences for a logo in a contest brief, setting the prize amount (between $200 and $1000), and setting the length of the contest (between one and 30 days). Once the contest has been launched, registered designers (i.e., contestants) on Logomyway.com can openly submit designs to the contest page until the contest's set end time. All submissions are displayed publicly on the contest page. Figure 3 shows an example of a typical contest page with contest brief and submitted designs.

Figure 3. Annotated Logomyway.com Contest Page



Contestants can submit an unlimited number of designs to a contest, and each submission is labeled with a submission number, a simple integer representing the position of a submission in the sequence of all submissions to a contest, and the username of the contestant. During the contest, feedback is provided by contest holders (if desired) on submissions primarily through rankings and labels. Contest holders rank submissions in the order of their preference (e.g., #1, #2, #3, …, #10) and can re-rank as often as desired. For those submissions which are considered promising, contest holders can label them with the phrase "elements we like" or, if not promising, "not interested." Additionally, as a secondary source of feedback, contest holders can post comments on specific designs or respond to designer questions on an open discussion thread on the contest page. The submitted designs and all comments are publicly displayed. Contestants can therefore receive direct feedback through rankings and comments on their own designs, and indirect feedback through the observation of rankings and comments on other contestants' designs. After the contest submission window has closed, the contest holder selects a winning design and the prize minus a 10% transaction fee collected by Logomyway.com is distributed to the winning contestant. Copyright of any submitted design remains with the contestant unless her design is selected as the winning design, at which point copyright is transferred to the contest holder.

Figure 4. Logomyway.com Designer Profile Page



As Figure 4 above represents, each registered designer is provided a profile page on Logomyway.com, which displays information such as the date she joined, as well as statistics about her participation history (e.g., number of contests in which she participated, number of total submissions) and her performance history (e.g., number of contest wins, 2^{nd} placings and 3^{rd} placings). Thus, while the prize amount in a contest is awarded only to the winning design in a contest, the extent of top three finishes by a designer based on her participation history is considered as an indicator of prior success on the contest platform. We discuss the data collection process in detail next.

4.2. Data Collection and Description

Our dataset consists of contest and submission details from a sample of 1,024 logo-design contests hosted on Logomyway.com. The data was collected from this website (with permission of the website's owner) using an automated HTML scraping tool built with the Java and Perl programming languages. Contest characteristics captured in our dataset include the prize amount, length of contest in days, number of submissions, number of participating designers, comments by the contest holder and designers during the contest, feedback events (e.g., rankings and labels), the number of views a contest webpage received, and whether the contest was public or private (i.e., whether the contest page on Logomyway.com required users to login in order to view the contest details). For each contest submission, we collected data on the designer, the submission sequence number for the corresponding contest (i.e., submission #50 was the 50th submission in the contest), and whether or not the designer placed in the top three in the contest.

In addition to contest data, we also collected profile information and data on the historical performance of every designer that participated in any of the design contests in our dataset, 2,626 designers in total. Designer data included information on the designer's home country, the number of contest placings received (i.e., first, second, and third place finishes), the total number of contests in which the designer had participated, number of submissions per contest, and the total number of submissions by the designer in all previous contests. It should be noted that for our analysis we established a data set using contest-designer pairs as the unit of analysis, since designers often appeared in multiple contests. Our dataset incorporates the changes in the number of submissions, participated contests and placings, etc., over time for each active designer based on her ongoing participation in the contests in our sample. For example, consider a single designer who participated in two contests, A and B, where contest A occurred prior to contest B. The number of prior submissions for the designer in contest B will be higher than that for contest A because the submissions made in contest A are now counted as prior submissions.

The data on contests was merged along with the data from the designers to create a comprehensive dataset of 44796 unique contest-designer pairs. Table 2 provides the description and summary statistics for the key variables of our model, based on the contest-designer pair unit of analysis[6].

Table 2: Description of Variables in the Study

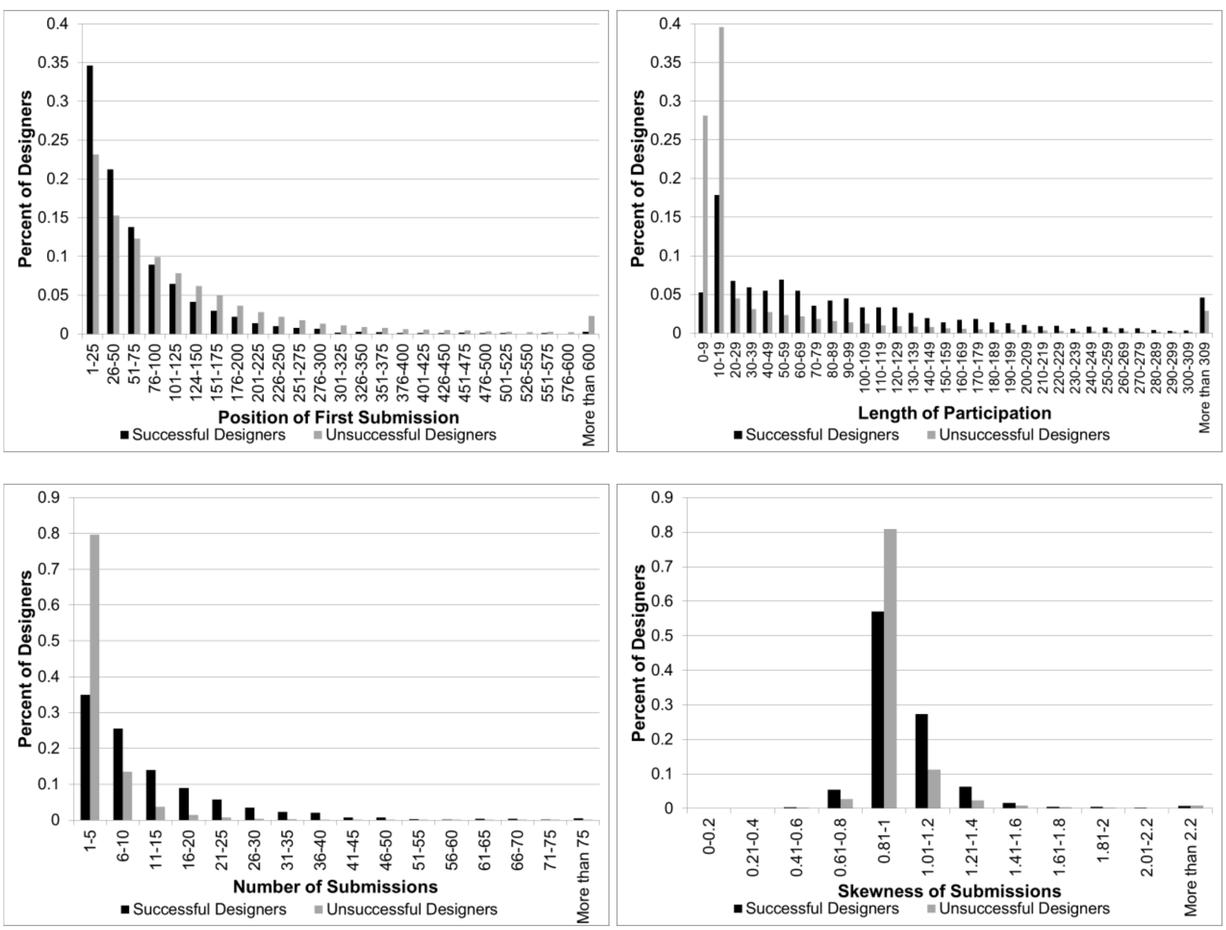
Variable Name	**Variable Description**	**Mean**	**Std. Dev.**
Dependent Variable			
Placed this Contest$_{ij}$	Denoted as 1 if designer *i* placed in the top three in contest *j* and 0 otherwise.	0.051	0.219
Problem-Solving Behavior Dimensions			
Position of First Submission$_{ij}$	The position of the first submission by designer *i* in the sequence of all submissions to the contest *j* (e.g., if contest *j* has 50 submissions when designer *i* first submits, the *Position of First Submission*$_{ij}$ = 51).	121.300	172.450
Number of Submissions$_{ij}$	Number of submissions by designer *i* in contest *j*.	4.483	6.175
Length of Participation$_{ij}$	Difference between the position of the last submission and the position of the first submission for designer *i* in contest *j*.	44.628	126.092
Skewness of Submissions$_{ij}$	Ratio of the mean of submission sequence numbers over median of submission sequence numbers submitted by designer *i* in contest *j*. Higher values suggest greater positive skewness.[7]	1.041	0.600
Control Variables			
Participation Experience$_{ij}$	Number of previous contests in which designer *i* had participated prior to her participation in contest *j*.	190.553	218.711
Placing Experience$_{ij}$	Ratio of the number of previous contests placed with respect to number of previous contests in which designer *i* participated, prior to her participation in contest *j*.	0.056	0.068
Contest Designers$_j$	Number of designers that participated in contest *j*.	61.615	39.150
Private$_j$	Denoted as 1 if the contest *j* was a private contest (i.e., only visible to designers who are registered on *Logomyway.com*) and 0 if otherwise.	0.327	0.469
Contest Duration$_j$	Number of days for which contest *j* was open for submissions.	12.004	9.648
Contest Views$_j$	The number of views the web page for contest *j* received.	1885.789	1301.585

[6] Summary statistics reported in Table 2 were calculated from data organized by the contest-designer unit of analysis. Therefore, they represent averages weighted by the number of times each corresponding contestant or contest appears in the dataset.

[7] We also carried out additional analysis using two other alternative measures of skewness, as discussed in §5.2, and obtained consistent results.

We have argued that contestant problem-solving behavior is likely to drive success in unblind innovation contests. As an initial analysis, we plot the distribution of the contest-designer observations in our sample for each problem-solving behavior dimension, split across contestants who were successful (i.e., placed in the top three) and unsuccessful in the corresponding contests. If problem-solving behavior has no impact on the likelihood of success, we would expect the distributions to be quite similar for these two groups. However, observable differences in problem-solving behavior can be seen in Figure 5. Specifically, we see that the successful designers tend to have an earlier first submission, participate longer, enter a larger number of submissions, and have a more positive skew (i.e., skewness > 1 as measured by the mean-median ratio) as compared to unsuccessful designers. These summary charts provide initial evidence; we next discuss the detailed econometric model specification we utilize to statistically test our hypotheses.

Figure 5. Distributions of Problem-Solving Behavior Dimensions



4.3. Model Specification

The hypothesized relationships in the study can be represented as a statistical model wherein problem-solving behavior dimensions are predicted to influence a contestant's likelihood of success. To measure success, we use *Placed this Contest*$_{ij}$ as our dependent variable, which is equal to one if contestant *i* finished in the top three ranked submissions of contest *j* and zero otherwise. Although, the prize is awarded only to the 1st ranked submission, using contest placing provides a more generalizable measure of success that is less susceptible to contest-holder idiosyncrasies and tastes in logo-design contests. Further, the use of a contestant-level fixed effect (discussed below) requires that each contestant appears in the dataset with at least one successful and one unsuccessful outcome. Since only a small fraction of contestants are winners on the contest platform, the use of winning as our measure of success reduces the sample to 323 contestants across 26194 contest-contestant observations. Using placing as our measure of success increases this to 551 contestants across 32384 contest-contestant observations.[8]

The data is structured as pooled cross-sectional with multiple observations for each contestant across different contests. This structure is similar to an unbalanced panel and derives from the fact that we do not observe all contestants participating in all contests in our sample. Given this data structure, it is necessary to use an estimation approach that controls for unobserved heterogeneity arising from stable characteristics of the contestants (i.e., characteristics that do not change over time). With binary dependent variables, this can be accomplished using a fixed effects logit model (Maddala 2001, Kennedy 2008). We model a contest holder's selection of a contestant *i* to place in a contest *j* as driven by attributes of contestant's *i* problem-solving behavior in contest *j* and a series of control variables in the form of contest and contestant attributes (both fixed and time-varying). The appropriateness of the fixed effects logit estimator is empirically verified by running a Hausman's test, which rejects the null hypothesis ($\chi 2 = 470.12$, $p < 0.001$) that the preferred specification is a random effects estimator. Equation (1) provides the linear representation of the fixed effects logit model.

$$\begin{aligned} Prob[Placed\ this\ Contest_{ij} = 1] = \ & \gamma_{1\text{-}6}[Control\ Variables]_{ij} \\ & + \gamma_{7}.Position\ of\ First\ Submission_{ij} + \gamma_{8}.Number\ of\ Submissions_{ij} \\ & + \gamma_{9}.Number\ of\ Submissions_{ij}^{2} + \gamma_{10}.Position\ of\ First\ Submission_{ij} \times Number\ of\ Submissions_{ij} \\ & + \gamma_{11}.Length\ of\ Participation_{ij} + \gamma_{12}Skewness\ of\ Submissions_{ij} + u_i + v_{ij} \end{aligned} \quad (1)$$

[8] Nonetheless, as discussed in §5.2, we also carried out analysis using *Won this Contest*$_{ij}$ as the dependent variable and obtained results that were consistent with those from the main model.

In the above equation, u_i represents the fixed effect for contestant *i*, which controls for unobserved heterogeneity across contestants, and v_{ij} represents the unobserved stochastic error term. The vector of control variables includes the time-varying contestant-level controls, *Participation Experience* and *Placing Experience*, as well as the contest attributes, *Contest Views*, *Contest Designers*, *Contest Duration*, and *Private*. We also note that the non-linear terms, *Number of Submissions*$_{ij}^{2}$ and *Sequence of First Submission*$_{ij}$ × *Number of Submissions*$_{ij}$, are known to be difficult to interpret in logit models (Ai and Norton 2003, Hoetker 2007). With quadratic terms in particular, concerns are introduced when the independent variable used contains negative values and thus the typical S-shaped curve of the logistical function is not maintained (Karaca-Mandic et al. 2012). To verify the true influence of these terms, we performed the appropriate marginal effects analysis, which is discussed in §5.

4.4. Correction for Endogeneity of Problem-Solving Behavior

It is possible that the problem-solving behavior dimensions in Equation (1) are driven by contestant characteristics and competitive reactions to the contest environment. We tested for endogeneity of the problem-solving behavior dimensions using the Durbin-Wu-Hausman's test (Maddala 2001), which rejected the exogeneity assumption ($\chi 2 = 494.982$, df = 4, $p<0.01$) and suggested a need to correct for the endogenous nature of each dimension. The inclusion of the contestant fixed-effects reduces endogeneity concerns arising from unobserved contestant heterogeneity; however, contest-level omitted variables and other environmental factors are still likely to be an issue. Following Angrist and Krueger (2001), we used a two-stage predictor substitution (2SPS) approach to examine the effects of problem-solving behavior on the contestants' likelihood of success in the contest. The 2SPS approach involves running first stage fixed-effects OLS regression models predicting each of the problem-solving behavior dimensions and generating predicted scores from each model. The predicted scores are then included in Equation (1) in place of the raw scores of the problem-solving behavior dimensions to correct for endogeneity.[9]

The first stage models for predicting problem-solving behavior dimensions include the contest and contestant attribute controls used in Equation (1) and a set of instrumental variables. Since we have already incorporated a contestant-level fixed effect, our goal in identifying instrumental variables was to control for contest-level and environmental omitted variables that could be driving endogeneity. We

[9] We adjusted the standard errors in the second stage using the standard bootstrapping approach (Guan 2003, Cameron and Trivedi 2010), to address the generated regressor issue.

identified three sets of instrumental variables for use in the first stage model.

First, the prize amount offered in the contest could determine the level of interest in a contest (Jeppesen and Lakhani 2010) and influence problem-solving behavior of contestants. Due to the fact that multiple overlapping contests are conducted at the same time, a contestant's problem-solving behavior could also be influenced by the number of ongoing overlapping contests as well as those that have a larger prize amount. A larger number of overlapping contests (*Number of Overlapping Contests*) would likely decrease the attention received by each contest, while a larger number of overlapping contests with higher prize amount (*Number of Overlapping Contests-High Prize Amount*) would reduce the attractiveness of a contest relative to other overlapping contests on the contest platform. Hence we included these variables in addition to *Prize Amount* as instruments in the first-stage models.

Second, a contestant's problem-solving behavior may be affected by the information provided in the contest. This information could take the form of feedback events and the comments of the contest holder and other contestants. We include two variables, *Contest Holder Comments* and *Contestant Comments*—which indicate the total number of comments posted by a contest holder and contestants on the contest page, respectively. With respect to feedback events, the contest holder can provide additional feedback by ranking contestant submissions or labeling them with the terms "Elements We Like" or "Not Interested". Therefore, we included an instrumental variable *Total Feedback Events,* which indicates the total number of submissions in the contest that were ranked or labeled. Additionally, the information provided in the contest brief may impact the problem-solving behavior of a contestant. Therefore, we included the natural log of the number of words used in the contest brief variable, *ln*(*Words*), as an instrument.

Third, since problem-solving behavior may change with time of year and over time for contestants we include two additional instruments. A series of month indicator variables (*September, October,…, February*) are included to capture any seasonal effects. Since prior problem-solving behavior may be a strong indicator of current problem-solving behavior, but does not affect the likelihood of succeeding in the current contest we also included the instrumental variable *Submissions per Participation,* which is the average number of submissions by a contestant in prior contests.

To test the validity of the instruments in the first-stage models, we conducted the Sargan-Hansen test for over-identification (Davidson and MacKinnon 2004, Baum et al. 2007). This test is based on the observation that the residuals should be uncorrelated with the set of exogenous variables in the second-stage model if the instruments are truly exogenous. A failure to reject the null hypothesis in this test provides evidence in favor of the exogeneity assumption of the instruments. The Sargan-Hansen test statistic in our analysis is statistically insignificant ($\chi 2$ = 10.04, df = 10, p=0.44). Additionally, the F-statistic, testing the null hypothesis that the slopes of all instruments are zero, exceeds 10 for all the problem-solving behavior dimensions, highlighting the relevance and sufficient predictive power of these instruments (Kennedy 2008).

Finally, in addition to the above instrumental variables, we account for potential interrelationships among the problem-solving behavior dimensions. Specifically, we include *Position of First Submission* as a predictor of *Number of Submissions*, *Length of Participation* and *Skewness of Submissions*; *Number of Submissions* as a predictor for *Length of Participation* and *Skewness of Submissions*; and *Length of Participation* as a predictor of *Skewness of Submissions*. Descriptive statistics and pairwise correlations associated with all variables in the first and second stage models are shown in Table A1 in the Appendix. Detailed results associated with the first stage regression models are provided in Table A2.

5. Analysis and Results

5.1. Model Estimation Results

The estimation of the fixed effects logit specification in Equation (1) requires variation in dependent variable for each contestant in the sample. In other words, for the estimation to proceed, each contestant should have placed at least once and not placed at least once in our sample. This leads to a final sample of 551 active designers and 32384 contest-designer pairs for carrying out the above estimation.

Table 3a summarizes the results of our econometric analysis. For ease of interpretation, we standardized the predicted scores of problem-solving behavior dimensions from the first stage instrumental variable regressions and included them along with the standardized values of all control variables (with the exception of the binary variable, *Private*) in the analysis. In total, six model specifications are presented. In column 1, we report the estimation results for the baseline model that includes only the control variables. Columns 2-5 present the results of our main analysis of the effects of problem-solving behavior dimensions on the likelihood of success. Column 2 presents the main effects model, column 3 introduces the quadratic effect for *Number of Submissions*, column 4 introduces the interaction effect *Sequence of First Submission* X *Number of Submissions*, and column 5 presents the full

Table 3a: Empirical Analysis Results Examining the Relationship between Problem-Solving Behavior and Likelihood of Success

	Fixed Effects Logit Model					Random Effects Logit Model
	(1)	(2)	(3)	(4)	(5)	(6)
Problem-solving behavior						
Position of First Submission		-2.723 (0.369)**	-2.771 (0.363)**	-2.225 (0.364)**	-2.451 (0.359)**	-0.338 (0.093)**
Number of Submissions		-0.448 (0.238)*	-0.168 (0.243)	-0.658 (0.250)**	-0.374 (0.263)	-0.075 (0.054)
Number of Submissions^2			-0.111 (0.033)*		-0.060 (0.035)†	-0.058 (0.001)**
Position of First Submission × Number of Submissions				-0.212 (0.056)**	-0.139 (0.078)†	-0.138 (0.031)**
Length of Participation		1.488 (0.080)**	1.506 (0.081)**	1.554 (0.080)**	1.536 (0.083)**	1.290 (0.036)**
Skewness of Submissions		0.350 (0.094)**	0.330 (0.090)**	0.442 (0.102)**	0.394 (0.103)**	0.081 (0.032)**
Control Variables						
Participation Experience	0.277 (0.130)*	0.484 (0.183)*	0.551 (0.183)**	0.460 (0.182)*	0.521 (0.185)**	0.269 (0.046)
Placing Experience	2.726 (0.310)**	2.894 (0.348)**	2.857 (0.348)**	2.885 (0.321)**	2.887 (0.343)**	0.830 (0.033)**
Contest Designers	-0.826 (0.068)**	-0.077 (0.214)	-0.021 (0.215)	-0.363 (0.221) †	-0.202 (0.219)	-0.970* (0.079)
Contest Views	0.140 (0.059)*	0.054 (0.112)	0.034 (0.113)	0.073 (0.112)	0.041 (0.113)	-0.484 (0.077)
Private	-0.037 (0.052)	0.023 (0.062)	0.003 (0.062)	0.018 (0.063)	0.003 (0.062)	-0.229 (0.059)
Contest Duration	-0.058 (0.039)	0.025 (0.047)	0.019 (0.047)	0.024 (0.048)	0.019 (0.047)	0.033† (0.039)
Constant						-3.786 (0.057)**
–Log-likelihood	6213.835	5219.934	5200.743	5203.028	5195.963	6859.270
χ2	290.260**	612.280**	652.740**	611.720**	640.040**	2154.770**
Pseudo R-Square	0.09	0.23	0.24	0.24	0.24	
Df	6	10	11	11	12	12
Number of Contest-Designer Pairs	32384	32384	32384	32384	32384	44796
Number of Designers	551	551	551	551	551	2623

† $p<0.1$, * $p<0.05$, ** $p<0.01$

Note: The standard errors for model coefficient estimates are shown in parentheses; all models used robust bootstrapped standard error estimation clustered by contestant. All variables presented, except for the binary variable, *Private*, were standardized prior to estimation. Constant terms are not estimated for fixed effects logit models. Unlike the fixed effects logit model, the random effects logit model does not require variation in the dependent variable for each conditioning stratum; hence we can use the overall sample to estimate Equation (1).

model. We also include a random effects model specification in column 6 to demonstrate the robustness of our model specification. In table 3b we present the odds ratios and marginal effects for the key variables in model 4.

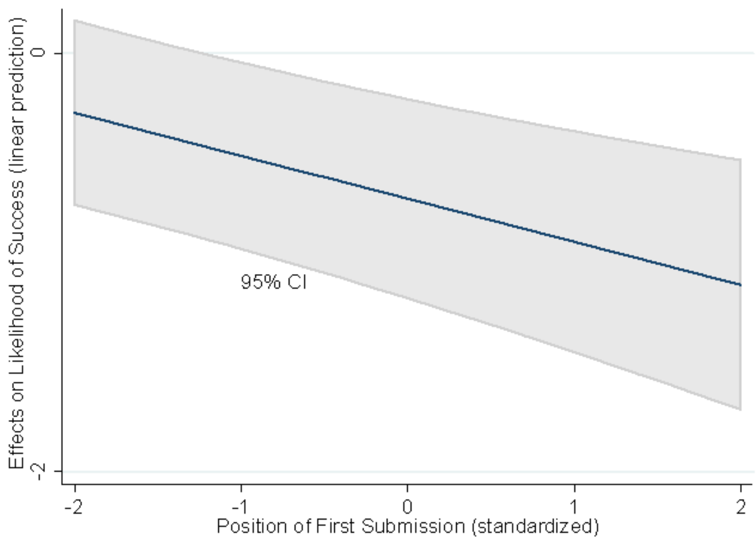
Table 3b: Marginal Effects and Odds Ratios for Model 4

Variable	Odds Ratio	Marginal Effect @ Mean	Average Marginal Effect
Position of First Submission	0.108	-0.467***	-0.278***
	(0.039) **	(0.052)	(0.029)
Number of Submissions	0.518	-0.138***	-0.082***
	(0.130) **	(0.033)	(0.019)
Position/Number Interaction	0.817	-0.042***	-0.025***
	(0.046)**	(0.008)	(0.004)
Length of Participation	4.731	0.325***	0.194***
	(0.380)**	(0.011)	(0.006)
Skewness of Submissions	1.556	0.093***	0.055***
	(0.158)**	(0.012)	(0.007)

Note: Marginal effects calculated based on the probability of a positive outcome (placing in the top 3), assuming the fixed effect is zero.

Hypothesis 1 predicts that making the first submission early in a contest becomes more beneficial when the contestant makes multiple submissions. From the results presented in Table 3, we observe a consistent significant negative effect of position of first submission in all models (e.g., $\beta = -2.451$, $p < 0.01$ in full model, column 5), which indicates that entering earlier is associated with a higher likelihood of success in the contest. The odds ratio for position of first submission tells us that increasing this variable by one standard deviation (i.e., entering the contest later) results in a decrease in the odds of success by 89% and the marginal effects analysis suggests that the likelihood of success decreases between 27% and 46% for each standard deviation increase in the position of first submission. In addition, we observe a consistent significant and negative interaction between the position of first submission and the number of submissions ($\beta= -0.212$, p-value < 0.01 in column 4 and $\beta= -0.139$, p-value <0.1 in column 5). Given that the logit estimation is nonlinear, additional marginal analysis is necessary to understand the true nature of this significant interaction term (Ai and Norton 2003, Hoetker 2007). Figure 6 provides a plot of the average marginal effect of number of submissions on the likelihood of success with respect to the position of first submission in a contest. The plot shows a downward slope indicating that the marginal benefit of a one unit increase in the number of submissions on the likelihood of success is greater at low values of the position of first submission compared to high values. The significant negative interaction effect observed in Table 3 and the plot of the marginal effects provide strong support for Hypothesis 1.

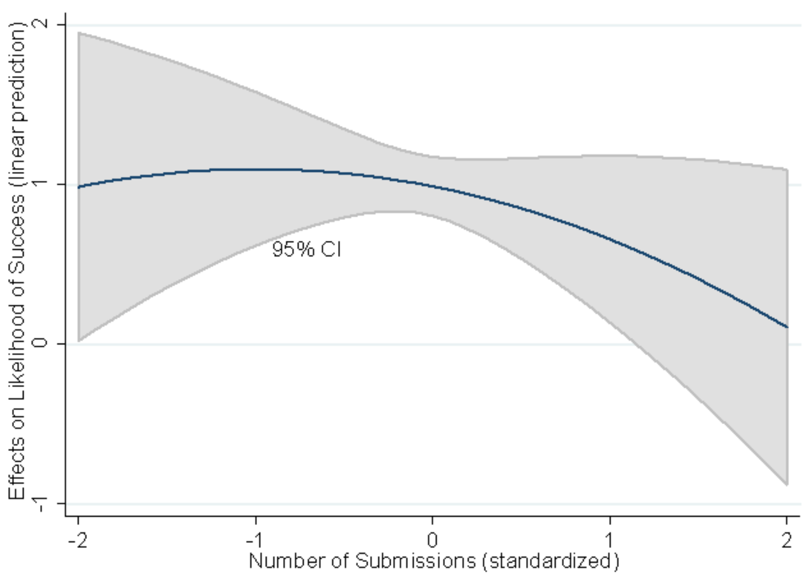
Figure 6. Marginal Effects of Number of Submissions and Sequence of First Submission Interaction Effect



Hypothesis 2 predicts that the number of submissions by a contestant has a curvilinear and concave relationship with likelihood of success in the contest. To test this hypothesis, we examined the coefficient of the number of submissions main effect and the squared term effect in column 3 (squared term model) and column 5 (full model) of Table 3. While the main effect is insignificant in column 3, the squared term effect is negative and strongly significant (β= -0.111, p-value < 0.01) suggesting that there are decreasing marginal returns to making additional submissions to the contest. Similar to our analysis of Hypothesis 1 above, we must look at the marginal effects in order to fully understand the nature of this effect. Figure 7 plots the effect of number of submissions on the likelihood of success in the contest for the model presented in column 3 (main effects plus the quadratic term). As can be seen in the figure, there is evidence of a curvilinear relationship with an initial increase in likelihood of success as a function of number of submissions followed by a decrease. Note however that while the main effect for the coefficient of number of submissions remains insignificant in the full model (column 5), the squared term effect is weakly significant in the model. Taken together, the above results provide limited support for Hypothesis 2.

Hypothesis 3 predicts that contestants who have a greater length of participation in an unblind logo-design contest are more likely to succeed. Consistent with our predictions, the results of our analysis show a positive and significant effect of length of participation on the likelihood of success in all models (e.g., $\beta = 1.536$, $p < 0.01$ in full model, column 5). The odds ratio tells us that increasing the length of participation by on standard deviation increases the odds of success by 4.7 times and the marginal effects analysis suggests that the same increase in length of participation is associated with a 19-32% increased likelihood of success. The consistency of the direction, magnitude and significance of this effect provides strong support for Hypothesis 3.

Figure 7. Marginal Analysis of Number of Submissions Quadratic Term



Hypothesis 4 predicts that contestants whose submissions are more positively skewed in an unblind logo-design contest are more likely to succeed. Recall that positive skewness in a contestant's submission pattern is visible when the bulk of the contestant's submissions are made in the first half of her participation in a contest. We observe a consistently positive and significant effect of skewness on the likelihood of success throughout all models (e.g., $\beta = 0.394$, $p<0.01$ in the full model, column 5), which provides strong support for Hypothesis 4. The odds ratio tells us that increasing the positive skewness of submissions by 1 standard deviation increases the odds of success by 55% and the marginal effects analysis suggests that a one standard deviation increase in positive skewness is associated with a 5-9%

increase in the likelihood of success.

Although the results associated with the control variables are not of direct interest to the study, we note particularly those associated with prior experience and success in the contest domain. The analysis results indicate a consistently positive and significant effect for both participation experience ($\beta = 0.521$, $p<0.01$ in the full model, column 5) and placing experience (e.g., $\beta = 2.887$, $p<0.01$ in the full model, column 5) on the likelihood of success. These results are consistent with arguments in the extant literature which highlight the importance of prior experience and success in the development of superior problem-solving routines (Archak et al. 2010, Boudreau et al. 2011).

In light of the significant results, we evaluate the relative importance of problem-solving behavior dimensions in predicting a contestant's success above and beyond her prior experience and success in the contest platform. Specifically, we examine the incremental explanatory power of the baseline model in column (1), which includes only the control variables, to that in column (2), which includes both the control variables and the problem-solving behavior dimensions. The change in pseudo R-square is 14% across the two models. Additionally, both the likelihood-ratio (LR) test and the chi-square difference test comparing the two models show a statistically significant improvement in fit results from including the problem-solving behavior dimensions (LR $\chi 2$ = 1987.80, $p<0.000$; $\Delta\chi 2$ = 396.65, Δdf = 4, $p<0.000$). These results provide collective support to the notion that, in unblind innovation contests, the problem-solving behavior of contestants is an important predictor of their success in a contest, above and beyond their prior experience and success on the contest platform.

5.2. Robustness Checks

In addition to alternative specifications of the overall model, we conducted robustness checks by using alternative specifications of the dependent and key independent variables.

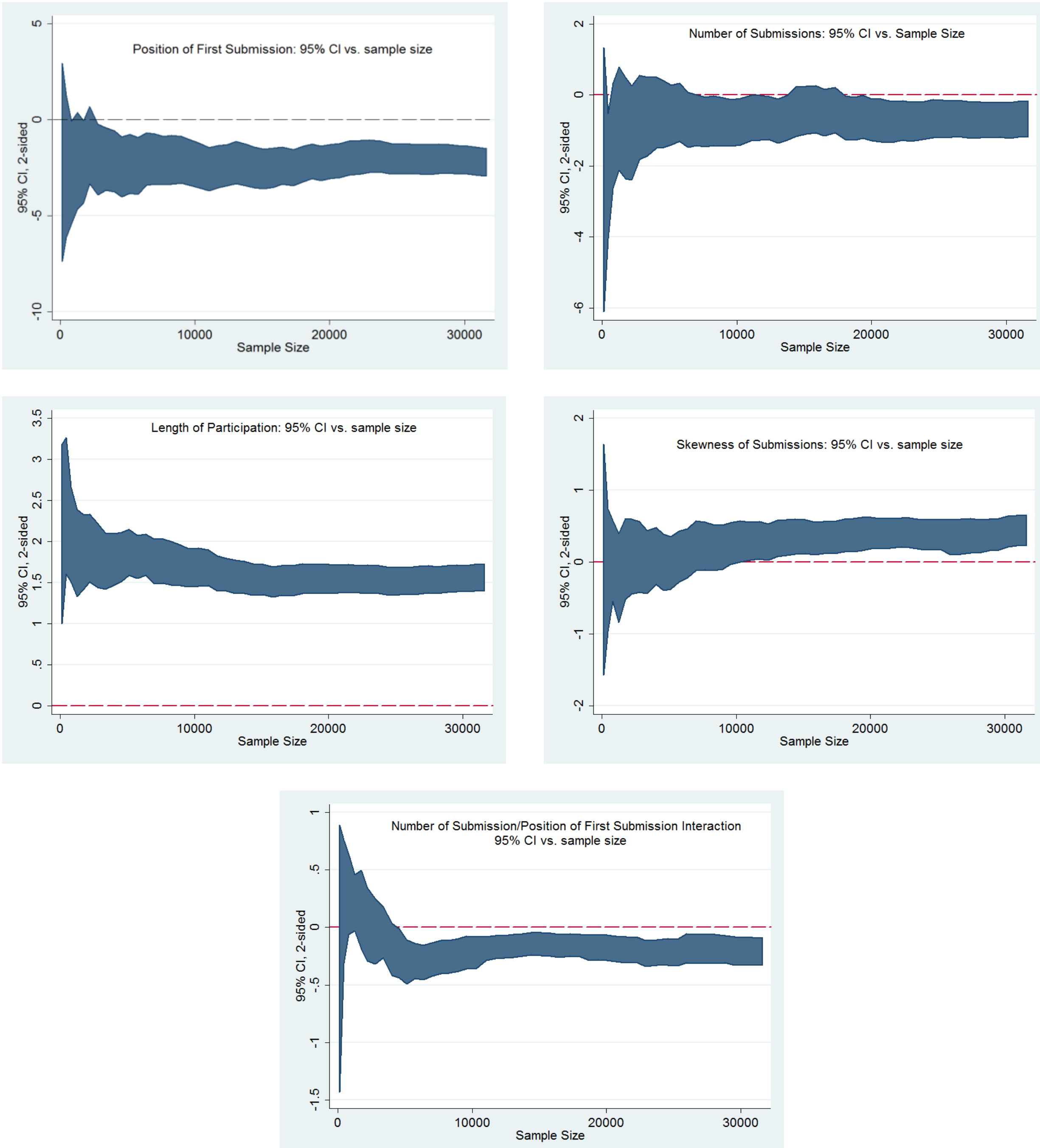
Alternative Specification of the Dependent Variable: As noted earlier, while the judging process on Logomyway.com allowed for second and third place ranks, all contests were "winner takes all" contests with the prize amount awarded to a single winner. We conducted additional analysis using a revised dependent variable, $\textit{Won this Contest}_{ij}$, for each contestant, which is coded as 1 if the contestant *i* won contest *j* and 0 otherwise. Since many contestants never won a contest in our dataset, using this revised measure resulted in data from 323 contestants across 26184 contest-designer pairs. The results from this analysis were consistent with the reported findings in Table 3 highlighting the robustness of our analysis.

Alternative Specification of Skewness: Skewness is measured in our study as the ratio of the mean to the median of the entry number (as defined in Table 2). We carried out additional analysis using alternative measures of skewness (Degroot and Schervish 2001). Specifically, we used: (a) an unbiased estimator of population skewness = $\left(\sqrt{n(n-1)}/(n-2)\right)\left(m_3/{m_2}^{3/2}\right)$, where m_2 and m_3 are the second and third moments of the given population and n is number of observations, and (b) the Pearson's median skewness coefficient, which is given by *PearsonSkewness* = $3(mean - median)/standard\ deviation.$ Results using these alternative measures of skewness were consistent with our original findings.

Alternative Model Specifications: In addition to the random effect logit presented in Table 3a, we estimated several alternative models to check for robustness of results. First, we estimated a fixed effect logit model using contest-level fixed effects to control for heterogeneity in the tastes and style of contestant holders. We also estimated a linear probability model with contestant-level fixed effects as well as a rare events logit model with contestant-level fixed effects to account for any potential issues that may arise from a substantially smaller number of positive outcomes (success in a contest) relative to the number of observed negative outcomes. All alternative model specifications provided results consistent with the models presented in Table 3a.

Confidence Interval Plots: Given the size of our dataset, one potential concern is that the statistically significant results are the product of a large sample size and thus narrow confidence intervals. Following the recommendations of Lin et al. (2013), we calculate confidence intervals for each of the main predictor variables over several sample sizes. Figure 8 presents these plots and additional evidence that the observed results are robust. One potential issue is observable in the plot for Number of Submissions, which suggests some instability in the estimate. Prior literature has suggested that increasing the number of entries results in higher likelihood of success, contrary to our findings. However, the confidence interval plot suggests that our estimate for this variable may not be accurate. Coupling this with the significant interaction term suggests that we should take care in interpreting the main effects related to Number of Submissions.

Figure 8. Confidence Interval Plots



6. Discussion and Conclusions

6.1. Summary of Findings

This study generates several new findings that inform our understanding of problem solving in unblind innovation contests. We find strong evidence that contestants' problem-solving behavior significantly influences their likelihood of success in a contest, above and beyond their prior experience and prior success in the contest environment. In particular, contestants who make their first submission in a contest earlier than others are more likely to succeed as they make multiple submissions. This finding is consistent with our arguments that a delay in the first submission in a contest not only reduces opportunities for contestants to experience greater engagement and obtain valuable contest holder feedback, but also reduces the opportunities available for contestants to act on the feedback and make additional submissions. The fact that we observe the benefits of an early first submission, despite the potential intellectual property losses, suggests that the risks of free information revelation may be lower than anticipated in unblind environments, particularly when appropriate mechanisms for addressing intellectual property concerns are present (von Hippel 2005).

Our findings further indicate that contestants who have a greater length of participation are more likely to succeed in the contest. This supports our prediction that staying active longer in a contest benefits contestants not only because it allows them to observe and assess their submissions with respect to the competition, but also because it helps them to update their understanding of the contest holder's requirements. To that end, making multiple submissions allows contestants to take advantage of the evolving information from the contest environment. However, the relationship between number of submissions by a contestant and her likelihood of success is not necessarily monotonic. We find evidence that the number of submissions exhibits a curvilinear and concave relationship with likelihood of success. These findings suggest the possible presence of a "quality-quantity" tradeoff in the submission process, but further research is needed to confirm this claim. Finally, our results with regard to positive skewness of submissions suggest that the distribution of a contestant's submissions has important implications. Contestants whose submissions are more positively skewed in a contest are more likely to succeed; and a positive skew implies a hybrid problem-solving approach, wherein contestants likely first engage in a selectionism approach by submitting multiple initial submissions, followed by a trial and error approach in which they iterate on promising submissions.

6.2. Contributions to Theory and Practice

Taken together, the above findings make the following contributions to the emerging literature on innovation contests. A key contribution arises from our focus on the economically significant and emerging "unblind" format. There has been significant growth in the use of the unblind contest format and such a format is becoming increasingly popular because of the potential benefits to contest holders (e.g., reduced repetition in solutions, iteration to obtain favorable solutions, etc.) and the greater opportunities it offers for contestants to learn and improve their skills in the contest domain; yet current research has focused mostly on studying blind contests where contest submissions are independent and problem-solving behavior is unobserved. However, unblind contests represent a distinct format and differ greatly from blind contests in terms of the visibility and the information structure of a contest. The additional information available in unblind contests can be used to shape submissions and subsequently influence contest outcomes. Our study highlights the implications of the unique characteristics of unblind contests by demonstrating the role of a contestant's problem-solving behavior as a key predictor of her success in a given contest.

A second, related contribution of this study arises from our efforts to conceptualize and measure problem-solving behavior in unblind contests across multiple dimensions. These dimensions provide measurable proxies for the problem-solving processes adopted by contestants. We identify key dimensions of problem-solving behavior in an unblind contest format and test the impact of each on a contestant's likelihood of success. To the best of our knowledge, this is the first study to develop a conceptual model that links multiple dimensions of problem-solving behavior to performance outcomes in innovation contests. In doing so, this study deviates from prior literature that has conceptualized the selection of the top-performing submissions in innovation contests as a set of random draws from an extreme value distribution (Dahan and Mendelson 2001). Our findings with respect to problem-solving behavior suggest that contest outcomes in unblind environments can be represented more accurately through a conditional extreme value distribution where the selection of the top performing submissions is conditional on the problem-solving behavior of contestants.

The third contribution of our study relates to our understanding of problem-solving approach in unblind innovation contests. Although prior studies in the innovation literature have identified the specific characteristics of the problem under which selectionism and trial and error learning are appropriate and complementary (Loch et al. 2006, Sommer et al. 2009), we know little about how such approaches apply to innovation contests. The absence of research in this area raises a fundamental question of *whether problem-solving approaches differ across individual contestants and whether such differences really matter*. Our findings indicate that the problem-solving approach enabled by an unblind contest platform (i.e., reflected in the distribution of a contestant's submissions), plays a significant, non-trivial role in a contestant's success on the platform.

Finally, although we find weak support for the curvilinear relationship between number of submissions and the likelihood of success, our findings extend prior research in the idea generation literature by highlighting the presence of a quality-quantity tradeoff in the submission process. Building on Osborn's (1953) seminal work, much of the existing literature in this stream has generally assumed a monotonic relationship between quantity and quality of ideas. Further, the number of potential ideas generated by an individual has often been denoted as the creative output by an individual with the implication that more creative output is always better (Simonton 2003, Bayus 2013). Our findings suggest that this positive relationship between quantity of ideas and overall quality of ideas (as represented by an individual placing in a contest) may not hold in unblind contest environments.

From a practical standpoint, the results of this study suggest several managerial insights for effective design and management of online innovation contest platforms. First, the key differences among blind and unblind innovation contests are the information structure and the level of interdependence among contest submissions. The results of our study suggest that the evolving information structure can significantly influence the outcomes of an unblind contest. Design choices related to information structure, such as the amount of transparency in submissions and feedback mechanisms, should be considered important parameters in the implementation of online innovation contest platforms and further research is needed to fully understand the extent to which specific configurations of the information structure impact contest outcomes. Second, our results suggest that problem-solving behavior can be a predictor of contestant success. Since the goal of the contest holder is to select the best quality solution that fits the specified requirements, it can be argued that problem-solving behavior dimensions that are positively correlated with success (e.g., position of first submission, length of participation, skewness of submissions) can be indicative of contestants that produce higher quality submissions in general. Therefore contest holders and platform providers in unblind innovation contests may want to encourage such behavior amongst all contestants. To increase the overall welfare generated by unblind innovation contests, platform providers could develop design guides and submission mechanisms that promote "successful" problem-solving behaviors. Specific recommendations on implementation and success of such mechanisms would require greater empirical validation.

6.3. Limitations and Potential Extensions

The study presented is not without limitations. First, as with all empirical studies using secondary data, there is a lack of control in the data generation process, which leads to potential biases in the results. In particular, we note that the absence of time stamps associated with a contestant's problem-solving behavior does not allow us to specifically capture the timing of first submission relative to the contest end date. In that regard, our review of other unblind innovation contest platforms (e.g., TaskCn.com, 99designs.com) indicates that submission time-stamps are generally not displayed on such platforms. This may be due to the fact that time stamps are not as relevant to other contestants and potential contestants as the information on the number of submissions already entered. Nonetheless, we explicitly note the absence of time stamps associated with contestants' problem-solving behavior as a limitation of our study. Additionally, another related limitation associated with the use of this secondary data source is our inability to track the amount of feedback received by each contestant from the contest holder during her active participation. Such level of granularity on feedback data would allow us to more precisely instrument the problem-solving behavior dimensions in our analysis. We have made significant efforts to reduce potential biases and obtain robust results through the use of several econometric techniques. However, using secondary data does not allow the researcher to "get inside the head" of contestants making it difficult to draw inferences about their behavioral decisions. A possible extension to this work is to develop and conduct a series of laboratory experiments to track problem-solving behavior, which would allow for tighter control and deeper insights into decision-making processes.

The goal of this study was to examine the dimensions of problem-solving behavior in unblind innovation contests and their relationship with the likelihood of success. The nature of competition in unblind innovation contests differs significantly from that in their blind counterparts. Understanding how contestants engage in problem solving in unblind innovation contests forms a critical, yet previously unaddressed, area of research in this domain. In closing, we hope that our research has shed new light on the roles of problem-solving behavior in unblind innovation contests and motivates future research in this domain.

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APPENDIX

Table A1: Descriptive Statistics and Correlation Matrix

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1 Placed this Contest	0.05	0.22	1.00																								
2 Position of First Submission	121.30	172.45	-0.07	1.00																							
3 Number of Submissions	4.48	6.18	0.29	0.00	1.00																						
4 Length of Participation	44.63	126.09	0.09	0.05	0.48	1.00																					
5 Skewness of Submissions	1.04	0.60	0.00	-0.04	0.01	0.11	1.00																				
6 Participation Experience	190.55	218.71	0.04	-0.01	0.00	0.06	0.03	1.00																			
7 Placing Experience	0.06	0.07	0.24	-0.02	0.17	0.05	0.01	0.11	1.00																		
8 Contest Designers	61.61	39.15	-0.09	0.63	0.09	0.41	0.03	-0.03	-0.02	1.00																	
9 Contest Views	1855.79	1301.59	-0.07	0.57	0.14	0.38	0.02	-0.03	0.00	0.82	1.00																
10 Private	0.33	0.47	-0.02	0.16	0.04	0.12	0.01	0.00	0.01	0.24	0.05	1.00															
11 Contest Duration	12.00	9.65	-0.02	0.14	0.06	0.07	0.00	0.01	0.00	0.19	0.43	0.05	1.00														
12 Contest Holder Comments	1.47	2.78	-0.01	0.12	0.10	0.09	0.00	0.01	0.02	0.09	0.24	0.07	0.21	1.00													
13 Contestant Comments	0.60	1.16	-0.04	0.35	0.08	0.27	0.02	-0.02	0.00	0.50	0.50	0.17	0.20	0.18	1.00												
14 Total Feedback Events	47.84	77.06	-0.04	0.58	0.14	0.44	0.02	-0.03	0.00	0.73	0.69	0.16	0.11	0.11	0.47	1.00											
15 Prize Amount	315.58	162.87	-0.06	0.52	0.10	0.36	0.03	-0.03	0.01	0.76	0.63	0.31	0.01	0.08	0.43	0.61	1.00										
16 Overlapping Contests	113.19	59.55	0.03	-0.14	0.00	-0.10	-0.02	0.00	0.00	-0.28	-0.07	-0.13	0.59	0.07	-0.06	-0.16	-0.53	1.00									
17 Overlapping Contests - Higher Prize	37.19	36.55	-0.02	0.14	0.06	0.06	-0.01	0.00	0.00	0.16	0.40	0.03	0.91	0.19	0.16	0.12	0.03	0.61	1.00								
18 ln(Words)	4.85	0.67	0.00	0.01	0.05	0.02	0.00	0.00	0.02	-0.03	0.05	0.08	0.07	0.19	0.02	-0.02	0.05	-0.05	0.07	1.00							
19 Submissions Per Participation	4.38	2.61	0.08	0.04	0.36	0.12	0.00	0.14	0.37	0.04	0.04	0.02	0.01	0.02	0.02	0.03	0.05	-0.03	0.01	0.01	1.00						
20 September	0.17	0.37	-0.01	-0.04	-0.02	-0.04	0.00	0.00	0.00	-0.04	-0.05	0.04	0.04	-0.03	-0.07	-0.09	-0.07	0.08	0.06	0.00	-0.01	1.00					
21 October	0.15	0.36	0.00	0.04	0.00	0.04	0.00	0.00	0.00	0.04	0.07	-0.05	-0.07	0.00	0.09	0.12	0.07	-0.03	-0.01	-0.02	-0.01	-0.19	1.00				
22 November	0.14	0.35	0.01	-0.05	0.00	-0.03	0.00	0.02	-0.01	-0.06	-0.02	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03	-0.05	0.00	0.00	-0.18	-0.17	1.00			
23 December	0.11	0.31	0.00	0.00	-0.01	-0.01	0.00	0.02	-0.01	0.04	0.02	-0.02	0.02	0.04	0.04	-0.01	-0.04	-0.13	-0.20	0.02	0.01	-0.16	-0.15	-0.14	1.00		
24 January	0.18	0.38	0.01	0.01	0.00	0.01	0.00	0.01	-0.01	0.01	-0.03	0.00	-0.07	-0.04	0.01	0.06	0.00	0.01	0.04	-0.02	0.00	-0.21	-0.20	-0.19	-0.16	1.00	
25 February	0.05	0.22	0.02	-0.06	-0.01	-0.04	-0.01	0.00	-0.01	-0.10	-0.12	-0.03	-0.09	-0.04	-0.08	-0.05	-0.04	-0.07	-0.13	-0.01	-0.01	-0.10	-0.10	-0.09	-0.08	-0.11	1.00

$|\rho| \geq 0.01$ significant at 0.05 level

Table A2: First Stage Models Predicting Problem-Solving Behavior

Independent Variables	Position of First Submission	Number of Submissions	Length of Participation	Skewness of Submissions
Participation Experience	25.500 (4.327)**	-0.811 (0.201)**	5.864 (3.249)†	0.011 (0.022)
Placing Experience	-2.994 (2.029)	0.754 (0.094)**	0.483 (1.524)	-0.002 (0.010)
Contest Designers	56.139 (1.374)**	-0.344 (0.065)**	35.600 (1.052)**	0.022 (0.007)**
Contest Views	15.785 (1.387)**	0.857 (0.065)**	9.974 (1.044)**	-0.004 (0.007)
Private	8.624 (1.414)**	0.416 (0.066)**	6.558 (1.062)**	-0.011 (0.007)
Contest Duration	-4.339 (1.784)*	-0.144 (0.083) †	-0.037 (1.339)	0.004 (0.009)
Contest Holder Comments	2.307 (0.227)**	0.132 (0.011)	0.783 (0.170)**	0.001 (0.001)
Contestant Comments	0.080 (0.610)	-0.036 (0.028)**	3.039 (0.458)**	-0.001 (0.003)
Total Feedback Events	0.490 (0.012)**	0.013 (0.001)	0.505 (0.009)**	0.000 (0.000)**
Prize Amount	11.712 (1.187)**	0.238 (0.055)**	15.479 (0.892)**	0.009 (0.006)
Overlapping Contests	-0.055 (0.030)†	0.001 (0.001)	-0.217 (0.022)**	0.000 (0.000)
Overlapping Contests—Higher Prize	0.210 (0.030)**	0.006 (0.001)**	0.348 (0.022)**	0.000 (0.000)
ln(Words)	2.389 (0.900)**	0.314 (0.042)**	1.200 (0.676)†	0.004 (0.005)
Submissions per Participation	-5.937 (1.187)**	-1.171 (0.055)**	-1.339 (0.893)	-0.004 (0.006)
September	-15.967 (2.186)**	-0.227 (0.102)**	-13.356 (1.641)**	-0.002 (0.011)
October	-26.527 (2.612)**	-0.449 (0.122)**	-16.205 (1.962)**	-0.013 (0.013)
November	-30.726 (2.981)**	0.000 (0.139)	-17.563 (2.240)**	0.001 (0.015)
December	-26.134 (3.622)**	-0.145 (0.168)	-20.772 (2.720)**	-0.019 (0.019)
January	-26.058 (3.493)**	-0.154 (0.162)	-12.668 (2.622)**	-0.012 (0.018)
February	-31.692 (4.567)**	-0.011 (0.212)	-20.054 (3.429)**	-0.025 (0.023)
Position of First Submission		-0.001 (0.000)**	-0.301 (0.004)**	0.000 (0.000)**
Number of Submissions			8.350 (0.079)**	-0.005 (0.001)**
Length of Participation				0.001 (0.000)**
Constant	124.501 (7.794)**	7.851 (0.363)**	38.731 (5.898)**	1.092 (0.040)**
F-value	1674.840***	145.040***	1831.590***	29.280***
df	20	21	22	23
Number of Contest-Designer pairs	44796	44796	44796	44796
Number of Designers	2623	2623	2623	2623

† $p<0.1$, * $p<0.05$, ** $p<0.01$